

References with abstracts for QWIM project: machine learning (and more) applied to market regimes, changepoints and anomaly detection in quantitative wealth and investment management

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1 Motivation for the project

There is much evidence that crash and bubble periods display much different patterns than normal markets, suggesting that forecasting models (and investing approaches) ought to be based on multiple regimes.

It was shown that asset performance over long time periods can be separated into distinctive periods, called regimes, which display common characteristics. Regime-based asset allocation has been shown to add value over rebalancing to static weights and, in particular, reduce potential drawdowns by reacting to changes in market conditions. regime based asset allocation can effectively respond to changes in financial regimes at the portfolio level, in an effort to provide better long-term results than more static approaches can offer.

Baltas and Karyampas (“Forecasting the equity risk premium: The importance of regime-dependent evaluation,” 2018):

”Is superior econometric predictability across the business cycle synonymous with predictability at all times?”

It appears that recently introduced forecasting models for equity risk premium ERP, which have been shown to generate econometrically superior ERP forecasts, have forecasting ability which is regime-dependent. They give rise to significant relative losses during market downturns, when it matters the most for asset allocators to retain assets and their client base intact. Conversely, any economic benefit occurring during market upswings is diminished for high risk-averse and leverage-constrained investors.

1.1 Market states in QWIM

It was observed empirically that there are two separate market states:

- low uncertainty (relatively stable and resilient) market
- high uncertainty (relatively chaotic and fragile) market

Markets in “**low uncertainty**” state:

- statistically well behaved
- can be modeled using standard statistical tools
- volatility is stable and low
- correlations relatively stable
- tail events (≥ 3 std deviations in either direction) quite rare.

Markets in “**high uncertainty**” state:

- not statistically well behaved
- vols and correlations change significantly on regular basis
- Tail events happen with much more regularity

To account for the two market states, practitioners use a relatively similar concept of “**risk on, risk off**”:

The “**high uncertainty**” state can incorporate multiple instances and multiple types of significant changes in time series:

- market regimes
- changepoints
- bubbles and crashes

1.2 Structural breaks: market regimes

Regime changes, some transitory, some recurring (recessions versus expansions) some permanent (structural breaks), are prevalent across a wide range of financial markets and in behavior of many macro variables. Examples of regimes considered in academia and/or practitioners:

- bull vs. bear market regimes
- inflationary vs. recessionary regimes
- high vs. low volatility regimes
- mean reverting vs. trending regimes

Regime shifts are challenging for investors because they cause portfolio performance, risk and behavior to depart significantly from ranges implied by long-term averages of means and covariances. Regime-based asset allocation was shown to deliver improved performance and risk profile

Good performance of investment strategies greatly enhanced with introduction of regime switching models RSMs. RSMs characterize market states using estimates of parameters of some underlying model, and use a transition matrix to quantify probability of moving from one state to another.

ML may be effective at detecting change (even in chaotic system), for example through robust anomaly detection. It can be enhanced to compute probability of observation in previously observed “market regimes” (defined as clusters in ML). Thus clustering algorithms can identify regimes in datasets. What they have in common with regular regime switching models is ability of producing probabilities of “switching” into another regime. ML can also feed on large amounts of data to detect preconditions of a break

1.3 Structural breaks: bubbles and crashes

Chaotic systems of the real world are comparable to stock market indices evolution. Log-periodic power law singularity (LPPLS) model captures well bubbles and crashes LPPLS framework successfully captures, ex-ante, most prominent bubbles across different time scales (Black Monday, Dot-com, and Subprime Crisis).

1.4 Structural breaks: changepoints

Change point detection (CPD) is the problem of finding abrupt changes in data when a property of the time series changes. Segmentation, edge detection, event detection, and anomaly detection are similar concepts within ML space.

Traditional changepoint detection methods only look for statistically-detectable boundaries that are defined as abrupt variations in the generative parameters of a data sequence. However, it is observed that breakpoints occur on more subtle boundaries non-trivial to detect with these statistical methods, but detectable using deep learning

2 Practical details for the project

The main purpose of the project described in this document is to provide exposure to students on important (and interesting) practical topics in quantitative wealth and investment management QWIM.

The level of complexity depends on the number of hours designated for the project. For example, 50-60 hours for a regular project, and 100-120 hours for a thesis/capstone project. Upon request, the scope (and the corresponding number of hours) of any given project can be extended.

The students would work on the project as part of a team (usually with 2-3 students).

All QWIM projects were selected such that the students’ efforts have a good chance of producing results relevant to the industry, and at least as good as the results presented in the QWIM literature. Thus for each project we may consider (on an optional basis, based primarily on students’ preference) to submit a corresponding article to journals widely followed by practitioners and academics in investment and wealth management, with participating students included as the leading coauthors of the submitted article.

The main challenge for each project is to identify the criteria for what would be considered **“good enough”**. Similar to projects in the industry, the meaning of “good enough” is based on a combination of comprehensive literature review, discussions within team and with me (and/or my colleagues) and analysis of results. Emphasis is placed on creating a narrative (with the aid of an interactive visualizer) for convincing the intended audience that what was done in the project delivers **“good enough”** outcome.

2.1 Interaction with students

For each project I would make myself available for meetings on a weekly basis (for discussions and guidance). Some of my colleagues have also expressed interest to participate in such meetings. Due to our work schedule and deliverables, most of the discussions will have to be scheduled outside working hours (in weekends or evenings). The meetings will take place through video conferencing such as WebEx, Zoom, Google Meet, Microsoft Teams, etc., based on the team’s preference. If the meetings are through WebEx, I would provide a link, while the student team will provide a link for any other video conferencing tool.

The students working on a given project can also send questions by email (my recommendation is to aggregate the questions from team members into an email sent once a day). We aim to provide answers within 1-2 days, either by email or through a phone discussion.

2.2 Data

Due to compliance reasons all projects would be based on publicly available, non-proprietary and non-confidential data (indices, ETFs, mutual funds, etc.). Since neither I nor my team are allowed to provide these datasets, I can only provide a list of suggested datasets. This list is included in a later section named Practical Info.

The datasets were selected to have the following features:

- be good proxies for most representative asset and subasset classes
- to be widely available
- to be as liquid as possible
- to have daily granularity
- to encompass periods with as many market regimes as possible (most proposed daily datasets are from 1990 or 1991)
- time series have “nicer” statistical properties compared to time series of, say, individual stocks or bonds

2.3 Private GitHub repository for the QWIM project

The team will create a private GitHub repository, which will store relevant project materials, including codes. The team will use Git Desktop application as source control repository linked to the GitHub repository.

2.4 Deliverables

The project deliverables include literature survey, numerical results, analysis and visualization. For each project references will be provided for a comprehensive literature survey, and students are encouraged to identify additional relevant literature. Regarding the implementation, the project will primarily use existing codes:

- Python and R packages from official repositories (PyPi for Python and CRAN for R)
- machine learning platforms such as TensorFlow, PyTorch, CNTK, Chainer, mlr3, H2O, PlaidML, mlpack, etc.
- implementations of articles through codes available in repositories such as GitHub, BitBucket, GitLab, etc.

Visualization of data and results visualization will be interactive and it will be based on Shiny R framework; to reduce programming effort, a template for such a Shiny visualizer will be provided in the team private GitHub repository.

The deliverables are:

- written report including literature survey and numerical results
- interactive visualizer (most likely Shiny-based visualizer using R and Python packages)
- (optional) presentation slides, and/or RMarkdown presentation, and/or Jupyter Notebook(s)

2.5 (Optional) Article submission to leading journals

On an optional basis (based primarily on students' preference), a version of the report can be prepared for submission to leading journals such as Journal of Financial Data Science, Journal of Portfolio Management, Journal of Asset Management, Journal of Investment Strategies, Quantitative Finance, Journal of Wealth Management, Journal of Investing, Journal of Machine Learning in Finance, etc.

3 Project tasks and timelines

For each project the main tasks are:

- 1) literature review
- 2) decide on the appropriate metrics and quantitative methods within context of "good enough" for the project
- 3) write-up summary of literature review: methods, metrics, testing procedures

- 4) identification of Python and/or R packages which are most appropriate for the selected methods and metrics
- 5) code design to decide on main code components
- 6) implementation of code components
- 7) interactive visualization of numerical results
- 8) project report containing description of methods, metrics, and tests, and analysis of results.

3.1 Suggested timelines for project tasks

The table below suggests a timeline for the project tasks and the corresponding percentages of project time:

Table 1: Suggested timeline for project tasks

Task ID	Task Name	Percentage of project time
1	Literature review	15%
2	Identification of "good enough" metrics and quantitative methods	5%
3	Write-up of summary of literature review	5%
4	Identification of appropriate packages in Python and/or R	10%
5	Code design for main components of project coding framework	5%
6	Implementation of coding framework and components	40%
7	Interactive visualizer using the provided Shiny template	10%
8	Project report and presentation	10%

3.2 Literature review

The first task is based on a comprehensive literature survey, included in the preliminary document of the project. Students are encouraged to identify additional relevant literature.

This task may be the most important of the project, since it provides an overview of what was done, what works well and less well, and what appear to be the most promising avenues to complete the project.

Emphasis is placed on information contained in the Main References, with analysis of the other References performed only as needed.

When reading the literature, there are 4 main directions to consider:

- 1) methods
- 2) metrics
- 3) testing procedures
- 4) numerical results

The primary focus would be on the the references included in "Main References" subsection of the document for your QWIM project. Then, to the extent there is time, to consider the other references included in the project document. In the same time, you are encouraged to identify other references that might be considered "Main references", and to share those references with me for discussion.

For the articles in Main References category, the suggested approach would be the following:

- For each article focus primarily on Abstract, Conclusion, and Numerical Results
- Do this for all articles considered to be Main References, such that you gain a high-level understanding of what is currently done in the literature
- Select the metrics that you may want to use in order to quantify the meaning of "good enough" for the project.
- Select the quantitative methods which appear to be most likely to be "good enough" for the project.
- Perform a "deeper dive" into the articles containing the approaches you consider the most promising,

For the articles which are not in "Main References" category, read Abstract, Conclusion, and Numerical Results, to see whether any of those articles might need to be considered for inclusion in your summary.

3.3 Write-up summary of literature review

The write-up summary summarizes the methods, metrics, testing procedures, and numerical results identified during the literature review. The write-up could also be incorporated within reports and/or presentations for the QWIM project.

3.4 Identification of appropriate Python and/or R packages

Based on the literature review and on discussions, we identify the most potentially useful methods, metrics and testing procedures. Then we identify the most appropriate implementations of the selected methods and metrics.

The primary sources of implementations are existing codes from:

- Python and R packages from official repositories (PyPi for Python and CRAN for R)
- machine learning platforms such as TensorFlow, PyTorch, CNTK, Chainer, mlr3, H2O, PlaidML, mlpack, etc.
- implementations of articles through codes available in repositories such as GitHub, BitBucket, GitLab, etc.

3.5 Code design

An important task is to have a code design session to decide in advance on the main code components, which are meant to be modular and encapsulated, such that the entire team can work on the codes.

Examples of such main code components are presented below:

- get data
- forecast
- optimization
- calculate metrics
- perform tests
- obtain results
- construct interactive visualizer

The code design procedure consists of:

- 1) visual display of major components of the coding framework
- 2) UML diagrams for each of the components.

The Appendix contains an illustrative example within context of a QWIM project on forecasting of financial time series. The first figure shows the major components, while the second figure shows UML diagrams of those components (the names of data members and methods are currently generic, and one would need to change them to appropriate names)

While these figures were obtained through Microsoft Visio using a code design file (.vsd file), there are other software tools (either online or installed locally) which can be used to create such code design diagrams. NOTE: if you have access to Microsoft Visio and you want to use it for code design diagrams, you can ask me for the .vsd file which was exported into the PDF from which I have extracted the snapshots.

List of software tools for code design diagrams, which are either free (open source) or have a free type of account

- Modelio (either [desktop](#) version or [online](#) version)
- LucidChart ([online](#))
- draw.io (either [desktop](#) version or [online](#) version, now called [app.diagrams.net](#))
- Visual Paradigm ([online](#))
- UMLet (either [desktop](#) or [online](#) version)
- [Curated list of UML tools – 2019 edition](#)
- [Top online UML modeling tools in 2019](#)

3.6 Implementation of coding framework and components

The implementation is done using identified packages or codes, in Python and/or R. The project will primarily use existing codes:

- Python and R packages from official repositories (PyPi for Python and CRAN for R)
- machine learning platforms such as TensorFlow, PyTorch, CNTK, Chainer, mlr3, H2O, PlaidML, mlpack, etc.
- implementations of articles through codes available in repositories such as GitHub, BitBucket, GitLab, etc.

3.7 Interactive visualizer

While visualization of data and numerical results can be done through various tools (including Jupyter notebooks or Dash in Python), my recommendation is to consider an interactive visualizer based on Shiny framework in R. A template for the Shiny visualizer will be provided in the private GitHub repository set up by the team for the project.

Some information about Shiny:

- [Shiny from RStudio: tutorials and gallery](#)
- [Why R Shiny Trumps UI and JavaScript Based Visualization Tools](#)
- [Shiny's Holy Grail: Interactivity with reproducibility](#)

3.8 Project report and presentation

The report containing description of methods, metrics, and tests, and analysis of results.

While the report can be written using various tools (including Microsoft Word), my recommendation is to use LyX to write both the project report and the project presentation. Two LyX templates for creating reports and, respectively, presentations will be provided in the private GitHub repository set up by the team for the project.

Some information about Shiny:

- [LyX features](#)
- [LyX tutorial](#) with PDF [here](#)
- LyX Tutorial video [Part One](#) and [Part Two](#)
- LyX tutorial video [Part One](#) and [Part Two](#) and [Part Three](#) and [Part Four](#)
- [Introduction to LyX](#)
- [Insert figures in LyX](#)
- [Essentials of LyX](#)

4 Literature Review

Main references:

- Costa and Kwon (“A regime-switching factor model for mean-variance optimization,” 2020),
Dal Pra et al. (“Regime Shifts in Excess Stock Return Predictability: An Out-of-Sample Portfolio Analysis,” 2018),
Demos and Sornette (“Birth or burst of financial bubbles: which one is easier to diagnose?” 2017),
Filimonov et al. (“Modified profile likelihood inference and interval forecast of the burst of financial bubbles,” 2017),
Fons et al. (“A novel dynamic asset allocation system using Feature Saliency Hidden Markov models for smart beta investing,” 2021),
Gerlach et al. (“Dissection of Bitcoin’s Multiscale Bubble History from January 2012 to February 2018,” 2018),
Lattanzi and Leonelli (“A changepoint approach for the identification of financial extreme regimes,” 2019),
Mizuno et al. (“Detecting Stock Market Bubbles Based on the Cross-Sectional Dispersion of Stock Prices,” 2020),
Nystrup et al. (“Dynamic Allocation or Diversification: A Regime-Based Approach to Multiple Assets,” 2018),
Nystrup et al. (“Dynamic portfolio optimization across hidden market regimes,” 2018),
Nystrup et al. (“Learning hidden Markov models with persistent states by penalizing jumps,” 2020),

Nystrup et al. (“Detecting change points in VIX and S&P 500: A new approach to dynamic asset allocation,” 2016),
 Nystrup et al. (“Regime-Based Versus Static Asset Allocation: Letting the Data Speak,” 2015),
 Pharasi et al. (“Market states: A new understanding,” 2020),
 Simonian (“Mixed Ag: A Regime-Based Analysis of Multi-Asset Agriculture Portfolios,” 2020),
 Simonian and Wu (“Factors in Time: Fine-Tuning Hedge Fund Replication,” 2019),
 Sornette et al. (“Can We Use Volatility to Diagnose Financial Bubbles? Lessons from 40 Historical Bubbles,” 2017),
 Wheatley et al. (“Are bitcoin bubbles predictable? combining a generalized metcalfe’s law and the LPPLS model,” 2018),

4.1 Market states, regimes and structural breaks of time series for investment strategies

References:

Bae et al. (“Dynamic asset allocation for varied financial markets under regime switching framework,” 2014),
 Costa and Kwon (“Risk parity portfolio optimization under a Markov regime-switching framework,” 2019),
 Costa and Kwon (“A regime-switching factor model for mean-variance optimization,” 2020),
 Fischer and Murg (“A combined regime-switching and Black Litterman model for optimal asset allocation,” 2015),
 Kim et al. (“Global Asset Allocation Strategy Using a Hidden Markov Model,” 2019),
 Komatsu and Makimoto (“Dynamic Investment Strategy with Factor Models Under Regime Switches,” 2015),
 Mulvey et al. (“Machine learning, economic regimes and portfolio optimisation,” 2018),
 Nystrup et al. (“Regime-Based Versus Static Asset Allocation: Letting the Data Speak,” 2015),
 Nystrup et al. (“Dynamic portfolio optimization across hidden market regimes,” 2018),
 Nystrup (“Regime-Based Asset Allocation: Do Profitable Strategies Exist?” 2014),
 Nystrup et al. (“Dynamic Allocation or Diversification: A Regime-Based Approach to Multiple Assets,” 2018),
 Papenbrock and Schwendner (“Handling risk-on/risk-off dynamics with correlation regimes and correlation networks,” 2015),
 Platanakis et al. (“Portfolios in a Regime Shifting Non-Normal World: Are Alternative Assets Beneficial?” 2017),
 Seidl (“Markowitz versus Regime Switching: An Empirical Approach,” 2012),
 Sheikh and Sun (“Regime Change: Implications of Macroeconomic Shifts on Asset Class and Portfolio Performance,” 2012),
 Simonian and Wu (“Minsky vs. Machine: New Foundations for Quant-Macro Investing,” 2019),

4.2 Regime-based asset allocation

References:

Ahmad et al. (“Regime dependent dynamics and European stock markets: Is asset allocation really possible?” 2015),
 Bae et al. (“Dynamic asset allocation for varied financial markets under regime switching framework,” 2014),
 Berger and Gencay (“Short-run wavelet-based covariance regimes for applied portfolio management,” 2020),
 Blin et al. (“A Macro Risk-Based Approach to Alternative Risk Premia Allocation,” 2017),
 Flint and Mare (“Regime-Based Tactical Allocation for Equity Factors and Balanced Portfolios,” 2019),
 Fons et al. (“A novel dynamic asset allocation system using Feature Saliency Hidden Markov models for smart beta investing,” 2021),
 Kritzman et al. (“Regime Shifts: Implications for Dynamic Strategies,” 2012),
 Lezmi et al. (“Portfolio Allocation with Skewness Risk: A Practical Guide,” 2018),
 Liszewski (“Asset allocation under multiple regimes,” 2016),
 Nystrup et al. (“Dynamic portfolio optimization across hidden market regimes,” 2018),
 Nystrup et al. (“Regime-Based Versus Static Asset Allocation: Letting the Data Speak,” 2015),
 Nystrup et al. (“Dynamic Allocation or Diversification: A Regime-Based Approach to Multiple Assets,” 2018),
 Oliveira and Valls Pereira (“Asset Allocation With Markovian Regime Switching: Efficient Frontier and Tangent Portfolio With Regime Switching,” 2018),
 Sheikh and Sun (“Regime Change: Implications of Macroeconomic Shifts on Asset Class and Portfolio Performance,” 2012),
 van Vliet and Blitz (“Dynamic strategic asset allocation: Risk and return across the business cycle,” 2011),
 Vo and Maurer (“Dynamic Asset Allocation under Regime Switching, Predictability and Parameter Uncertainty,” 2013),

4.3 Detection and usage of bubbles, crashes and business cycles for investment strategies

References:

- Astill et al. ("Real-Time Monitoring for Explosive Financial Bubbles," 2018),
Bianchi ("The Great Depression and the Great Recession: A view from financial markets," 2020),
Cram ("Late to Recessions: Stocks and the Business Cycle," 2020),
Engle and Ruan ("Measuring the probability of a financial crisis," 2019),
Gerlach et al. ("Crash-sensitive Kelly Strategy built on a modified Kreuser-Sornette bubble model tested over three decades of twenty equity indices," 2020),
Gobel and Araujo ("Indicators of economic crises: a data-driven clustering approach," 2020),
Kole and van Dijk ("How to Identify and Forecast Bull and Bear Markets?" 2016),
Kreuser and Sornette ("Super-Exponential RE bubble model with efficient crashes," 2019),
Mehta ("The Mechanism behind the Bursting of Financial Bubbles and Market Crashes," 2020),
Mizuno et al. ("Detecting Stock Market Bubbles Based on the Cross-Sectional Dispersion of Stock Prices," 2020),
Smug et al. ("Predicting Financial Market Crashes Using Ghost Singularities," 2017),
Sornette ("Dragon-kings and Predictions: Diagnostics and Forecasts for the World Financial Crisis," 2014),
Sornette and Cauwels ("Financial bubbles: mechanisms and diagnostics," 2014),
Sornette et al. ("Real-time prediction and post-mortem analysis of the Shanghai 2015 stock market bubble and crash," 2015),
Sornette et al. ("Resolving Persistent Uncertainty by Self-Organized Consensus to Mitigate Market Bubbles," 2016),
Sornette et al. ("Can We Use Volatility to Diagnose Financial Bubbles? Lessons from 40 Historical Bubbles," 2017),
Viebig ("Exuberance in Financial Markets: Evidence from Machine Learning Algorithms," 2020),
Wang and Zong ("Are Crises Predictable? A Review of the Early Warning Systems in Currency and Stock Markets," 2020),
Yan and Huang ("Financial cycle and business cycle: An empirical analysis based on the data from the U.S," 2020),
Yao and Li ("A study on the bursting point of Bitcoin based on the BSADF and LPPLS methods," 2021),
Zhang et al. ("LPPLS bubble indicators over two centuries of the S&P 500 index," 2016),

References

- Ahmad, W., Bhanumurthy, N. R., and Sehgal, S. (2015). “Regime dependent dynamics and European stock markets: Is asset allocation really possible?” In: *Empirica* 42(1), pp. 77–107.
- In this study, we examine the regime shifts and volatility in stock market returns of eighteen European stock markets and the USA and utilize these regimes in asset allocation and risk management contexts. Using a Markov regime switching model, the study finds strong evidence of regime switching characterized by two regimes over the sample period from February, 1996 to January, 2012. Smoothed probabilities and time-varying conditional volatilities also highlight the meaningful turning points including the recent global financial crisis (2008) and Eurozone crisis (2009). Analyzing the market synchronization and Sharpe ratios, the study finally concludes that sample markets provide very limited scope of asset allocation and risk diversification.
- Astill, S., Harvey, D. I., Leybourne, S. J., Sollis, R., and Taylor, A. M. R. (2018). “Real-Time Monitoring for Explosive Financial Bubbles.” In: *Journal of Time Series Analysis* 39(6), pp. 863–891.
- We propose new methods for the real-time detection of explosive bubbles in financial time series. Most extant methods are constructed for a fixed sample of data and, as such, are appropriate only when applied as one-shot tests. Sequential application of these tests, declaring the presence of a bubble as soon as one of these statistics exceeds the one-shot critical value, would yield a detection procedure with an unknown false-positive rate likely to be far in excess of the nominal level. Our approach sequentially applies the one-shot tests of Astill et al. (2017), comparing sub-sample statistics calculated in real time during the monitoring period with the corresponding sub-sample statistics obtained from a prior training period. We propose two procedures: one based on comparing the real-time monitoring period statistics with the maximum statistic over the training period, and another that compares the number of consecutive exceedances of a threshold value in the monitoring and training periods, the threshold value obtained from the training period. Both allow the practitioner to determine the false-positive rate for any given monitoring horizon, or to ensure that this rate does not exceed a specified level by setting a maximum monitoring horizon. Monte Carlo simulations suggest that the finite-sample false-positive rates lie close to their theoretical counterparts, even in the presence of time-varying volatility and serial correlation in the shocks. The procedures are shown to perform well in the presence of a bubble in the monitoring period, offering the possibility of rapid detection of an emerging bubble in a real-time setting. An empirical application to monthly stock market index data is considered.
- Bae, G. I., Kim, W. C., and Mulvey, J. M. (2014). “Dynamic asset allocation for varied financial markets under regime switching framework.” In: *European Journal of Operational Research* 234(2), pp. 450–458.
- Asset allocation among diverse financial markets is essential for investors especially under situations such as the financial crisis of 2008. Portfolio optimization is the most developed method to examine the optimal decision for asset allocation. We employ the hidden Markov model to identify regimes in varied financial markets; a regime switching model gives multiple distributions and this information can convert the static mean-variance model into an optimization problem under uncertainty, which is the case for unobservable market regimes. We construct a stochastic program to optimize portfolios under the regime switching framework and use scenario generation to mathematically formulate the optimization problem. In addition, we build a simple example for a pension fund and examine the behavior of the optimal solution over time by using a rolling-horizon simulation. We conclude that the regime information helps portfolios avoid risk during left-tail events.
- Baltas, N. and Karyampas, D. (2018). “Forecasting the equity risk premium: The importance of regime-dependent evaluation.” In: *Journal of Financial Markets* 38(March), pp. 83–102.
- Asset allocation is critically dependent on the ability to forecast the equity risk premium (ERP) out-of-sample. But, is superior econometric predictability across the business cycle synonymous with predictability at all times? We evaluate recently introduced ERP forecasting models, which have been shown to generate econometrically superior ERP forecasts, and find that their forecasting ability is regime-dependent. They give rise to significant relative losses during market downturns, when it matters the most for asset allocators to retain assets and their client base intact. Conversely, any economic benefit occurring during market upswings is diminished for high risk-averse and leverage-constrained investors.
- Berger, T. and Gencay, R. (2020). “Short-run wavelet-based covariance regimes for applied portfolio management.” In: *Journal of Forecasting* 39(4), pp. 642–660.
- Decisions on asset allocations are often determined by covariance estimates from historical market data. In this paper, we introduce a wavelet-based portfolio algorithm, distinguishing between newly embedded news and long-run information that has already been fully absorbed by the market. Exploiting the wavelet decomposition into short- and long-run covariance regimes, we introduce an approach to focus on particular covariance components. Using generated data, we demonstrate that short-run covariance regimes comprise the relevant information for periodical portfolio management. In an empirical application to US stocks and other international markets for weekly, monthly, quarterly, and yearly holding periods (and rebalancing), we present evidence that the application of wavelet-based covariance estimates from short-run information outperforms portfolio allocations that are based on covariance estimates from historical data.

Bianchi, F. (2020). “The Great Depression and the Great Recession: A view from financial markets.” In: *Journal of Monetary Economics* 114, pp. 240–261.

Similarities between the Great Depression and the Great Recession are documented with respect to the behavior of financial markets. A Great Depression regime is identified by using a Markov-switching VAR. The probability of this regime has remained close to zero for many decades, but spiked for a short period during the most recent financial crisis, the Great Recession. The Great Depression regime implies a collapse of the stock market, with small-growth stocks outperforming small-value stocks. A model with financial frictions and uncertainty about policy makers’ intervention suggests that policy intervention during the Great Recession might have avoided a second Great Depression. A multi-country analysis shows that the Great Depression and Great Recession were not like any other financial crises.

Blin, O., Ielpo, F., Lee, J., and Teiletche, J. (2017). “A Macro Risk-Based Approach to Alternative Risk Premia Allocation.” In: *Factor Investing*. Elsevier, pp. 285–316.

Alternative risk premia are encountering growing interest from investors. The vast majority of academic literature has been focusing on describing the alternative risk premia (typically, momentum, carry and value strategies) individually. In this chapter, we investigate the question of the allocation across a range of cross-asset alternative risk premia. For this, we design an active macro risk-based framework that notably aims to exploit alternative risk premia’s varying behavior in different macro regimes. We build long-term strategic portfolios across economic regimes, which we dynamically tilt based on point-in-time signals related to regimes nowcasting and current carry. We perform back tests of the allocation strategy in an out-of-sample setting.

Costa, G. and Kwon, R. H. (2019). “Risk parity portfolio optimization under a Markov regime-switching framework.” In: *Quantitative Finance* 19(33), pp. 453–471.

We formulate and solve a risk parity optimization problem under a Markov regime-switching framework to improve parameter estimation and to systematically mitigate the sensitivity of optimal portfolios to estimation error. A regime-switching factor model of returns is introduced to account for the abrupt changes in the behaviour of economic time series associated with financial cycles. This model incorporates market dynamics in an effort to improve parameter estimation. We proceed to use this model for risk parity optimization and also consider the construction of a robust version of the risk parity optimization by introducing uncertainty structures to the estimated market parameters. We test our model by constructing a regime-switching risk parity portfolio based on the Fama-French three-factor model. The out-of-sample computational results show that a regime-switching risk parity portfolio can consistently outperform its nominal counterpart, maintaining a similar ex post level of risk while delivering higher-than-nominal returns over a long-term investment horizon. Moreover, we present a dynamic portfolio rebalancing policy that further magnifies the benefits of a regime-switching portfolio.

Costa, G. and Kwon, R. H. (2020). “A regime-switching factor model for mean-variance optimization.” In: *Journal of Risk* 22(4), pp. 31–59.

We formulate a novel Markov regime-switching factor model to describe the cyclical nature of asset returns in modern financial markets. Maintaining a factor model structure allows us to easily derive the asset expected returns and their corresponding covariance matrix. By design, these two parameters are calibrated to better describe the properties of the different market regimes. In turn, these regime-dependent parameters serve as the inputs during mean-variance optimization, thereby constructing portfolios adapted to the current market environment. Through this formulation, the proposed model allows for the construction of large, realistic portfolios at no additional computational cost during optimization. Moreover, the viability of this model can be significantly improved by periodically rebalancing the portfolio, ensuring proper alignment between the estimated parameters and the transient market regimes. An out-of-sample computational experiment over a long investment horizon shows that the proposed regime-dependent portfolios are better aligned with the market environment, yielding a higher ex post rate of return and lower volatility than competing portfolios.

Cram, R. G. (2020). “Late to Recessions: Stocks and the Business Cycle.” In: *SSRN e-Print*.

I find that returns are predictably negative for several months after the onset of recessions, and only become high thereafter. I identify business-cycle turning points by estimating a state-space model using macroeconomic data. Conditioning on the business cycle further reveals that returns exhibit momentum in recessions, whereas in expansions they display the mild reversals expected from discount rate changes. A market timing strategy that optimally exploits this business-cycle pattern produces a 60% increase in the buy-and-hold Sharpe ratio. I find that a subset of hedge funds add value for their clients in part by avoiding stock market crashes during recessions.

Dal Pra, G., Guidolin, M., Pedio, M., and Vasile, F. (2018). “Regime Shifts in Excess Stock Return Predictability: An Out-of-Sample Portfolio Analysis.” In: *The Journal of Portfolio Management* 44(3), pp. 10–24.

The authors analyze the out-of-sample performance of asset allocation decisions based on financial ratio predictability of aggregate stock market returns under linear and regime-switching models. The authors adopt both a statistical perspective to analyze whether models based on valuation ratios can forecast excess equity returns, and an economic

approach that turns predictions into portfolio strategies. These consist of a portfolio switching approach, a mean-variance framework, and a long-run dynamic model. The authors find a disconnect between the statistical perspective, whereby the ratios yield a modest forecasting power, and a portfolio approach, by which a moderate predictability is often sufficient to yield significant portfolio outperformance, especially before transaction costs and when regimes are taken into account. However, also when regimes are considered, predictability gives high payoffs only to long horizon, highly risk-averse investors. Moreover, different strategies deliver different performance rankings across predictors.

Demos, G. and Sornette, D. (2017). “Birth or burst of financial bubbles: which one is easier to diagnose?” In: *Quantitative Finance* 17(5), pp. 657–675.

Abreu and Brunnermeier (2003) have argued that bubbles are not suppressed by arbitrageurs because they fail to synchronise on the uncertain beginning of the bubble. We propose an indirect quantitative test of this hypothesis and confront it with the alternative according to which bubbles persist due to the difficulty of agreeing on the end of bubbles. We present systematic tests of the precision and reliability with which the beginning t_1 and end t_c of a bubble can be determined. For this, we use a specific bubble model, the log-periodic power law singularity (LPPLS) model, which represents a bubble as a transient noisy super-exponential price trajectory decorated by accelerated volatility oscillations. Generalising the estimation procedure to endogenise the beginning of the fitting time interval, we quantify the uncertainty on the calibrated t_1 and t_c (as well as the other model parameters) via the eigenvalues of the Hessian matrix, which characterise the shape of the calibration cost function in the different directions in parameter space, on many synthetic data and four historical bubble cases. We find overwhelming evidence that the beginning of bubbles is much better constrained than their end. Our results are robust over all four empirical bubbles and many synthetic tests, as well as when changing the time of analysis (the present) during the development of the bubbles. As a bonus, we find that the two structural parameters of the LPPLS model, the exponent m controlling the super-exponential growth of price and the angular log-periodic frequency ω describing the log-periodic acceleration of volatility, are very rigid according to the Hessian matrix analysis, which supports the LPPLS model as a reasonable candidate for describing the generating process of prices during bubbles.

Engle, R. F. and Ruan, T. (2019). “Measuring the probability of a financial crisis.” In: *Proceedings of the National Academy of Sciences* 116(37), pp. 18341–18346.

This study develops quantitative estimates of the level of systemic risk in the financial sector that precipitates a financial crisis. When financial firms are undercapitalized, they face difficulty in covering losses in a downturn. The natural response to such vulnerability, reducing leverage through asset sales, can start a financial crisis. Perilous excessive credit growth is reflected in the undercapitalization of the financial sector. Market-based indicators of systemic risk such as SRISK, which stands for systemic risk, measure such weakness in real time. We develop a probability of crisis measure and an SRISK capacity measure for 23 developed countries. Our analysis highlights the important global externality whereby the risk of a crisis in one country depends on the undercapitalization of the rest of the world.

Filimonov, V., Demos, G., and Sornette, D. (2017). “Modified profile likelihood inference and interval forecast of the burst of financial bubbles.” In: *Quantitative Finance* 17(8), pp. 1167–11861–20.

We present a detailed methodological study of the application of the modified profile likelihood method for the calibration of nonlinear financial models characterized by a large number of parameters. We apply the general approach to the Log-Periodic Power Law Singularity (LPPLS) model of financial bubbles. This model is particularly relevant because one of its parameters, the critical time signalling the burst of the bubble, is arguably the target of choice for dynamical risk management. However, previous calibrations of the LPPLS model have shown that the estimation of is in general quite unstable. Here, we provide a rigorous likelihood inference approach to determine , which takes into account the impact of the other nonlinear (so-called ?nuisance?) parameters for the correct adjustment of the uncertainty on . This provides a rigorous interval estimation for the critical time, rather than the point estimation in previous approaches. As a bonus, the interval estimates can also be obtained for the nuisance parameters (, damping), which can be used to improve filtering of the calibration results. We show that the use of the modified profile likelihood method dramatically reduces the number of local extrema by constructing much simpler smoother log-likelihood landscapes. The remaining distinct solutions can be interpreted as genuine scenarios that unfold as the time of the analysis flows, which can be compared directly via their likelihood ratio. Finally, we develop a multi-scale profile likelihood analysis to visualize the structure of the financial data at different scales (typically from 100 to 750 days). We test the methodology successfully on synthetic price time series and on three well-known historical financial bubbles.

Fischer, E. O. and Murg, M. (2015). “A combined regime-switching and Black Litterman model for optimal asset allocation.” In: *Journal of Investment Strategies* 4(3), pp. 1–36.

Traditionally, portfolios are optimized with a single-regime Markowitz model, using volatility as the risk measure and historical return as the expected return. This paper shows what effects a regime-switching framework, alternative risk measures (modified value-at-risk and conditional value-at-risk) and return measures (capital asset pricing model estimates and Black Litterman estimates) can have on asset allocation as well as the absolute and relative performance of

portfolios. We show that the combination of alternative risk and return measures within the regime-switching framework gives significantly better results in terms of performance and a modified Sharpe ratio. The use of alternative risk and return measures also mitigates the issue that asset returns are not often normally distributed or serially correlated. To eliminate the empirical shortcomings of asset returns, an unsmoothing algorithm in combination with the Cornish-Fisher expansion is used.

Flint, E. J. and Mare, E. (2019). “Regime-Based Tactical Allocation for Equity Factors and Balanced Portfolios.” In: *South African Actuarial Journal* 19(1), pp. 27–52.

It is now an accepted fact that the majority of financial markets worldwide are neither normal nor constant, and South Africa is no exception. One idea that can be used to understand such markets and has been gaining popularity recently is that of regimes and regime-switching models. In this research, we consider whether regimes can add value to the asset allocation process. Four methods for regime identification – economic cycle variables, fundamental valuation metrics, technical market indicators and statistical regime-switching models – are discussed and tested on two asset universes – longonly South African equity factor returns and representative balanced portfolio asset class returns. We find several promising regime indicators and use these to create two regime-based tactical allocation frameworks. Out-of-sample testing on both the equity factor and balanced asset class data shows very promising results, with both regime-based tactical strategies outperforming their respective static benchmarks on an absolute return and risk-adjusted return basis. We also turn our attention to a potentially major recent development in the local fund management space; namely, the introduction of Capped Shareholder-Weighted indices as new benchmarks. We provide comparative analysis between the capped and uncapped Shareholder-Weighted indices in terms of sector weights, stock concentration, currency exposure and factor risk contributions.

Fons, E., Dawson, P., Yau, J., Zeng, X.-j., and Keane, J. (2021). “A novel dynamic asset allocation system using Feature Saliency Hidden Markov models for smart beta investing.” In: *Expert Systems with Applications* 163, pp. 113720+.

The financial crisis of 2008 generated interest in more transparent, rules-based strategies for portfolio construction, with smart beta strategies emerging as a trend among institutional investors. Whilst they perform well in the long run, these strategies often suffer from severe short-term drawdown (peak-to-trough decline) with fluctuating performance across cycles. To manage short term risk (cyclicality and underperformance), we build a dynamic asset allocation system using Hidden Markov Models (HMMs). We use a variety of portfolio construction techniques to test our smart beta strategies and the resulting portfolios show an improvement in risk-adjusted returns, especially on more return-oriented portfolios (up to 50% of return in excess of market adjusted by relative risk annually). In addition, we propose a novel smart beta allocation system based on the Feature Saliency HMM (FSHMM) algorithm that performs feature selection simultaneously with the training of the HMM, to improve regime identification. We evaluate our systematic trading system with real life assets using MSCI indices; further, the results (up to 60% of return in excess of market adjusted by relative risk annually) show model performance improvement with respect to portfolios built using full feature HMMs.

Gerlach, J.-C., Demos, G., and Sornette, D. (2018). “Dissection of Bitcoin’s Multiscale Bubble History from January 2012 to February 2018.” In: *arXiv e-Print*.

We present a detailed bubble analysis of the Bitcoin to US Dollar price dynamics from January 2012 to February 2018. We introduce a robust automatic peak detection method that classifies price time series into periods of uninterrupted market growth (drawups) and regimes of uninterrupted market decrease (drawdowns). In combination with the Lagrange Regularisation Method for detecting the beginning of a new market regime, we identify 3 major peaks and 10 additional smaller peaks, that have punctuated the dynamics of Bitcoin price during the analyzed time period. We explain this classification of long and short bubbles by a number of quantitative metrics and graphs to understand the main socio-economic drivers behind the ascent of Bitcoin over this period. Then, a detailed analysis of the growing risks associated with the three long bubbles using the Log-Periodic Power Law Singularity (LPPLS) model is based on the LPPLS Confidence Indicators, defined as the fraction of qualified fits of the LPPLS model over multiple time windows. Furthermore, for various fictitious present analysis times t_2 , positioned in advance to bubble crashes, we employ a clustering method to group LPPLS fits over different time scales and the predicted critical times t_c (the most probable time for the start of the crash ending the bubble). Each cluster is argued to provide a plausible scenario for the subsequent Bitcoin price evolution. We present these predictions for the three long bubbles and the four short bubbles that our time scale of analysis was able to resolve. Overall, our predictive scheme provides useful information to warn of an imminent crash risk.

Gerlach, J.-C., Kreuser, J. L., and Sornette, D. (2020). “Crash-sensitive Kelly Strategy built on a modified Kreuser-Sornette bubble model tested over three decades of twenty equity indices.” In: *SSRN e-Print*.

We present a modified version of the super-exponential rational expectations “Efficient Crashes” bubble model of (Kreuser and Sornette, 2019) with a different formulation of the expected return that makes clearer the additive nature of corrective jumps. We derive a Kelly trading strategy for the new model. We combine the strategy with a simplified estimation procedure for the model parameters from price time series. We optimize the control parameters of the trading

strategy by maximizing the return-weighted accuracy of trades. This enables us to predict the out-of-sample optimal investment, purely based on in-sample calibration of the model on historical data. Our approach solves the difficult problem of selecting the portfolio rebalancing time, as we endogenize it as an optimization parameter. We develop an ex-ante backtest that allows us to test our strategy on twenty equity asset indices. We find that our trading strategy achieves positive trading performance for 95% of tested assets and outperforms the Buy-and-Hold-Strategy in terms of CAGR and Sharpe Ratio in 60% of cases. In our simulations, we do not allow for any short trading or leverage. Thus, we simply simulate allocation of 0-100% of one's capital between a risk-free and the risky asset over time. The optimal rebalancing periods are mostly of duration around a month; thus, the model does not overtrade, ensuring reasonable trading costs. Furthermore, during crashes, the model reduces the invested amount of capital sufficiently soon to reduce impact of price drawdowns. In addition to the Dotcom bubble, the great financial crisis of 2008 and other historical crashes, our study also covers the most recent crash in March 2020 that happened globally as a consequence of the economic shutdowns that were imposed as a reaction to the spread of the Coronavirus across the world.

Gobel, M. and Araujo, T. (2020). "Indicators of economic crises: a data-driven clustering approach." In: *Applied Network Science* 5(1) (44).

The determination of reliable early-warning indicators of economic crises is a hot topic in economic sciences. Pinning down recurring patterns or combinations of macroeconomic indicators is indispensable for adequate policy adjustments to prevent a looming crisis. We investigate the ability of several macroeconomic variables telling crisis countries apart from non-crisis economies. We introduce a self-calibrated clustering-algorithm, which accounts for both similarity and dissimilarity in macroeconomic fundamentals across countries. Furthermore, imposing a desired community structure, we allow the data to decide by itself, which combination of indicators would have most accurately foreseen the exogeneously defined network topology. We quantitatively evaluate the degree of matching between the data-generated clustering and the desired community-structure.

Kim, E.-c., Jeong, H.-w., and Lee, N.-y. (2019). "Global Asset Allocation Strategy Using a Hidden Markov Model." In: *Journal of Risk and Financial Management* 12(4), p. 168.

This study uses the hidden Markov model (HMM) to identify the phases of individual assets and proposes an investment strategy using price trends effectively. We conducted empirical analysis for 15 years from January 2004 to December 2018 on universes of global assets divided into 10 classes and the more detailed 22 classes. Both universes have been shown to have superior performance in strategy using HMM in common. By examining the change in the weight of the portfolio, the weight change between the asset classes occurs dynamically. This shows that HMM increases the weight of stocks when stock price rises and increases the weight of bonds when stock price falls. As a result of analyzing the performance, it was shown that the HMM effectively reflects the asset selection effect in Jensen's alpha, Fama's Net Selectivity and Treynor-Mazuy model. In addition, the strategy of the HMM has positive gamma value even in the Treynor-Mazuy model. Ultimately, HMM is expected to enable stable management compared to existing momentum strategies by having asset selection effect and market forecasting ability.

Kole, E. and van Dijk, D. (2016). "How to Identify and Forecast Bull and Bear Markets?" In: *Journal of Applied Econometrics* 32(1), pp. 120–139.

Because the state of the equity market is latent, several methods have been proposed to identify past and current states of the market and forecast future ones. These methods encompass semi-parametric rule-based methods and parametric Markov switching models. We compare the mean-variance utilities that result when a risk-averse agent uses the predictions of the different methods in an investment decision. Our application of this framework to the S&P 500 shows that rule-based methods are preferable for (in-sample) identification of the state of the market, but Markov switching models for (out-of-sample) forecasting. In-sample, only the mean return of the market index matters, which rule-based methods exactly capture. Because Markov switching models use both the mean and the variance to infer the state, they produce superior forecasts and lead to significantly better out-of-sample performance than rule-based methods. We conclude that the variance is a crucial ingredient for forecasting the market state.

Komatsu, T. and Makimoto, N. (2015). "Dynamic Investment Strategy with Factor Models Under Regime Switches." In: *Asia-Pacific Financial Markets* 22(2), pp. 209–237.

A model for dynamic investment strategy is developed where assets' returns are represented by multiple factors. In a mean variance framework with factor models under regime switches, we derive a semi-analytic solution for the optimal portfolio with transaction costs. Due to the existence of transaction costs, the optimal portfolio is characterized as a linear combination of current and target portfolios, the latter of which maximizes the value function in the current regime. For some special cases of interest, we also derive simplified analytical solutions. To see the effect of regime switches, the proposed model is applied to US equity market in which small minus big and high minus low are employed as factors. Investment strategy based on our model demonstrates empirically that the regime switching models exhibit superior performance over the single regime model for such performance measures as realized utility and Sharpe ratio which are of particular interest in practice. Taking a close look at the time series of portfolio returns, the result shows

the usefulness of the regime switching model as investors flexibly optimize asset allocations depending on the state of the market.

Kreuser, J. and Sornette, D. (2019). “Super-Exponential RE bubble model with efficient crashes.” In: *The European Journal of Finance* 25(4), pp. 338–368.

We propose a dynamic Rational Expectations (RE) bubble model of prices, combining a geometric random walk with separate crash (and rally) discrete jump distributions associated with positive (and negative) bubbles. Crashes tend to efficiently bring back excess bubble prices close to a “normal” process. Then, the RE condition implies that the excess risk premium of the risky asset exposed to crashes is an increasing function of the amplitude of the expected crash, which itself grows with the bubble mispricing: hence, the larger the bubble price, the larger its subsequent growth rate. This positive feedback of price on return is the archetype of super-exponential price dynamics. We use the RE condition to estimate the real-time crash probability dynamically through an accelerating probability function depending on the increasing expected return. After showing how to estimate the model parameters, we obtain a closed-form approximation for the optimal investment that maximizes the expected log of wealth (Kelly criterion) for the risky bubbly asset and a risk-free asset. We demonstrate, on seven historical crashes, the promising outperformance of the method compared to a 60/40 portfolio, the classic Kelly allocation, and the risky asset, and how it mitigates jumps, both positive and negative.

Kritzman, M., Page, S., and Turkington, D. (2012). “Regime Shifts: Implications for Dynamic Strategies.” In: *Financial Analysts Journal* 68(3).

Regime shifts present significant challenges for investors because they cause performance to depart significantly from the ranges implied by long-term averages of means and covariances. But regime shifts also present opportunities for gain. The authors show how to apply Markov-switching models to forecast regimes in market turbulence, inflation, and economic growth. They found that a dynamic process outperformed static asset allocation in backtests, especially for investors who seek to avoid large losses.

Lattanzi, C. and Leonelli, M. (2019). “A changepoint approach for the identification of financial extreme regimes.” In: *arXiv e-Print*.

Inference over tails is usually performed by fitting an appropriate limiting distribution over observations that exceed a fixed threshold. However, the choice of such threshold is critical and can affect the inferential results. Extreme value mixture models have been defined to estimate the threshold using the full dataset and to give accurate tail estimates. Such models assume that the tail behavior is constant for all observations. However, the extreme behavior of financial returns often changes considerably in time and such changes occur by sudden shocks of the market. Here we extend the extreme value mixture model class to formally take into account distributional extreme changepoints, by allowing for the presence of regime-dependent parameters modelling the tail of the distribution. This extension formally uses the full dataset to both estimate the thresholds and the extreme changepoint locations, giving uncertainty measures for both quantities. Estimation of functions of interest in extreme value analyses is performed via MCMC algorithms. Our approach is evaluated through a series of simulations, applied to real data sets and assessed against competing approaches. Evidence demonstrates that the inclusion of different extreme regimes outperforms both static and dynamic competing approaches in financial applications.

Lezmi, E., Malongo, H., Roncalli, T., and Sobotka, R. (2018). “Portfolio Allocation with Skewness Risk: A Practical Guide.” In: *SSRN e-Print*.

In this article, we show how to take into account skewness risk in portfolio allocation. Until recently, this issue has been seen as a purely statistical problem, since skewness corresponds to the third statistical moment of a probability distribution. However, in finance, the concept of skewness is more related to extreme events that produce portfolio losses. More precisely, the skewness measures the outcome resulting from bad times and adverse scenarios in financial markets. Based on this interpretation of the skewness risk, we focus on two approaches that are closely connected. The first one is based on the Gaussian mixture model with two regimes: a normal regime and a turbulent regime. The second approach directly incorporates a stress scenario using jump-diffusion modeling. This second approach can be seen as a special case of the first approach. However, it has the advantage of being clearer and more in line with the experience of professionals in financial markets: skewness is due to negative jumps in asset prices. After presenting the mathematical framework, we analyze an investment portfolio that mixes risk premia, more specifically risk parity, momentum and carry strategies. We show that traditional portfolio management based on the volatility risk measure is biased and corresponds to a short-sighted approach to bad times. We then propose to replace the volatility risk measure by a skewness risk measure, which is calculated as an expected shortfall that incorporates a stress scenario. We conclude that constant-mix portfolios may be better adapted than actively managed portfolios, when the investment universe is composed of negatively skewed financial assets.

Liszewski, O. (2016). “Asset allocation under multiple regimes.” MA thesis. Erasmus University.

In this paper we examine the performance of the Markov Switching model with intra-regimes changes such as the bull market correction and bear market rallies. We accommodate this short time rehearsals by imposing restrictions on the transition probability matrix. We compare the model with classic mean-switching and dynamic VAR models in an asset allocation problem with different number of regimes, initial states choices and asset distributions used in the estimation process. In an out-of-sample and bootstrap verification we give evidence that the constrained model outperforms other models in terms of risk-adjusted returns in the long horizon above 2 years.

Mehta, P. (2020). “[The Mechanism behind the Bursting of Financial Bubbles and Market Crashes](#).” In: *SSRN e-Print*.

This article proposes to deliver an algorithm to envisage the distribution of the critical points of bubbles, may it be a financial bubble or an asset bubble. The study comprehensively examines the use of Log periodic Power law in various articles from renowned authors from the first paper that was published by Didier Sornette in 1996 to the present day. The paper scrutinizes the prerogatives and robustness of the LPPL for large market falls and the anti-bubbles that build in a market. The LPPL fit has been attempted to fit into various crashes in different stock markets that were predicted previously to establish the smooth working of the model.

Mizuno, T., Ohnishi, T., and Watanabe, T. (2020). “[Detecting Stock Market Bubbles Based on the Cross-Sectional Dispersion of Stock Prices](#).” In: *Proceedings of the 23rd Asia Pacific symposium on intelligent and evolutionary systems*. Ed. by H. Sato, S. Iwanaga, and A. Ishii. Vol. 12. Springer International Publishing, pp. 194–202.

A statistical method is proposed for detecting stock market bubbles that occur when speculative funds concentrate on a small set of stocks. The bubble is defined by stock price diverging from the fundamentals. A firm financial standing is certainly a key fundamental attribute of that firm. The law of one price would dictate that firms of similar financial standing share similar fundamentals. We investigate the variation in market capitalization normalized by fundamentals that is estimated by Lasso regression of a firm financial standing. The market capitalization distribution has a substantially heavier upper tail during bubble periods, namely, the market capitalization gap opens up in a small subset of firms with similar fundamentals. This phenomenon suggests that speculative funds concentrate in this subset. We demonstrated that this phenomenon could have been used to detect the dot-com bubble of 1998-2000 in different stock exchanges.

Mulvey, J. M., Hao, H., and Li, N. (2018). “[Machine learning, economic regimes and portfolio optimisation](#).” In: *International Journal of Financial Engineering and Risk Management* 2(4), p. 260.

In portfolio models, the depiction of future outcomes depends upon a representative accounting of economic conditions. There is much evidence that crash periods display much different patterns than normal markets, suggesting that forecasting models ought to be based on multiple regimes. We apply two techniques from machine learning in our empirical study to improve robustness: 1) trend-filtering - to distinguish regimes possessing relatively homogeneous patterns; 2) a shrinkage/cross validation approach within a factor analysis of performance. A scenario-based portfolio model is proposed and designed to address multiple regimes. The worst-case events are well described within the framework, as compared with mean-variance Markowitz models that treat equally all historical performance.

Nystrup, P. (2014). “[Regime-Based Asset Allocation: Do Profitable Strategies Exist?](#)” MA thesis. Technical University of Denmark.

Regime shifts present a big challenge to traditional strategic asset allocation, demanding a more adaptive approach. In the presence of time-varying investment opportunities, portfolio weights should be adjusted as new information arrives. Regime-switching models can match the tendency of financial markets to change their behavior abruptly and the phenomenon that the new behavior often persists for several periods after a change. They are well suited to capture the stylized behavior of many financial series including skewness, leptokurtosis, volatility persistence, and time-varying correlations. This thesis builds on this empirical evidence to develop a quantitative framework for regime-based asset allocation. It investigates whether regime-based investing can effectively respond to changes in financial regimes at the portfolio level in an effort to provide better long-term results when compared to more static approaches. The thesis extends previous work by considering both discrete-time and continuous-time models, models with different numbers of states, different univariate and multivariate state-dependent distributions, and different sojourn time distributions. Out-of-sample success depends on developing a way to model the non-linear and non-stationary behavior of asset returns. Dynamic asset allocation strategies are shown to add value over strategies based on rebalancing to static weights with rebalancing in itself adding value compared to buy-and-hold strategies in an asset universe consisting of a global stock index, a global government bond index, and a commodity index. The tested strategies based on an adaptively estimated two-state Gaussian hidden Markov model outperform a rebalancing strategy out of sample after accounting for transaction costs, assuming no knowledge of future returns, and with a realistic delay between the identification of a regime change and the portfolio adjustment.

Nystrup, P., Hansen, B. W., Larsen, H. O., Madsen, H., and Lindstrom, E. (2018a). “[Dynamic Allocation or Diversification: A Regime-Based Approach to Multiple Assets](#).” In: *The Journal of Portfolio Management* 44(2), pp. 62–73.

This article investigates whether regime-based asset allocation can effectively respond to changes in financial regimes at the portfolio level in an effort to provide better long-term results when compared to a static 60/40 benchmark. The potential benefit from taking large positions in a few assets at a time comes at the cost of reduced diversification. The authors analyze this trade-off in a multi-asset universe with great potential for static diversification. The regime-based approach is centered around a regime-switching model with time-varying parameters that can match financial markets' behavior and a new, more intuitive way of inferring the hidden market regimes. The empirical results show that regime-based asset allocation is profitable, even when compared to a diversified benchmark portfolio. The results are robust because they are based on available market data with no assumptions about forecasting skills.

Nystrup, P., Hansen, B. W., Madsen, H., and Lindstrom, E. (2015). "Regime-Based Versus Static Asset Allocation: Letting the Data Speak." In: *The Journal of Portfolio Management* 42(1), pp. 103–109.

Regime shifts present a big challenge to traditional strategic asset allocation. This article investigates whether regime based asset allocation can effectively respond to changes in financial regimes at the portfolio level, in an effort to provide better long-term results than more static approaches can offer. The authors center their regime-based approach around a regime-switching model with time-varying parameters that can match financial markets' tendency to change behavior abruptly and the fact that the new behavior often persists for several periods after a change. In an asset universe consisting of a global stock index and a global government bond index, they show that, even without any level of forecasting skill, holding a static portfolio may not be optimal.

Nystrup, P., Lindstrom, E., and Madsen, H. (2020). "Learning hidden Markov models with persistent states by penalizing jumps." In: *Expert Systems with Applications* 150, p. 113307.

Hidden Markov models are applied in many expert and intelligent systems to detect an underlying sequence of persistent states. When the model is misspecified or misestimated, however, it often leads to unrealistically rapid switching dynamics. To address this issue, we propose a novel estimation approach based on clustering temporal features while penalizing jumps. We compare the approach to spectral clustering and the standard approach of maximizing the likelihood function in an extensive simulation study and an application to financial data. The advantages of the proposed jump estimator include that it learns the hidden state sequence and model parameters simultaneously and faster while providing control over the transition rate, it is less sensitive to initialization, it performs better when the number of states increases, and it is robust to misspecified conditional distributions. The value of estimating the true persistence of the state process is illustrated through a simple trading strategy where improved estimates result in much lower transaction costs. Robustness is particularly critical when the model is part of a system used in production. Therefore, our proposed estimator significantly improves the potential for using hidden Markov models in practical applications.

Nystrup, P., Madsen, H., and Lindstrom, E. (2018b). "Dynamic portfolio optimization across hidden market regimes." In: *Quantitative Finance* 18(1), pp. 83–95.

Regime-based asset allocation has been shown to add value over rebalancing to static weights and, in particular, reduce potential drawdowns by reacting to changes in market conditions. The predominant approach in previous studies has been to specify in advance a static decision rule for changing the allocation based on the state of financial markets or the economy. In this article, model predictive control (MPC) is used to dynamically optimize a portfolio based on forecasts of the mean and variance of financial returns from a hidden Markov model with time-varying parameters. There are computational advantages to using MPC when estimates of future returns are updated every time a new observation becomes available, since the optimal control actions are reconsidered anyway. MPC outperforms a static decision rule for changing the allocation and realizes both a higher return and a significantly lower risk than a buy-and-hold investment in various major stock market indices. This is after accounting for transaction costs, with a one-day delay in the implementation of allocation changes, and with zero-interest cash as the only alternative to the stock indices. Imposing a trading penalty that reduces the number of trades is found to increase the robustness of the approach.

Nystrup, P., William Hansen, B., Madsen, H., and Lindstrom, E. (2016). "Detecting change points in VIX and S&P 500: A new approach to dynamic asset allocation." In: *Journal of Asset Management* 17, pp. 361–374.

The purpose of dynamic asset allocation (DAA) is to overcome the challenge that changing market conditions present to traditional strategic asset allocation by adjusting portfolio weights to take advantage of favorable conditions and reduce potential drawdowns. This article proposes a new approach to DAA that is based on detection of change points without fitting a model with a fixed number of regimes to the data, without estimating any parameters and without assuming a specific distribution of the data. It is examined whether DAA is most profitable when based on changes in the Chicago Board Options Exchange Volatility Index or change points detected in daily returns of the S&P 500 index. In an asset universe consisting of the S&P 500 index and cash, it is shown that a dynamic strategy based on detected change points significantly improves the Sharpe ratio and reduces the drawdown risk when compared with a static, fixed-weight benchmark.

Oliveira, A. B. and Valls Pereira, P. L. (2018). "Asset Allocation With Markovian Regime Switching: Efficient Frontier and Tangent Portfolio With Regime Switching." In: *SSRN e-Print*.

Asset allocation is important for diversifying risk and realizing gains in the financial market. It involves decisions taken under uncertainty based on statistical methods. Returns on financial assets generally present regime switching and there are different distributions of returns in bull and bear markets. Regime switching in the data generating process for returns makes it necessary to reformulate the asset allocation problem. This paper develops asset allocation models with regime switching. Due to the comparative study of asset allocation, portfolios with regime switching enable the space of risk and return to be increased, reduce the risk for each level of return at the mean variance efficient frontier, and have the best risk-return relationship over time.

Papenbrock, J. and Schwendner, P. (2015). “[Handling risk-on/risk-off dynamics with correlation regimes and correlation networks](#).” In: *Financial Markets and Portfolio Management* 29(2), pp. 125–147.

In this paper, we present a framework for detecting distinct correlation regimes and analyzing the emerging state dependences for a multi-asset futures portfolio from 1998 to 2013. These correlation regimes have been significantly different since the financial crisis of 2008 than they were previously; cluster tracking shows that asset classes are now less separated. We identify distinct risk-on and risk-off assets with the help of correlation networks. In addition to visualizing, we quantify these observations using suitable metrics for the clusters and correlation networks. The framework will be useful for financial risk management, portfolio construction, and asset allocation.

Pharasi, H. K., Seligman, E., and Seligman, T. H. (2020). “[Market states: A new understanding](#).” In: *arXiv e-Print*.

We present the clustering analysis of the financial markets of S&P 500 (USA) and Nikkei 225 (JPN) markets over a period of 2006-2019 as an example of a complex system. We investigate the statistical properties of correlation matrices constructed from the sliding epochs. The correlation matrices can be classified into different clusters, named as market states based on the similarity of correlation structures. We cluster the S&P 500 market into four and Nikkei 225 into six market states by optimizing the value of intracluster distances. The market shows transitions between these market states and the statistical properties of the transitions to critical market states can indicate likely precursors to the catastrophic events. We also analyze the same clustering technique on surrogate data constructed from average correlations of market states and the fluctuations arise due to the white noise of short time series. We use the correlated Wishart orthogonal ensemble for the construction of surrogate data whose average correlation equals the average of the real data.

Platanakis, E., Sakkas, A., and Sutcliffe, C. (2017). “[Portfolios in a Regime Shifting Non-Normal World: Are Alternative Assets Beneficial?](#)” In: *European Financial Management Association Annual Meeting Athens*.

Adding five alternative assets to equity and bond portfolios is harmful for US investors. We use nineteen portfolio models in conjunction with dummy variable regression, and measure out-of-sample performance by both certainly equivalent ratios and Sharpe ratios. The presence of harmful diversification is robust to different estimation periods and levels of risk aversion, and to the use of two regimes. Harmful diversification is not primarily due to transactions costs or non-normal returns, but to estimation risk. Large estimation errors during the credit crisis (2007-09) account for the harmful diversification of three of the five alternative assets over the 1997-2015 period.

Seidl, I. (2012). “[Markowitz versus Regime Switching: An Empirical Approach](#).” In: *The Review of Finance and Banking* 04(1), pp. 033–043.

This article discusses an adjusted regime switching model in the context of portfolio optimization and compares the attained portfolio weights and the performance to a classical mean-variance set-up as introduced by Markowitz (1952). The model postulates different asset price dynamics under different regimes, and jumps between regimes are driven by a Markov process. For examples, ‘bear’ and ‘bull’ markets could be such regimes. Given a particular regime, portfolio weights are set based on the conditional means and variance-covariance structure of the asset dynamics. The model is evaluated in an out-of-sample period of the last three years with a moving window and a forecast of only one period. It is found that with the adjusted regime switching portfolio selection algorithm as applied here, the performance of the optimal portfolio is highly improved even where portfolio weights are constrained to realistic values.

Sheikh, A. Z. and Sun, J. (2012). “[Regime Change: Implications of Macroeconomic Shifts on Asset Class and Portfolio Performance](#).” In: *The Journal of Investing* 21(3), pp. 36–54.

It is a well-recognized empirical observation that different asset classes respond differently to different economic drivers. It is also well recognized that asset class behavior can vary significantly over shifting economic scenarios. This article builds on this empirical evidence to develop a quantitative framework for regime-based asset allocation. It investigates whether regime-based investing can effectively respond to changes in economic regimes at the portfolio level in an effort to provide better long-term results when compared to a more static approach. Results indicate that it is both possible and practical to develop a regime-based investing approach that can potentially add value over time. Success depends on identifying key factors that influence asset class performance, and then developing a way to model those non-linear relationships. Regime-based investing also requires a healthy degree of economic forecasting skill, which need not be perfect to add value. Based on the authors’ analysis, regime based investing can offer investors a compelling alternative to a more static approach.

Simonian, J. (2020). “Mixed Ag: A Regime-Based Analysis of Multi-Asset Agriculture Portfolios.” In: *The Journal of Portfolio Management* 46(6), pp. 135–146.

For some time now, the prospect that the world is entering a new epoch of elevated prices for agricultural commodities has been a focus of both policymakers concerned with the food security of their citizens and investors looking to benefit from a potential secular uptrend in the demand for food. Investors most commonly access agriculture in public markets through funds that invest in agricultural commodity futures or the common stock of companies that engage in agribusiness. In general, funds that invest in agricultural commodities are either dedicated equity or futures managers. However, there are potentially significant performance benefits to investing in agricultural commodities through a single multi-asset vehicle composed of both agricultural commodity futures and agribusiness stocks. To that end, in this article the author examines the performance of a multi-asset agriculture portfolio in periods of high and low economic growth and compares it with the performance of its individual equity and futures components, as well as the broader stock market and investment-grade bonds. The author finds that in terms of return generation, risk mitigation, and diversification potential relative to core stocks and bonds, the multi-asset agriculture strategy makes a compelling case for inclusion alongside traditional strategies within institutional investors portfolios.

Simonian, J. and Wu, C. (2019a). “Factors in Time: Fine-Tuning Hedge Fund Replication.” In: *The Journal of Portfolio Management* 45 (3), pp. 159–164.

Hedge fund replication has become a cottage industry in investing. Among the most popular hedge fund replication frameworks are factor models based on ordinary least squares (OLS) regression, a development that is no doubt due to its simplicity and familiarity among investment practitioners. Despite their widespread use, the OLS regression-based factor models that form the basis for many hedge fund replication programs are often overfitted to a single sample, severely undercutting their predictive effectiveness. As a remedy to the latter shortcoming, in this article the authors apply the regularization method known as regression to the replication of hedge fund strategies. Ridge regression works by formally imbuing a regression with additional bias in exchange for a reduction in the variance between training and test samples. Using a simple yet robust methodology, the authors show how to dynamically calibrate the predictively optimal level of bias without significantly reducing the backward-looking explanatory power of a given model. In doing so, the authors demonstrate that ridge regression can help produce generalizable models that are useful in both the ex post risk analysis and ex ante replication of hedge fund strategies.

Simonian, J. and Wu, C. (2019b). “Minsky vs. Machine: New Foundations for Quant-Macro Investing.” In: *The Journal of Financial Data Science* 1(2), pp. 94–110.

Systematic macro investors use of the regime-switching models that have been developed in academia over the last several decades is infrequent at best and, when used, generally tangential to their core investment process. The roots of this less-than-enthusiastic uptake can be found in two familiar sources: models that possess an overly complex formal structure and poor predictive ability. As a remedy to the current state of affairs, the authors present a new foundation for regime-based investing, one based on spectral clustering, a graph theoretic approach to classifying data. Drawing inspiration from the work of Hyman Minsky and John Geanakoplos, the authors present a macro framework that uses measures of growth, inflation, and leverage to define regimes and drive portfolio decisions. To the latter end, the authors show how the framework can be used to build portfolios using information about regimes as defined, to outperform a no-information equal-weight portfolio both out-of-sample and in bootstrapped and cross-validated simulations. The authors thus show that spectral clustering can provide both an elegant mathematical description of the leverage cycle and a robust foundation for quant-macro investing.

Smug, D., Ashwin, P., and Sornette, D. (2017). “Predicting Financial Market Crashes Using Ghost Singularities.” In: *SSRN e-Print*.

We analyse the behaviour of a non-linear model of coupled stock and bond prices exhibiting periodically collapsing bubbles. By using the formalism of dynamical system theory, we explain what drives the bubbles and how foreshocks or aftershocks are generated. A dynamical phase space representation of that system coupled with standard multiplicative noise rationalises the log-periodic power law singularity pattern documented in many historical financial bubbles. The notion of ‘ghosts of finite-time singularities’ is introduced and used to estimate the end of an evolving bubble, using finite-time singularities of an approximate normal form near the bifurcation point. We test the forecasting skill of this method on different stochastic price realisations and compare with Monte Carlo simulations of the full system. Remarkably, the former is significantly more precise and less biased. Moreover, the method of ghosts of singularities is less sensitive to the noise realisation, thus providing more robust forecasts.

Sornette, D. (2014). “Dragon-kings and Predictions: Diagnostics and Forecasts for the World Financial Crisis.” In: *SSRN e-Print*.

We develop the concept of “dragon-kings” corresponding to meaningful outliers, which are found to coexist with power laws in the distributions of event sizes under a broad range of conditions in a large variety of systems. These dragon-kings reveal the existence of mechanisms of self-organization that are not apparent otherwise from the distribution of

their smaller siblings. We present a generic phase diagram to explain the generation of dragon-kings and document their presence in six different examples (distribution of city sizes, distribution of acoustic emissions associated with material failure, distribution of velocity increments in hydrodynamic turbulence, distribution of financial drawdowns, distribution of the energies of epileptic seizures in humans and in model animals, distribution of the earthquake energies). We emphasize the importance of understanding dragon-kings as being often associated with a neighborhood of what can be called equivalently a phase transition, a bifurcation, a catastrophe (in the sense of Rene Thom), or a tipping point. The presence of a phase transition is crucial to learn how to diagnose in advance the symptoms associated with a coming dragon-king. Several examples of predictions using the derived log-periodic power law method are discussed, including material failure predictions and the forecasts of the end of financial bubbles.

Sornette, D., Andraszewicz, S., Murphy, R. O., Rindler, P. B., and Sanadgol, D. (2016). “Resolving Persistent Uncertainty by Self-Organized Consensus to Mitigate Market Bubbles.” In: *SSRN e-Print*.

We propose a new paradigm to study coordination in complex social systems, such as financial markets, that accounts for fundamental uncertainty. This new context has features from prediction markets that have been shown previously to mitigate price bubbles in classical asset market experiments. Our setup is more realistic as it offers multiple securities that are continuously traded over days and, importantly, there is no true underlying price. Nonetheless, the market is designed such that its rationality can be evaluated. Quick consensus emerges early yielding pronounced market bubbles. The overpricing diminishes over time, indicating learning, but does not disappear completely. Traders’ price estimates become progressively more independent via a collective realization of communal ignorance, pushing the market much closer to rationality, with forecasts that are close to the realized outcomes.

Sornette, D. and Cauwels, P. (2014). “Financial bubbles: mechanisms and diagnostics.” In: *arXiv e-Print*.

We define a financial bubble as a period of unsustainable growth, when the price of an asset increases ever more quickly, in a series of accelerating phases of corrections and rebounds. More technically, during a bubble phase, the price follows a faster-than-exponential power law growth process, often accompanied by log-periodic oscillations. This dynamic ends abruptly in a change of regime that may be a crash or a substantial correction. Because they leave such specific traces, bubbles may be recognised in advance, that is, before they burst. In this paper, we will explain the mechanism behind financial bubbles in an intuitive way. We will show how the log-periodic power law emerges spontaneously from the complex system that financial markets are, as a consequence of feedback mechanisms, hierarchical structure and specific trading dynamics and investment styles. We argue that the risk of a major correction, or even a crash, becomes substantial when a bubble develops towards maturity, and that it is therefore very important to find evidence of bubbles and to follow their development from as early a stage as possible. The tools that are explained in this paper actually serve that purpose. They are at the core of the Financial Crisis Observatory at the ETH Zurich, where tens of thousands of assets are monitored on a daily basis. This allow us to have a continuous overview of emerging bubbles in the global financial markets. The companion report available as part of the Notenstein white paper series (2014) with the title “Financial bubbles: mechanism, diagnostic and state of the World (Feb. 2014)” presents a practical application of the methodology outlines in this article and describes our view of the status concerning positive and negative bubbles in the financial markets, as of the end of January 2014.

Sornette, D., Cauwels, P., and Smilyanov, G. (2017). “Can We Use Volatility to Diagnose Financial Bubbles? Lessons from 40 Historical Bubbles.” In: *SSRN e-Print*.

We inspect the price volatility before, during, and after financial asset bubbles in order to uncover possible commonalities and check empirically whether volatility might be used as an indicator or an early warning signal of an unsustainable price increase and the associated crash. Some researchers and finance practitioners believe that historical and/or implied volatility increase before a crash, but we do not see this as a consistent behavior. We examine forty well-known bubbles and, using creative graphical representations to capture robustly the transient dynamics of the volatility, find that the dynamics of the volatility would not have been a useful predictor of the subsequent crashes. In approximately two-third of the studied bubbles, the crash follows a period of lower volatility, reminiscent of the idiom of a “lull before the storm”. This paradoxical behavior, from the lenses of traditional asset pricing models, further questions the general relationship between risk and return.

Sornette, D., Demos, G., Zhang, Q., Cauwels, P., Filimonov, V., and Zhang, Q. (2015). “Real-time prediction and post-mortem analysis of the Shanghai 2015 stock market bubble and crash.” In: *Journal of Investment Strategies* 4(4).

The authors assess the performance of the real-time diagnostic, available to the public on the website of the Financial Crisis Observatory (FCO) at ETH Zurich, of the bubble regime that began developing in Chinese stock markets in mid-2014 and started to burst in June 2015. The analysis is based on (i) the economic theory of rational expectation bubbles; (ii) the behavioral mechanisms of imitation and the herding of investors and traders; (iii) the mathematical formulation of the log-periodic power lawsingularity (LPPLS), which describes the critical approach toward a tipping point in complex systems. The authors document how the real-time predictions were presented in the automated analysis of the FCO, as well as in their FCO Cockpit report of June 2015. A complementary post-mortem analysis of the nature

and value of the LPPLS methodology in diagnosing the Shanghai Composite Index bubble and its termination is also given.

van Vliet, P. and Blitz, D. (2011). “Dynamic strategic asset allocation: Risk and return across the business cycle.” In: *Journal of Asset Management* 12(5), pp. 360–375.

We propose a practical investment framework for dynamic asset allocation across different phases in the business cycle, which we illustrate using a sample of US data from 1948 to 2007. We identify four phases in the business cycle and find that these capture pronounced time variation in the risk and return properties of asset classes. Time variation is also observed in the risk of a traditional, static strategic asset mix. In order to stabilize risk across the business cycle, we propose a dynamic strategic asset allocation approach, which has the potential to enhance expected return as well. The proposed investment framework is found to be robust to variations in the variable composition of the business cycle indicator and can easily be extended with different economic variables and/or additional assets.

Viebig, J. (2020). “Exuberance in Financial Markets: Evidence from Machine Learning Algorithms.” In: *Journal of Behavioral Finance* 21(2), pp. 128–135.

Motivated by Campbell and Shiller (1998), we show that the probability that abnormally low returns over long-term investment horizons occur in the future is disproportionately high when equity markets trade at extremely high valuation levels. Support vector machines are able to learn patterns from fundamental data with high precision rates. Decision boundaries calculated with machine learning algorithms can help investors to detect irrational exuberance in financial markets followed by abnormally low returns.

Vo, H. T. and Maurer, R. (2013). “Dynamic Asset Allocation under Regime Switching, Predictability and Parameter Uncertainty.” In: *SSRN e-Print*.

This paper solves the dynamic asset allocation problem under stock return predictability based on the dividend price ratio with regime shifts and parameter uncertainty in a fully Bayesian framework. Intertemporal hedging demands are simultaneously induced by predictability, regime shifts, parameter uncertainty, and learning about the regimes. Optimal policies display non-monotonic horizon effects whereby regime shifts tend to induce negative hedge demands in the short-run, while predictability induces positive hedge demands in the long-run. The economic costs of ignoring regime switching and predictability are high even in the light of regime and parameter uncertainty.

Wang, P. and Zong, L. (2020). “Are Crises Predictable? A Review of the Early Warning Systems in Currency and Stock Markets.” In: *arXiv e-Print*.

The study efforts to explore and extend the crisis predictability by synthetically reviewing and comparing a full mixture of early warning models into two constitutions: crisis identifications and predictive models. Given empirical results on Chinese currency and stock markets, three-strata findings are concluded as (i) the SWARCH model conditional on an elastic thresholding methodology can most accurately classify crisis observations and greatly contribute to boosting the predicting precision, (ii) stylized machine learning models are preferred given higher precision in predicting and greater benefit in practicing, (iii) leading factors sign the crisis in a diversified way for different types of markets and varied prediction periods.

Wheatley, S., Sornette, D., Huber, T., Reppen, M., and Gantner, R. N. (2018). “Are bitcoin bubbles predictable? combining a generalized metcalfe’s law and the LPPLS model.” In: *SSRN e-Print*.

We develop a strong diagnostic for bubbles and crashes in bitcoin, by analyzing the coincidence (and its absence) of fundamental and technical indicators. Using a generalized Metcalfe’s law based on network properties, a fundamental value is quantified and shown to be heavily exceeded, on at least four occasions, by bubbles that grow and burst. In these bubbles, we detect a universal super-exponential unsustainable growth. We model this universal pattern with the Log-Periodic Power Law Singularity (LPPLS) model, which parsimoniously captures diverse positive feedback phenomena, such as herding and imitation. The LPPLS model is shown to provide an ex-ante warning of market instabilities, quantifying a high crash hazard and probabilistic bracket of the crash time consistent with the actual corrections; although, as always, the precise time and trigger (which straw breaks the camel’s back) being exogenous and unpredictable. Looking forward, our analysis identifies a substantial but not unprecedented overvaluation in the price of bitcoin, suggesting many months of volatile sideways bitcoin prices ahead (from the time of writing, March 2018).

Yan, C. and Huang, K. X. D. (2020). “Financial cycle and business cycle: An empirical analysis based on the data from the U.S.” In: *Economic Modelling* 93, pp. 693–701.

In this paper, we first study the relationship between the financial cycle and the business cycle in the time and frequency domain. Then we also explore the interactions and dynamic mechanisms of the financial cycle, the business cycle, real interest rate and exchange rate by the VAR model. The empirical results show that the financial cycle is closely related to the business cycle, especially at medium-term frequencies (8-30 years), the business cycle leads the financial cycle with a high positive correlation. However, the relationship between them is not significant during the Great Moderation at business-cycle (2-4 years). In addition, the financial cycle not only becomes a main driver of real interest rate, the

financial cycle and the business cycle, but also serves as an important source of the business cycle fluctuations. In general, our results lay some theoretical foundation for the policy practice of financial and economic stability.

Yao, C.-Z. and Li, H.-Y. (2021). “A study on the bursting point of Bitcoin based on the BSADF and LPPLS methods.” In: *The North American Journal of Economics and Finance* (101280), Early View.

We aim to reveal the characteristics and mechanism of the Bitcoin bubble in 2019. First, we identify the period during which two important Bitcoin bubbles occurred based on the generalized supremum augmented Dickey-Fuller (GSADF) method. There are two significant bubble cycles. The first bubble lasted approximately 26 days from November 25, 2017, to December 21, 2017, while the second bubble lasted approximately one week from June 22 to June 29, 2019. The occurrence of the first bubble was related to the considerable expansion of initial coin offerings (ICOs) in 2017, while the formation of the second bubble was affected by the release of Libra. Second, as the GSADF method cannot be used to accurately infer the time at which a bubble bursts, we employ the log-periodic power law singularity (LPPLS) model for this purpose. We verify that the LPPLS method can not only infer the timing of a bubble burst but also shows stable results. Finally, we demonstrate the implications of the 2019 bubble. During the 2019 bubble, due to the increased supervision of European and American governments and the impact of hedging assets, the bubble’s duration was shorter, and the positive feedback mechanism was not as strong as that of the 2017 bubble. In addition, the oscillating frequency of the bubble in 2019 was low and unstable, which means that it would be more beneficial for investors to hold the currency for a long time.

Zhang, Q., Sornette, D., Balcilar, M., Gupta, R., Ozdemir, Z. A., and Yetkiner, H. (2016). “LPPLS bubble indicators over two centuries of the S&P 500 index.” In: *Physica A: Statistical Mechanics and its Applications* 458, pp. 126–139.

Novel tests for early causal diagnostic of bubbles in the US S&P 500 index. Large testing period of more than two hundred years. Construction of efficient end-of-bubble signals. Horse-race between LPPLS versus exponential curve fitting and generalized sup ADF test approaches. Detection of eight positive bubbles and two negative bubbles from January 1814 to August 2014. The aim of this paper is to present novel tests for the early causal diagnostic of positive and negative bubbles in the S&P 500 index and the detection of End-of-Bubble signals with their corresponding confidence levels. We use monthly S&P 500 data covering the period from August 1791 to August 2014. This study is the first work in the literature showing the possibility to develop reliable ex-ante diagnostics of the frequent regime shifts over two centuries of data. We show that the DS LPPLS (log-periodic power law singularity) approach successfully diagnoses positive and negative bubbles, constructs efficient End-of-Bubble signals for all of the well-documented bubbles, and obtains for the first time new statistical evidence of bubbles for some other events. We also compare the DS LPPLS method to the exponential curve fitting and the generalized sup ADF test approaches and find that DS LPPLS system is more accurate in identifying well-known bubble events, with significantly smaller numbers of false negatives and false positives.