Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

New Directions in Active Portfolio Management: Stability Analytics, Risk Parity, Rating and Ranking, and Geometric Shape Factors

Diethelm Würtz, Yohan Chalabi, and Tobias Setz

No. 2013-03

ETH Econohysics Working and White Papers Series
Online at https://www.rmetrics.org/WhitePapers

New Directions in Active Portfolio Management

Stability Analytics - Risk Parity - Rating & Ranking – Geometric Shape Factors

Diethelm Würtz, Yohan Chalabi, Tobias Setz
Institute for Theoretical Physics - Econophysics Group
Swiss Federal Institute of Technology Zurich

First Versions May 2012
This Version August 2012, Last Update 3. January 2013

Modern Portfolio Theory founded by Harry Markowitz [1952] celebrates this year his 60th anniversary. When he published more than half a century ago his article *Portfolio Selection* in the Journal of Finance, our knowledge in mathematical finance, financial time series analysis and statistics as well as computer science was much less developed compared with the options and the tools we have today at our hands. So it is worth not only to look back, but also to make use of recent developments in the mentioned fields. Within this short overview we like to report on a bundle of new ideas based on modern concepts of stability analytics to have an alternative view on risk in funds and portfolios and their impact on indexation techniques and tactical portfolio management. The main topics we like to ad-dress are based on univariate and multivariate statistical methods to identify instabilities and to detect and explore vulnerabilities in financial time series. With this approach we like to reinvestigate and to contribute to better understand performance and risk in market indices, funds and portfolios. The indicators derived from our approach allow us to create a distinct view on the weaknesses of classical asset allocation and modern portfolio theory and to think in alternatives and new directions.

In this review we concentrate on recent results from new style indexation techniques and close-to-index managed funds and portfolios. The key points include:

1. Stability analytics for better benchmark indices and portfolios
2. Stability control and parity risk indexation for alternative benchmarks
3. Stability rating and ranking of assets for a refined quality selection process
4. Geometric shape factor models to visualize and predict risk in portfolios

In the following we present for each topic a short description of our new ideas, concepts, and methods. We like to keep this report comprehensive. Whenever we have published preliminary results we focus on the principles and give references to further information and details.

Contact Address: PD Dr. Diethelm Würtz, *wuertz@phys.ethz.ch*

1 Stability Analytics for Benchmark Indices and Portfolios

Würtz et. al [2010] have reported at the *Computational Finance Workshop* in Singapore 2010 about a new approach to identify and locate structural change points in financial time series. The approach they named *BCP Stability Analytics* is based on the work of Barry and Hartigan [1993] on the partitioning of a time series in strings with different parameter settings. These parameters are the same within each partition but change from one to the next partition. The method makes use of *Bayesian statistics* and a *Monte Carlo Markov Chain* approach, Erdman, and Emerson [2008]. The analytics can be used to evaluate financial markets and financial investments before, during and after critical financial and economic periods. These include for example the Big Depression, World War II, the Oil Crisis, the stock market crashes in 1987 and 1997, and the more recent 'dot com' bubble, the sub prime crisis, the food speculation bubble, or the European debt crisis. The result of a BCP stability analytics for the U.S. small cap equity market over the last 40 years is shown in figures 1 and 2. We can clearly identify from such a graph all major financial and economic crisis during that time.

But before we continue let us explain our understanding of stability in time series pro–cesses. From a „stable" financial time series, for example an index, we expect a steady increase in the cumulated returns that goes with a low volatility, small drawdowns and short recovery times. Unfortunately a quantitative measurement of instabilities may not be unique. But we can take different statistical views on a time series. For example, not only change points and structural breaks can characterize instabilities, there exist several other analytics to identify them. We like to mention two other approaches, the robust pattern based principal component outlier estimator of Filzmoser [2004] and Filzmoser, Maronna nad Werner [2008], and the Morlet wavelet spectrum analysis of Torrence and Compo [1998] to visualize non-stationarities and multi-fractal behaviour. The PCA outlier analytics and a typical wavelet spectrum for commodities are shown figures 3 and 4.

Würtz, Setz and Chalabi [2012] have shown that he Bayesian change point analytics, the principal component outlier analytics, and the Morlet wavelet analytics are three flavours of analyzing and quantifying the vulnerabilities to external forces of a time series process. In all three cases we can define a figure to measure the structure and strength of instabilities appearing over time. Even more, they have shown that the time dependent process of stability that is recorded on a rolling window allows to re-define average returns and average risk measures. They can be used to compute a stability weighted performance attribution, for example a stability weighted Sharpe ratio. We can also derive a cumulated stability index, see figure 4, and from the distribution of its changes we can derive and calculate measures like value-at-stability or an expected shortfall stability, measure as we know them from the financial returns for the value-at-risk and the expected shortfall risk. Also many performance measures as described by Bacon [2006] can now be re-designed as stability weighted figures.

2 Stability Control and Risk Parity Indexation

Risk control indices are offered by all major index providers. The idea behind this class of style indices is to invest in two different instruments, usually an equity index and a low risk or risk free admixture, for example bonds or cash. Then one switches between these two investments. The trigger for the rebalancing of risk control indices is usually the volatility. When a predefined volatility threshold is exceeded, then the investment is moved onto the cash site, and below the threshold we are invested in the equities.

Stability analytics allows to extent this idea to protect an index from losses by replacing volatility by stability. We call this *Stability Control Indexation*. Like in the case of volatility risk control we generate a binary switching investment process. How to measure the degree of stability depends again on our view and our strategy to measure it. We have tested this approach in the case of the Bayesian change point stability and achieved a much better protection against losses.

Risk Parity Indexation describes a risk diversification portfolio design that is quite different from traditional approaches. Parity indexation tells us not to build an index or portfolio only on the values of total return and total risk, but also to take care on the individual amount of risk contributed by each component. This results in an investment that is much better risk diversified. Risk parity indexation can be interpreted as an optimization design trying to achieve a risk composition where all individual contributions are of the same size. This is also known under the name risk budgeting, see Pearson [2002], and Meillard, Roncalli, Teiletche [2010]. There exist several flavours of risk budging, for example covariance risk budgeting, value-at-risk budgeting, or expected shortfall risk budgeting, Boudt, Petersen, Croux [2008]. Beside this we have also designed portfolios constrained by conditional drawdown and tail risk budgets, Würtz [2011]. Risk parity indexation has recently found its marketing in the FTSE Risk Parity Index [2012].

This approach can be extended to use also stability in the context of risk budgeting. We call this concept *stability budgeting* or *stability parity indexation*. The underlying principle is simple, compose an index or portfolio in such a way that the total stability will be as high as possible and the individual stability of the components will be best diversified. This is achieved when we substitute the traditional risk measure by covariance or expected shortfall stabilities. Within our stability parity indexation concept reward and risk will be reduced to constraints in the portfolio optimization process, stability will become the determining objective. Stability budgeting is the main key that the optimal weights guarantee a higher stability and broader diversification of stability variations of the individual components.

To develop further the ideas and concepts in such an approach we have introduced a first version of a *cumulated stability index*. This allows to formulate like in any risk management process a new scorecard of enhanced controls built from new measures like *covariance stability*, *value-at-stability*, *conditional value-at-stability, conditional drawdowns-at-stability* among others. Figure 5 shows the wealth of the CRB commodity index with its cumulated stability index. Figures 6 to 8 give further insight in stability concepts showing the stabilization of the S&P500 index and the risk/reward diagram of 25 further world major equity indices. We are convinced that *stability control* and *stability parity indexation* will become a powerful additional layer to the already existing risk budgeting approaches.

3 Stability Rating and Ranking

Stability analytics can also be used for rating and ranking investments according to the stability weighted performance of individual members of an index, fund or portfolio. We consider it as a refined quality selection process for partitioning and classification of equities or bonds. In the case of stability ranked investments we start from an index and its components. This may be any type of index, e.g. large or small cap stock indices, style or theme indices, or indices composed from bonds or other interest rate instruments. The concept of our approach is in all instances the same, i.e. to assign a stability score to each component of the considered index, fund or portfolio.

In a preliminary investigation we have computed scores from stability weighted performance and risk measures. The rating given by the scores then allows for a ranking of the individual index components. From the 100 components of the S&P 100 index we have selected those 80 series with the longest history ignoring for the moment a possible survivor bias. We divided the stocks in four groups or quartiles. The first group was assigned to the 20 best stability rated stocks, the second and third group each to the next 20 best intermediate performing stocks, and the last group to those 20 stocks with the lowest stability scores. The process is rebalanced every end of month, but it is left to the researcher and investment manager to explore shorter or longer time horizons. What we get results in an impressive separation of the four quantiles with an almost perfect ordering of the performance and drawdowns from the stabilized equities. The equal weighted index composed from the 80 stocks separates clearly the first two from the last two quartiles. The results are presented in figure 9.

Such a separation is not obvious and not expected at all. Many index providers and investment firms have tried to score and rank equities or other investments according to a fundamental quality approach. In this context we are aware of the *company attractiveness ranking* applied by Niederer et al. [2011], and the approach of Nomura securities [2005] based on work developed by Arnitt [2005].

We believe that stability rating and ranking will add a powerful method to supplement other score methods when it comes to the selection of individual instruments from a given asset class. In our approach stability control is considered as the driving force when we look for the most stable components in an index or an asset class as part of a pension fund portfolio. Since stability analytics can be expressed from different views, there will be a broad diversity to construct new measures for partitioning, grouping and clustering similar assets.

4 Geometric Shape Factor Modelling

Factor models in portfolio optimization are models that make use of the structure of the financial markets through underlying variables (the factors) that can help to explain common components describing the movements of return and risk. The aim is to determine a few independent factors to make the dependency structure of the variables better manageable and interpretable. In this sense we consider factor modelling as a data reducing approach. Starting from the observed dependencies between factors and their development in time we can formulate assumptions concerning the structure of portfolios and proof expectations about their future formation. Thus we consider factor modelling in its broadest sense as a hypothesis generating approach.

In our concept of geometrical shape factor models of portfolios we describe the *feasible set* of all possible portfolio realizations by a simple geometric object, i.e. by an ellipse. The ellipse is determined from the first 4 moments of its geometric shape. The shape factors are the centre of mass, the area, the excentricity and the orientation. They are the same for the true feasible set and the approximated shape. Rolling along a time window we can follow the dynamics of the feasible set and its hull. The time dependency of the factors can be used to give additional information on the structure of the portfolio and may also forecast its structural evolution.

Würtz et al. [2011] have analysed a stock market portfolio composed from equity indices of selected major developed countries, MSCI [2012]. The goal of the study was to estimate the shape of the feasible set on a rolling window as a function of time. The most impressive result, figure 10, was returned by the orientation factor, Würtz et al. [2011]. The graph displays a cyclic behaviour that shows the same pattern between two stock market crashes. After a crash, the orientation of the feasible set first remains constant, then it drops down and further on it turns to diverge when the next stock market crash will be approached.

Würtz and Senner [2012] have explored the growing gap in the bond prices of selected member countries of the Eurozone. We have divided Barclays Government bond prices [2012] into 4 periods of equal length in time, starting with the introduction of the Euro in January 1999 and ending July 2012. Figure 11 shows the dynamical evolution of the feasible set and the growing gap due to the divergence of the south European member countries.

Although there are many other methods in multivariate statistics, like clustering, partitioning, or grouping to detect dissimilarities in data sets, we are confident in our stability approach, that the time dependent exploration of the feasible set will result in a new view and a broader understanding of the dynamical behaviour of indices and/or pension fund portfolios. We can embed the geometric shape factor models in a rigorous statistical framework. The real power of this approach will be to consider its time dependent parameters as a dynamical process. This makes possible to identify turning points and cycles in an investment process. Furthermore the shape factors can be used to forecast changes of the geometric form of the feasible set which are thought to serve as leading indicators to predict the future key ratios of indices and portfolios. We can also learn from the speed how the parameters evolve in time together with their acceleration of growth.

References

Arnott R.D., Hsu J., Moore P., [2005], Fundamental Indexation, Financial Analysts Journal 61

Bacon C.R. [2006], Practical Portfolio Performance Measurement and Attribution, John Wiley and Sons Ltd., Chichester, England.

Barclays Index Products, [2012], Government Bond Prices, ecommerce.barcap.com

Barry D., and Hartigan J. A. [1993], A Bayesian Analysis for Change Point Problems, Journal of the American Statistical Association 35, 309-319.

Boudt K., Peterson B, Croux C., [2008], Estimation and decomposition of downside risk for portfolios with non-normal returns, Journal of Risk 11, pp. 79-103.

Erdman Ch., and Emerson J. W. [2008], A fast Bayesian change point analysis for the segmentation of microarray data, Bioinformatics vol. 24, pp. 2143-2148.

Filzmoser P. [2004], A Multivariate Outlier Detection Method, Working Paper, Univ. Vienna.

Filzmoser P., Maronna R., and Werner M. [2008], Outlier Identification in High Dimensions, Computational Statistics and Data Analysis 52, 1694--1711.

FTSE, [2012]. Ground Rules for the construction and maintenance of the Lyxor SmartIX ERC Euro Index, pp. 14, www.ftse.com

iShares Exchange Traded Fund Database [2012], www.ishares.com

Maillard S., Roncalli T., Teiletche J., [2010], The Properties of Equally Weighted Risk Contribution Portfolios, Journal of Portfolio Management.

Morningstar [2011], Ibbotson SBBI Classic Yearbook, corporate.morningstar.com

Niederer U. et al., [2011], Artico Company Booklet, www.artico-partners.com

Nomura Securities, [2005], Global Fundamental Indices, Security Analysts Journal, 43

Pearson N.D., [2002], Risk Budgeting: Portfolio Problem Solving with Value-at-Risk, Wiley Finance, John Wiley and Sons.

Rmetrics, Financial Computing Environment and Software packages, www.rmetrics.org.

Sharpe W. F. [1994], The Sharpe Ratio, Journal of Portfolio Management, Vol. 21, pp. 49-58.

Torrence Ch., and Compo G.P. [1998], A Practical Guide to Wavelet Analysis, Bulletin of the American Meteorological Society 79, 61-78.

Würtz D., Chalabi Y., Ellis A. Chen W., and Theussl S. [2010], Postmodern Approaches to Portfolio Design: Portfolio Optimization with R/Rmetrics, Proceedings of the Singapore R/Rmetrics Workshop 2010, Rmetrics and Finance Online Publishing, Zurich, pp. 205-213.

Würtz D. [2011a], Tools for Portfolio Optimzation from R/Rmetrics, Proceedings of the Meielisalp Summerschool and Workshop 2011, Rmetrics Association and Finance Online Publishing, Zurich, pp. 220-229.

Würtz D., Setz T., and Chalabi Y. , [2011b], Stability Analytics of Vulnerabilities in Financial Time Series, Econophysics ETH Zurich, Working Paper, December 2011.

Würtz D., Beiler H., Chalabi, Y., Grimson F., and Setz T. [2011c], Long Term Statistical Analysis of U.S. Asset Classes, Rmetrics and Finance Online Publishing, Zurich, April 2011.

Würtz D., Senner R. [2012], The time evolution of Government bond prices in the Eurozone: A New Stability Analytics Approach, Econophysics ETH Zurich, Working Paper, Dec. 2011.

Disclaimer

All calculations were done with the *R* and *Rmetrics* statistical software environment, see www.rmetrics.org

.

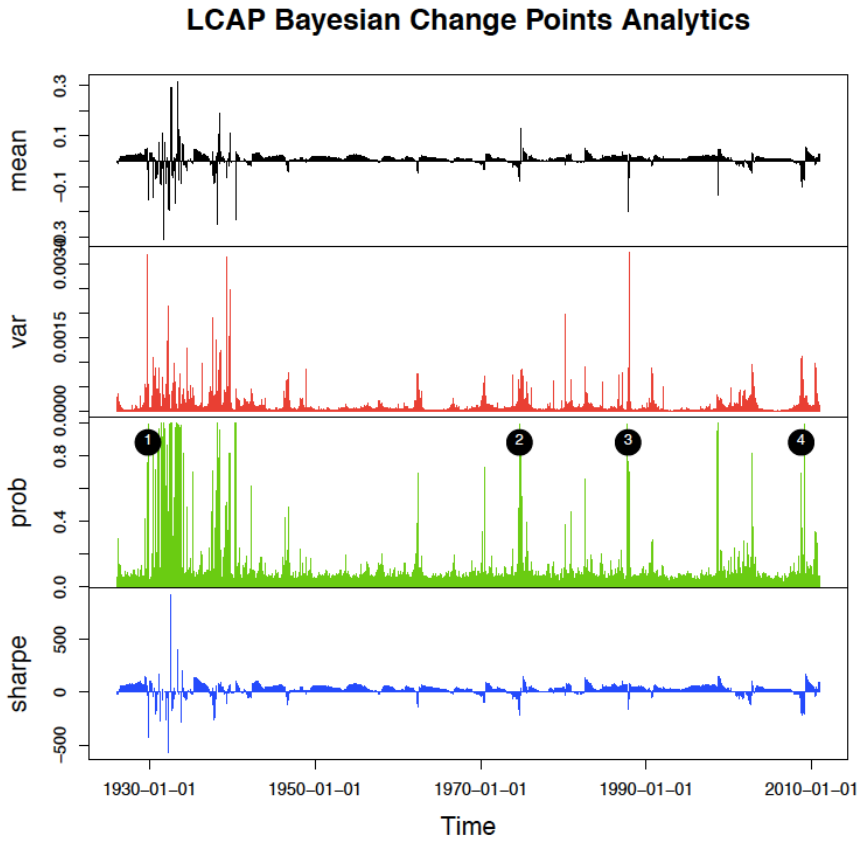

Figure 1:

The graph displays a Bayesian change point analysis of monthly recorded continuous returns of the U.S. large cap stock market represented by Standard & Poors SP500 index. The data records go back until December 1925 and end in December 2010. From up to down the curves show the posterior mean (black), the posterior variance (red), the posterior probability that a point is a change point (green), and the probability weighted (local) Sharpe ratio (blue) as derived from the posterior mean, the MCMC standard deviation, and the posterior probability. The four black dots mark (1) the Black Thursday 1929, (2) the Oil and Shock Crisis 1973/74, (3) the Black Monday 1987, and (4) the collapse of Lehman Brothers.

Conclusion: Locating instabilities and vulnerabilities in a time series by Bayesian change point analysis is a powerful indicator for a retroactive analysis of financial and economic markets

Data Source: Ibbotson Morningstar.

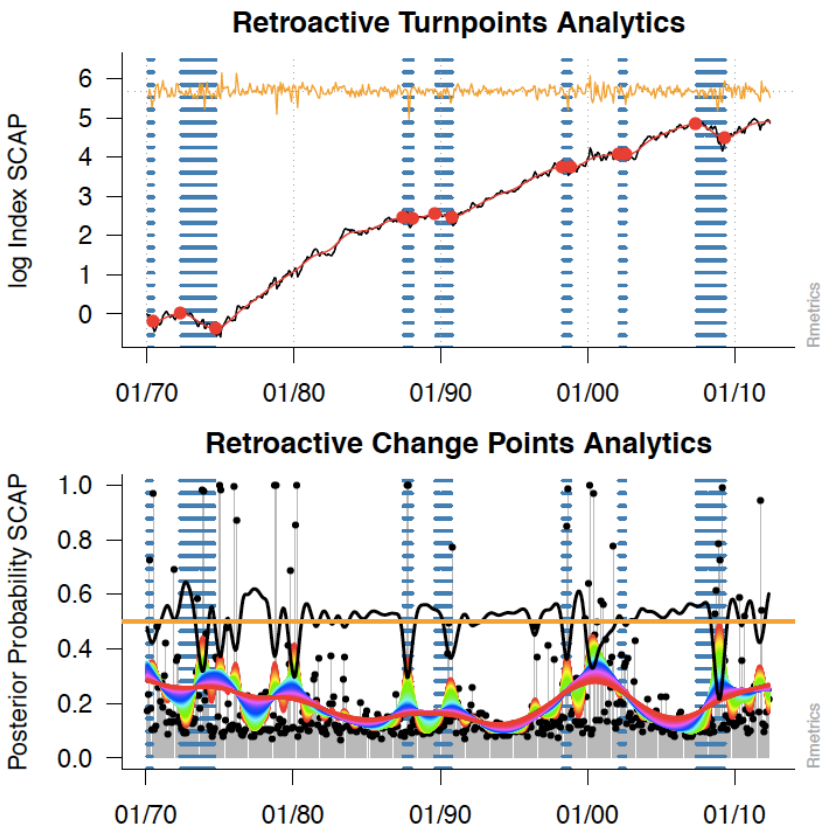

Figure 2:

Turning point and Bayesian change point analytics for the U.S. small cap market represented by the Russell 2000 Index. The upper graph shows the end of month values of the logarithmic values of the wealth index, the red curve is filtered by a spline smoother. The red dots mark the turn points and the blue horizontal bars mark the down periods. The orange curve shows the structure of the returns. Note, the scale of the returns is not included in the plot. The lower graph displays the results from the retroactive BCP analytics. The grey bars with a black dot on top mark the posterior probabilities for each time series point. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colours. From their peaks and divergences we can identify more stable, less stable or even unstable regions. The black curve twisting around 1/2 is a measure for the divergence or spread of the stability.

Conclusion: From Bayesian change point analytics we can generate powerful indicators for probability weighted performance and risk measures. They can show different flavours just tailored for the individual needs of investment and risk managers.

Data Source: Ibbotson Morningstar, Russell, and iShares.

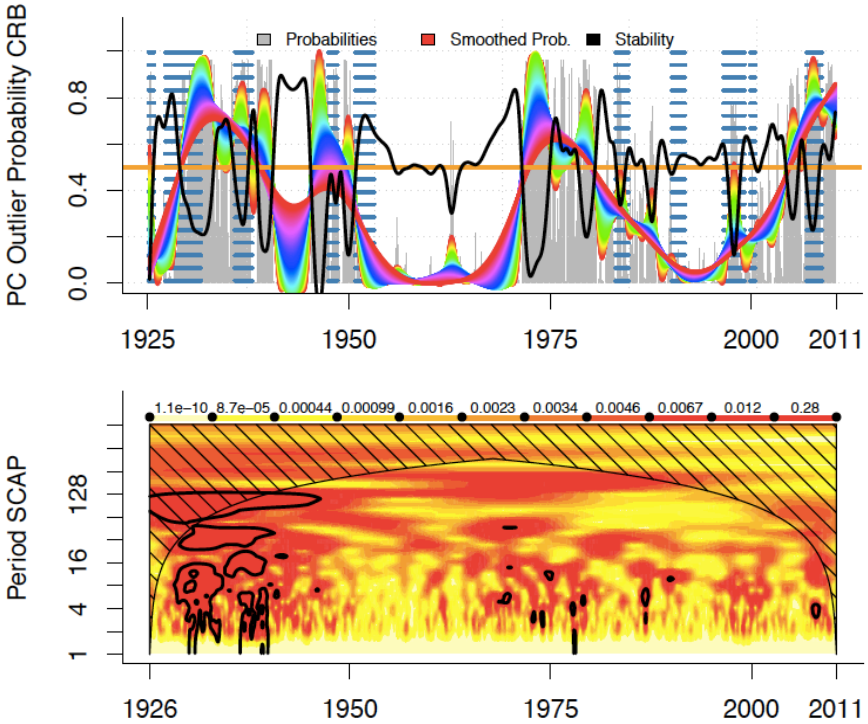

Figure 3 and 4:

Two other views on stability measures. The upper graph displays a stability indicator built on top of a robust principal component analytics. This results in a measure between zero and one describing the strength or probability that a point in the time series is an extreme or outlying value. The graph displays the dynamical evolution of log returns computed from the CRB commodity price index for the years 1925 until 2010. The vulnerabilities during the big depression, the oil price shock, and the recent food price bubble are clearly located and identified. The lower Graph shows the wavelet spectrum for a long-term portfolio 1926-2011 composed from small Cap U.S. equities. The red regions identify periods with high instabilities. We can again easily observe the Great Depression, the oil shock in the seventies, the stock market crash 1997, and the recent sub prime crisis.

Conclusion: Stability is like variability a measure that cannot be expressed by one number. Stability is mostly described and characterized by individual views of the investment or manager with his or her personal preferences. These may be change points, structural breaks, extreme and outlying values, non-stationarities or multi-fractal behaviour.

Data Source: Fred2 Federal Reserve, Bureau of Labour Statistics, Commodity Research Bureau Office, Thompson-Reuters, Ibbotson Morningstar.

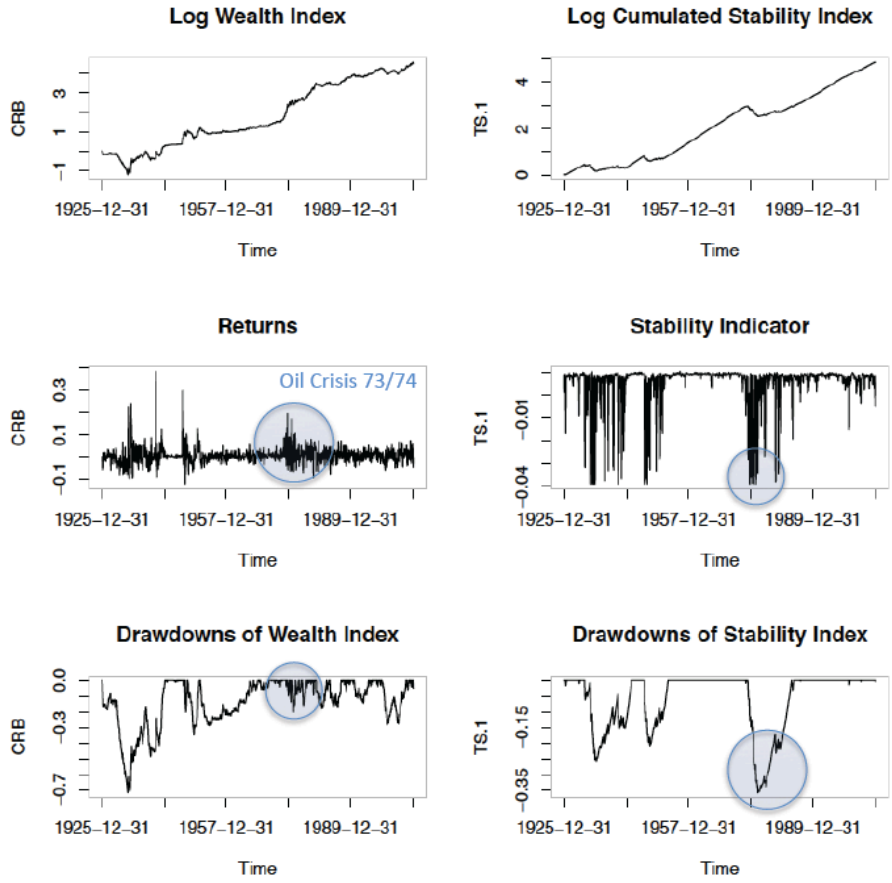

Figure 5:

The left column displays graphs on a long-term scale from 1925 until now commodity prices expressed through the CRB wealth index (indexed to December 1925 = 1), its changes over time computed from log returns, and the resulting drawdowns together with their recovery times. This traditional view is confronted on the right column of graphs with the related measures obtained from a Bayesian change point stability analysis: We created a cumulated stability index from which we computed indicators for the changes over time, and risk indicators which measure stability drawdowns and their recovery time. Especially during the oil crisis 1973/74 we get a more distinctive indicator on irregular price movements and drawdowns.

Conclusion: Stability analytics enhances our views and our understanding of extreme risk. New measures can be designed including for example covariance stability, value-at-stability, expected shortfall stability, or drawdown stabilities among others. This results under many circumstances in better risk diversified compositions.

Data Source: Fred2 Federal Reserve, Bureau of Labour Statistics, Commodity Research Bureau Office, Thompson-Reuters.

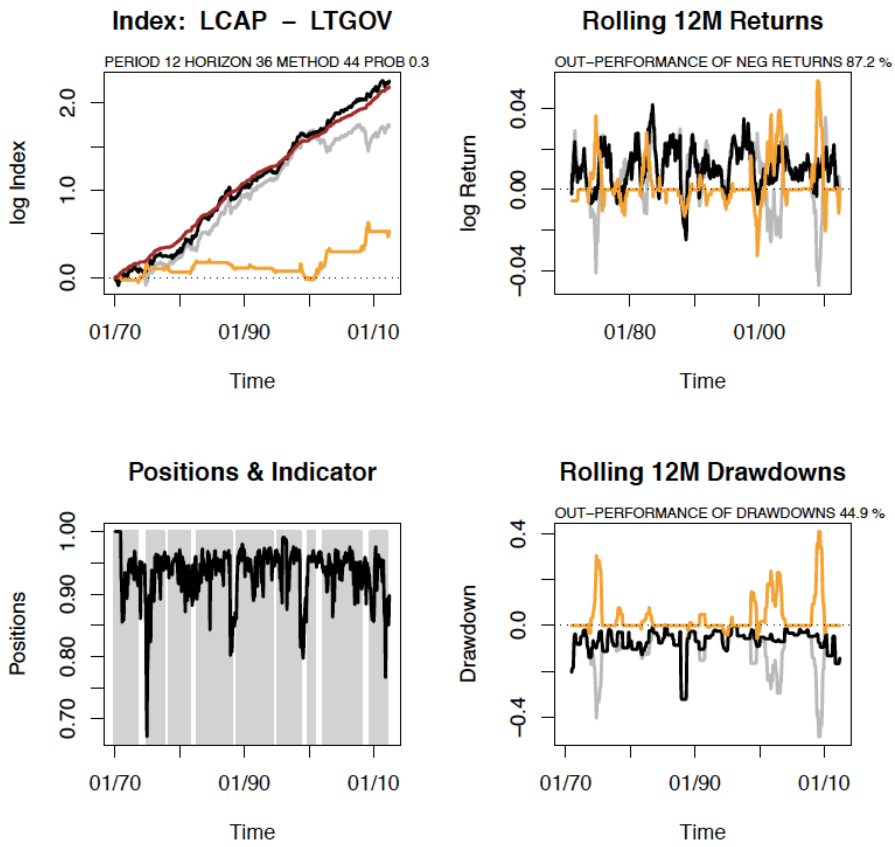

Figure 6:

The charts show the stabilization of the SP500 large cap index with long-term U.S. Government Bonds. For example, such a strategy can be realized by exchange traded funds. The first chart shows the curves for the indices, the second the forecasted positions and the rebalancing indicator curve (computed out-of-sample), and the third and fourth graphs the 12 months rolling returns and rolling drawdowns.

- Chart 1 (upper left) displays the wealth series for the equity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown).
- Chart 2 (lower left) shows the positions and the stability indicator trigger.
- Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (grey), the risk controlled index (black), and the premium (orange).
- Chart 4 (lower right) displays the 12 months rolling maximum drawdowns of returns series for the equity index (grey), the risk controlled index (black), and the premium (orange).

The *binary switching stability strategy* outperforms in 87% of the cases negative returns in the underlying SP500, and shows in 45% of the cases lower drawdowns. We also observe shorter recovery times.

Conclusion: With stabilization objectives we can actively manage and tailor funds and portfolios and achieve a steady increase in wealth with smaller drawdowns and shorter recovery times.

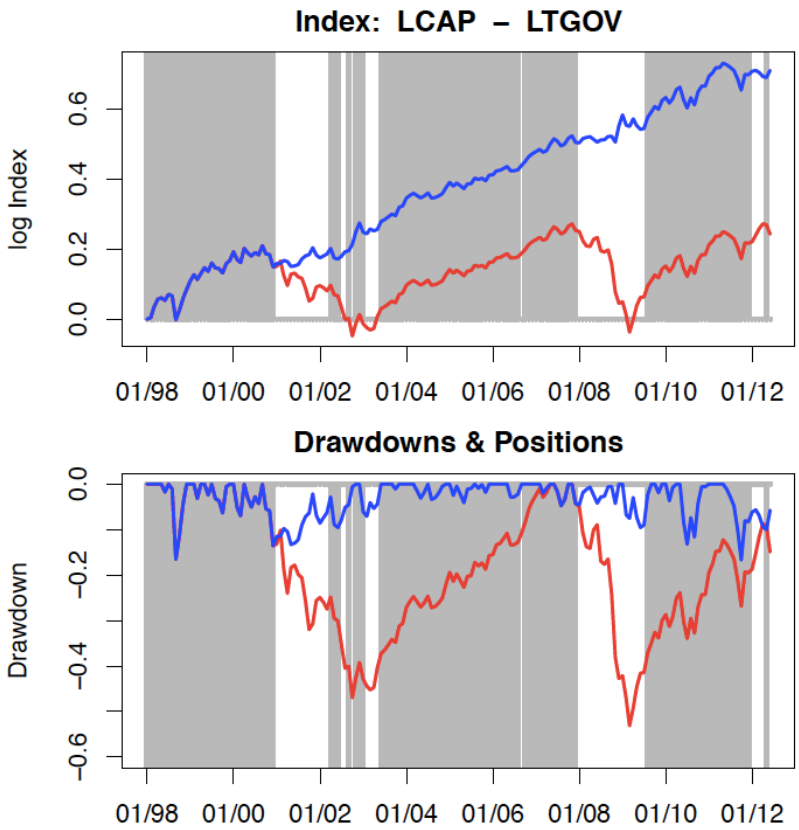

Figure 7:

Logarithmic large cap S&P 500 Index (red curves) rescaled to December 1997 = 1 together with the chart for the drawdowns and recovery times. The capital protected index including long-term Government Bonds and their drawdown risk (blue curves) is obtained from our *binary stability switching investment* strategy. The grey background marks periods during which the portfolio is fully invested in the S&P500, and the white ones those periods during which we have moved to less risky U.S. Government bonds. The underlying strategy was build from exchange traded funds using monthly rebalancing dates.

Conclusion: Stabilization is indeed a powerful concept that favours for funds and portfolios a steady increase in wealth with the objective in small drawdowns and short recovery times.

Data Source: Standard and Poor's, Morningstar, and iShares.

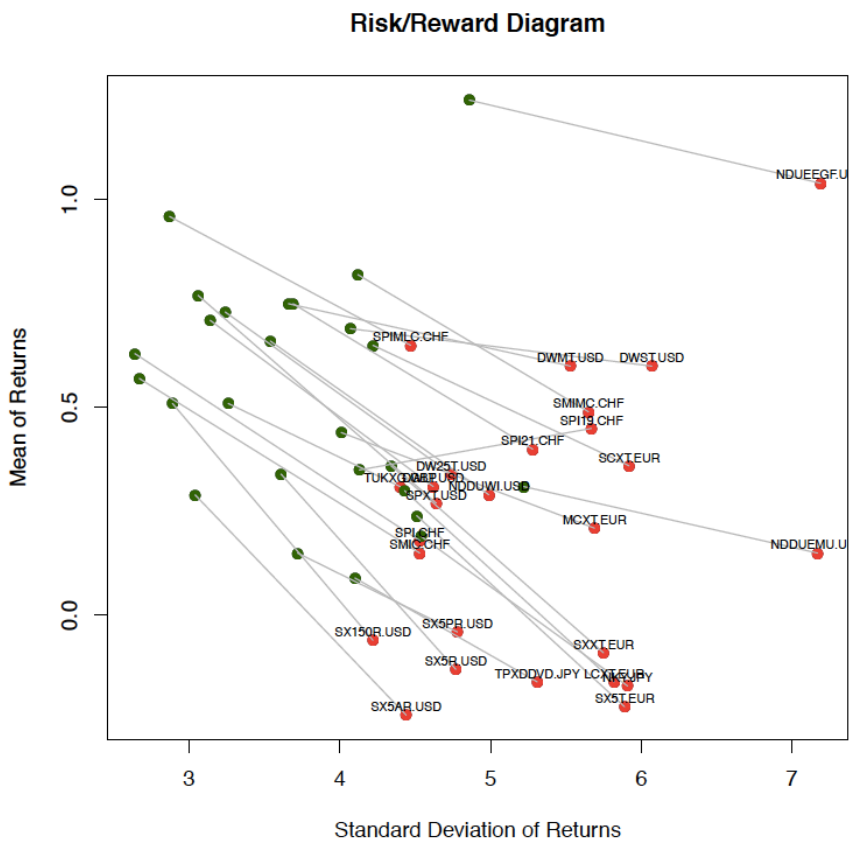

Figure 8:

Risk reward diagram for 26 equity indices (red dots) and their stability controlled counterparts (green) by an admixture of cash. For the indices we observe due to our stability control a performance and risk attribution towards higher mean returns and lower standard deviations. The result is unique for all 26 equity indices.

All indices are total return indices and marked by their Bloomberg symbols:

Switzerland:	SPI, SPI19 (large), SPIMLC, (mid), SPI21 (small Cap), SMIC, SMIMC
United States:	SPXT (SP500), DW25T (Dow Wilshire), DWLT (large), DWMT (mid), DWST (small)
Europe:	SX5T (Eurostoxx50), SXXT (Eurozone), LCXT (large), MCXT (mid), SCXT small Cap),
UK and Japan:	TUKXG (FTSE100), NKY (Nikkei 225), TPXDDVD (TOPIX)
World:	NDDUWI (MSCI World), NDDUEMU (MSCI MU), NDDUEEGF (Emerging Markets),
Regions:	SXG150T (Eurostoxx Global150), SXEU50T (Europe), SXNA50T (North America), SXAP50T (Asia/Pacific)

Conclusion: Binary stability switching investments of equity indices and cash has been successfully tested.

Data Sources: Bloomberg, Standard & Poors, Dow Jones, Stoxx, FTSE, MSCI.

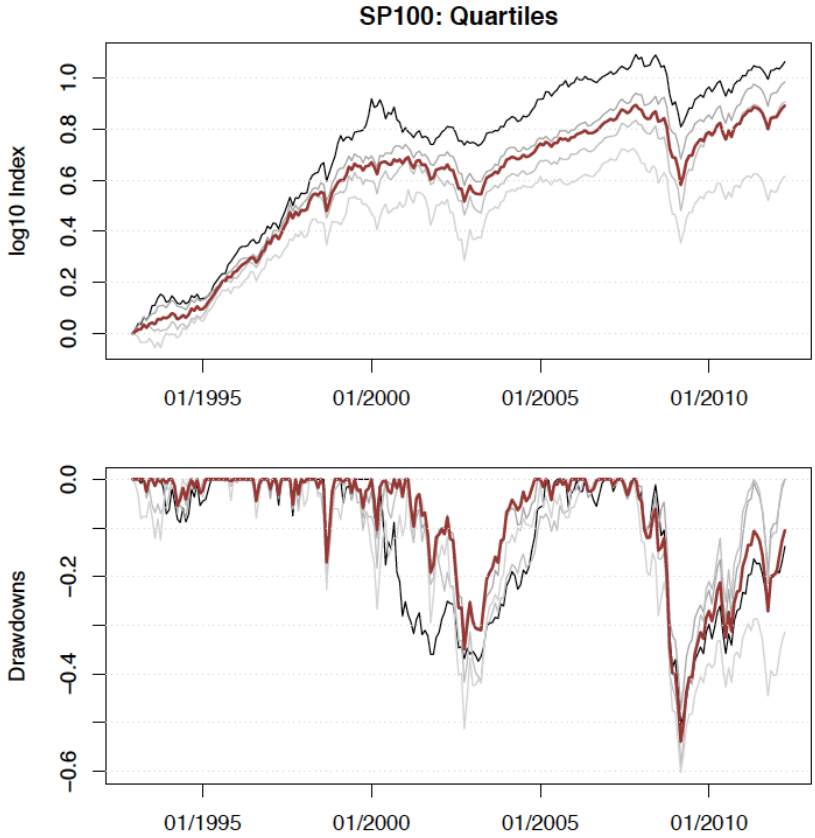

Figure 9:

S&P 100 stability rating and ranking of the 80 stocks with the longest history in the index. We have divided the socks in four groups containing the 20 best, the second and third 20 best, and finally the worst 20 stocks on a rolling window over time. Stability scores were assigned to each equity ranking performance and risk attribution. For each quartile the logarithm of the index and the drawdowns are shown. The colours of the four groups are black, dark grey, grey, and light grey. The quantile separation is quite impressive with a perfect ordering of the performance stabilized sub-indices. The equally weighted index that is composed from the 80 stocks is shown by the thick brown line.

Conclusion: A stability based stock picking process can help to identify the best performing components from a large group of equities. Funds and portfolios can improve essentially their overall performance and risk attribution.

Data Source: Standard & Poors, Yahoo Finance.

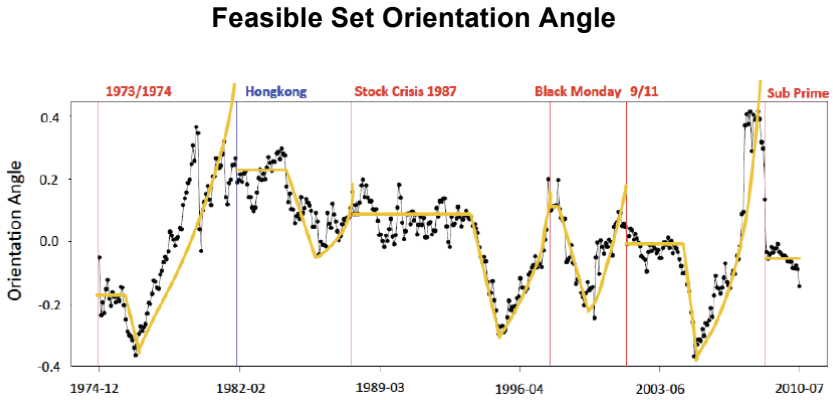

Figure 10:

The graph shows for a selected set of monthly recorded developed country market indices from MSCI the time evolution of the orientation angle of the feasible set. The data series start in December 1974 and end July 2012. The orientation angle of the feasible set shows distinct shapes with a cyclic structure. After a crash, the orientation of the feasible set first remains constant, then it drops down and further on it turns up to diverge when the next stock market crash will be approached. These patterns can be observed for all major crisis: 1973/74, Hong Kong, Stock Market Crash 1987, Black Monday 1997, 9/11, and the recent sub prime crisis. Even more one can observe several cascades before the Hong Kong crisis.

Conclusion: Modelling the feasible set by the evolution of geometric factor shapes can serve as a powerful instrument to detect and even to predict to a certain extent unstable stock market periods. This creates highly valuable views for decision makers.

Data Source: MSCI Morgan Stanley Capital.

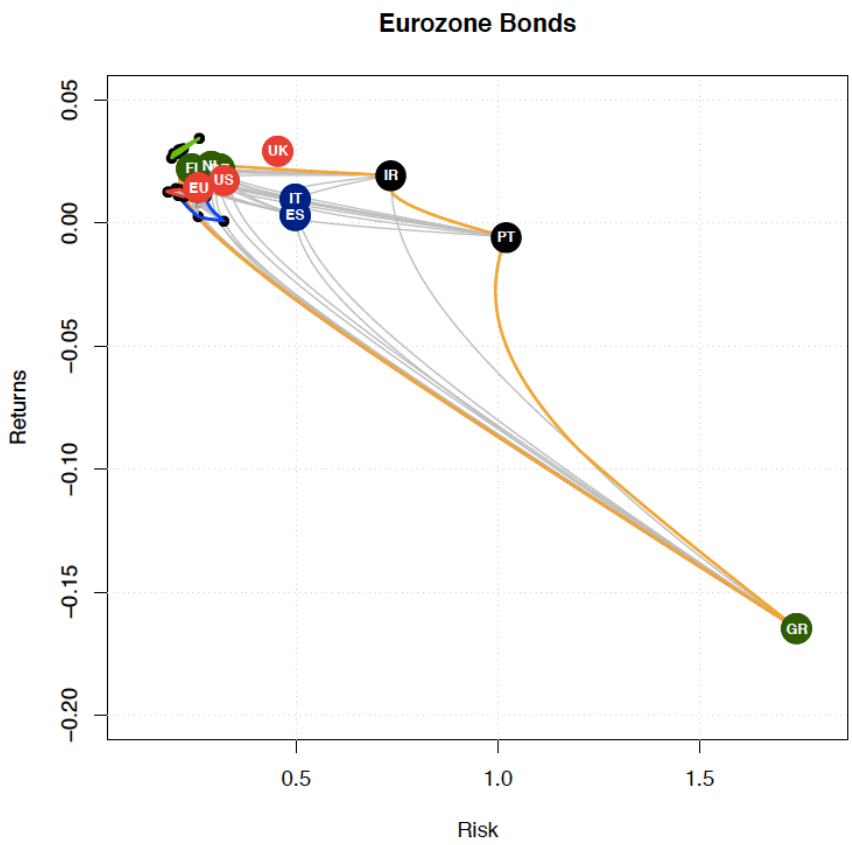

Figure 11:

Time evolution of the feasible set and its hull for Barclays all maturities Eurozone Government Bond Price Index. The time from January 1999 when the Eurozone was founded until June 2012 was divided in 4 periods of equal lengths, these are coloured in chronological order in red, green, blue, and orange. For the last period we have marked Ireland, Portugal and Greece, to see how far they have moved away from the other countries. The dots IR, PT, and GR position the risk calculated from he standard deviation of the returns and the mean returns. The dark blue dots show the move for Italy and Spain. Most stable conditions can be found in decreasing order for Finland, the Netherlands, and Germany. For comparisons we have also added as red dots the Government Bonds for the Eurozone, U.S.A, and UK. The plot can be extended to a stability attribution versus mean stability performance diagram.

Conclusion: From the time evolution of the feasible set, and the movement and divergence of its individual components an investment or risk manager can create more healthy and robust investment decisions.

Data Source: Barclays Capital.