Bayesian Stability Concepts for Investment Managers

Tobias Setz
Diethelm Würtz

Rmetrics Association & Finance Online Publishing

R/Rmetrics eBook Series

"R/Rmetrics eBooks" is a series of electronic books and user guides aimed at students, and practitioners entering the increasing field of using R/Rmetrics software in the analysis of financial markets.

Book Suite:

Basic R for Finance (2010),
Diethelm Würtz, Tobias Setz, Yohan Chalabi, Longhow Lam, Andrew Ellis

Chronological Objects with Rmetrics (2010),
Diethelm Würtz, Tobias Setz, Yohan Chalabi, Andrew Ellis

Financial Market Data for R/Rmetrics (2010)
Diethelm Würtz, Tobias Setz, Andrew Ellis, Yohan Chalabi

Portfolio Optimization with R/Rmetrics (2010),
Diethelm Würtz, Tobias Setz, William Chen, Yohan Chalabi, Andrew Ellis

Asian Option Pricing with R/Rmetrics (2010)
Diethelm Würtz

Indian Financial Market Data for R/Rmetrics (2010)
Diethelm Würtz, Mahendra Mehta, Andrew Ellis, Yohan Chalabi

Free Documents:

A Discussion of Time Series Objects for R in Finance (2009)
Diethelm Würtz, Yohan Chalabi, Andrew Ellis

Long Term Statistical Analysis of US Asset Classes (2011)
Diethelm Würtz, Haiko Bailer, Yohan Chalabi, Fiona Grimson, Tobias Setz

R/Rmetrics Workshop Meielisalp 2010
Proceedings of the Meielisalp Summer School and Workshop 2010

Editor: Diethelm Würtz

R/Rmetrics Workshop Singapore 2010
Proceedings of the Singapore Workshop 2010
Editors: Diethelm Würtz, Mahendra Mehta, David Scott, Juri Hinz

Contributed Authors:

tinn-R Editor (2010)
José Cláudio Faria, Philippe Grosjean, Enio Galinkin Jelihovschi and Ricardo Pietrobon

Topics in Empirical Finance with R and Rmetrics (2013)
Patrick Hénaff

Under Preparation:

Advanced Portfolio Optimization with R/Rmetrics (2014),
Diethelm Würtz, Tobias Setz, Yohan Chalabi

R/Rmetrics Meielisalp 2011
Proceedings of the Meielisalp Summer School and Workshop 2011
Editor: Diethelm Würtz

R/Rmetrics Meielisalp 2012
Proceedings of the Meielisalp Summer School and Workshop 2012
Editor: Diethelm Würtz

Bayesian Stability Concepts for Investment Managers

Tobias Setz
Diethelm Würtz

July 2014

Series Editors:
Professor Dr. Diethelm Würtz
Institute for Theoretical Physics and
Curriculum for Computational Science
ETH - Swiss Federal Institute of Technology
Hönggerberg, HIT G 32.3
8093 Zurich

Contact Address:
Rmetrics Association
Zeltweg 7
8032 Zurich
info@rmetrics.org

Authors:
Diethelm Würtz, ETH Zurich
Tobias Setz, ETH Zurich

Dr. Martin Hanf
Finance Online GmbH
Zeltweg 7
8032 Zurich

Publisher:
Finance Online GmbH
Swiss Information Technologies
Zeltweg 7
8032 Zurich

ISBN: 978-3-906041-21-6

© 2010-2015, Rmetrics Association and Finance Online GmbH, Zurich
Permission is granted to make and distribute verbatim copies of this manual provided the copyright notice and this permission notice are preserved on all copies.
Permission is granted to copy and distribute modified versions of this manual under the conditions for verbatim copying, provided that the entire resulting derived work is distributed under the terms of a permission notice identical to this one.
Permission is granted to copy and distribute translations of this manual into another language, under the above conditions for modified versions, except that this permission notice may be stated in a translation approved by the Rmetrics Association, Zurich.

Limit of Liability/Disclaimer of Warranty: While the publisher and authors have used their best efforts in preparing this book, they make no representations or warranties with respect to the accuracy or completeness of the contents of this book and specifically disclaim any implied warranties of merchantability or fitness for a particular purpose. No warranty may be created or extended by sales representatives or written sales materials. The advice and strategies contained herein may not be suitable for your situation. You should consult with a professional where appropriate. Neither the publisher nor authors shall be liable for any loss of profit or any other commercial damages, including but not limited to special, incidental, consequential, or other damages.

Trademark notice: Product or corporate names may be trademarks or registered trademarks, and are used only for identification and explanation, without intent to infringe.

PREFACE

In shipbuilding and nautical science, the term stability is used to describe a ship's ability to maintain an upright position or to right itself independently after listing. The shape and size of the hull, the mass and distribution of mass by the body of the ship, the cargo weight and the distribution of load by the body of the ship, not forgetting the dynamic behaviour when the ship changes course at high speed, are essential factors that need to be taken into account in order to ensure safe passage. Additional factors that can endanger a ship include rough seas and high winds.

The financial markets can be described in a similar way. They need excellent shipbuilders and experienced captains to keep the ship on course. Building and managing a portfolio is no easy task and should not be underestimated, especially in times of impending crisis.

Conventional portfolio management methods are seldom up to these tasks and that is all the more reason why there is a need from a scientific and technological standpoint for systems that are capable of monitoring investments effectively and identifying risks early on. It should also not be the case that just one eye is kept on return and the other eye on risk but rather that both eyes together should also monitor the stability of investments.

This is the focus of our approach. For several years now, we have been closely monitoring developments that have enabled the identification of structural changes in dynamic systems. Such systems are highly versatile and have achieved successful results in financial market analysis in particular.

The aim of this collection of articles and reports is to show how the latest statistical methods can be used in portfolio analysis and portfolio management. The idea of promoting stability concepts for portfolio analysis and portfolio management goes back to 2008. At the time we were in the middle of the financial crisis and we were busy identifying structural

changes in dynamic processes at the Institute of Theoretical Physics at ETH Zurich prior to the shockwaves in the financial markets. The results were presented for the first time in 2010 at a scientific conference in Singapore. Today, we can say that we have methods, processes and software to hand that enable us to monitor portfolios and identify structural changes in their dynamic behaviour early on.

Last but not least we like to thank ETH Zurich, Rmetrics Association Zurich, Finance Online GmbH Zurich, Record Currency Management Windsor, Clariden Leu (now Credit Suisse) and Theta AG Zurich for their continuous support.

We hope that you enjoy reading the articles and reports.

Diethelm Würtz
Tobias Setz
Zurich, July 2014

CONTENTS

PREFACE III

CONTENTS VII

INTRODUCTION 1

I Theoretical Background 5

1 VULNERABILITIES IN TIME SERIES 7

2 BAYESIAN CHANGE POINT ANALYSIS 25

3 STABILITY IN A NUTSHELL 57

II Applications 61

4 RATING AND RANKING BY STABILITY 63

5 STABILITY PARITY INDEXATION 89

6 BAYESIAN SWITCHING STRATEGIES 137

7 STABILIZATION OF PORTFOLIOS 153

8 SECTOR ROTATION AND EQUITIES 189

9 FORWARD AND SPOT FX MARKETS 209

III Appendix 213

10 RMETRICS ASSOCIATION 215

11 RMETRICS TERMS OF LEGAL USE 219

About the Authors **221**

INTRODUCTION

This book is a collection of research reports and material collected from work done in the Econophysics Research Group at ETH Zurich. Most of the work was so far unpublished and only available through working papers.

The book is divided into three parts.

PART I:

The first part is dedicated to motivate why we are interested in stability concepts, and to explain the algorithms and approaches we are use to understand the mechanisms behind stability monitoring and control.

The first public available working paper was written by Yohan Chalabi, Tobias Setz und Diethlem Würtz [2011]. In this paper they have investigated monthly records of the S&P 500 index going back to the year 1925. In this paper we applied four retroactive approaches to monitor structural changes: (i) turning points and cycle analytics, (ii) Bayesian structural change points analytics, (iii) PCA extreme values and outlier analytics, and (iv) non-stationarities and multifractal wavelet analytics. All four approaches deliver valuable information about the structure of vulnerabilities of financial time series.

The most powerful algorithm for the analysis of the dynamical structure of the financial time series was the *Bayesian Change Point* method, BCP, as introduced by Barry and Hartigan [1992, 1993]. We have reprinted Chapter II of the Master Thesis of Tobias Setz [2012] where he explains the BCP algorithm and how we have applied it in all investigations. The example he shows explores the dynamics of the Swiss Markets, the respective time series are the Swiss Performance Index, the Swiss Bond Market Index, the Swiss Bill Market Index and the Swiss Inflation Index.

PART II:

In the second part we present six applications. Some of them we have implemented Shiny web applications.

In section 4 we present a paper written by Diethelm Würtz, Yohan Chalabi, and Tobias Setz [2011] that discusses a rating and ranking approach based on the Bayesian binary switching approach. We have ranked the 80 stocks from the S&P 100 with the longest history in the index. The ranking was done by stability quartiles. The first group contains the 20 best, the second and third group the next 20 best, and the last group contains the stocks with the worst 20 stocks from the index. The Quantile separation works quite impressive with an almost perfect ordering of the performance with respect to the four quartile stabilized subindices.

The second reprint presented in section 5 by Diethelm Würtz and Tobias Setz [2012] applies the Bayesian binary switching strategy to portfolio management and design.

The topic of the third reprint in section 6 is dedicated to Bayesian switching strategies. It is shown how indicators and signals can be generated from the Bayesian change point approach. When instabilities increase we switch from a risky asset to a riskless one. We show examples of blends constructed from investable stock market indices and cash. This approach can be considered a very successful wealth protection mechanism.

In section 7 we consider the stabilization of portfolios. The portfolio components consist of risky assets represented by stock indices, less risky assets represented by government bonds, and riskless assets represented by Libor rates or cash. The Bayesian switching strategy is used to build a cascade from risky to riskless assets when instabilities increase.

The eighth section deals with industry sector rotation and equity stability indexation. The idea behind this is to stabilize financial instruments from a lower hierarchy level. We start with industry sectors and stabilize each sector by its own. Then we compose portfolios from investable stabilized sector indices. The same procedere of stabilization is applied to individual equities that compose a stability weighted portfolio.

In section 9 we have added an abstract from a scientific conference briefly summarizing our work in Forward and Spot FX Markets.

PART III:

In this section we show how the Rmetrics Association has contributed to the stability concept approach developed in the ETH Econophysics research group.

First it is very important to have a powerful statisitcal software environment at hand. In all our software implementations we use R. But this is not enough. One also needs computational finance and financial engineering tools with the most recent algorithms implemented. Here comes Rmetrics into play. We report the role of the Rmetrics Association, and the worldwide open source software developments which made our results feasible and possible.

PART I

THEORETICAL BACKGROUND

CHAPTER 1

VULNERABILITIES IN TIME SERIES

Stability Analytics of Vulnerabilities in Financial Time Series
Yohan Chalabi, Tobias Setz, Diethelm Würtz
Econophysics Group, Swiss Federal Institute of Technology Zurich
Econophysics Working Paper, Unpublished, ETH Zurich, September 2011

This chapter reprints an unpublished working paper written in 2012. The report describes the idea and the major concepts on how to locate and to quantify change points and structural breaks in a financial time series. The underlying statistical concepts for analyzing change points and structural breaks, for detecting extreme values and outliers and for exploring non-stationarities and multifractal behavior are briefly summarized. The analytics are applied to the long term U.S. Large Cap Stocks Index and the Commodity Research Bureau Index ranging back to 1925.

Stability Analytics of Vulnerabilities in Financial Time Series

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

First Version September 30, 2011
This Version April 16, 2012, Last Update August 2012

Abstract

In this article we give a brief overview to the recently introduced stability analytics to analyze and quantify vulnerabilities in financial time series. We present the underlying statistical concepts for analyzing change points and structural breaks, for detecting extreme values and outliers and for exploring non-stationarities and multifractal behavior. The analytics are applied to the long term U.S. Large Cap Stocks Index and the Commodity Research Bureau Index ranging back to 1925.

1 Introduction

To identify and quantify risk in a financial time series several statistical measures were introduced in literature. These include rolling measurements of sample variances, volatilities, value at risk, expected shortfall, spectral risk measures and distortion risk measures amongst others. In this paper we like to follow a different approach which allows to quantify "risk" by analyzing (i) structural changes and break points, (ii) extreme values and outliers, and (iii) non-stationarities caused by multifractal behavior in financial time series. These three measures can be considered as indicators for the *stability* of the generating process underlying a financial time series.

In the following we investigate the stability of prices and indices of financial market instruments. Note, this should not be confused with financial stability analysis where stress testing is used to explore the stability conditions of financial systems. The major uncomfortable feelings of any investor are those of large losses, deep drawdowns, and long recovery times. The measures presented in the following are concerned with risk as well but they also describe unstable changing conditions of the environment which influences the time series process. It is the goal of this paper to define and explore measures which define risk from a stability point of view.

In section 2 we briefly discuss methods to detect turning points in a financial time series process. We use a retroactive spline smoothing approach to determine the up and downs. In section 3 we apply the Bayesian product partition model of Barry and Hartigan [1992] in the Monte Carlo Markov Chain approximation to detect change and break points in a financial return series. In section 4 we embed the univariate time series in phase space and apply the robust

principal component analysis to detect multivariate patterns of extreme values and outliers. The formulation we use is that of Filzmoser, Maronna, and Werner [2008]. In section 5 we compute the Morlet wavelet spectrum to make non-stationarities caused by multifractal behavior visible. We use the Morlet wavelet spectrum as formulated by Torrence and Compo [1998].

A preliminary description of the *Stability Analytics* was already presented by Würtz et al. [2010ab, 2011a] and applied in the chapter about "Advanced Analytics" in the handbook *Long Term Statistical Analysis of U.S. Asset Classes* by Diethelm Würtz et al. [2011]. From this book we have also overtaken the data sets for the US large cap stocks [2011] and the CRB commodity research bureau index [2011] used in this paper. All calculations were done with the R statistical software environment [2012] and the financial computing environment Rmetrics [2012].

2 Turning Points and Cycles

In the business cycle analysis of economic indicators, turning points play an important role. They identify the datings and durations of changing economic conditions like expansions and contractions. For financial data we can use similar ideas and concepts to identify increasing (bull) and decreasing (bear) market periods. The method we use is a retrospective approach which smoothes the index (or price) series to a given degree. This helps to identify the peaks and/or the pits of the series. From the forecasting point of view, a turning points analysis can help to predict changing market conditions.

Vanhaelen, Dresse and De Mulder [2000] formulate the following general principles for the detection of turning points: (i) The choice of turning points should not be affected by aberrant observations, extremes or outliers, (ii) irregular movements in the series should be excluded and (iii) the application of the method should not delay the identification of the turning points for too long. The authors also suggest additional requirements which may be imposed in accordance with stylized facts of the financial time series. This may concern the succession of peaks and troughs, a minimum length for the phases and cycles and possibly a minimum amplitude for the movements.

In the business cycle literature we find that the most used approach for detecting turning points is the method of Bry and Boschan [1971]. This approach (i) first involves the detection of extremes and outliers and their replacement by a moving average. (ii) Then an initial set of turning points is identified in a smoothed series, by applying a moving average filter. (iii) The turning points detected at the different stages are checked for the alternation of peaks and troughs, for a minimum span of 15 months between two successive peaks or two successive troughs, and of 5 months between two successive turning points. Finally, (iv) turning points in the first or the last 6 months of the series are rejected, Vanhaelen, Dresse and De Mulder [2000].

Other approaches use filters to smooth the financial time series. Two examples are the (i) HP filter of Hodrick and Prescott [1997], and the (ii) CF filter of Christiano and Fitzgerald [1999], which yield smooth cycles, and as a result the Bry-Boschan routine simplifies. Usually the filtered cycles do not require several iteration steps since phase and cycle length-constraints are getting better satisfied by smoothing, Gyomai and Guidetti [2008].

Here we use an alternative approach. We found out, that one can achieve with spline smoothing, see Hastie and Tibshirani [1990], Chambers and Hastie [1992], and Green and Silverman [1994], the same effects as obtained by filtering. Therefore we applied first spline smoothing to the

index values, according to Ripley and Mächler [2011], and then we searched for the peak and trough points, Ibanez [1982]. The result of the retroactive turning points analysis using the formalism of Ibanez, Grosjean, and Etienne [2011], is shown in figure 1 for two asset classes, i.e. for the (i) U.S. large cap stocks (LCAP) and the (ii) commodity research bureau index (CRB). The turning points (red bullets) as shown in figure 1 were extracted from the spline smoothed monthly index values (red curve). Note, that the index (black curve) is plotted on a logarithmic scale. The shaded areas (blue) reflect bear markets. Also, the axis for the returns (orange curve) is suppressed.

The number of bear markets depends on the level of smoothing. For a medium smoothing parameter, we observe in the case of the U.S. large cap stocks 6 down periods. The major down-periods are related to the U.S. great depression, to the U.S. sub prime crisis, and to the recent European debt crisis. For the commodities we observe 11 down-periods. The most significant ones are related to the great depression, to the oil crisis, and the recent food speculation. To identify these periods have a look at figure 1.

3 Bayesian Structural Change and Break Points Analytics

The aim of change point analysis is to partition the series into different segments that are connected and ordered with increasing time. This is done by clustering the elements of the series keeping the time order. The result is a set partition where within each segment the elements have a common parameter or a set of parameters. In the detection of change points this parameter is usually the mean. The cuts between the segments are known as change or break points. There are several models for segmentation and partitioning by piecewise mean, variance, correlation or distributional parameters.

Frequentist change point detection methods rely on hypothesis testing. The major frequentist tests are summarized by Zeileis et al. [2007]. The procedures they discuss are concerned with testing or assessing deviations from stability in the classical linear regression model. In these methods the breakpoints are located by minimizing the residual sum of squares of a piecewise linear regression model. The ideas behind the implementation can be found in Zeileis [2003]. Another approach is *Circular Binary Segmentation*, see Sen [1975] and Olshen [2004]. Circular binary segmentation methods use likelihood ratio statistics to test the null hypothesis of no change point. If the null hypothesis is rejected the series is split and the test is repeated on the sub-segments till no additional changes are detected, see Olshen [2007].

Here we use a *Bayesian Change Point Detection* method to identify change points in the mean and variance of the series. The *Bayesian Product Partition Model* introduced by Barry and Hartigan [1992] allows us to determine the probability of there being a change point at each location in the series. This becomes very advantageous in the stability analysis context as information about which time periods have frequently high change point probabilities and are therefore less stable than when the probability of a change is low. The Bayesian product partition model may also provide estimates of the parameters at each moment in time as well as the posterior distributions of the partitions and the number of change points. This was later extended by Loschi [2005] to give the posterior distribution of the probability that each instant in time is a change point. While frequentist procedures for change point analysis estimate specific locations of change points, the Bayesian procedure offers the probability of a change point at each location in the series. In a retroactive stability study this probability information may be more important

than the location of historical changes which are often already known and are easily located. For further discussions and applications we refer to the work of Erdman and Emerson [2008].

For the two asset classes, U.S. large cap stocks (LCAP) and the commodity research bureau index (CRB) we have computed the posterior mean, the posterior variance, and the probability for observing a change point or break points in the dynamical price process of the two instruments, LCAP and CRB, respectively. The results are shown in figure 2 and 3. From the ratio of the posterior mean and the square root of the posterior variance we have also calculated a modified performance measure in the sense of the Sharpe Ratio. Further performance measures as described in the book of Bacon [2006] can be derived in the same spirit. For both indices the stability analytics give a clear indication for the periods of instabilities.

The posterior probabilities for the LCAP and CRB logarithmic returns have been smoothed by splines on several levels and are expressed by the rainbow colored curves in figure 4. The black curve about the 0.5 level expresses the difference between the strongest smoothed curve and the weakest smoothed curve which serves as a measure for stability. Less stable periods are below the 0.5 levels and above this level stability increases. The troughs of this curve indicate the lows in the stability of the LCAP and CRB indices.

The first unstable periods in the LCAP index can be found for the Great Depression. The great depression started in about 1929 and lasted until the late 1930s or early 1940s. The dot-1 in figures 2 and 4 indicates October 24, 1929, known as the *Black Thursday* when the stock market in New York abruptly felt. The next severe instabilities appeared 1973 as a consequence of the *Oil Price Shock* along with the stock bear market between January 1973 and December 1974. This crisis can be regarded as the first event since the Great Depression which had a persistent effect on the world economy. The dot-2 marks end of August 1974. The dot-3 event was caused by the *Black Monday* October 19, 1987, when stock markets around the world crashed while the dot-4 marks the collapse of Lehman Brothers during the U.S. Sub Prime crisis.

In figure 3 and 4 where we have plotted the posterior probabilities for the CRB Commodity Research Bureau Index, the dots mark the following events: as of December 1932 the *Great Depression*, as of mid of 1947 the *Post World War II* period, as of December 1973 the *Oil Crisis*, and as of March 2008 the world *Food Price Crisis*. Food price speculation increased dramatically in 2007 and during the 1st and 2nd quarter of 2008 creating a global crisis and causing political and economical instabilities and social unrest in both poor and developed nations. For further information and discussions on the economic and financial instabilities we refer to Wikipedia, and the references given there.

4 PCA Extreme Values and Outlier Analytics

Outlier detection methods are a way of searching for extreme and outlying patterns in the data. Identifying possible outliers and periods with many outlying data points helps to identify periods of instability. The *principal component outlier analytics* can be regarded in this respect. It helps to identify and locate extreme and outlying values. It is a robust method which gives an effective indication when extremes and outliers start to dominate the financial or economic time series process and create periods of high risk.

There are many different methods of outlier detection. In this study we focus on a principal components (PC) outlier detection method where we use the Mahalanobis distance as the measure

of "outlyingness". The method is able to detect outlying points in a way that is both computationally efficient and robust, Filzmoser, Maronna and Werner [2008]. A principal components analysis returns the set of principal components. The PC's are a set of orthogonal variables which each maximize the variance in their respective directions. They are selected such that the first component explains the most variance in the data, the second component the second most and so on. Outlying data points increase the variance of the data. As the PC's are the directions which maximize the amount of variance along each component, it is plausible that the extremes will appear more visible in PC space than in the original data space.

For the LCAP and CRB indices we performed a principal component analysis on overlapping weekly patterns binded row by row to a multivariate time series. We identified the outlying patterns using the algorithm of Filzmoser, Maronna and Werner [2008]. Based on the robustly sphered data, semi-robust principal components are computed within their approach which are needed for determining distances for each observation. Separate weights for location (mean) and scatter (variance) outliers are then computed based on these distances. The combined weights are finally used for outlier identification. For each observation the algorithm returns a numeric vector with final weights where small values indicate potential (multivariate) outliers. Also returned are two vectors with weights for the locations and scatters from which we can derive weighted means and variances.

In figure 5 we show the results from the PCA extreme value and outlier analytics for the monthly logarithmic returns calculated from the LCAP and CRB indices. We have also added to this graph, as in the case of the BCP Analytics, the rainbow colored smoothed curves of the numeric weights for each observation. The maximum dispersion of these curves gives us again an indication of the stability of the underlying time series process.

5 Non-Stationarities and Multifractal Wavelet Analytics

Stationarity is the fundamental requirement for any real world forecastable time series model. In this case we assume that the distribution of previous observations can be used to predict future ones. In other terms, the joint probability distribution of the observations is assumed to be stationary over time, i.e. its moments including the mean and volatility are constant. However, we often observe events in financial returns that cannot be described by the distribution of past observations. When such points are observed, the time series is considered to be non-stationary.

Our choice to analyze non-stationary behavior in asset returns is the multi-resolution approach in time/frequency space using wavelet analysis. Wavelet analysis is a widespread technique that offers the user the possibility to decompose a time series into time/frequency space, see Gencay, Selcuk, and Whitcher [2002], Mallat [2009], and Nason [2008]. This allows one to determine the dominant modes of variability in the series and how they vary over time. The signal can be examined in time and frequency simultaneously. The wavelet transform has been found to be particularly useful for series that are aperiodic, noisy, irregular, intermittent and so on, see Addison [2002].

Wavelet functions are localized waveforms that can be altered in two ways, either moved in location along the series or altered in frequency - a stretching or squeezing of the wavelet form. At each desired location and frequency (scale) the resulting wavelet is compared to the original series to determine how well it matches. A good match results in a large transform value and vice versa. The transform values for each particular location and scale are plotted on a contour

plot. For the Morlet wavelet form, the transform value is a complex number and different possibilities to plot those values are thinkable. We use the square of the absolute value (power spectrum) which has an expectation value that is approximately equal to the variance of the series, Torrence, and Compo [1998]. By examining the patterns in the wavelet contour plot it is possible to see changes in the frequency and variance of the signal as well as jumps and discontinuities very clearly.

For the monthly logarithmic returns of the LCAP and CRB indices we have computed the wavelet power spectrums. Figure 6 shows the transform values of the time series for each location and scale considered. The location or x-axis marks end-of-month dates, the scale or y-axis counts periods given in months. The contours of the image plot were taken on equidistant quantile levels ranging from yellow to red. The thick line belongs to the 95% significance level. The cross-hatched regions on either end of the graph indicate the *cone of influence*, where edge effects become important.

The big depression is highly visible for both indices, the LCAP and CRB. For the CRB the instabilities last much longer until the 50s. After World War II we observe a prosperous increase in the indices going together with a high stability. The first oil crisis in the 1973/74 becomes quite evident in the CRB wavelet spectrum with minor influence in the large cap stock market. The period of instability caused by the oil crisis as marked by the 95% level contours extends to more than a decade. The most recent instabilities in the commodities can be related to the 2010 food speculation. The short but nevertheless significant crashes in the stock market can be identified in the LCAP wavelet spectrum: Black Monday in October 1987, Dot Com Bubble in April 2000, 9/11 Attack in September 2001, and Sub Prime Crisis in February 2007.

6 Summary and Outlook

Bayesian change point analytics, principal component extreme value and outlier analytics, and the wavelet analytics are three flavors of analysing and quantifying the vulnerabilities to external forces of a time series process. In all three cases we can define a number to measure the strength of instabilities appearing over time.

Evenmore, the time dependent process of stability measured on a rolling window can be used to define (like for the volatility) a value for the average (mean) and variability (variance) of the changing stability over time. We can derive a cumulated stability index, and from the distribution of its changes we can derive and calculate measures like value-at-stability or an expected shortfall stability 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 be designed from stabilities, like we know it for example from the Sharpe ratio of financial returns.

The stability measures can also be used for rating and ranking equities or other financial assets. In this case we select those instruments with the highest stability and with lowest fluctuations. On the other hand we can formulate a stability parity approach in portfolio optimization or for the creation of new indices based on stability parity indexation concepts. Like in risk budgeting, see for example Demey, Maillard, and Roncalli [2011], we can introduce the concept of stability budgeting which can help to design better diversified portfolios and indices. Finally we like to remark that stability analytics can also be used to compute the sensitivity with respect to market stability, and to construct scenarios for the identification of vulnerabilities.

Turning Points and Cycles Analysis

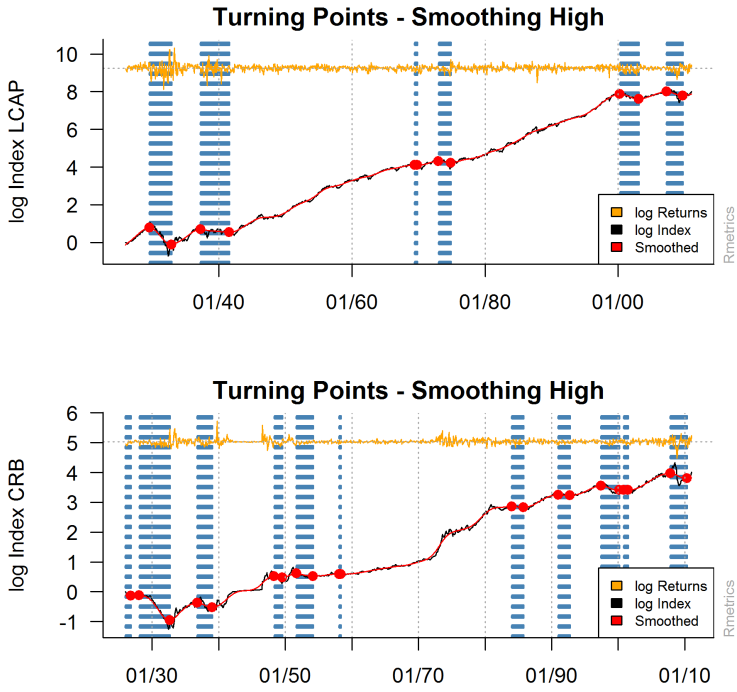


Figure 1: Monthly turning points analytics of the U.S. Large Cap Stocks Index (upper graph) the CRB Commodity Research Bureau Index (lower graph) starting in December 1925 and ending in December 2010. For a detailed description we refer to the text.

LCAP – Bayesian Change Point Analytics

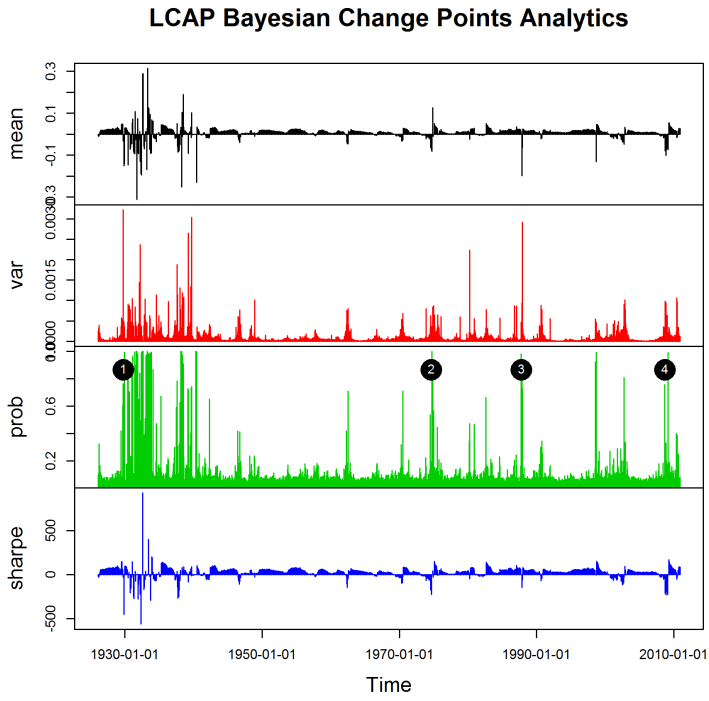


Figure 2: Monthly Bayesian change points analytics of the logarithmic returns of the Large Cap Stocks Index starting in December 1925 and ending in December 2010. From up to down the curves show the posterior mean, the posterior variance, the posterior probability, and the probability weighted ratio of the posterior mean and standard deviation (root of variance). The four dots mark (1) the Black Thursday 1929, (2) the Oil and Stock Crisis 1973/74, (3) the Black Monday 1987, and (4) the collapse of Lehman Brothers.

CRB – Bayesian Change Point Analytics

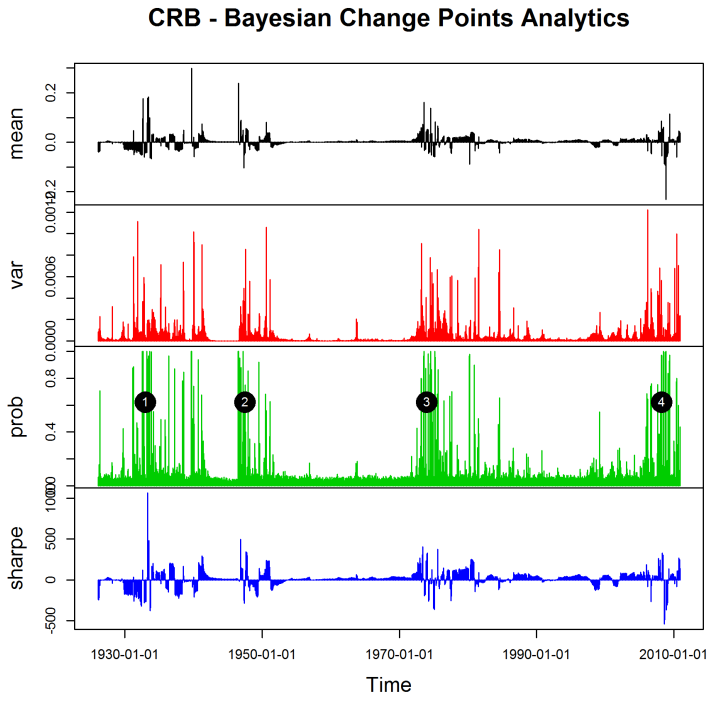


Figure 3: Monthly Bayesian change points analytics of the logarithmic returns of the Commodity Research Bureau Index starting in December 1925 and ending in December 2010. From up to down the curves show the posterior mean, the posterior variance, the posterior probability, and the probability weighted ratio of the posterior mean and standard deviation (root of variance). The four dots mark (1) the Great Depression as end of 1932, (2) the Post World War II period as mid of 1947 (3) the Oil Price Crisis as end of 1973, and (4) the food price speculation as end of the first quarter of 2008.

LCAP / CRB – Bayesian Change Point Indicators

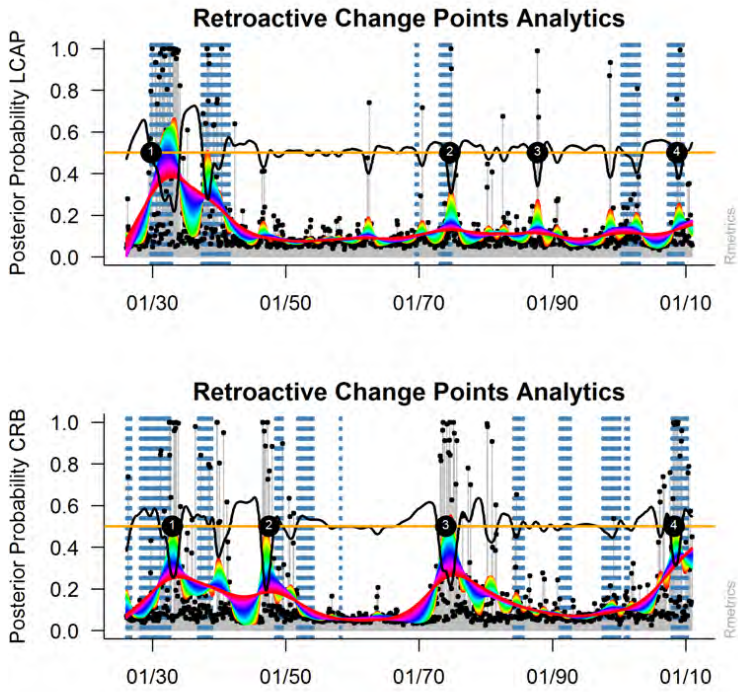


Figure 4: Monthly Bayesian change points analytics of the U.S. Large Cap Stocks Index (upper graph) and the CRB Commodity Research Bureau Index (lower graph) starting in December 1925 and ending in December 2010. For a detailed description we refer to the text. The dots number the same events as in figures 2 (LCAP) and 3 (CRB).

LCAP / CRB – Principal Component Outlier Indicators

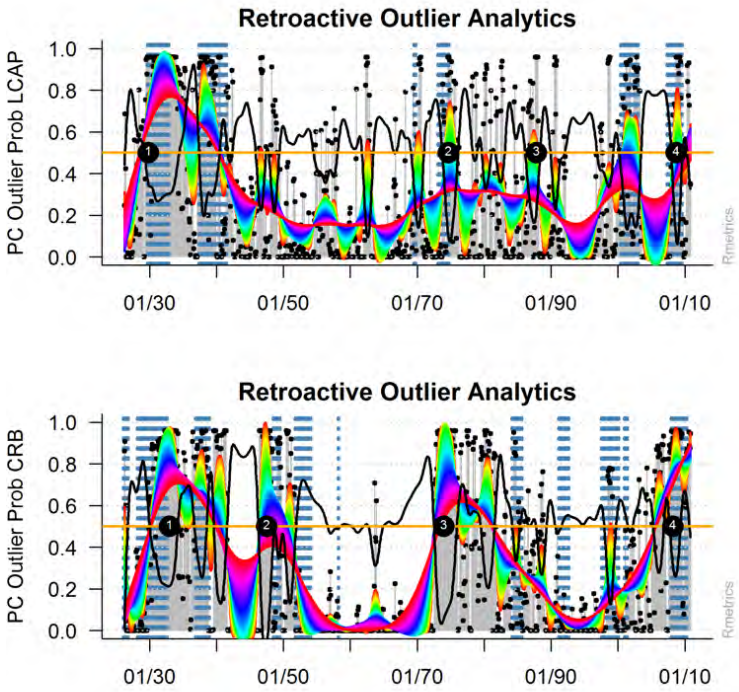


Figure 5: PC Outlier Analytics - U.S. Large Cap Stocks and CRB Commodity Research Bureau Index: The figures show the posterior probability for each date of having an outlier within the time series. The rainbow colored time series are smoothed curves of the original probability series. The black curve is the difference between the strongest smoothed curve and the weakest smoothed curve which serves as a measure for stability. The dots number the same events as in figures 2 (LCAP) and 3 (CRB).

LCAP / CRB – Morlet Wavelet Analytics

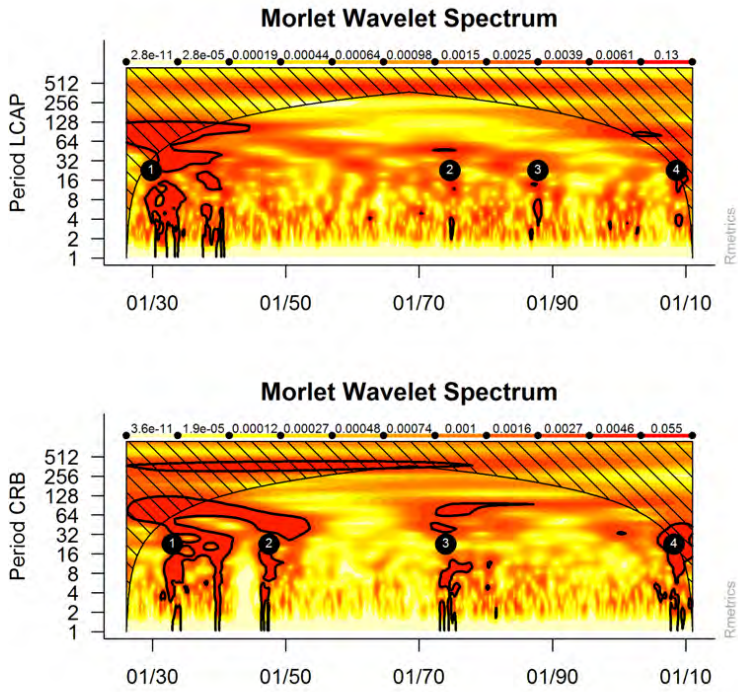


Figure 6: Wavelet Analytics - U.S. Large Cap Stocks (upper) and CRB Commodity Research Bureau Index (lower image). The dots number the same events as in figures 2 (LCAP) and 3 (CRB).

References

Addison P.S. [2002], The Illustrated Wavelet Transform Handbook, Institute of Physics Publishing Ltd., Bristol and Philadelphia.

Andersen T.G., Davis R.A., Kreiss J.-P., Mikosch Th., Editors [2009] Handbook of Financial Time Series, Springer Verlag, Heidelberg.

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

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

Barsky R.B., and Kilian L. [2004], Oil and the Macroeconomy Since the 1970s, Journal of Economic Perspectives 18, 115–134.

Basseville M., and Nikiforov I.V. [1993], Detection of Abrupt Changes: Theory and Application, Prentice Hall, Englewood Cliffs, New Jersey, USA.

Bernanke B.S. [1995], The Macroeconomics of the Great Depression: A Comparative Approach, Journal of Money, Credit, and Banking 27.

Bry G., and Boschan C., [1971], Cyclical Analysis of Time Series: Selected Procedures and Computer Programs, Technical Paper 20, NBER.

Bunn A.G., Korpela M., Biondi F., Qeadan F., and Zang Ch. [2011], Dendrochronology Program Library in R, R dplR package, www.r-cran.org.

Chambers J.M., and Hastie T.J. [1992], Statistical Models in S, Wadsworth and Brooks Cole.

Christiano L.J., and Fitzgerald T.J., [1999], The Band Pass Filter, NBER Working Paper No. W7257.

Commodity Research Bureau Index [2011], Sources: Global Financial Data, BLS, Jeffries Reuters Thompson.

Demey P., Maillard S., Roncalli T. [2011], Risk-Based Indexation, Working Paper, Lyxor Asset Management.

Erdman Chandra, and Emerson John W. [2008], A fast Bayesian change point analysis for the segmentation of microarray data, NA

Erdman Chandra, and Emerson John W. [2007], bcp: An R Package for Performing a Bayesian Analysis of Change Point Problems, Journal of Statistical Software 23.

Erdman Chandra, and Emerson John W. [2011], A Package for Performing a Bayesian Analysis of Change Point Problems R bcp package, www.r-cran.org

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

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

Filmoser P., and Gschwandtner M. [2011], Multivariate outlier detection based on robust methods, R mvoutlier package, www.r-cran.org.

Gencay R., Selcuk F., and Whitcher B. [2002], An Introduction to Wavelets and Other Filtering Methods in Finance and Economics, Academic Press, Elsevier, London, UK.

Green P.J., and Silverman B.W. [1994], Nonparametric Regression and Generalized Linear Models: A Roughness Penalty Approach, Chapman and Hall.

Gyomai G., and Guidetti E. [2008], OECD System of Composite Leading Indicators, Working Paper, OECD.

Hastie T.J., and Tibshirani R.J. [1990], Generalized Additive Models, Chapman and Hall.

Hodrick R.J., and Prescott E.C. [1997], Postwar U.S. Business Cycles: An Empirical Investigation, Journal of Money Credit and Banking 29, 1–16.

Ibanez, F., [1982], NA series chronologiques planctoniques, Journal of Experimental Marine Biology and Ecology 4, 619–632.

Ibanez F., Grosjean Ph., and Etienne M. [2011], Package for Analysis of Space-Time Ecological Series R pastec package, www.r-cran.org.

Kendall M.G. [1976], Time Series, 2nd ed., Charles Griffin and Co, London.

Loschi R.H., and Cruz F.R.B. [2005], Extension to the Product Partition Model: Computing the Probability of a Change, Computational Statistics and Data Analysis 48, 255–268.

Malat A. [2009], Wavelet Tour for Signal Processing, Academic Press, Elsevier Inc., Burlington, MA, USA.

Nason G.P. [2008], Wavelet Methods in Statistics with R, Springer, Scientific Series, New York, USA.

Olshen A.B., Venkatraman E.S., Lucito R., and Wigler M. [2004], Circular Binary Segmentation for the Analysis of Array-based DNA Copy Number Data, Biostatistics 5, 557–572.

R, Statistical computing environment, www.cran-project.org

Ripley B., and M. Mächler [2011], R stats package: Fit a smmothing spline, www.r-cran.org.

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

Sen A., and Srivastava M. [1975], On Tests for Detecting Change in Mean, The Annals of Statistics3, 98–108.

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

US Large Cap Stocks [2011], Sources: Ibbotson SBBI Yearbook 2010, Standard and Poors, and iShares ETF Database.

Venkatraman E.S., and Olshen A.B. [2007], A faster circular binary segmentation algorithm for the analysis of array CGH data, Bioinformatics 23, 657–663.

Varmuza K., and Filzmoser P. [2008], Introduction to Multivariate Statistical Analysis in Chemometrics, Taylor and Francis, CRC Press, Boca Raton Florida, USA.

Wahl P. [2008], Food Speculation: The Main Factor of the Price Bubble in 2008, Briefing Paper, World Economy, Ecology and Development, Berlin.

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

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, Eds. D. Würtz, M. Mehta, D. Scott, and J. Hinz, Rmetrics Association and Finance Online Publishing, Zurich, pp. 205–213.

Würtz D. [2011], Tools for Portfolio Optimzation from R/Rmetrics, Proceedings of the Meielisalp Summerschool and Workshop 2011, Eds. D. Würtz, S. Iacus, M. Mehta, D. Scott, Rmetrics Association and Finance Online Publishing, Zurich, pp. 220–229.

Zeileis A., Kleiber C., Krämer W., and Hornik K. [2003], Testing and Dating of Structural Changes in Practice, Computational Statistics and Data Analysis 44, 109–123.

CHAPTER 2

BAYESIAN CHANGE POINT ANALYSIS

Bayesian Change Point and Wavelet Based Stability Analysis of the Swiss Market - Investigation of a Century of Financial and Economic Benchmarks
Tobias Setz
Econophysics Group, Swiss Federal Institute of Technology Zurich
Master Thesis, Chapter II, ETH Zurich, July 2012

Tobias Setz has applied in his Master Thesis [2012] the BCP approach of Barry and Hartigan [1992, 1993] in the implementation of Erdman and Emerson [2007] to various Long Term Swiss Investment time series. Here we have reprinted part II "Stability" of his Master Thesis. In section 5 he gives a brief Introduction, in section 6 he describes the theoretical background, and in section 7 he analyses the Swiss market. Conlusions in section 8 complete his report.

Bayesian Change Point and Wavelet based Stability Analysis of the Swiss Market

Investigation of a century of financial and economic benchmarks

Tobias Setz

ETH Zurich
Institute for Theoretical Physics
Econophysics Group

THIS VERSION: ETH ZURICH, SEPTEMBER 2014
Original Version: Master Thesis, ETH Zurich, July 2012

Contents

About this Document 5
Introduction 7

I. Swiss Benchmarks 11

1. Introduction 11

2. The Disagregation Method 12
2.1. Theory . . . 13
2.1.1. The basic principles . . . 13
2.1.2. The scale parameter . . . 13
2.2. From Annual to Monthly Data . . . 14
2.2.1. MSCI Total Return - MSCI Total Return . . . 15
2.2.2. MSCI Total Return - MSCI Price . . . 16
2.2.3. MSCI Total Return - SBC Price . . . 16

3. Construction of the Swiss SBBI market index family 19
3.1. The Swiss Stock Market Index . . . 19
3.1.1. Description of Available Data . . . 19
3.1.2. Construction of the Swiss Stock Market Index . . . 21
3.2. The Swiss Bond Market Index . . . 25
3.2.1. Description of Available Data . . . 25
3.2.2. Construction of the Swiss Bond Market Index . . . 27
3.3. The Swiss Bill Market Index . . . 33
3.3.1. Description of Available Data . . . 33
3.3.2. Construction of the Swiss Bill Market Index . . . 34
3.4. The Swiss Inflation Market Index . . . 36
3.4.1. Description of Available Data . . . 36
3.4.2. Construction of the Swiss Inflation Market Index . . . 36

4. Conclusions 38

II. Stability Analysis 41

5. Introduction 41

6. Bayesian Change Point Analytics 41
6.1. Motivation . . . 41
6.2. Product Partition Models for Change Point Problems . . . 42
6.2.1. Prior Design . . . 42

6.2.2. Posterior Design 43
6.2.3. Exact Calculation 44
6.3. Bayesian Analysis for Change Point Problems 45
6.3.1. Standard Approach 45
6.3.2. Full Bayesian Approach 46
6.3.3. Markov Chain Monte Carlo 48

7. Stability Analytics of the Swiss SBBI market index family **50**
7.1. Stability Measures 50
7.1.1. BCP analytics 51
7.1.2. Wavelet analytics 51
7.2. Stability of the SBBI indices 53
7.2.1. The Swiss Stock Market Index 55
7.2.2. The Swiss Bond Market Index 57
7.2.3. The Swiss Bill Market Index 59
7.2.4. The Swiss Inflation Index 61

8. Conclusions **63**

Summary **65**

Acknowledgements **67**

Appendix **69**

9. Technical Notes **69**

10. Swiss Benchmarks **69**

11. SBBI tables **70**

12. Stability Analysis - Additional Plots **79**

References **85**

Part II.
Stability Analysis

5. Introduction

In this part of the thesis the SBBI market index family constructed in part I of this thesis will be examined concerning their stabilities. For that the Bayesian change point (BCP) analysis as presented by Barry and Hartigan [1993] will be used as well as a wavelet approach. The BCP method will be explained in detail while for the wavelet method a detailed description was given in my semester thesis (Setz, [2011]) which is based on the "Practical Guide to Wavelet Analysis" by Torrence and Compo [1998].

Motivation and Outline

During the last decade financial markets and economies were shocked by crashes like the burst of the dot-com bubble or the recent subprime crises. If we denote such times as unstable and times when the market is healthy as stable then it would be of advantage to have stability measures that can determine the current state of the market and possibly tell us something about the future.
The BCP method offers a measure that tells us for every point of a time series how likely it is that the underlying dynamics of that time series are going to change. The method will be explained in detail in section 6. The wavelet method decomposes a time series into time-frequency space and therefore offers a view into the dominant modes of a time series and how they change over time.
What we exactly use as stability measures after applying the BCP or wavelet method on a time series will be explained in section 7. Within the same section those stability measures will then be calculated and visualized for the SBBI market index family.

6. Bayesian Change Point Analytics

The calculations and plots of the Bayesian change point analyses were done by using the `bcp` library (version 3.0.1) (Erdman and Emerson, [2012]). The implementation within that library is based on Barry and Hartigan's paper "A Bayesian Analysis for Change Point Problems" [1993]. Therefore the content and notations within this section follow that paper very closely.

6.1. Motivation

Let's suppose that we have a sequence of observations which undergoes sudden changes at unknown times and let's call those times change points. Then that sequence can be partitioned into different blocks separated by the change points. We also suppose that every observation can be described by a parameter value which does not change within

one block. Observations in different blocks are then assumed to be independent. As an example we could define that the observations are normally distributed whereas the mean is different in every block.
The "Bayesian Analysis for Change Point Problems" described by Barry and Hartigan [1993] will give us a framework to estimate the parameter value for every observation and to estimate the probability of an observation to be a change point. Calculating those probabilities for every observation within a financial time series will give us a measure about how likely the parameter under examination is going to change and therefore serves us as a measure of stability.

6.2. Product Partition Models for Change Point Problems

Since we are performing a Bayesian analysis we have to assign probability distributions to the change points as well as the parameters. The "Product Partition Models for Change Point Problems" described by Barry and Hartigan [1992] is doing exactly this and can therefore be used for our purposes.
A partition describes a specific division of the observations into blocks. We first define a prior Product Partition Model (PPM) (see section 6.2.1) by specifying prior probability distributions for the partitions and the parameters. Given the observations and using Bayesian principles we can use the prior distributions to define a posterior PPM by calculating posterior probability distributions for the partitions and the parameters. This will allow us to make inferences about parameters and change points by just using the available observations.

6.2.1. Prior Design

We assume that for our sequence of observations $\vec{X} = X_1, X_2, \ldots, X_n$ every observation X_i has a density depending on a parameter θ_i (or a set of parameters), which leads to a sequence of parameters $\theta_1, \theta_2, ..., \theta_n$ where the values are supposed to be constant within blocks. That is, there exists a partition $\rho = (i_0, i_1, \ldots, i_b)$ of the set $1, 2, \ldots, n$ such that

$$0 = i_0 < i_1 < i_2 < \ldots < i_b = n \ ,$$

and

$$\theta_i = \theta_{i_r} \quad \text{where} \quad i_{r-1} < i \leq i_r \ .$$

This means that the parameter values will change at the change points $i_1 + 1, i_2 + 1, \ldots, i_{b-1} + 1$. Furthermore the sequence of time points $i + 1, \ldots, j$ shall be denoted as ij and the corresponding observations $X_{i+1}, \ldots, X_j$ as X_{ij}.

One assumption in our framework is that the observations $X_1, X_2, ..., X_n$ are independent in different blocks. Now let's consider the case where the partition and the parameters are given. Then there is a probability density f_{ij} associated with each block such that

$$f(\vec{X}|\rho, \vec{\theta}) = f(X_1, ..., X_n | i_0, ..., i_b, \theta_{i_1}, ..., \theta_{i_b})$$

$$= f_{0i_1}(X_1, ..., X_{i_1}|\theta_{i_1}) \cdots f_{i_{b-1}i_b}(X_{i_{b-1}+1}, ..., X_{i_b}|\theta_{i_b}) \ ,$$

where $f_{ij}(X_{ij}|\theta_j)$ describes the block density of the observations. Any joint distribution on partitions and observations that satisfies the product condition for partitions [1] and the independence condition for observations given the partition [2] will be called a Product Partition Model.

The prior probability density of the partitions ρ is defined as

$$f(\rho) = K c_{i_0 i_1} c_{i_1 i_2} \cdots c_{i_{b-1} i_b} \ ,$$

where c_{ij} are the prior cohesions specified for each possible block ij. The cohesions are basically a measure for the probability that a block having length $j - i$ exists. The relevances r_{ij} describe the probability that a block ij is included into any partition ρ

$$r_{ij} = \frac{\lambda_{0i} c_{ij} \lambda_{jn}}{\lambda_{0n}} \quad \text{where} \quad \lambda_{ij} = \sum \prod_{k=1}^{b} c_{i_{k-1} i_k} \ .$$

The summation for λ_{ij} is over all sets of integers $i = i_0 < i_1 < i_2 < \ ... \ < i_b = j$. Which means that the quantity λ_{ij} is the sum of products over all possible partitions of the set $\{i + 1, i + 2, \ ... \ , j\}$. Recursive formulas requiring $O(n^2)$ elementary operations to calculate λ_{ij} are given within the paper of Yao [1984].

For the prior distributions of the parameters $\theta_1, \theta_2, ..., \theta_n$ we demand that given a partition ρ having b blocks, the quantities $\theta_{i_1}, \theta_{i_2}, ..., \theta_{i_b}$ are independent, with θ_{i_j} having block density $f_{i_{j-1} i_j}(\theta_{i_j})$ with respect to some measure on Θ (which will be represented in integrals as $d\theta$). Note that this joint density on partitions and parameters given ρ is a product partition model.

Making all the above assumptions we can now calculate the block prior density $f_{ij}(X_{ij})$ which is also called the data factor

$$f_{ij}(X_{ij}) = \int f_{ij}(X_{ij}|\theta) f_{ij}(\theta) d\theta \ .$$

Again, this joint distribution on partitions and observations given ρ fulfills the conditions of a product partition model.

6.2.2. Posterior Design

We can now define a posterior model that allows us to make inferences about the unknown partitions and parameters given the observations.

[1] not true if e.g. the block parameters or cohesions depend on each other

[2] which means that the observations in one block do not depend on the observations in another block

The posterior probability density $f(\rho|\vec{X})$ and the posterior relevances $r_{ij}(\vec{X})$ can be calculated analogous to the prior case (see section 6.2.1) by just using the posterior cohesions $c_{ij}(\vec{X}) = c_{ij} f_{ij}(X_{ij})$ instead of the prior cohesions c_{ij}. The $\vec{X}$ inside the brackets of the posterior cohesions and relevances just indicates that the observations are given.

By using Bayes' law we can now calculate the conditional density of partition and parameters given the observations as

$$f_{ij}(\theta_j|X_{ij}) = \frac{f_{ij}(X_{ij}|\theta_j) f_{ij}(\theta_j)}{f_{ij}(X_{ij})} \ .$$

Note that this density fulfills the conditions of a product partition model as well.

If all our assumptions are true and if we know the true partition ρ then we have now a model that allows us to compute the density of every block parameter given the observations and therefore also the expectation values of all block parameters.
Even if the assumption of a product partition model is not true but the observations are sharp enough to dominate the prior distribution, the posterior distribution for parameters will be usefully approximated by a product model.
Models where the densities of different block parameters depend on each other are called Markov models. While this is a plausible mechanism the simple calculations of the product model are not possible within those models.
Barry and Hartigan [1993] compared various models against each other. According to them their method does never much worse than the best method and avoids the disaster of other methods for sharp short-lived changes.

6.2.3. Exact Calculation

We don't know the true partition itself but what we have is the posterior probability density of the partitions. This allows us to take into consideration all possible partitions which results in the final product partition model

$$f(\theta_k|\vec{X}) = \sum_{\rho} f(\theta_k|\vec{X}, \rho) f(\rho|\vec{X}) = \sum_{\rho} f_{ij}(\theta_k|X_{ij}) f(\rho|\vec{X}) \ ,$$

where $k = 1, 2, ..., n$ and $i < k \leq j$. Alternatively the final density can also be calculated using the posterior relevances

$$f(\theta_k|\vec{X}) = \sum_{i<k\leq j} f_{ij}(\theta_k|X_{ij}) r_{ij}(\vec{X}) \ ,$$

where ij are all possible sets that contain k. This procedure is computationally efficient and the effort to calculate all $f(\theta_k|\vec{X})$ is of order $O(n^3)$. By considering all the possible partitions we will allow the data to adapt to the true partition.

Of more interest than the densities are the posterior expectation values of θ_k. They can be calculated analogous to the densities above:

$$E(\theta_k|\vec{X}) = \sum_{\rho} E(\theta_k|\vec{X},\rho) f(\rho|\vec{X}) = \sum_{i<k\leq j} E_{ij}(\theta_k|X_{ij}) r_{ij}(\vec{X}) \ ,$$

6.3. Bayesian Analysis for Change Point Problems

The model presented in section 6.2 does not make any specific assumptions about the prior density functions for the partitions, parameters or observations. Within this section we will present in detail the approach of Barry and Hartigan [1993] as it is implemented within the `bcp` library and shall call it Bayesian change point (BCP) approach in the proceedings. As in Barry and Hartigan [1993] the formulas given will not be derived from scratch since this would be a paper on its own.

6.3.1. Standard Approach

The BCP approach assumes that the observations $\vec{X} = X_1, X_2, \ldots, X_n$ are independent and normally distributed

$$f_{ij}(X_{ij}|\mu_j) \sim N(\mu_j, \sigma^2) \ .$$

To specify the product partition model we have to define the prior cohesions c_{ij} as well as the prior parameter distribution $f_{ij}(\mu_j)$.

The prior cohesions are defined as

$$c_{ij} = (1-p)^{j-i-1}p, \quad j < n \ ,$$

$$c_{ij} = (1-p)^{j-i-1}, \quad j = n \ ,$$

where $0 \leq p \leq 1$. So the block probabilities are identically and geometrically distributed.

The prior parameter distribution is defined as

$$f_{ij}(\mu_j) \sim N(\mu_0, \sigma_0^2/(j-i)) \ ,$$

which means that larger deviations from μ_0 are expected in short blocks than in long blocks. This makes sense since it is not feasible to identify small deviations in short blocks.

Having defined the prior densities we can calculate the data factor which leads to

$$f_{ij}(X_{ij}) = \int f_{ij}(X_{ij}|\mu) f_{ij}(\mu) d\mu = \frac{1}{(2\pi\sigma^2)^{(j-i)/2}} \left(\frac{\sigma^2}{\sigma_0^2+\sigma^2}\right)^{1/2} e^{V_{ij}} \ ,$$

where

$$V_{ij} = -\frac{\sum_{l=i+1}^{j}(X_l - \bar{X}_{ij})^2}{2\sigma^2} - \frac{(j-i)(\bar{X}_{ij}-\mu_0)^2}{2(\sigma_0^2+\sigma^2)} \ ,$$

and

$$\bar{X}_{ij} = \sum_{l=i+1}^{j} \frac{X_l}{j-i} \ .$$

We will additionally define $w = \sigma^2/(\sigma_0^2 + \sigma^2)$.

Given the partition ρ, the estimate of μ_k given the partition and the observations can now be calculated as

$$\hat{\mu}_k = E_{ij}(\mu_k|X_{ij}) = (1-w)\bar{X}_{ij} + w\mu_0 \ ,$$

where $k \in ij \in \rho$.

Together with the posterior relevances $r_{ij}(\vec{X}) = c_{ij} f_{ij}(X_{ij})$ (see section 6.2.2) it is now possible to calculate the posterior means as outlined in section 6.2.3

$$E(\mu_k|\vec{X}) = \sum_{i<k\leq j} E_{ij}(\mu_k|X_{ij}) r_{ij}(\vec{X}) \ ,$$

where $k = 1, 2, ..., n$. This is not yet the BCP approach proposed by Barry and Hartigan [1993]. The proposed approach will follow in section 6.3.2 and section 6.3.3.

This model depends on the four parameters: p, μ_0, σ_0^2 and σ^2. One possibility to handle these parameters is to estimate them by maximizing the following likelihood function (as proposed by Yao [1984])

$$L(p, \mu_0, \sigma_0^2, \sigma^2) = \sum_{\rho} f(\vec{X}|\rho) f(\rho) \ ,$$

where $f(\vec{X}|\rho) = \prod_{ij\in\rho} f_{ij}(X_{ij})$ and $f(\rho)$ is the prior probability of ρ (see section 6.2.1). Since $L(1, \mu_0, \sigma_0^2, 0)$=$L(p, \mu_0, 0, \sigma^2)$ for any values of p, μ_0 and σ^2, the model is not identifiable.

6.3.2. Full Bayesian Approach

Because of the inelegancies of the maximum likelihood estimation, Barry and Hartigan [1993] propose a fully Bayesian approach. For that independent prior densities are specified for the parameters p, μ_0, σ^2 and $w = \sigma^2/(\sigma_0^2 + \sigma^2)$ as

$$\begin{aligned} f(\mu_0) &= 1, \quad -\infty \leq \mu_0 \leq \infty \ , \\ f(\sigma^2) &= 1/\sigma^2, \quad 0 \leq \sigma^2 \leq \infty \ , \\ f(p) &= 1/p_0, \quad 0 \leq p \leq p_0 \ , \\ f(w) &= 1/w_0, \quad 0 \leq w \leq w_0 \ , \end{aligned}$$

where p_0 and w_0 are prespecified numbers in $[0, 1]$. The first two priors assure that the estimates are invariant under location and scale changes while the last two priors are designed to make the technique effective when there are not too many changes (p small) and when the changes that occur are of reasonable size (w small).

If we use a prior density for the change probability, the prior probability of ρ can be reformulated as follows:

$$f(\rho) = \frac{1}{p_0}\int_0^{p_0} f(\rho|p)dp = \frac{1}{p_0}\int_0^{p_0} p^{b-1}(1-p)^{n-b}dp \ ,$$

where b is the number of blocks in ρ.

If we use a prior density for the variance of the observations, we can reformulate the model density as

$$f(\vec{X}|\rho, \mu_0, w) \propto \int_0^{\infty} \frac{1}{\sigma^2}\prod_{ij\in\rho} f_{ij}(X_{ij})d\sigma^2 \propto \frac{w^{b/2}}{[W + Bw + wn(\mu_0 - \bar{X})^2]^{n/2}} \ ,$$

where

$$\bar{X} = \sum_{i=1}^{n}\frac{X_i}{n}, \quad B = \sum_{ij\in\rho}(j-i)(\bar{X_{ij}} - \bar{X})^2, \quad W = \sum_{ij\in\rho}\sum_{l=i+1}^{j}(X_l - \bar{X_{ij}})^2 \ ,$$

and b is again the number of blocks in ρ. Averaging also over μ_0 and w leads to:

$$f(\vec{X}|\rho) \propto \int_0^{w_0} \frac{w^{(b-1)/2}}{(W + Bw)^{(n-1)/2}}dw \ .$$

We can now use this expressions to calculate the posterior probability density

$$f(\rho|\vec{X}) = \frac{f(\vec{X}|\rho)f(\rho)}{f(\vec{X})} \propto \left[\int_0^{w_0} \frac{w^{(b-1)/2}}{(W + Bw)^{(n-1)/2}}dw\right]\left[\frac{1}{p_0}\int_0^{p_0} p^{b-1}(1-p)^{n-b}dp\right] \ .$$

Note that these integrals are incomplete beta integrals (see also section 6.3.3).

This allows us now to calculate the posterior means as outlined in section 6.2.3:

$$E(\mu_k|\vec{X}) = \sum_{\rho} E(\mu_k|\vec{X}, \rho)f(\rho|\vec{X}) = \sum_{\rho} E((1-w)\bar{X}_{ij} + w\mu_0|\vec{X}, \rho)f(\rho|\vec{X}) \ ,$$

where $k = 1, 2, ..., n$. Note that in the full Bayesian approach w and μ_0 are depending on the partition and the observations as well. Therefore we have to calculate the expectation values of those quantities as well:

$$E(\mu_0|w, \vec{X}, \rho) = \bar{X} \ ,$$

$$E(w|\vec{X},\rho) = w^* = \frac{\int_0^{w_0} \frac{w^{(b+1)/2}}{(W+Bw)^{(n-1)/2}} dw}{\int_0^{w_0} \frac{w^{(b-1)/2}}{(W+Bw)^{(n-1)/2}} dw} \ ,$$

which leads to the final formula for the posterior means

$$E(\mu_k|\vec{X}) = \sum_{\rho} [(1-w^*)\bar{X}_{ij} + w^*\bar{X}] f(\rho|\vec{X}) \ .$$

Calculating the exact values for $\{E(\mu_k|\vec{X}) : k = 1, 2, \ldots, n\}$ using the formula above presents some problems. On the one hand $f(\rho|\vec{X})$ is not in product form and therefore the computational procedure mentioned in section 6.2.3 is not possible. On the other hand $f(\vec{X})$ which is needed to calculate $f(\rho|\vec{X})$ is not specified. Both of those problems can be solved by using a MCMC approach which is much more efficient and where $f(\vec{X})$ will cancel out.

6.3.3. Markov Chain Monte Carlo

To overcome the rather intensive computational effort ($O(n^3)$) to calculate the posterior means ($\hat{\mu}_k$), Barry and Hartigan [1993] introduce a Markov chain Monte Carlo (MCMC) method which reduces the effort to $O(n)$.

The goal of using MCMC is that we want to generate partitions ρ which are distributed according to $f(\rho|\vec{X})$. Since if we generate partitions like that we can calculate the posterior means as

$$\langle E(\mu_k|\vec{X}) \rangle = \frac{1}{M} \sum_{\rho} [(1-w^*)\bar{X}_{ij} + w^*\bar{X}] \ ,$$

where M is the number of generated partitions according to $f(\rho|\vec{X})$.

This can be achieved by generating a Markov chain. For that we describe a partition as $\rho = (U_1, U_2, ..., U_n)$ where $U_i = 1$ describes a change point at position $i+1$. To start the process an initial partition is generated where $U_i = 0$ for $i < n$ and $U_n = 1$. We then generate a new partition by iterating through the old partition and at each position i we set $U_i = 1$ with probability p_i:

$$p_i = \frac{r}{1+r} \ ,$$

$$r = \frac{f(\rho_1|\vec{X})}{f(\rho_0|\vec{X})} = \frac{P(U_i = 1|\vec{X}, U_j, j \neq i)}{P(U_i = 0|\vec{X}, U_j, j \neq i)} =$$

$$\frac{\left[\int_0^{w_0} \frac{w^{b/2}}{(W_1+B_1 w)^{(n-1)/2}} dw\right] \left[\int_0^{p_0} p^b (1-p)^{n-b-1} dp\right]}{\left[\int_0^{w_0} \frac{w^{(b-1)/2}}{(W_0+B_0 w)^{(n-1)/2}} dw\right] \left[\int_0^{p_0} p^{b-1} (1-p)^{n-b} dp\right]} \ ,$$

where $P(U_i = \{0,1\}|\vec{X}, U_j, j \neq i)$ describes the probability of the partition when the observations $\vec{X}$ and the current values of $U_j, j \neq i$ are given. This is actually the ratio between $f(\rho_1|\vec{X})$ where the change point is accepted and $f(\rho_0|\vec{X})$ where the change point is not accepted. Therefore $f(\vec{X})$ cancels out as mentioned in section 6.3.2.

To make a link to the physical world; this procedure is very similar to the glauber dynamics used in statistical physics. This raises some interesting questions like the presence of critical phenomena or the impact of correlations between different partitions.

It shall also be mentioned here that the calculations of $f(\rho_i|\vec{X})$ are computationally very unstable. More precisely the integration over w either diverges or goes to 0 for long sequences. Since those integrals are incomplete beta integrals the ratio r can be reexpressed as

$$r = \left(\frac{W_0}{W_1}\right)^{\frac{n-b-2}{2}} \left(\frac{B_0}{B_1}\right)^{\frac{b+1}{2}} \sqrt{\frac{W_1}{B_1}} \frac{\int_0^{\frac{B_1 w_0/W_1}{1+B_1 w_0/W_1}} p^{(b+2)/2}(1-p)^{(n-b-3)/2}dp \int_0^{p_0} p^b(1-p)^{n-b-1}dp}{\int_0^{\frac{B_0 w_0/W_0}{1+B_0 w_0/W_0}} p^{(b+1)/2}(1-p)^{(n-b-2)/2}dp \int_0^{p_0} p^{b-1}(1-p)^{n-b}dp} \ ,$$

which is numerically stable. See also Erdman and Emerson [2007].

The partitions generated in this way are now distributed according to $f(\rho|\vec{X})$ and for every new partition we can now calculate the posterior mean given the observations and the partition

$$\hat{\mu_k} = E(\mu_k|\vec{X}, \rho) = (1 - w^*)\bar{X}_{ij} + w^*\bar{X} \ ,$$

for $k = 1, 2, \ldots, n$. After generating M partitions and calculating $\hat{\mu_k}$ we can calculate the posterior means m_k and the "naive" posterior variances s_k given the observations as

$$m_k = \langle\hat{\mu_k}\rangle_M = \frac{1}{M}\sum_\rho \hat{\mu_k} = \langle E(\mu_k|\vec{X})\rangle \ ,$$

$$s_k = \frac{n}{n-1}\left(\langle\hat{\mu_k}\hat{\mu_k}\rangle_M - \langle\hat{\mu_k}\rangle_M\langle\hat{\mu_k}\rangle_M\right) \ .$$

To get the posterior probabilities p_i if the point $i+1$ is a change point we can use the generated partitions which hold for every point i a 0 (no change point) or a 1 (change point)

$$p_k = \frac{1}{M}\sum_\rho U_k \ .$$

7. Stability Analytics of the Swiss SBBI market index family

7.1. Stability Measures

There are a lot of different opinions on how stability in the context of market behavior should be interpreted. In the following our view on it shall be explained. First; we consider an index as stable if the statistical key figures describing the index are nearly constant over time. If they tend to change in a way that cannot be explained by common fluctuations we assume that we get into a new regime having different dynamics where historically working strategies might start to fail. Following this interpretation shrinking markets that are stable or growing markets that are unstable are not contradictive. Such cases might be rare but they do exist. Second; we prefer to have a measure delivering a probability between 0 and 1 on how likely it is that one gets into a new regime. Having such a measure is much easier to understand than for example the volatility; especially for statistically inexperienced people.

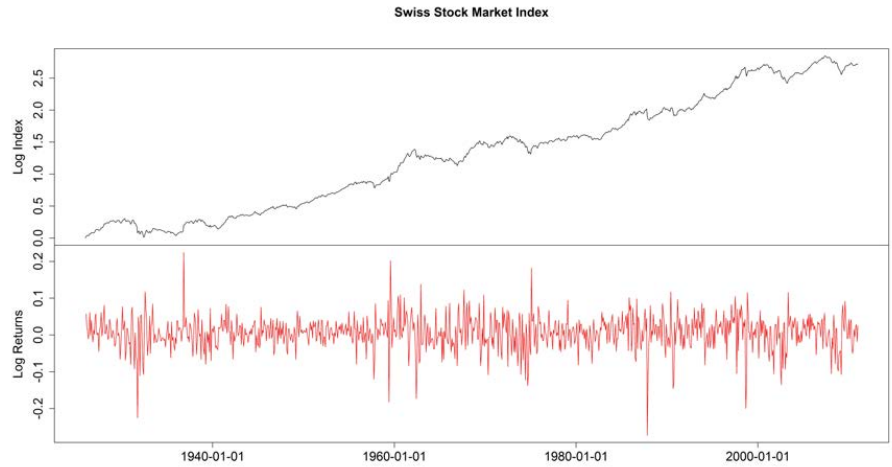


Figure 22: The Swiss stock market.

The results for the BCP and the wavelet method both offer the possibility to create an alternative measure to the volatility which is much more sophisticated. For the BCP method this are just the posterior means as they result from the standard calculations (see section 7.1.1). For the wavelet analysis a measure will be presented by using the wavelet spectrum (see section 7.1.2).
Both measures will be visualized by using the monthly recorded log-returns of the Swiss stock market (see figure 22) as we have composed them in part I. The same plots for the Swiss bond and bill markets as well as the Swiss inflation can be found within the appendix (see section 12).

7.1.1. BCP analytics

After we have performed a BCP analysis of a time series we get as a result the posterior means m_k, the posterior variances s_k and the posterior probabilities p_k where $k = 1, 2, \ldots, n$ are the time points within a time series of length n.

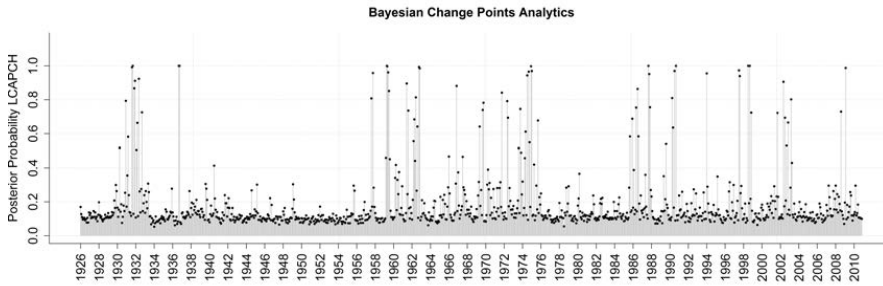


Figure 23: BCP stability of the Swiss stock market.

The posterior mean p_k is a probability measure that describes how likely it is that at time $k+1$ we will get into a new regime. If we assume that our observations are normally distributed having mean μ_k then p_k describes the probability that the observation $k+1$ belongs to a new block where the mean is different. Therefore the posterior means will serve us as a measure for stability without further modifications. An example of how those stabilities look like is given in figure 23 for the Swiss stock market.
The stability might be high for an index that goes down or low for an index that goes up. Usually this is not the case but it should be thought very carefully about this fact in order to identify a period correctly. The posterior means and variances can be of help to achieve this.
Comparing the BCP probabilities (figure 23) to measures based on volatilities or wavelets (figure 25) it can be seen that the BCP probabilities are less smooth. The method of determining the partition distribution which is very different from wavelets or volatilities seems to offer indeed an advantage in detecting sharp short lived changes.

7.1.2. Wavelet analytics

The wavelet analysis of a time series delivers a spectrum as for example shown in figure 24. But there is no probability measure directly at hand. Therefore we will present here a method on how a stability measure can be computed using the wavelet spectrum. My semester thesis (Setz, [2011]) describes in much detail how a wavelet analysis works and illustrates the resulting spectras for several real and artificial stochastic time series. Therefore I will only explain very briefly how a wavelet transformation works and how the spectrum can be interpreted.
Performing a wavelet analysis on a time series will decompose that series into it's time-frequency space. In figure 24 the wavelet transformation of the log-returns of the Swiss

stock market index is shown. It shows for each point in time k (x-axis) how dominant a certain scale s (y-axis) is within the time series. The scale is proportional to the fourier frequency and the spectrum can basically be calculated as

$$W_k(s) = \sum_{k'=0}^{N-1} r_{k'} \cdot \Psi^* \left[\frac{(k'-k)\delta t}{s} \right] \ ,$$

where r_k are the returns and Ψ represents a wavelet function. By assuming that the observations are a AR(1) process the expectation values of the points within the spectrum can be calculated from

$$E(|W_k(s)|^2) = P_s \sigma^2 \ ,$$

where P_s is a constant depending on the scale s. It is also possible to derive the distribution of the spectrum values which is a chi-square distribution having two degrees of freedom (χ^2_2). Therefore it is also possible to derive the significance levels L for the spectrum values which are again different for every scale and can be calculated from

$$L_s = \frac{1}{2} \sigma^2 P_s \chi^2_2(p) \ ,$$

where p is a value between 0 and 1 describing the quantile. The thick contour lines in figure 24 encircle the values within the spectrum that lie above the $p = 95\%$ significance levels.

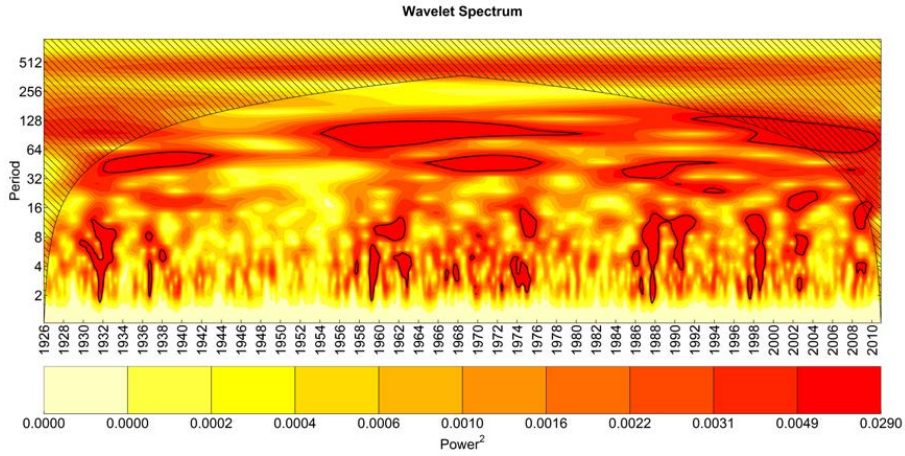


Figure 24: Wavelet spectrum of the Swiss stock market.

The expectation values of the spectrum are proportional to the variance of the observations. Therefore the higher those values at a certain point in time the higher the probability that the variance at that point in time cannot be explained anymore with common fluctuations.

We can now create a stability measure by calculating for every point in time the ratio between spectrum values above a certain significance level and the total number of spectrum values as follows:

$$p_k = \frac{1}{N} \sum_s \left[|W_k(s)|^2 > L_s \right] \quad ,$$

where N is the total number of considered scales s. The result of doing this with the spectrum in figure 24 is shown in figure 25 for $p = 0.75$.

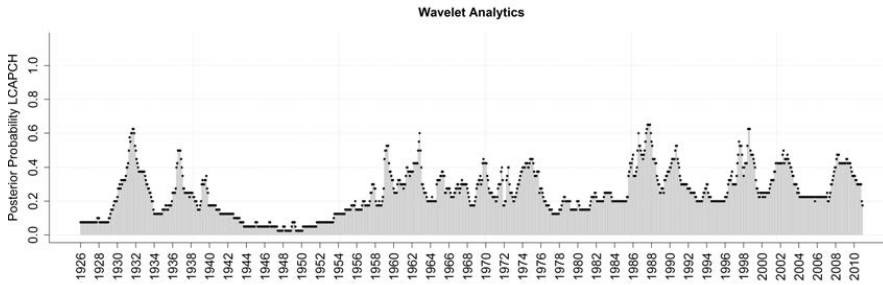


Figure 25: Wavelet stability of the Swiss stock market.

The result looks more smooth than the result of the BCP approach (figure 23). In fact it resembles a volatility analysis, which can be expected. The interesting property of the wavelet stability is that we can calculate the ratio p_k only for a certain part of the spectrum and therefore filter out unnecessary information. Also we can change the value of $p = 0.75$. This certainly can bring some advantage against the direct volatility approach. One interpretation of the frequencies is the so called trader model (Gençay et al., [2002]) which proposes that high frequencies should be associated with short term traders and long frequencies with long term traders.

7.2. Stability of the SBBI indices

In the following remaining sections the BCP and wavelet stabilities will be calculated and visualized for the Swiss stock, bond and bill market as well as the Swiss inflation. As an example the plots of the Swiss stock market index (section 7.2.1) will be explained here. The plots of the Swiss bond (section 7.2.2) and bill (section 7.2.3) market indices as well as the Swiss inflation (section 7.2.4) are done in the same spirit.

Figure 27 shows the turning points of the log-index. These are determined by first smoothing the series and then determining the periods where the slope of the smoothed curve is negative. Those periods are also indicated by the blue horizontal bars in the background of all the plots. The algorithm used is a common spline smoother. The extent of how much the curve is smoothed can be varied by setting the smoothing parameter

sp to a value between 0 and 1. The higher the value the stronger the smoothing. We did set the parameter for all plots and indices to $sp = 0.5$. The reason to determine those turning points is to visualize the periods where the market has a negative trend.
Figure 28 shows the probabilities of the BCP analysis as defined in section 7.1.1. The original probabilities are plotted in the background and then overlaid by the rainbow and the stability curves. For figure 28 the probabilities are identical to the ones shown in figure 23. The rainbow curve is actually an ensemble of smoothed probabilities. Which means that every color represents a smoothed version of the probabilities with a different smoothing parameter. There are 100 curves having a smoothing parameter between 0.3 and 0.8. The same spline smoother as for the turning points was used. Finally the black stability curve is the difference between the smoothed probability curve having a parameter of 0.8 and the smoothed probability curve having a parameter of 0.3. The purpose of the rainbow and the stability curves is just to make those plots better readable. In the sense that unstable times can be spotted conveniently by eye. For market analyses or investment decisions the probabilities should not be spline smoothed.
Figure 29 shows the probabilities of the wavelet analysis as defined in section 7.1.2. The probabilities in the background are identical to the ones shown in figure 25. The rainbow and stability curves are done in the same way as for the BCP case. To calculate the probabilities we did set $p = 0.75$ and considered the whole spectrum.
Finally figure 26 summarizes all the findings by showing the log-index and the log-returns as well as the stability curves from the BCP and the wavelet analyses. Additionally the turning points are shown in the background as well as some historical events. It's purpose is to get an idea about the performance of the stability indices and how they compare against each other.

Note that the picture given in figure 26 is still very rough. First; it depends on the smoothing parameter for the turning points on how much down periods will be shown. Therefore the stability curves can be low without having a turning point at the same time. On the other hand cases of low stability curves and upwards trends are no contradiction. They might refer to periods where a bubble is building up.
Second; the stability indicators are smoothed to construct the stability curves. Smoothing is a process that uses information from the future and especially for the BCP indicator, the benefit of detecting sharp short lived changes may get lost by smoothing. Further on, for both, the BCP as well as the wavelet indicator, the probabilities are always depending on all the observations.
Therefore; should those indicators be used for market analyses or investment decisions, it would be necessary to calculate them on a sliding window without having any information from the future and smoothing should be done very carefully. But using those indicators for such activities would be the next step after this thesis. The purpose of this thesis is to explain the indicators and make a first guess if they might be of benefit for further applications. For that figure 26 and its counterparts are well suited.

7.2.1. The Swiss Stock Market Index

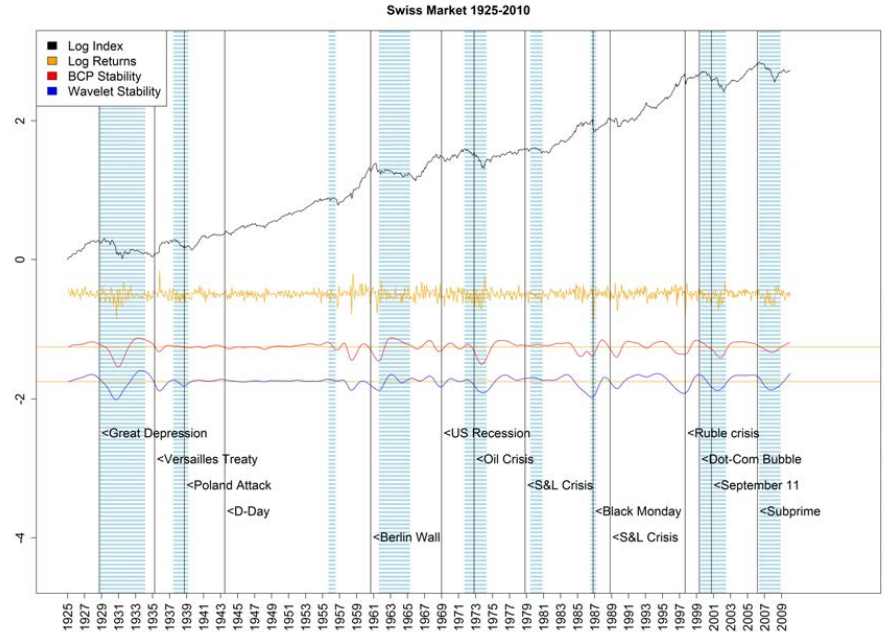


Figure 26: The log-index (most upper curve) and its returns as well as the BCP and wavelet stabilities (two lower curves) for the Swiss stock market. Additionally the turning points (horizontal lines in the background) and some important historical events are added.

Generally the stability curves seem to be low during periods where the market goes down. This can e.g. be seen during the great depression, the time after the dot-com bubble burst and the recent sub-prime crisis. Looking closely at the times where the stability is low there can usually be seen a drop within the index.
But as already indicated there are reversed cases as well. The low stability after the versailles treaty belongs to an upwards jump. Also is the downwards period after the fall of the Berlin wall considered as stable. Cases like that are rare but do exist. It is just difficult to identify them. The posterior mean and variance can be of help. On the other hand; jumps and drops that come out of the blue and do not announce themselves somehow will never be predicted by any method.
It can be expected that the BCP and wavelet curves are somehow similar since both of them react on unusual periods. Just by eye it can be seen that during crises like e.g. during the great depression also the wavelet curve goes down. But the answer to the question on how good the indicators are compared to each other lies within details that are hard to spot by eye or to describe by single numbers. One key figure, the correlation

between the BCP and wavelet curves, is plotted at the side of figure 26.
To really find out how good they perform it needs further investigations about the nature of the different indicators. Also a trading model where the indicators directly compete against each other might be of help.

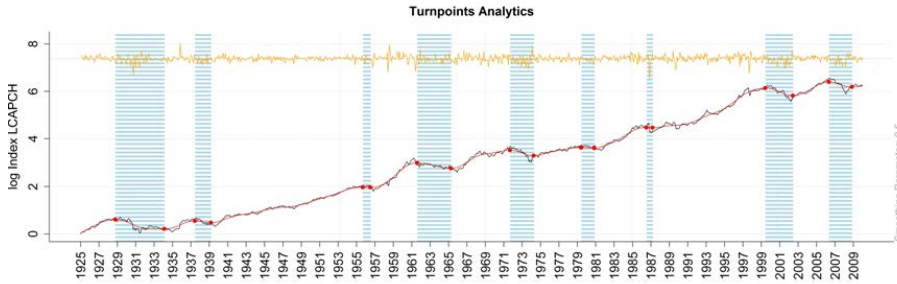


Figure 27: The turning point analytics for the Swiss stock market.

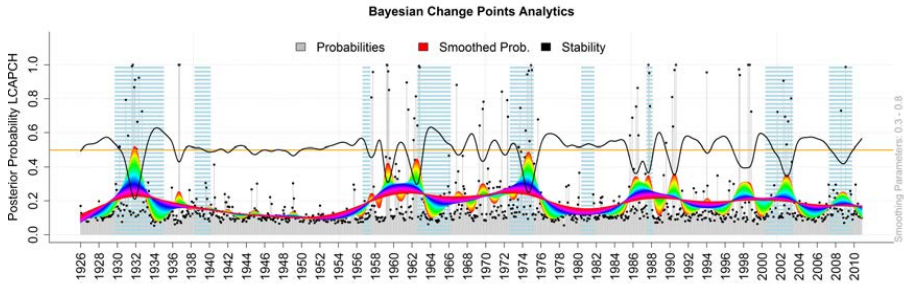


Figure 28: The BCP analytics for the Swiss stock market.

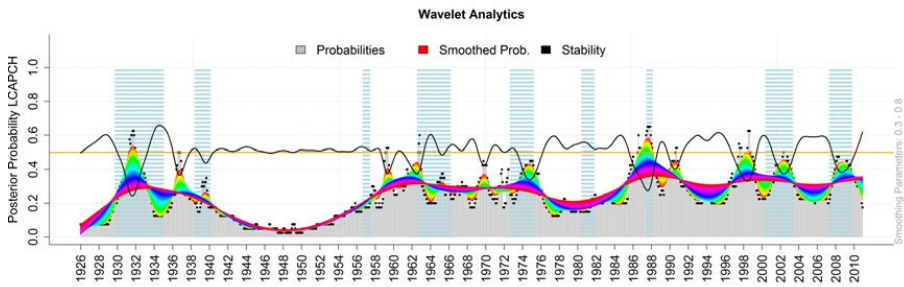


Figure 29: The wavelet analytics for the Swiss stock market.

7.2.2. The Swiss Bond Market Index

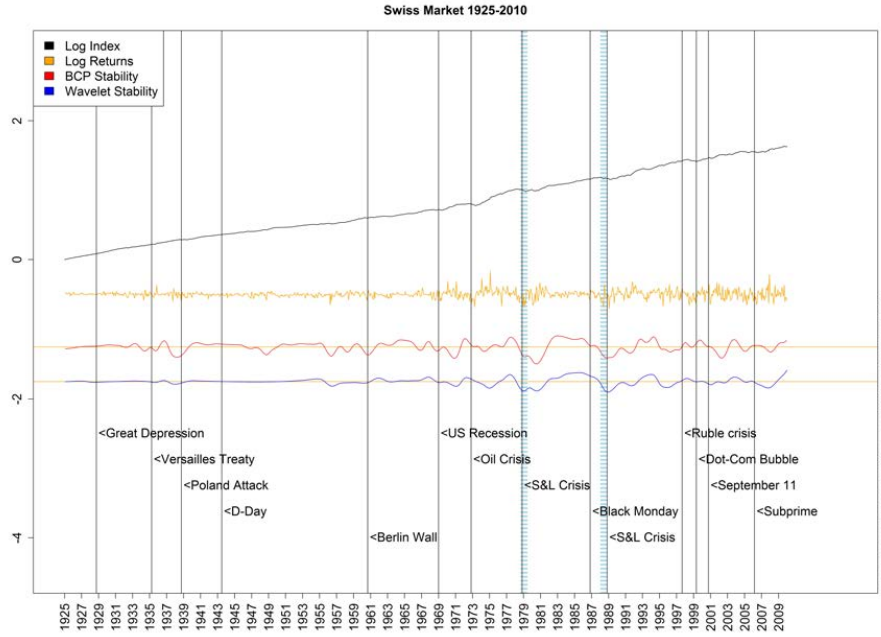


Figure 30: The log-index (most upper curve) and its returns as well as the BCP and wavelet stabilities (two lower curves) for the Swiss bond market. Additionally the turning points (horizontal lines in the background) and some important historical events are added.

The statements made in section 7.2.2 do also count for the case of bonds as e.g. can be seen during the periods with a negative drift around the savings & loans (S&L) crises. By examining figure 32 and figure 33 and the returns it can be seen that there are two regimes having different variance. They are approximately separated by the year of 1969. Generally it was very had to find historical analyses concerning events within the Swiss financial market. I personally think that the two regimes are caused by the Bretton Woods system which started to collapse around that time.
The probabilities in figure 33 are dramatically rising as time goes by. This makes sense since the variance is considerably higher after 1969 as before and therefore the returns after 1969 dominate the spectrum (see also figure 45). Also the BCP probabilities shown in figure 33 are generally higher after 1969 since the trends within the index are much less stable as before 1969 and therefore change points are considered to be much more likely after 1969.
Since the BCP and wavelet analyses take all available observations into consideration to calculate the probabilities, the two different regimes influence the results strongly.

The effect that the presence of two regimes dominates the results would be minimized and eventually get lost by trading and rebalancing strategies based on a rolling window. During the transit phase this effect would lead to more conservative investments which is reasonable for such times.

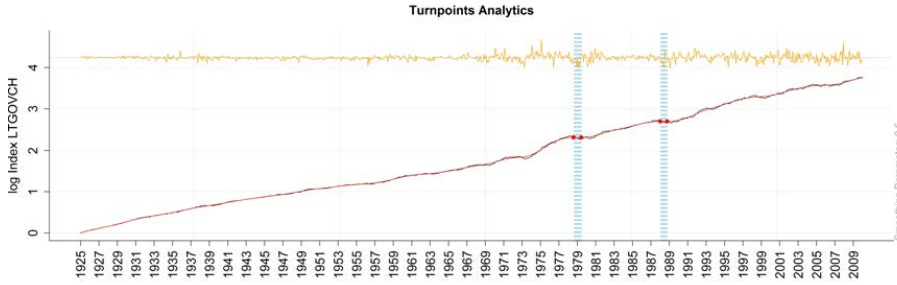


Figure 31: The turning point analytics for the Swiss bond market.

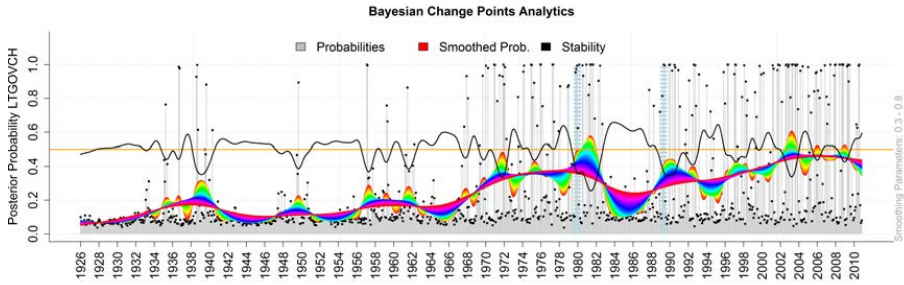


Figure 32: The BCP analytics for the Swiss bond market.

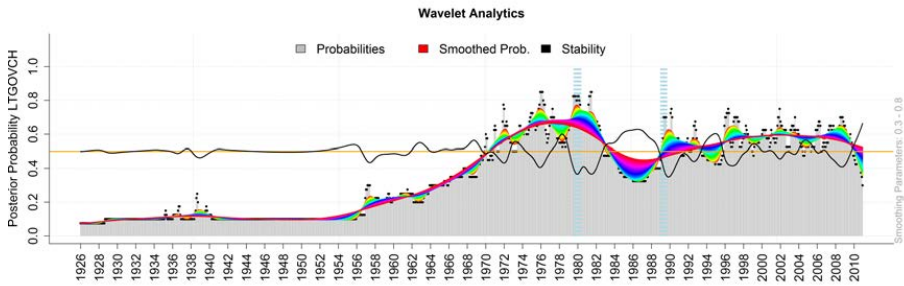


Figure 33: The wavelet analytics for the Swiss bond market.

7.2.3. The Swiss Bill Market Index

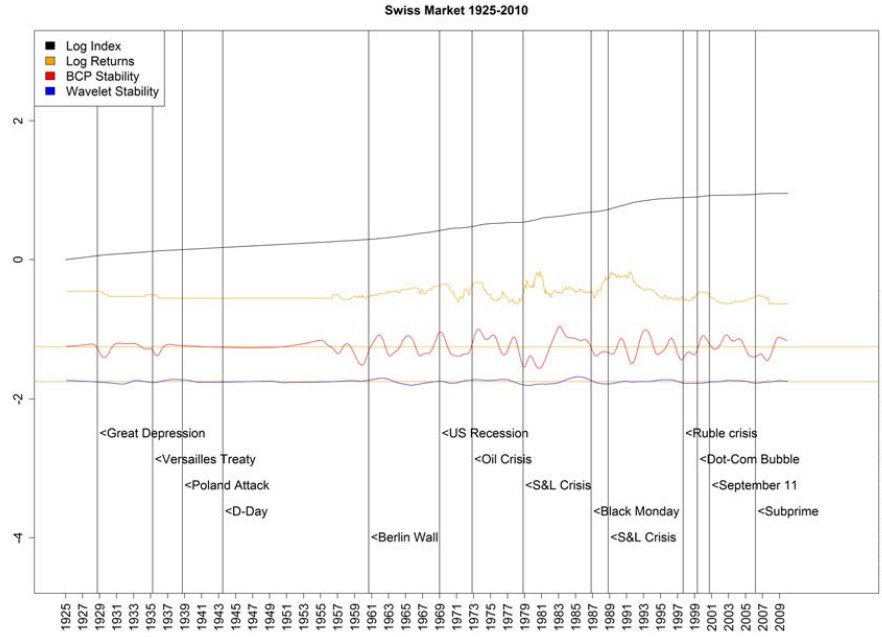


Figure 34: The log-index (most upper curve) and its returns as well as the BCP and wavelet stabilities (two lower curves) for the Swiss bill market. Additionally the turning points (horizontal lines in the background) and some important historical events are added.

Rate for bills are usually positive and slowly changing over time as can be seen by looking at the index and its returns in figure 34. So even the returns show index like behavior and there cannot really be a distribution assigned to them. Therefore a BCP or wavelet analysis is not really suited. Also it is questionable to develop trading strategies on the bill market since this is usually the last resort of investment.
Nevertheless those results can help us to understand the indicators better. First both indicators indicate a regime change in 1958. This is due to the construction of the Bill index that changes in 1958 from SNB discount rates towards 3-month time deposits. Note that this effect can also be seen within the returns of Ibbotson Morningstar [2011] for the US market and the commercial Swiss bill index from Global Financial Data [2012].
By looking at the wavelet spectrum (see figure 49) it can be seen that besides the regime change the index like behavior is quite dominant since the spectrum values are strongly growing in scale direction. Thus leading to very smooth probabilities (see figure 37). The BCP probabilities (see figure 36) indicate that the mean might change a lot after

1958 which is indeed true. But still the method is able to detect e.g. the great depression which is almost lost in the wavelet approach.

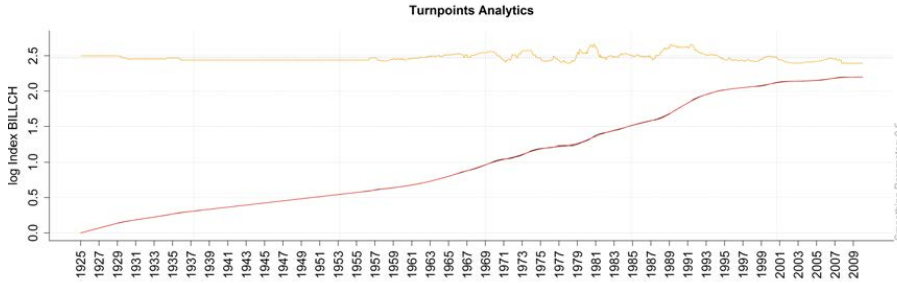


Figure 35: The turning point analytics for the Swiss bill market.

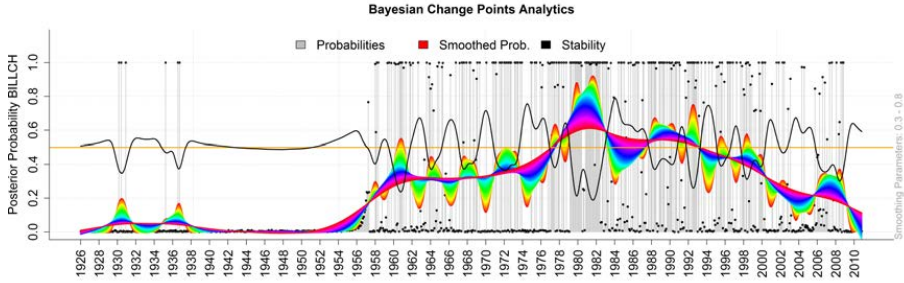


Figure 36: The BCP analytics for the Swiss bill market.

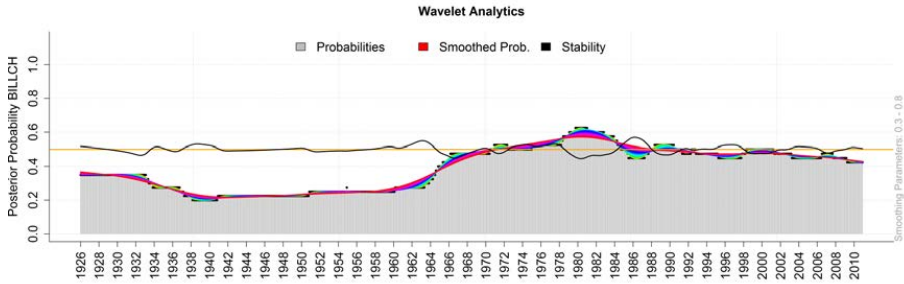


Figure 37: The wavelet analytics for the Swiss bill market.

7.2.4. The Swiss Inflation Index

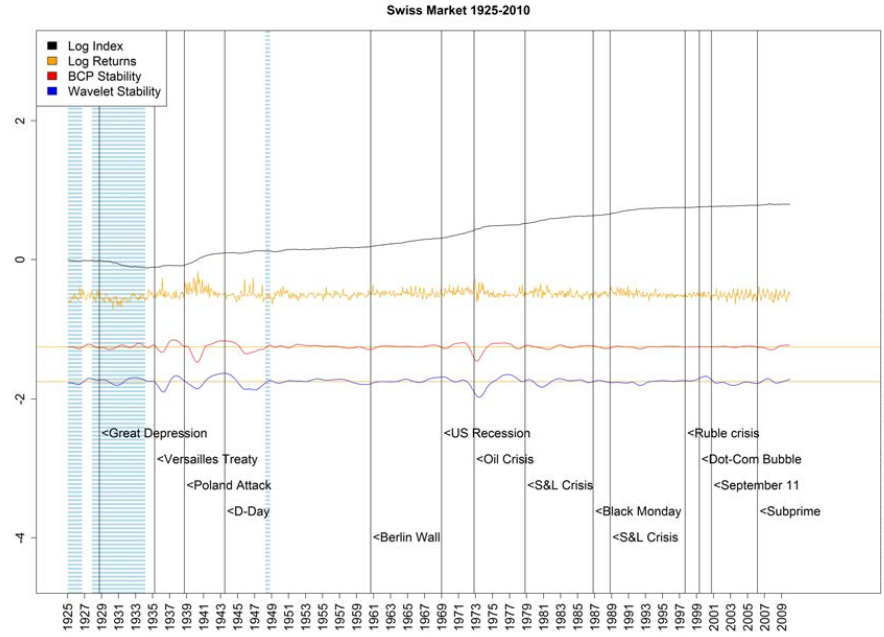


Figure 38: The log-index (most upper curve) and its returns as well as the BCP and wavelet stabilities (two lower curves) for the Swiss inflation. Additionally the turning points (horizontal lines in the background) and some important historical events are added.

We can not only apply the BCP and wavelet approach on assets ready to trade but also on economic indices like the inflation. Inflation is an important figure used to describe the situation of an economy. Usually healthy economies have a low stable inflation. Problems are deflation and hyper inflation. It will therefore be interesting to see how the stability measures react on such times.
Generally the results for the wavelet analysis (see figure 41) and the BCP approach (see figure 40) show similar behavior again. But the results of the BCP approach seem to be more pronounced where two minimas within the stability curve can be seen very clearly. The first one corresponds to the second world war where the inflation was very high and the second one to the oil crises in 1972 where the inflation became high again. Around the time of the great depression the inflation became negative. For all of those cases the probabilities tend to be high; but for the cases where the inflation shows above average growth the results are more pronounced.
This indicates that the inflation becomes especially unstable for hyperinflation which is characterized by an accelerating growth. Tendencies like that can also be discovered

in financial markets; possibly because a bubble is building up. Nevertheless; financial markets usually get especially unstable if the index goes down.

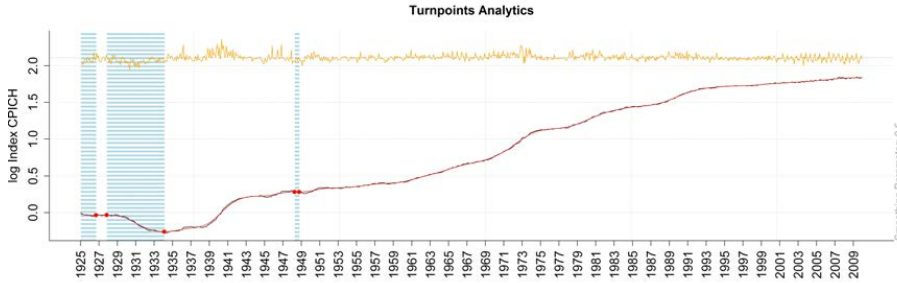


Figure 39: The turning point analytics for the Swiss inflation.

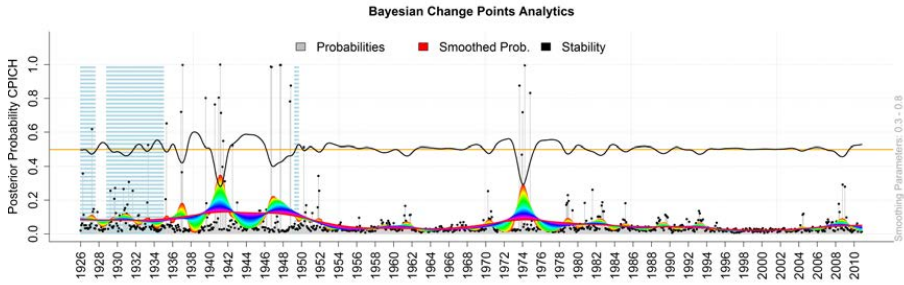


Figure 40: The BCP analytics for the Swiss inflation.

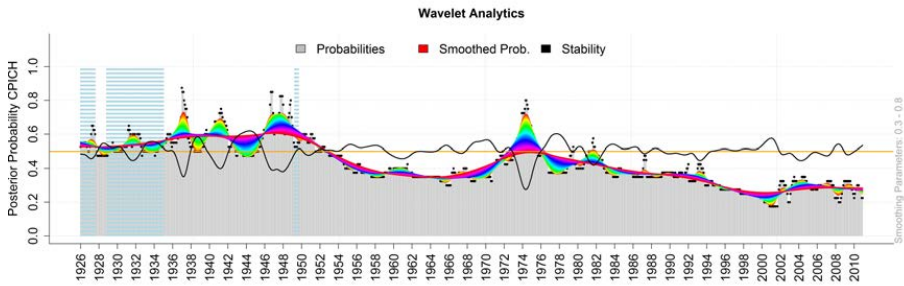


Figure 41: The wavelet analytics for the Swiss inflation.

8. Conclusions

Summary

In part II of this thesis the Bayesian change point analytics as introduced by Barry and Hartigan [1992][1993] have been explained in detail. Also it has been taken care about the fact that the implementation of the `bcp` package inherits some additional steps towards the final numerical results by formulating and explaining them as well. Having the results of the BCP as well as an alternative wavelet approach it has been shown how those results could be used as stability measures and how those measures can be understood.

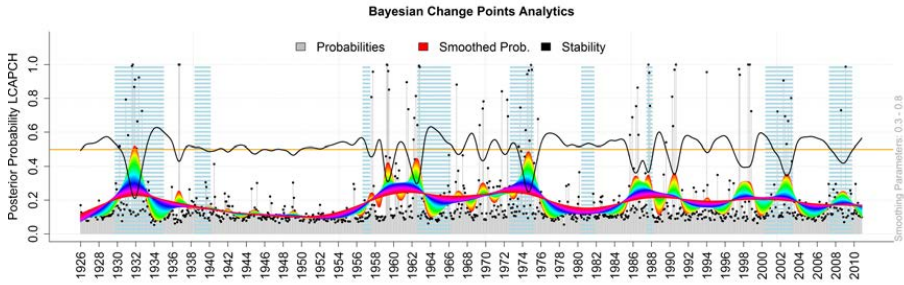


Figure 42: The BCP analytics for the Swiss stock market.

Once that the stability measures were defined they were applied to the SBBI index family as presented in part I. While the BCP method delivers a probability for every point in time on how likely the following observation belongs to a different independent partition having a different mean, the values delivered by the wavelet approach can be described as the probability on how likely the current variance is an outlier.
Both approaches deliver similar results. While the wavelet approach looks familiar to a volatility analysis, the BCP approach seems to deliver more pronounced results detecting also sharp short lived changes. Also does the BCP approach seem to be less sensitive than the wavelet approach if applied on a scenario having two very different regimes.
In contrary to the inflation, the Swiss stock, bond and bill indices usually showed low stability for times where the market tends to fall and high stability to times where the market tends to raise. In our understanding of stability, periods behaving the other way round are no contradiction and indeed they do exist. Periods where the stability is low but the index is growing seem to be connected to an accelerating growth which is often connected to the formation of a bubble. Also there were times where the market was going down having a high stability. The posterior mean and variance of the BCP method might be of help in detecting such times.
This part of the thesis has been a first step into a new concept of judging economic and financial markets by describing them with stability measures that express the possibility that the dynamics of the market are going to change and that strategies working in the

past might fail in the future. By using more sophisticated methods and moving away from simple volatility and alike models, statements about the condition of a market promise to be more reliable. Besides that, using a probability measure to describe the market is much better understandable for people that don't have a statistical background.
Therefore we think that further research in that area is strongly justified in order to reach the goal of a reliable rapid alert system for financial and economic markets that is also understandable to the layperson.

Outlook

For the BCP approach the cases of unstable growth and stable shrinkage processes should be further examined by keeping the posterior mean and variance (which are delivered by the BCP method) in mind. Also the link to statistical physics (Glauber dynamics) offers some interesting fields that could be studied; like critical phenomena, correlation structures or scaling laws. The wavelet method also provides the possibility to consider only certain scales of the spectrum. By neglecting part of the spectrum unnecessary information (noise) could be eliminated.
Especially the BCP approach promises advantages over simple volatility based approaches since it is based on partitions; a quite different approach. To truly find out about the performance of such a measure in judging markets and how they compete against each other they have to be tested in real world applications.
Also are those methods not restricted to finance or economic data but could also be used in climate, air pollution or any other field dealing with statistics for time series.

References

Barry D., and Hartigan J.A. [1992], Product Partition Models for Change Point Problems, The Annals of Statistics, Vol. 20, No.1, 260–279.

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

Bunn A.G., Korpela M., Biondi F., Qeadan F., and Zang Ch. [2012], Dendrochronology Program Library in R, R dplR package, www.r-cran.org.

Credit Suisse Research Institute [2012], *Global Investment Returns Yearbook*, www.credit-suisse.com

Dimson E., March P., and Staunton M. [2002], *Triumph of the Optimists: 101 Years of Global Investment Returns*, press.princeton.edu

Dimson E., March P., Staunton M., and Elgeti R. [2008], *Global Investment Returns Yearbook*, ABN-AMRO

Enz M. for Bank Clariden Leu [2008], *Opportunities and risks in the financial markets: Historical analyses since 1950 point the way to an individual investment strategy*, Clariden Leu, Zurich.

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

Erdman Chandra, and Emerson John W. [2007], bcp: An R Package for Performing a Bayesian Analysis of Change Point Problems, Journal of Statistical Software 23.

Erdman Chandra, and Emerson John W. [2012], A Package for Performing a Bayesian Analysis of Change Point Problems R bcp package, www.r-cran.org

Fritsch F. N., and Carlson R. E. [1980], *Monotone Piecewise Cubic Interpolation*, SIAM Journal on Numerical Analysis 17, pp. 238-246.

Gençay R., Selcuk F., and Whitcher B. [2002], An Introduction to Wavelets and Other Filtering Methods in Finance and Economics, Academic Press, Elsevier, London, UK.

Global Financial Data [2012], The GFDatabase, www.globalfinancialdata.com

Huber Gérard [1986], *Evidence sur la performance relative des marchés obligataire et des actions en Suisse 1960-1983*, unpublished working paper Pictet & Cie, Geneva.

Ibbotson SBBI Classic Yearbook [2011], *U.S. Stocks, Bills, Bonds and Inflation Yearbook*, corporate.morningstar.com

Pictet & Cie [2012], The Performance of Shares and Bonds in Switzerland 1926-2011, Zurich, www.pictet.ch

Rätzer Ernst [1983], *Die Pensionskasse aus ökonomischer Sicht*, Paul Haupt Publishing, Bern and Stuttgart, 1983.

Setz Tobias [2011], Wavelet Analysis on Stochastic Time Series, Semester Thesis ETH Zürich, ITP Econophysics (Würtz D.), www.rmetrics.org

Setz Tobias [2012], Bayesian Change Point and Wavelet based Stability Analysis of the Swiss Market - Investigation of a century of financial and economic benchmarks, Master Thesis ETH Zürich, ITP Econophysics (Würtz D.)

Shiller Robert [2000], *Irrational Exuberance*, Princeton University Press, 2nd Edition 2005.

Siegel Jeremy [1994], emphStocks for the Long Run, McGraw Hill Companies, 4th Edition 2006.

Swiss National Bank [2007][2012], *Foreign Exchange Rates, Bills, Bonds, Equities, and Commodities*, pdf, txt and xlsx Files, www.snb.ch/2007, www.snb.ch/2012

Swiss Statistical Office (BFS) [2012] Landesindex der Konsumentenpreise (Monthly Index of Swiss Inflation) bfs.admin.ch

SWX Swiss Exchange [2012] *Share and Bond Indices*, Rules, Factsheets and Data, http://www.six-swiss-exchange.com

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

Wydler D. for Pictet & Cie [1998], *The Performance of Shares and Bonds in Switzerland: An empirical study covering the years since 1925*, Zurich, www.pictet.ch

Wydler D. [1989], *Swiss Stocks, Bonds, and Inflation, 1926-1987*, The Journal of Portfolio Management 15, Winter 1989, pp. 27-32.

Yao Y.C. [1984], Estimation of a Noisy Discrete-Time Step function: Bayes and Empirical Bayes Approaches The Annals of Statistics, 12, 1434–1447

CHAPTER 3

STABILITY IN A NUTSHELL

Stability Analytics Flyer 2014
Tobias Setz and Diethelm Würtz

Stability Analytics

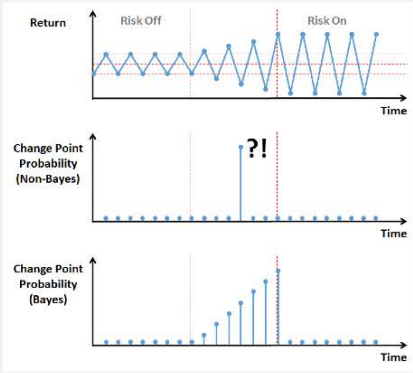
The Bayesian Change Point Method

Description:

Stability can be expressed through various **views** on a time series. If we think about a time series as a **random process which changes its dynamics over time** then the Bayesian Change Point (BCP) method offers an excellent description. It does not only offer a **probability** about how likely the assumptions of the underlying dynamics are about to **change** but also delivers a Bayesian estimate of the **performance and risk**.

Details:

Methodology



Features:

- Early warning signal for changing environments.
- Real time description of transition.
- Bayesian: fast and parameter less.

Relevance:

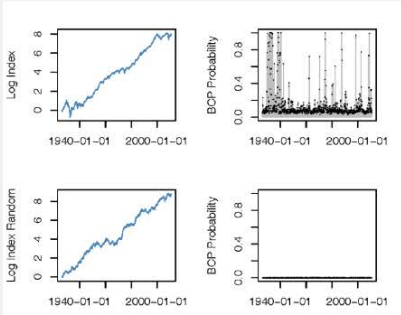
- Minimizing drawdowns and recovery times.
- Volatility reduction.
- Confident trading.
- Support of discretionary decision making.
- Selection of stable assets.

On Going Research:

- BCP method for other dynamics than the normal distribution.
- Online methods for faster signals.

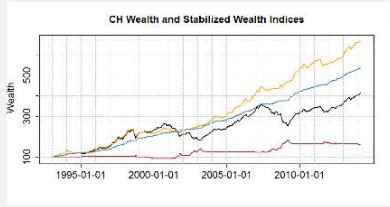
Application

Proof of Concept



The picture shows the BCP analysis of the S&P500 (top) and a random walk (bottom) having the same mean and standard deviation as the S&P500. **Random walks are clearly detected**.

Trading Model Example



BCP Analysis → BCP Indicator → BCP Signals

The black line is an Equal Weights Portfolio consisting of risky assets (Euro Large Caps, Small Caps, Real Estate) and 3 Month Bonds. The orange line uses the monthly signals to leave the risky assets for bonds or cash (1 month libor).

Further applications include: Portfolio Optimization, Rating and Raking, and Exposure Scaling.

Further development in research and models for trading can be sponsored with exclusive access to newest results.

Feel free to contact us any time: info@rmetrics.org

PART II

APPLICATIONS

CHAPTER 4

RATING AND RANKING BY STABILITY

Financial Risk Monitoring by Stability Control Strategies
Diethelm Würtz, Yohan Chalabi, Tobias Setz
Econophysics Group, Swiss Federal Institute of Technology Zurich
Econophysics Working Paper, Unpublished, ETH Zurich, December 2011

This was the first research report we have written in December 2011 about financial risk monitoring by stability control strategies. The work gives a brief summary about stability concepts and then discusses examples on enhanced Bayesian risk monitoring. Two new risk control strategies were explained: Stability monitoring based on Bayesian binary switching strategies, and a stability weighted rating and ranking approach.

Financial Risk Monitoring by Stability Control Strategies

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

First Version December 22, 2011
This Version June 27, 2012, Last Update August 2012

Abstract

In this article we give a brief overview and examples on enhanced risk monitoring using recent developed stability control strategies. These are new useful tools for a better capital protection, risk and stability management in life insurance and pension fund companies. Two new risk control strategies are explained: *Binary Switching Stability Monitoring*, and *Stability Weighted Rating and Ranking*. The strategies presented here are tailored to valuate risk by a steady increase, by low volatilities, by small drawdowns and by short recovery times.

This document is a preliminary draft of ongoing research. It is not allowed to distribute it without permission from the authors.[1]

1 Introduction

In this paper we introduce new risk management and stability monitoring strategies which were created with emphasis on life insurance and pension funds companies to help them for doing better risk control and investment decisions.

Such strategies were developed and investigated by Diethelm Wuertz et al.. Our risk control concepts are build on a capital protecting and stability preserving strategy to conserve the overall performance of an underlying investment. The goals are to achieve a steady increase of the wealth, to decrease the volatility, to improve the Sharpe Ratio or any other performance measure, to lower the drawdowns, and to shorten their recovery times. Taking care of both aspects performance and stability at the same time, we can create common rules for better indices as benchmarks for investments.

[1]Contact address: Diethelm Würtz, wuertz@phys.ethz.ch

The expectations are the following:

- High Performance and high Stability - we expect a market increase
- High Performance and high Instability - we expect a market decrease (mean reversion)
- Low Performance and high Stability - we expect a further decrease of the market
- Low Performance and high Instability - we expect a mean reversion in the direction of better market conditions

There are several options to measure market performance. The most natural one is to measure mean sample returns over a given period. We can improve this approach when we consider stability weighted returns and volatilities. Even more the Sharpe ratio [1994] and many other performance measures, see Bacon [2006], allow us to include explicitely performance variabilities into the measurement process. In the case of the Sharpe ratio we measure performance by the ratio of sample means and sample variations of the returns. We can consider as an alternative to the sample Sharpe ratio stability weighted Sharpe ratios which will be our choice in the following performance measurements. There exist also different options to measure stability from different kinds of views on the dynamic process, see Wuertz et al. [2012]: Bayesian changepoint analytics, robust principal component outlier analytics, or Morlet Wavelet analytics amongst other views. Here we use stability probabilities and convex transformations of these probabilities as a stability indicator. Our performance/stability indicator concatenates the outcome of the stability weighted performance measure with the outcome of the stability measure and follows the above described stability rules.

The data used in the show cases for the stabilization of major asset classes and indices and their equity components include small cap stocks (SCAP), large cap stocks, (SCAP), high yield corporate bonds (HYCORP), and long term corporate bonds (LTCORP). For the low risk component, here we use long term (LTGOV) Government bonds. Note we can also use intermediate term Government bonds, or bills and cash. The abbreviations we use in the following to refer to the financial index and return series are given in parentheses. The data sets are generated from total return values, monthly recorded, and range back until December 1969. They were taken from iShares ETF database [2012] and can be updated on a monthly base. In previous time periods where ETF investments were not yet available we used total return index data from the SBBI Ibbotson database [2010]. For the large cap segment we used the *SP500 Total Return Index* represented by iShares' IVV ETF, for the small cap investment we used the *RUSSELL2000 Total Return Index* represented by iShares' IWM ETF, for the long term corporate bond index we used the *iBoxx USD Liquid Investment Grade Index* represented by iShares' LQD ETF, and for the high yield corporate bond index we used the *iBoxx USD Liquid High Yield Index* represented by iShares HYG ETF. For the investigations of stocks we used the constituents of the SP100. These stocks are also part of the SP500. All data are recorded end of month.

This document is organized in the following way: In section 2 we introduce and explain *Stability Analytics* and how it can be used to detect and quantify structural changes and breaks as drivers for the occurence of instabilities in financial return series. In section 3 we introduce *Binary Switching Stability Indices*. The goal of this investment style is to stabilize an asset class by an admixture of a low risk or riskless asset to generate a more stable outcome. In section 4 we show how stability monitoring can be used to rate and rank components. We call this approach *Stability Based Rating and Ranking*. The selection of the most stable subset from the original universum will achieve a much better investment with lower volatility, smaller drawdowns, and shorter recovery times. In Section 5 we summarize our results and give a brief outlook of further

research.

2 Stability Analytics

Before we start we like to inspect the properties of the data used in this investigation. Figure 1 shows the logarithm of the wealth indices (indexed to December 1969 = 1) of the SCAP, LCAP, HYCORP, LTCORP, and LTGOV indices. Figure 2 shows the logarithmic returns of the five indices. The highest volatility comes with the small caps, and the lowest with the long term Government bonds. There exists higher correlations bewtween the equity indices and also between the bond indices. As expected they are lower when we compare equity with bond indices.

To measure the stability of the individual indices we use the Bayesian change point method, introduced by Barry and Hartigan [1993]. Their product partition approach allows to identify structural changes and breaks in a time series process and to determine the probability if there being a change point at a given location in the series. A *Monte Carlo Markov Chain* approximation was implemented by Erdman and Emerson [2008] to compute the probability information. An overview about stability analytics including other methods and approaches was recently given by Würtz et al. [2010, 2011]. They used stablilty analytics based on volatility, on extreme and outlying values, on non-stationarities and on the analysis of non-stationary and multifractal behaviour. We can also think of other approaches making use of weighted trimmed likelihood methods, the generalized lambda distribution and optimially-biased robust estimators. Each of the approaches takes a different view on the instabilities which may occur in a financial time series most likely representing an index, prices, cumulated returns, or a wealth index.

In the following we use stability analytics based on change points and structural breaks. Such instabilities are often caused by changes in the underlying dynamics of the financial returns. These become visible as structural changes and/or structural breaks. To detect them we apply Baysian statistical analytics which measures the probability to which degree a point in the financial returns is not part of the regular dynamical behavior but influenced by structural changes and breaks. We call this approach in the following *BCP analytics*.

To show how BCP stability analytics works we have analyzed the LCAP, SCAP, LTCORP, and HYCORP total return indices. The results in figures 3 to 6 show an retroactive turnpoint analytics and the retroactive BCP analytics. Retroactive computations are based on the whole regime of data points. Note, for risk control we use later out-of-sample stability analyticsmon rolling windows which are used in the computation for performance/stability forecasts.

3 Binary Switching Stability Indices

Binary switching stability indices describe investments build from two components. The first component is a high performing investment instrument (the index), the second a capital protecting and stability preserving admixture. As (risky) high performing instruments we consider for example large cap stock market investments (LCAP). Others may build from small cap investments (SCAP), or (less risky) long term corporate (LTCORP), and high yield corporate bond market investments (HYCORP). As capital protecting and stability preserving admixtures we

can consider here long term government bonds (LTGOV), but we can also rely on intermediate term government bonds, or bills and money market instruments, or just cash. In principle binary switching stability indices can be constructed from any risky underlying: Applications include the stabilization of high yield dividend equity indices, high fundamental quality equity indices, or sustainable equity indices.

Wealth Stabilization of Major Asset Classes:

We have built and investigated stability control indices for the LCAP, SCAP, LTCORP, and HYCORP indices combined with a less risky component. Here we use the long term government bonds, LTGOV, to protect and risk control the capital of the investment. The stability indicator is a combination of a BCP stability weighted Sharpe ratio and the BCP probabilities that a point in the financial returns is a change point or structural break and is not part of the regular underlying dynamical process.

To better understand how the stability approach works, figure 7 shows the log wealth and the drawdowns for the stability protected LCAP investment (SP500) since December 1997 until today (as of June 2012). In figure 8 the stability weighted performance indicator and our measure for the instabilities is shown.

Figures 9-12 show the results derived from the performance/stability protection rules for all 4 indices SCAP, LCAP, HYCORP, and LTCORP. Each chart consists of 4 graphs showing back to Decmber 1969 the following curves:

- Chart 1: Wealth series for the quity index, for the risk controlled index, for the premium, and the benchmark series.
- Chart 2: Positions and stability indicator which serves as the rebalancing trigger.
- Chart 3: 12 months rolling mean of returns series for the equity index, the risk controlled index and the premium.
- Chart 4: 12 months rolling maximum drawdowns of returns series for the equity index, the risk controlled index and the premium.

As an additional benchmark we have introduced what we called *No-Loss/Half Gain Benchmark*. This benchmark is constructed as: For index returns lower than the low risk or risk free rate, we count the reurns from the admixture, in the opposite case we count half of the (risky) index returns. This reflects our expectation that we can avoid all negative retutns in unstable periods, and that we can at least realize half of the returns during the stable periods. This benchmark is also added to the performance/stability charts. During the first 36 months the risk control process equilibrates. Therefore we have displayed the charts starting with a delay of 3 years from starting point of the data.

Equal Weights Indices:

Evenmore, binary switching indices can easily be combined together to create new indices, funds or portfolios. We prefer to use equal weighted combinations since these investments are usually better diversified compared to portfolios on the efficient frontier.

Figures 13 and 14 compare the logarithm of the wealth index for several portfolios. The investigation starts in December 1969 (figure 13) and in December 1997 (figure 14). Shown are the LCAP index, a balanced 50/50% of a LCAP/LTGOV blend, and the LTGOV index. Added are

the stabilized index of an equal weight portfolio composed from the LCAP, SCAP, HYCORP, and LTCORP components and the stabilized LTCAP index. The stabilizing component is again for all computations the LTGOV index.

4 Stability Based Rating and Ranking of Stocks

Our methodology can also be used for scoring, rating and ranking indices or other investments according to the stability weighted performance of individual members of an index, fund or portfolio. In the case of stability ranked investments we start from an index and its components. Here we can consider 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 in this approach is to rate the components of the considered index by a measures which assigns scores to each component in the index. The scores are computed from stability weighted performance and stability protective indicators and a rating process which orders the components. The ordering is then related to the ranking. Similar calcutions have been presented by Artico [2011] who ranked stocks by company attractiveness factors.

As a first example we look at the SP 100 Index and generate a dynamic stability based rating and ranking process. From the 100 components of the index we selected the 80 series which have the longest history. We are aware that this selection process may produce a survivior bias. We divide the stocks in four groups (quartiles). The first group will be assigned to the 20 best performance/stability rated stocks, the second and third group each to the next 20 best intermediate performing stocks, and the last group to the 20 worst performance/stability weighted stocks. This process is rebalanced every end of month. The result is shown in figure 15. The Quartile separation is quite impressive with a perfect ordering of the performance from the stabilized subindices. The equal weighted index composed from the 80 stocks separates clearly the first two from the last two quartiles. To be fair, the chart will depend on the starting point. The reason is that stocks which lost more in a declining market have a higher potential for recovery.

In figure 16 we did a comparison of the stability ranked index with alternative investment decisions. Comparison for the stability protected quartile investment is made with the best quartile SP 100 investment, with the equal weights SP 100 portfolio from the 80 selected stocks, and with the SP500. The improvement in the increase in the stability becomes evident.

5 Summary and Outlook

Stability Control Strategies provide a new and powerful concept of designing new indices which figure out to be much better capital protected compared to traditional capitalized indices. From a risk management point of view stabilized investments have lower volatilities, smaller drawdowns, and shorter recovery times. In overall they offer a much better diversification than other investment styles. Our new stability design process allows to optimize *Binary Switching Stability Indices* and to design *Stability Based Ratings and Rankings* for a better risk control and more reliable investment decisions.

Description of the US Data Sets

In this appendix we briefly describe the time series we used for the analyses of the US long term data sets.

The first set of data are 7 monthly recorded index series from the U.S. market.

- *LCAP:* As a proxy for the U.S. large cap stocks we use the *SP500* total return index. Index levels are calculated from iShares' investable ETF Fund IVV ranging back until March 2001. For earlier dates we refer to the Standard and Poors, SBBI and GFD databases. We abrreviate this time series in the following by *LCAP*.

- *SCAP:* As a proxy for the U.S. small cap stocks we use the *Russell2000* total return index. Index levels are calculated from iShares' investable ETF Fund IWM ranging back until March 2001. For earlier dates we refer to SBBI and GFD databases. We abrreviate this time series in the following by *SCAP*.

- *HYCORP:* As a proxy for the U.S. high yield corporate bonds we use the *iBoxx USD Liquid High Yield Index*. Index levels are calculated from iShares' investable ETF Fund HYG ranging back until May 2007. For earlier dates we refer to the Morningstar database. We abrreviate this time series in the following by *HYCORP*.

- *LTCORP:* As a proxy for the U.S. long term corporate bonds we use the *iBoxx USD Liquid Investment Grade Index*. Index levels are calculated from iShares' investable ETF Fund LQD ranging back until August 2002. For earlier dates we refer to the SBBI database. We abrreviate this time series in the following by *LTCORP*.

- *LTGOV:* As a proxy for the U.S. long term government bonds we use *Barclays Capital U.S. 10 to 20 Years Treasury Bond Index*. Index levels are calculated from iShares' investable ETF Fund TLH ranging back until May 2007. For earlier dates we refer to the SBBI database. We abrreviate this time series in the following by *LTGOV*.

The second data set are monthly price and equity data representing U.S. stock market by the Standard & Poors index SP100 (OEX)and its components. The data set used contained dividend adjusted end-of-month closing prices starting in December 1991. They were downloaded from Yahoo's finance web site.

Indices of Major U.S. Asset Classes

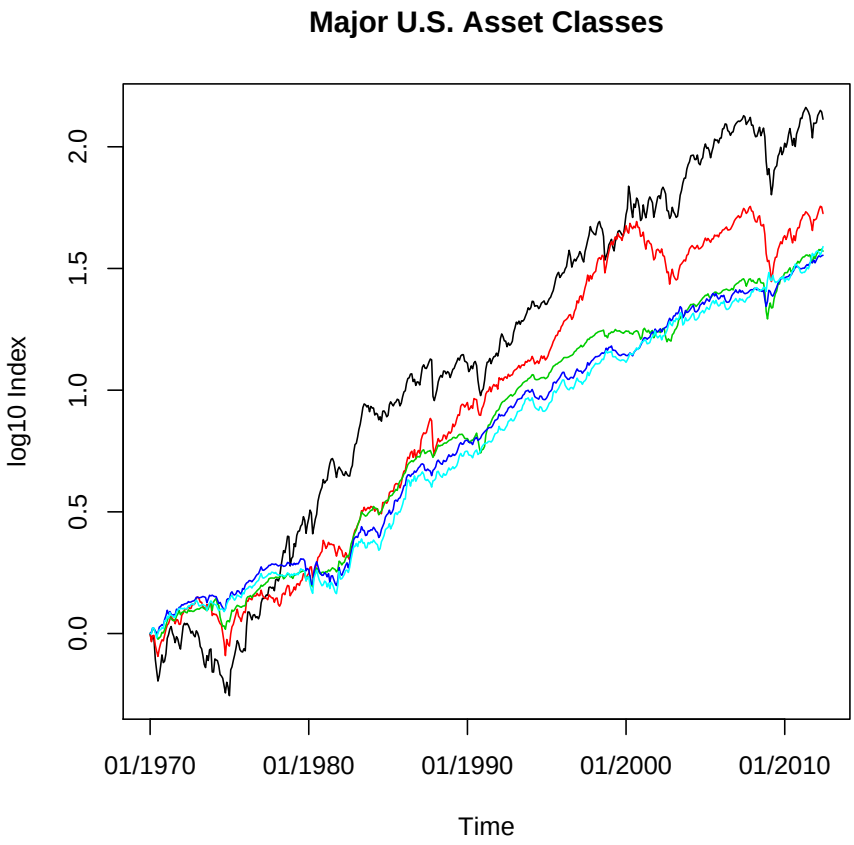


Figure 1: Logarithm of the index values of major US asset classes. The series are indexed to January 1998 = 1. The indices include small (SCAP, black) and large capitalized (LCAP, red) stocks, high yield (HYCORP, green) and long term corporate (LTCORP, blue) bonds, and long term Government (LTCORP, cyan) bonds.

Returns of Major U.S. Asset Classes

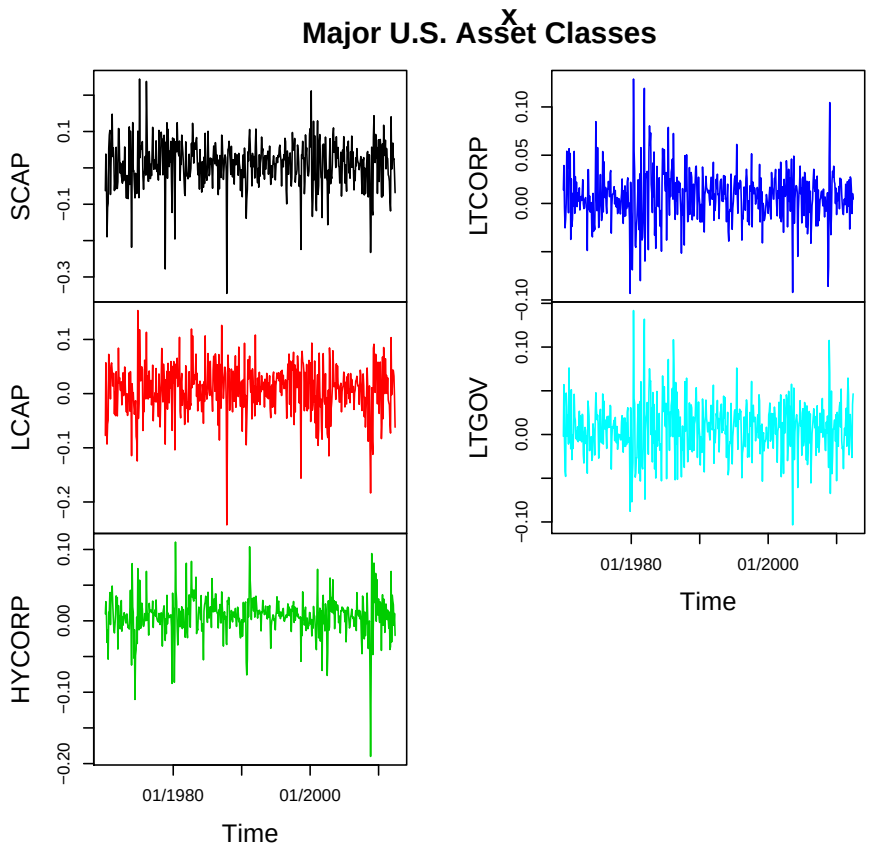


Figure 2: Monthly log-return values of major US asset classes. The series are the same as in Figure. 1.S mall (SCAP, black) and large capitalized (LCAP, red) stock indices, high yield (HYCORP, green) and long term corporate (LTCORP, blue) bond indices, and long term Government (LTCORP, cyan) bond.

Large Capital Stocks Bayesian Change Point Analytics

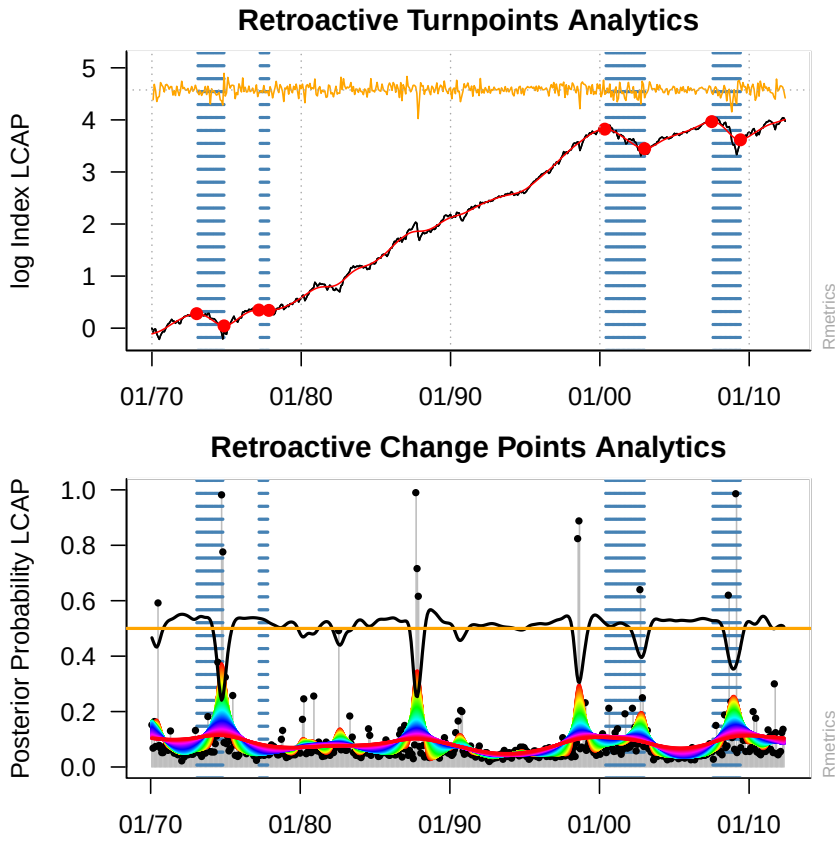


Figure 3: LCAP (SP 500) Bayesian Change Point Analytics. The upper graph displays a retroacitve turning point analysis. The black curve shows the end of month values of the logarithm of the wealth index, the red curve is filtered by a spline smoother. The red dots mark the turning points, the blue horizontal bars mark the down periods. The orange curve shows the structure of the returns. The lower graph displays the results from the retroactive BCP analytics. The gray bars with a black dot on top mark the probabilities for each time series points. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colors. From their peaks and divergencies we can identify more stable, less stable or even unstable regions. The black curve twisting around 1/2 is a measure for the extraction or divergence of the stability.

Small Capital Stocks Bayesian Change Point Analytics

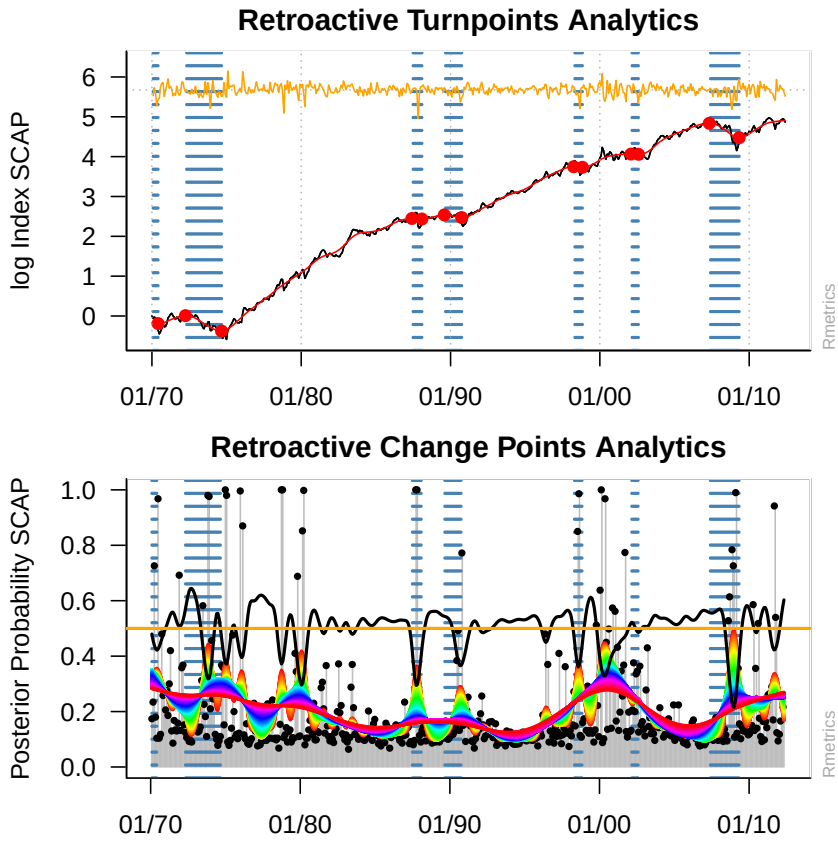


Figure 4: SCAP (Russel 2000) Bayesian Change Point Analytics. The upper graph displays a retroacitve turning point analysis. The black curve shows the end of month values of the logarithm of the wealth index, the red curve is filtered by a spline smoother. The red dots mark the turning points, the blue horizontal bars mark the down periods. The orange curve shows the structure of the returns. The lower graph displays the results from the retroactive BCP analytics. The gray bars with a black dot on top mark the probabilities for each time series points. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colors. From their peaks and divergencies we can identify more stable, less stable or even unstable regions. The black curve twisting around 1/2 is a measure for the extraction or divergence of the stability.

Long Term Corporate Bonds Bayesian Change Point Analytics

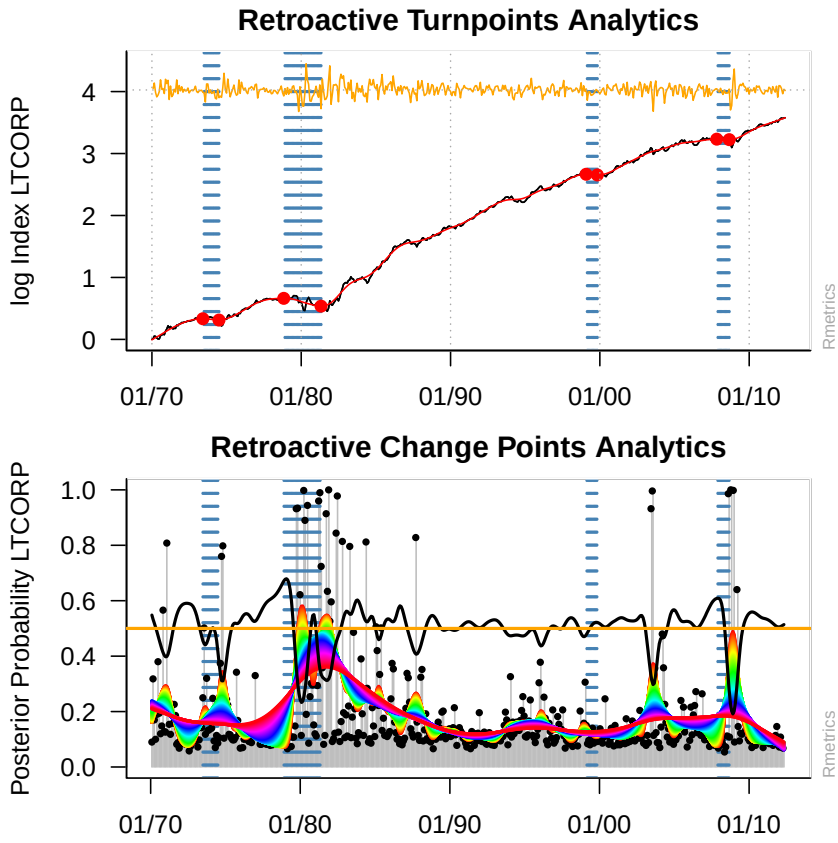


Figure 5: LTCORP Bayesian Change Point Analytics. The upper graph displays a retroacitve turning point analysis. The black curve shows the end of month values of the logarithm of the wealth index, the red curve is filtered by a spline smoother. The red dots mark the turning points, the blue horizontal bars mark the down periods. The orange curve shows the structure of the returns. The lower graph displays the results from the retroactive BCP analytics. The gray bars with a black dot on top mark the probabilities for each time series points. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colors. From their peaks and divergencies we can identify more stable, less stable or even unstable regions. The black curve twisting around 1/2 is a measure for the extraction or divergence of the stability.

High Yield Corporate Bonds Bayesian Change Point Analytics

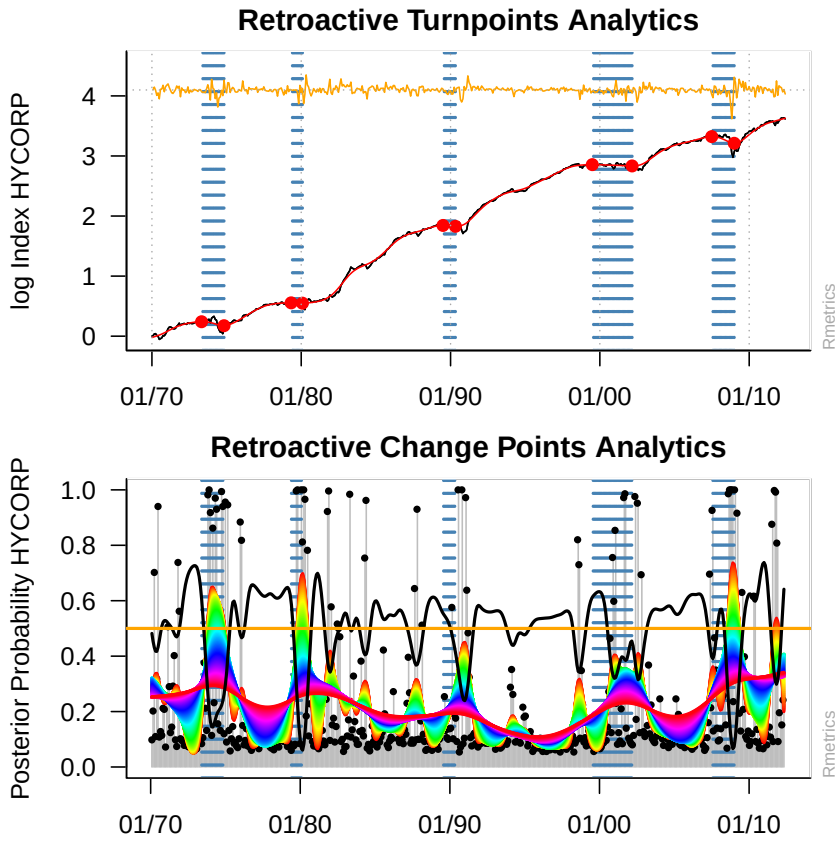


Figure 6: HYCORP Bayesian Change Point Analytics. The upper graph displays a retroacitve turning point analysis. The black curve shows the end of month values of the logarithm of the wealth index, the red curve is filtered by a spline smoother. The red dots mark the turning points, the blue horizontal bars mark the down periods. The orange curve shows the structure of the returns. The lower graph displays the results from the retroactive BCP analytics. The gray bars with a black dot on top mark the probabilities for each time series points. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colors. From their peaks and divergencies we can identify more stable, less stable or even unstable regions. The black curve twisting around 1/2 is a measure for the extraction or divergence of the stability.

LCAP Stability protected by LTGOV

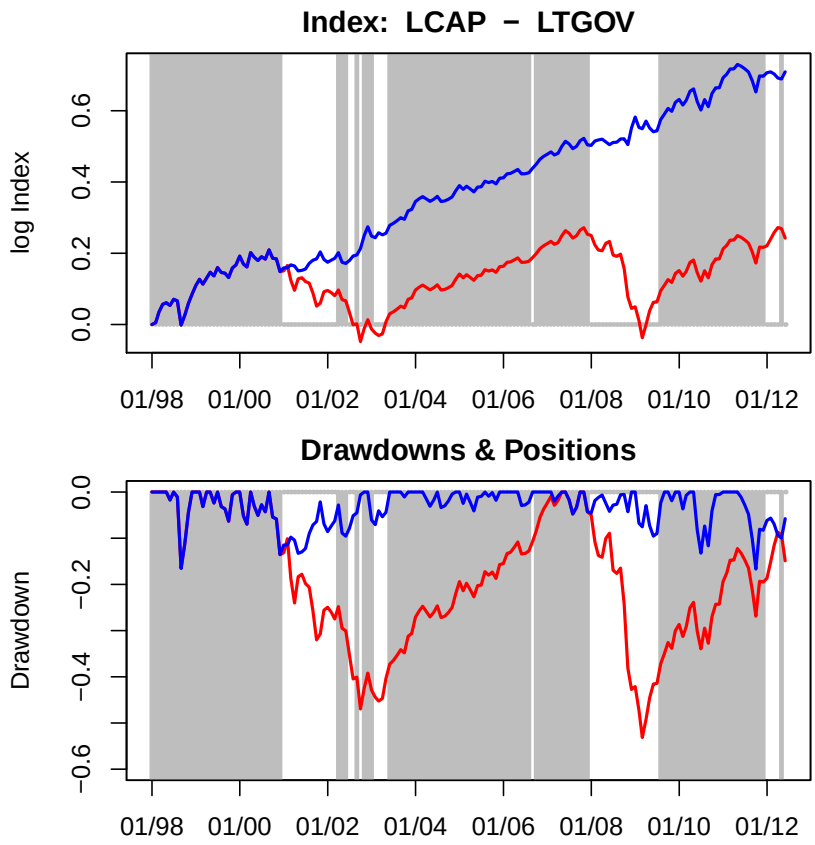


Figure 7: LCAP Stability Protection: The graphs show the log10 wealth index and the drawdowns for the unprotected and the stability protected SP500 index. The investigation starts January 1998. The first 12 months are used as warmup period.

LCAP Performance and Stability Indicators

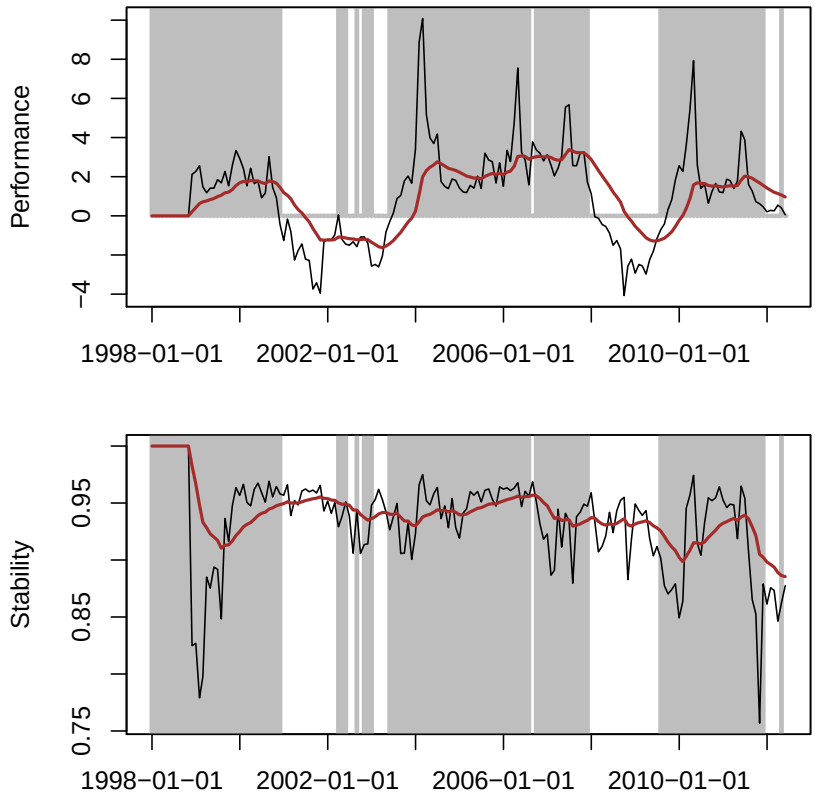


Figure 8: Performace and stability indicator for the large cap stock segments starting January 1998.Note, the first 12 months are used as warmup period. The upper graph shows the stability weighted Sharpe ratio measuring performance and the lower graph measures instability. From these two indicators the rebalancing signals are created.

LCAP Stability protected by LTGOV

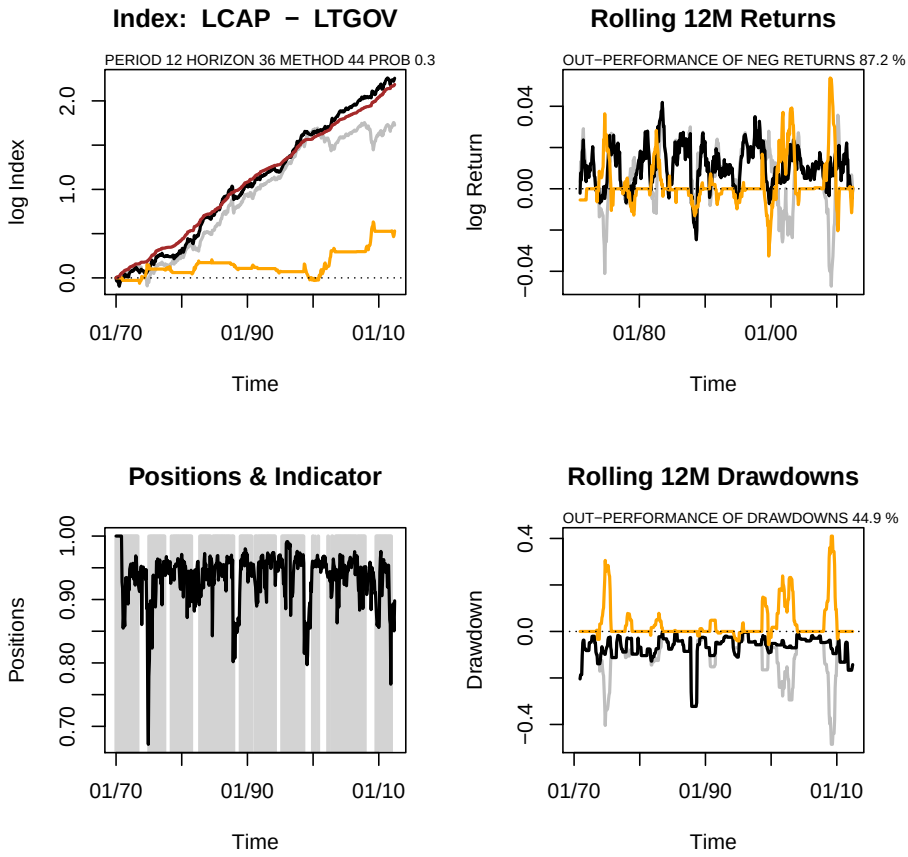


Figure 9: LCAP stability controlled indexation: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

SCAP Stability protected by LTGOV

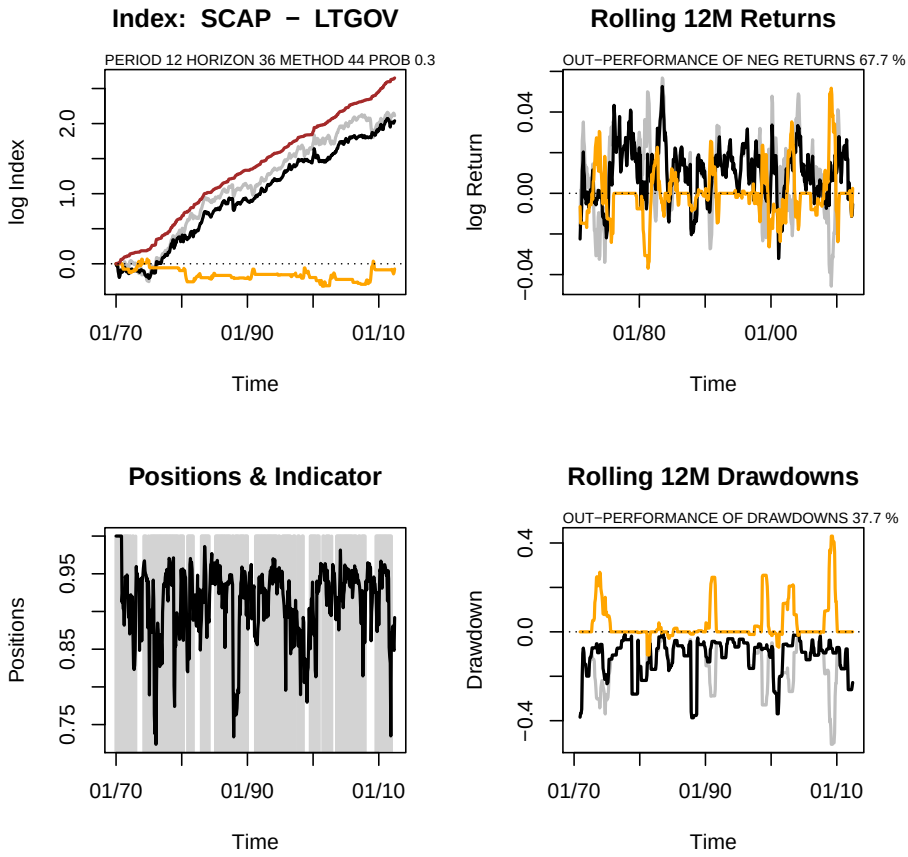


Figure 10: SCAP stability controlled indexation: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

HYCORP Stability protected by LTGOV

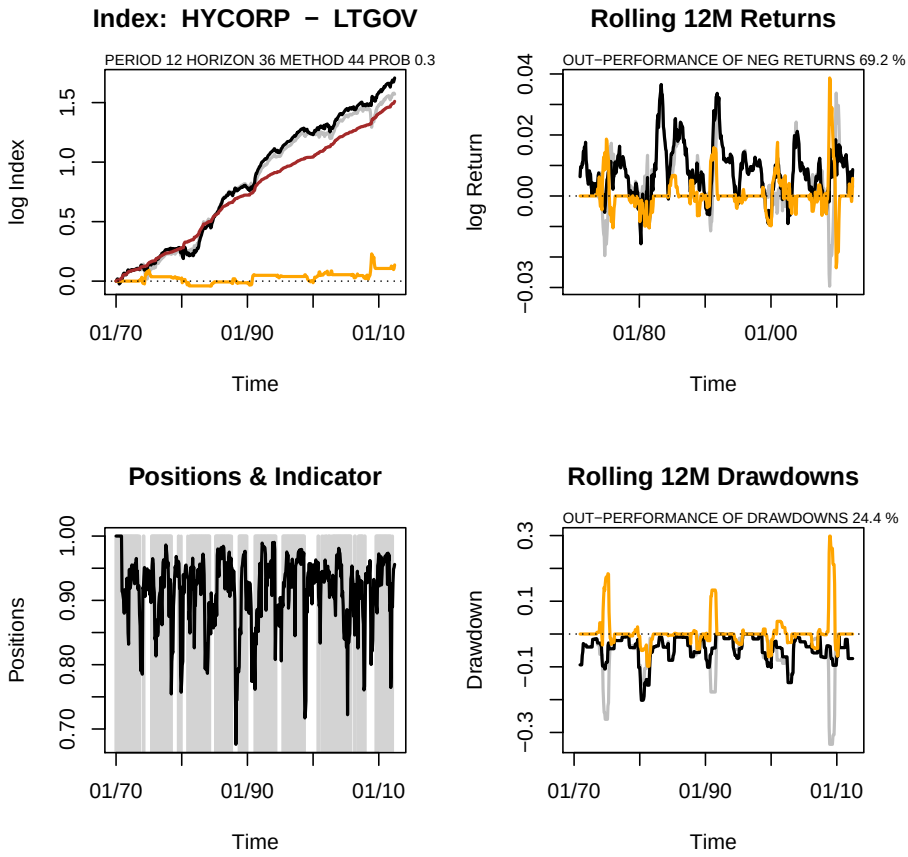


Figure 11: HYCORP stability controlled indexation: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

LTCORP Stability protected by LTGOV

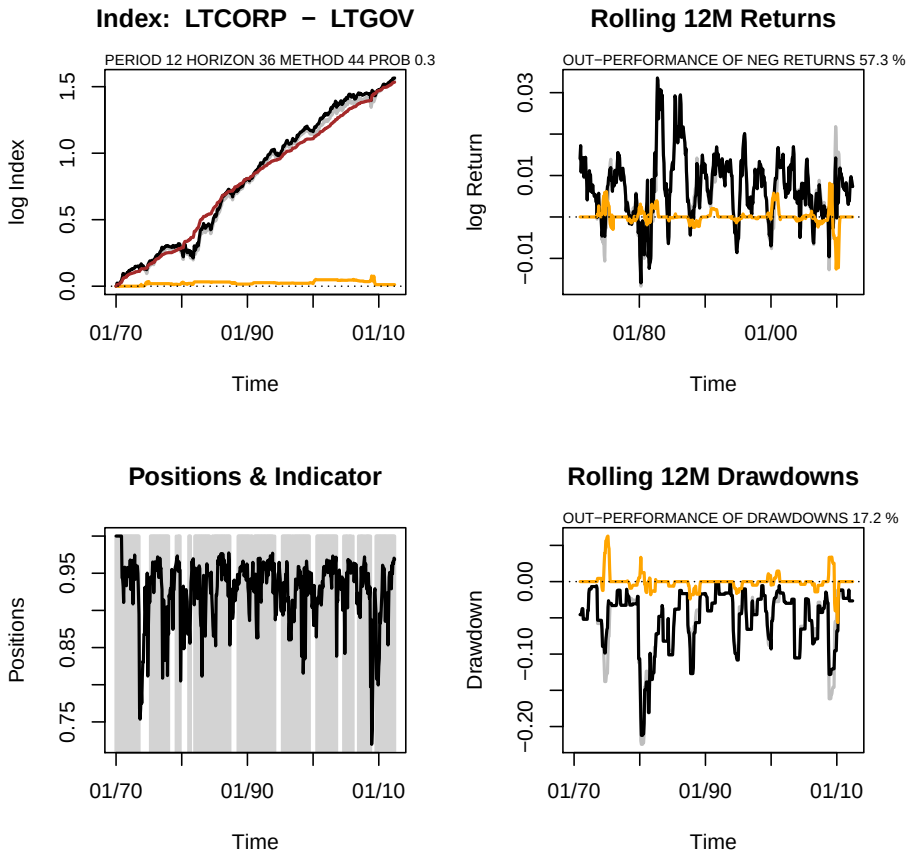


Figure 12: LTCORP stability controlled indexation: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Comparison of Balanced Porfolios Charts Since 1970

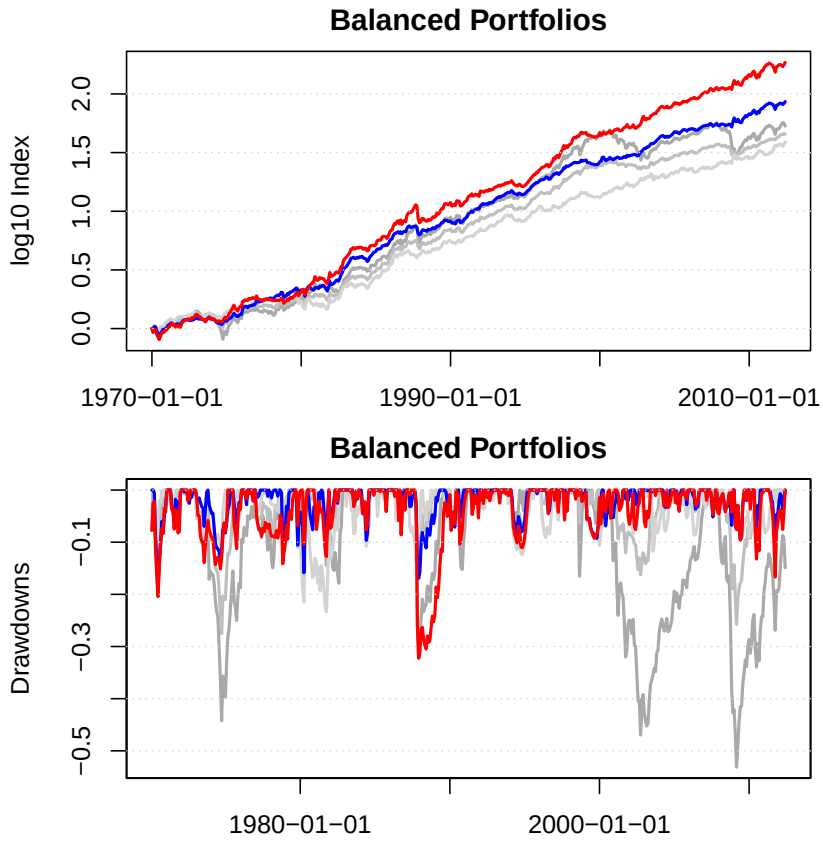


Figure 13: The graphs compare the logaruthm of the wealth index for several portfolios. The investigation starts in 1970. Shown are the LCAP index (darkgrey), a balanced 50/50% of a LCAP/LTGOV blend (grey), and the LTGOV index (light grey). The blue line presents the stabilized index of an equal weight portfolio composed from the LCAP, SCAP, HYCORP, and LTCORP components. The red line prsents the stabilized LTCAP index. The stabilizing component is the LTGOV index.

Balanced and Stabilized Portfolios Charts Since 1998

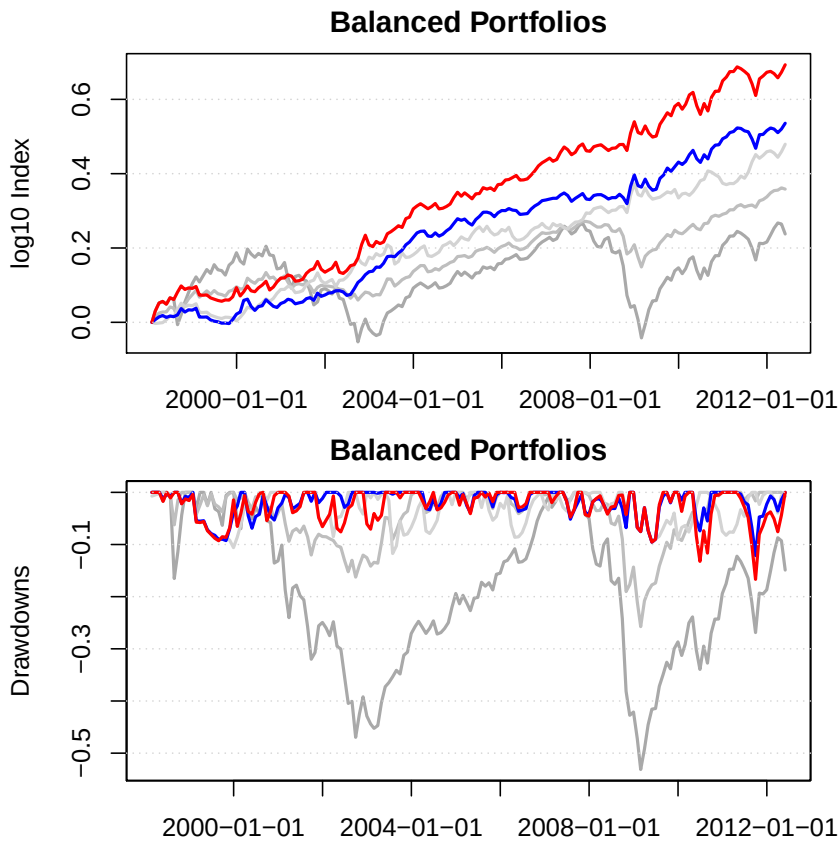


Figure 14: The graphs compare the logaruthm of the wealth index for several portfolios. The investigation starts in 1999. Shown are the LCAP index (darkgrey), a balanced 50/50% of a LCAP/LTGOV blend (grey), and the LTGOV index (light grey). The blue line presents the stabilized index of an equal weight portfolio composed from the LCAP, SCAP, HYCORP, and LTCORP components. The red line prsents the stabilized LTCAP index. The stabilizing component is the LTGOV index.

SP100 Stability Ranking

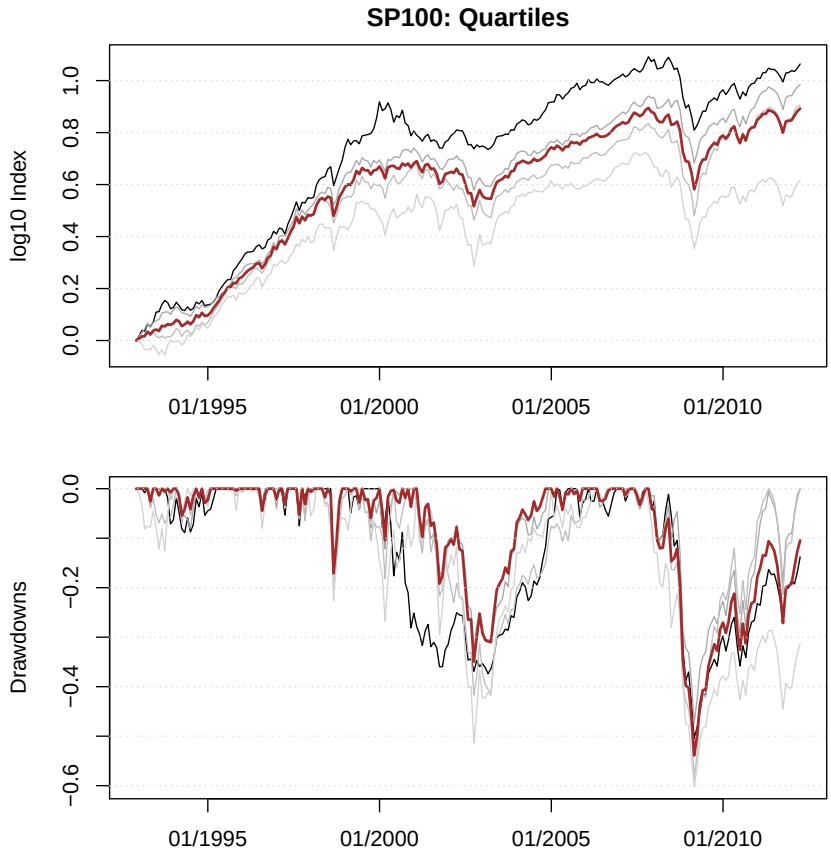


Figure 15: SP100 Stability Ranking of the 80 stocks with the longest history in the index. The four groups contains the 20 best, the second and third 20 best, and finally the worst 20 performance/stability weighted stocks from the index. The colors of the for groups are black, dark grey, grey, and light grey. The Quantile separaion is quite impressive with a perfect ordering of the performance stabilized subindices. The equal weighted index composed from the 80 stocks is shown by the thick brown line.

Stabilized SP100 / SP500 Comparison

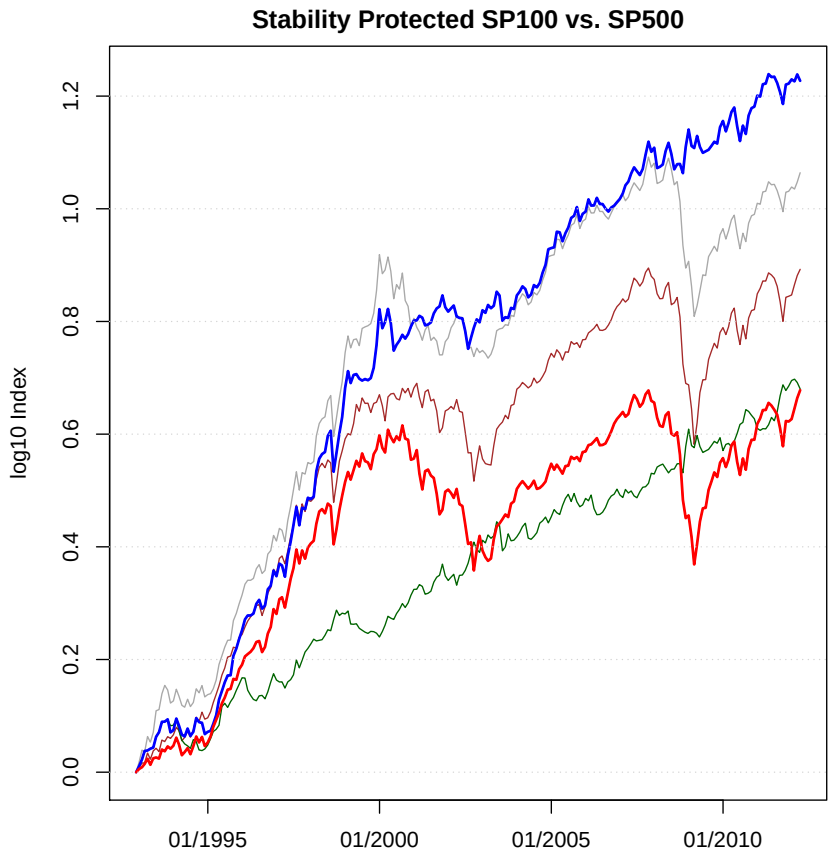


Figure 16: The graphs show compaisons of the logarithmic wealths of the SP500 (red), of the equally weighted SP100 of the 80 stocks with the longest history, of the best quartile performance stability selected index, and of the stability protective index of the best quartile index. The lowest curve (darkgreen) shows the log return of the protective component, the long term Government Bond Index LTGOV.

References

Artico Partners [2011], Artico Company Booklet, http://www.artico-partners.com

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

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

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.

ihares ETF Database [2012], www.ishares.com

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

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

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, Eds. D. Würtz, M. Mehta, D. Scott, and J. Hinz, Rmetrics Association and Finance Online Publishing, Zurich, pp. 205–213.

Würtz D. [2011], Tools for Portfolio Optimzation from R/Rmetrics, Proceedings of the Meielisalp Summerschool and Workshop 2011, Eds. D. Würtz, S. Iacus, M. Mehta, D. Scott, Rmetrics Association and Finance Online Publishing, Zurich, pp. 220–229.

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

CHAPTER 5

STABILITY PARITY INDEXATION

Binary Switching Stability Indexation: 26 New Strategy Equity Indices
Diethelm Würtz and Tobias Setz
Econophysics Group, Swiss Federal Institute of Technology Zurich
Econophysics Working Paper, Unpublished, ETH Zurich, March 2012

In this paper we were working on several algorithms to improve traditional covariance, expected shortfall, and tail risk budgeting strategies for portfolio optimization. It was then quite natural to also ask if it would be possible to create concepts for stability budgeting. What we found out is described in the working research report about binary switching stability indexation.

Binary Switching Stability Indexation
26 New Strategy Equity Indices

Diethelm Würtz and Tobias Setz
Econophysics Group
Institute for Theoretical Physics
Swiss Federal Institute of Technology Zurich

First Version March 13, 2012
This Version July 27, 2012, Final Update August 2012

Abstract

Stability control indices are build from two components. The first component is a high performing investment instrument, the second a capital protecting and stability preserving admixture. The goals of the underlying strategy are to achieve a steady increase of the wealth, to decrease the volatility, to improve the Sharpe Ratio, to lower the drawdowns, and to shorten their recovery times. In this document we present the results for 26 new theme equity indices, called *Stability Controlled Indices*. The new indices can be used for a better capital protection, risk and stability management in life insurance and pension fund companies.

This document is an internal working paper of ongoing research. It is not allowed to distribute it without permission from the authors.[1]

1 Introduction

Binary switching stability indexation, short *BSSI* is a new approach to generate risk controlled and capital protected equity market indices. The underlying idea and concept is similar to the traditional volatility controlled indices like the *SMI Risk Control Indices* or the *MSCI Risk Control Indices*. These indices are balanced between the equity index and a low risk or risk free investment, usually a money market instrument. In the case of the SMI risk control indices this will be achieved by a rebalancing process between the SMI total return index and the Swiss overnight rate, the *SARON*. Whenever the SMI equity index exceeds a given volatility level the investment will be switched to the SARON, and below the volatility level the investment will be in the SMI index. Additionally the SMI risk control index concept also allows for a leveraged investment (up to a maximum of 1.5) in the respective equity index.

[1]Contact address: Diethelm Würtz, wuertz@phys.ethz.ch

In our case we extend this approach to a more general view. Instead of using the volatility which measures the variability of the returns, we consider the stability weighted performance and risk attribution of the returns as a threshold indicator for the rebalancing between the two components. Stability measures not only variability, it takes also structural changes, dynamical breaks, and extreme and outlying values of the return series into account. So we expect a much better indexation compared to a volatility based risk control.

2 Concept of Stability Control

The measure of stability for a financial time series is calculated from Hartigan's Bayesian change point algorithm, short *BCP*, which returns the probability that a point is influenced by vulnerabilites in the underlying dynamical process. Performance is then derived from the stability weighted Sharpe ratio. Taking care of both aspects performance and stability at the same time, we can create rules for a better indexation.

Our expectations are the following:

- High Performance and high Stability:
  we expect a market increase
- High Performance and high Instability:
  we expect a market decrease by mean reversion
- Low Performance and high Stability:
  we expect a further decrease of the market
- Low Performance and high Instability:
  we expect a mean reversion in the direction of better market conditions

3 Stability Controlled Equity Indices

The the following we present stability controlled total return indices for 26 major equity markets.

Selection of Indices

The indices were selected in such a way that they cover a broad spectrum: Country indices from Switzerland, USA, UK, and Japan; regional indices from Europe, Eurozone, North America, Asia/Pacific, Emerging Markets and Global World, and Style indices for BlueChips, Broad, Large, Mid and Small Cap markets. To become more precise, included are from Switzerland (6) the SPI and SMI families, from the U.S.(5) the SP500 and the family of Dow Jones Wilshire indices, Stoxx Eurozone (4) indices, from UK (1) the FTSE100 index, from Japan (2) the NIKKEI and TOPIX indices, the MSCI (3) WORLD, EMU and MSCI Emerging Market indices, and as regional indices (4) the Stoxx Global150 family covering the European, the North American and Asia/Pacific areas. All indices are recorded end-of-month and start December 1998. For naming and identification we use the Bloomberg symbols.

Model Parameters and Settings

The computation of stability controlled indices depends on the selection and setting of a few parameters. The degree of stability control is quantified by the LEVEL parameter which deetermines the quantile threshold of a historical stability weighted performance measures along a predetermined time window or horizon The horizon is specified by the HORIZON parameter. The levels are given as probability values ranging between zero and one. If the last computed indicator value crosses the desired threshold a rebalancing will be done for the next month. The indicator values used to compute this rebalancing trigger are computed on a rolling window with length given by the parameter PERIOD. Beside these parameters we have also to define the stability control function, lets call it STABFUN. There are several choices thinkable, in this investigation we used a stability weighted performance derived from the BCP algorithm. The three parameters, LEVEL, HORIZON and PERIOD and the indicator function STABFUN completely specify the risk control process.

No-Loss/Half-Gain Benchmark

First the results will be compared to the underlying equity index. In a addition we introduce a second benchmark derived from the underlying equity indices which is constructed in the following way: In the case of equity index returns which are smaller than the low risk index, we will take the return from the low risk index (although this may be not any time the case due false rebalancing signals). And for equity index returns which are above the low risk index returns we are willing to loose not more than half of the return (again due to rebalancing signals from false forecasting positions) and thus count and cumulate half of the equity index return. We call this index *No-Loss/Half-Gain Benchmark*.

4 Discussion of Results

In this section we briefly describe and discuss the results form our stability controlled indices. The tables and charts can be found in the Appendix.

Parameters and Settings

We consider in this investigation the following parameters and settings:

- Equity Indices: 26 end-of-month major stock market indices starting December 1998.
- Risk free component: cash (no interest).
- Benchmark Series: No-Loss/Half-Gain Benchmark. We compare the equity indices and the stability controlled indices with this measure derived from the equity indices.
- Conrol Indicator: Rolling 12 Month BCP stability weighted performance measure STABFUN; PERIOD = 12 months.
- Threshold Trigger: Probability level (between 0 and 1, by default LEVEL=0.3) computed from from the 36 months rolling control indictor; HORIZON = 36 months.

The list of the selected 26 equity indices is given in the Appendix.

Performance and Risk Summaries

Summaries of the results from all 26 stability controlled indices are shown in the Appendix in Figures 1 to 8. These include bar charts on

- Annualized Mean Returns
- Annualized Standard Deviations
- 12 Months Rolling Average of Mean Returns
- 12 Months Rolling Maximum Drawdowns
- Sharpe Ratios
- Information Ratios
- Average Number of Rebalances p.a.
- Average Unchanged Position Lengths in Months

Detailed numbers from which the figures were created can be taken from the tables in Figure 9 and Figure 10.

Risk Return Diagram

The risk versus return diagram for all 26 equity indices and their stability controlled counterparts are shown in Figure 12. The numbers were taken from Figure 9. In all cases we observe an increase in the mean of the returns and a decrease in the standard deviation of returns which reflects risk.

Levels of Stability

The level of stability can be be chosen by a parameter between zero and one. In the zero limit level we approach the equity index. In the limit that the level parameter approaches 1 the investment will become the same as that for the low risk or risk free index. In between we expect an optimal threshold value. We have computed the stability controlled indices for a set of level parameters in the zero-one range for all 26 equity indices. We observe a maximum of stabilization about a level value of 0.3. The results are shown in Figure 13.

Stability Control Charts

For each of the 26 indices four charts are given in Figures 14 to 39.

- Chart 1: Wealth series for the quity index, for the risk controlled index, for the Premium, and the benchmark series.
- Chart 2: Positions and stability indicator trigger.
- Chart 3: 12 months rolling mean of returns series for the equity index, the risk controlled index and the premium.

- Chart 4: 12 months rolling maximum drawdowns of returns series for the equity index, the risk controlled index and the premium.

During the first 36 months the risk control process equilibrates. Therefore we display the charts starting on January 2002 three years later than data records are available. Note, the three years delay results from the startup horizon window of 36 months.

5 Summary

The *Stability Control* approach was developed and investigated in the Econophysics Group headed by Diethelm Würtz at ETH Zurich. The approach is not restricted to indexation, it also provides a new and powerful concept of designing investments which are much better capital protected compared to traditional investments. This is expressed by the fact that stabilized investments have lower volatilities, smaller drawdowns and shorter recovery times. In overall they offer a much better diversification than traditional investments.

List of Equity Indices

The table lists the indices. The first column holds the Bloomberg symbols, the second column lists the (local) currency, the last column gives a short description of the index.

```
# SWITZERLAND:
    SPI         CHF          Swiss Performance TR Index
    SPI19       CHF            Large Cap
    SPIMLC      CHF            Mid Cap
    SPI21       CHF            Small Cap
    SMIC        CHF          Swiss Market TR Index
    SMIMC       CHF            Mid Cap

# UNITED STATES:
    SPXT        USD          SP500 TR Index
    DW25T       USD          Dow Wilshire TR Index
    DWLT        USD            Large Cap
    DWMT        USD            Mid Cap
    DWST        USD            Small Cap

# EUROZONE:
    SX5T        EUR          Eurostoxx50 TR Index
    SXXT        EUR          Eurozone TR Indices
    LCXT        EUR            Large Cap
    MCXT        EUR            Mid Cap
    SCXT        EUR            Small Cap

# UNITED KINGDOM:
    TUKXG       GBP         FTSE100 TR Index

# JAPAN:
    NKY         JPY         NIKKEI225 TR Index
    TPXDDVD     JPY         TOPIX TR Index

# WORLD:
    NDDUWI      USD        MSCI World TR Index
    NDDUEMU     USD        MSCI European Monetary Unit TR Index
    NDDUEEGF    USD        MSCI Emerging Markets TR Index

# REGIONS:
    SXG150T     EUR       Stoxx Global 150 TR Index
    SXEU50T     EUR         Europe TR Index
    SXNA50T     EUR         North America TR Index
    SXAP50T     EUR         Asia/Pacific TR Index
```

Figure 1: List of Indices.

Performance and Risk Summaries

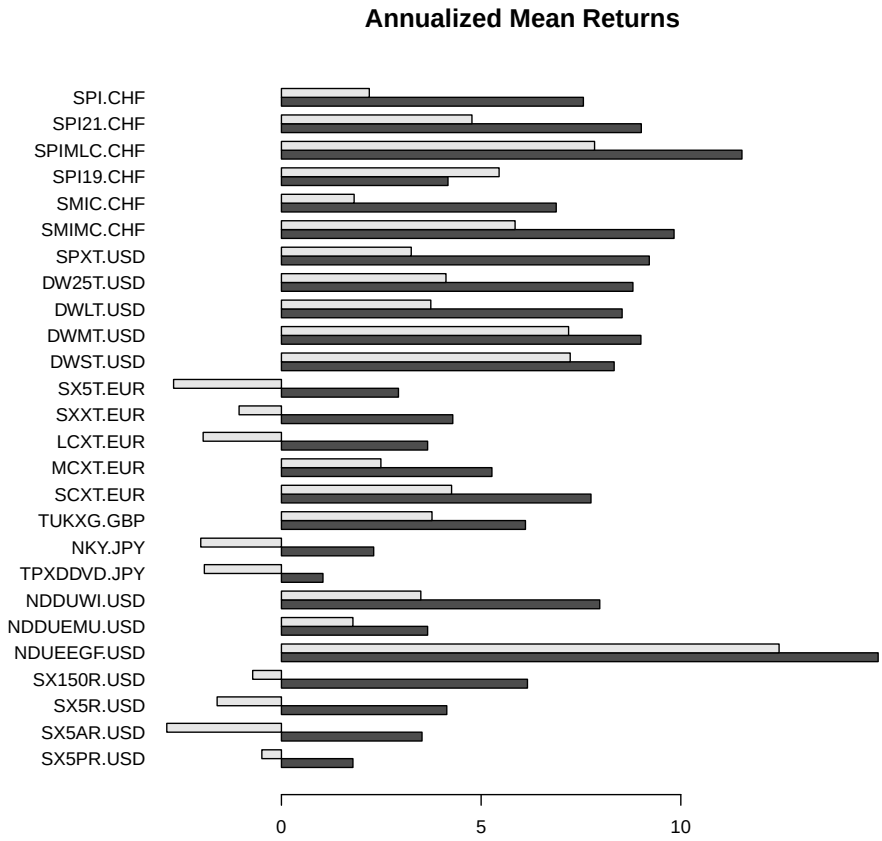


Figure 2: Annualized Mean Returns.

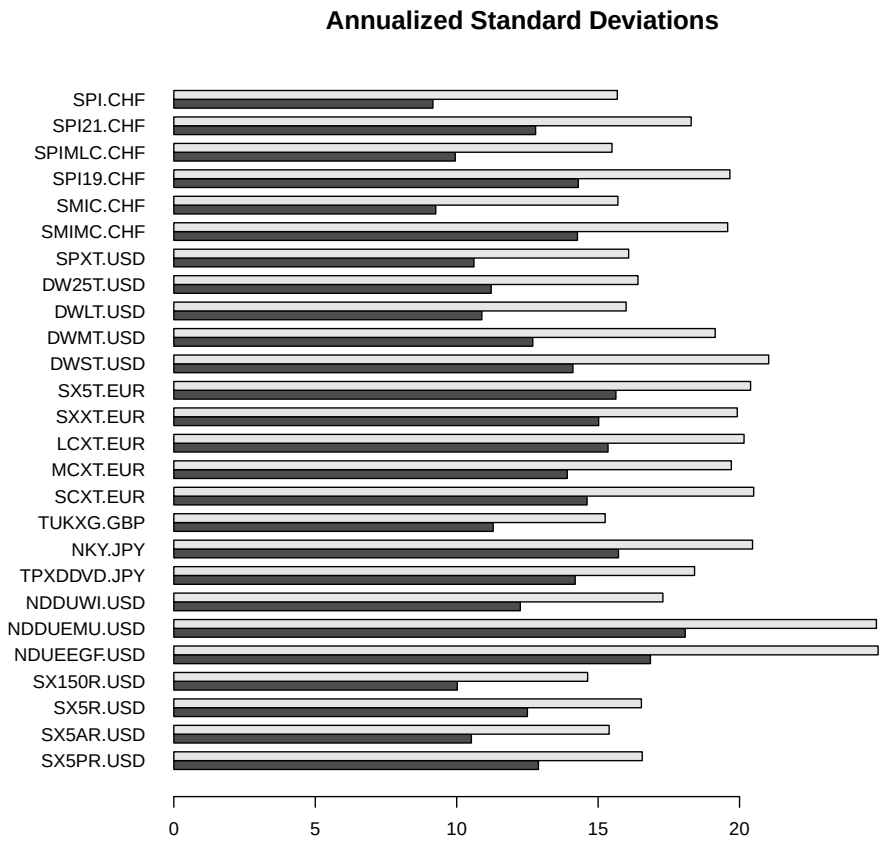


Figure 3: Annualized Standard Deviations.

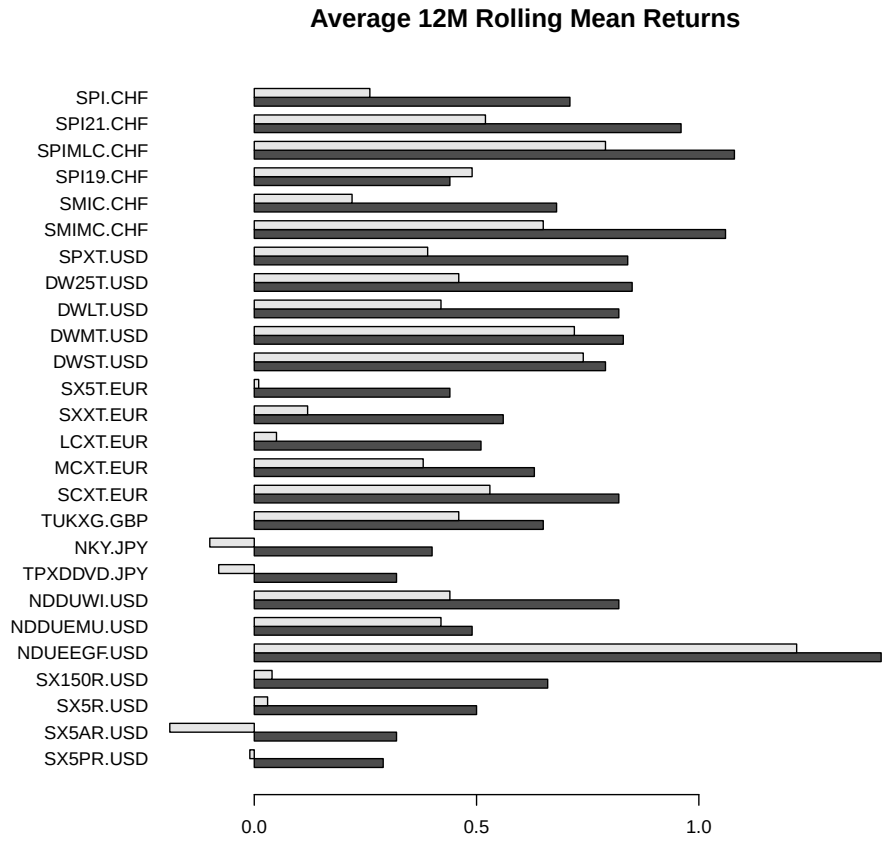


Figure 4: 12 Months Rolling Average of Mean Returns.

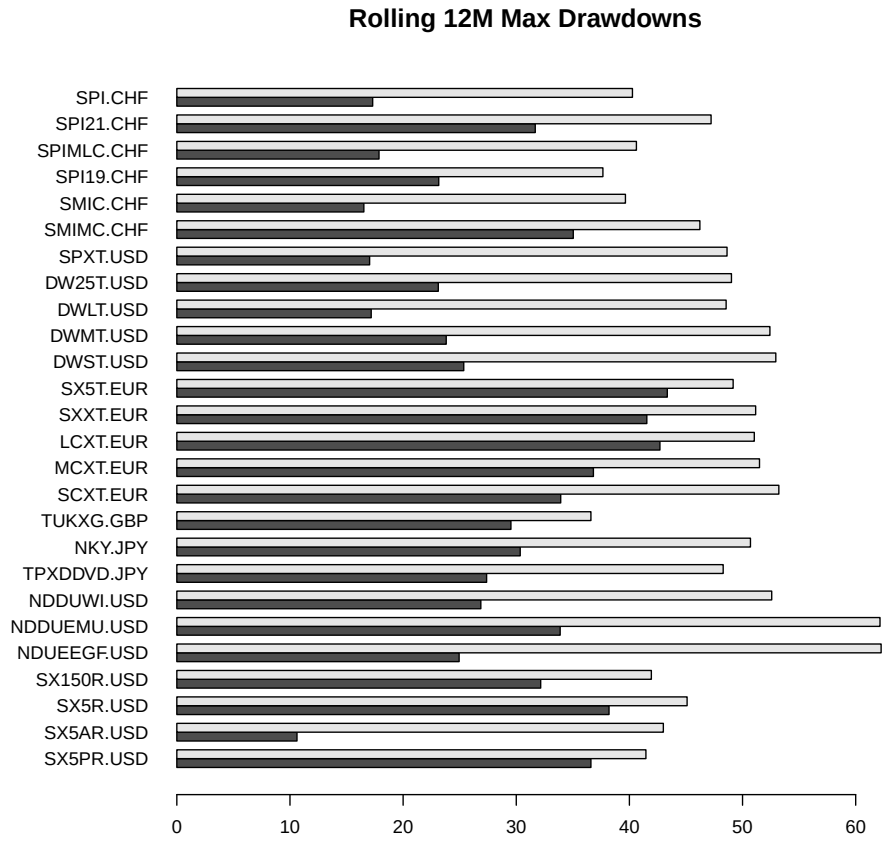


Figure 5: 12 Months Rolling Maximum Drawdowns.

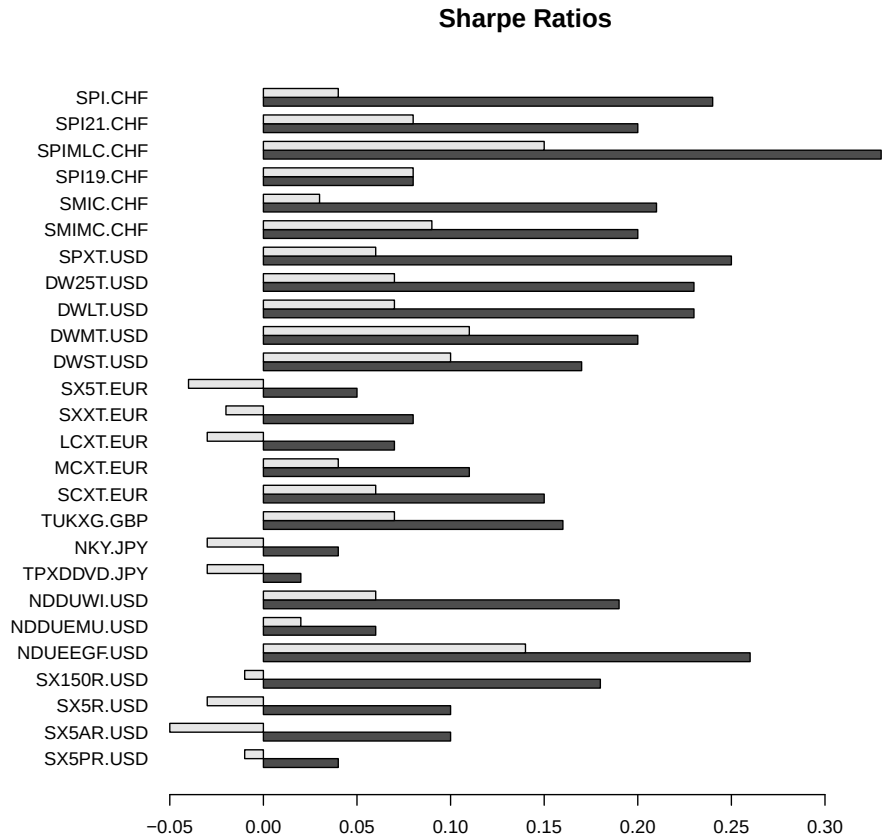


Figure 6: Sharpe Ratios.

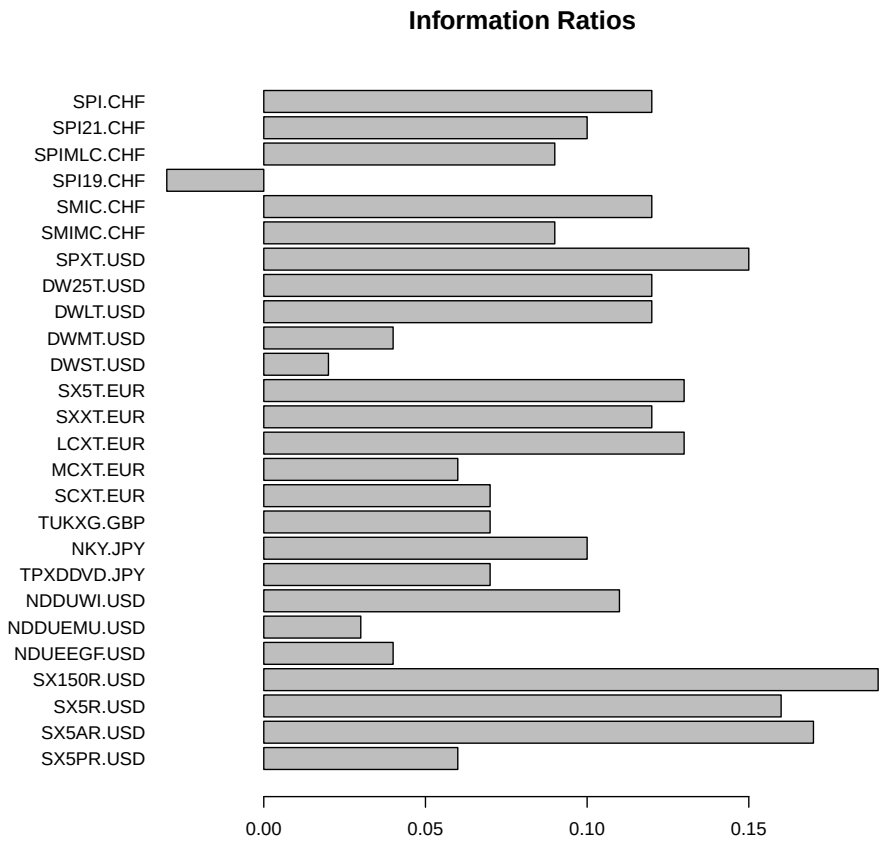


Figure 7: Information Ratios

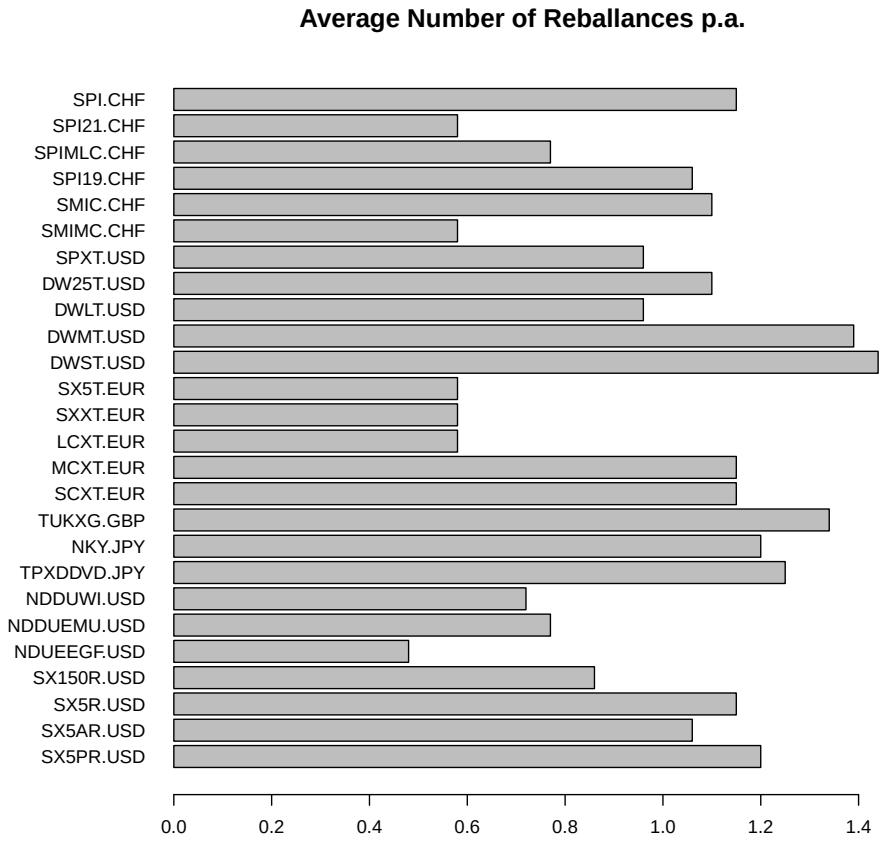


Figure 8: Average Number of Reballances p.a..

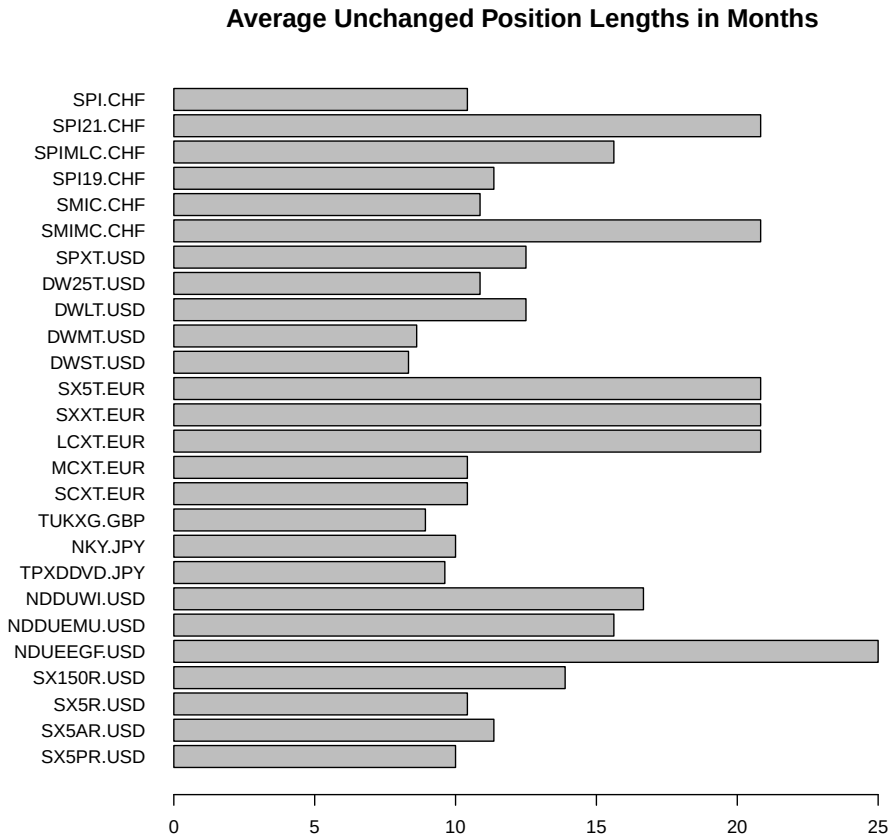


Figure 9: Average Unchanged Position Lengths in Months.

Risk/Reward Analysis

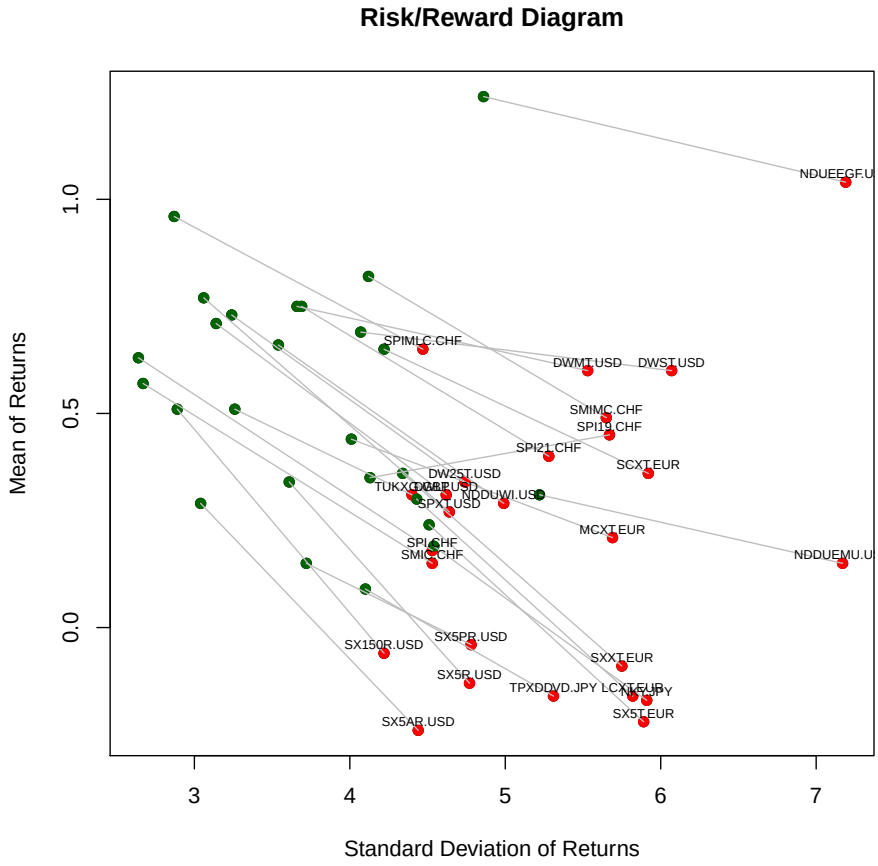


Figure 10: Risk reward diagram for the 26 equity indices (green) and their stability controlled counterparts (red). For all indices we observe an increase of performance and risk towards higher mean returns and lower standard deviations.

Dependence on Level Values

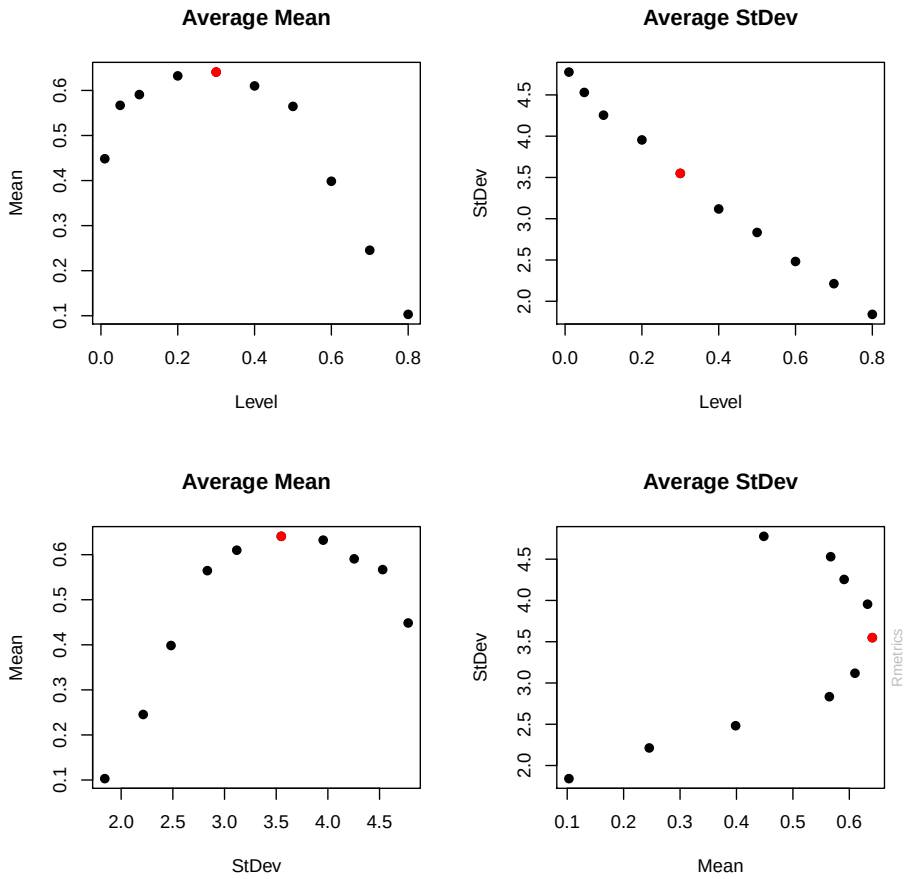


Figure 11: Level dependence of averaged mean and standard deviation of returns.

Risk Controlled Index Charts

In the following we present for each of the 26 stability control indices detailed information in form of a two page factsheet. The first page summarizes returns, volatilities, and risk measures in table format and the second page offers a graphical display of four charts with curves on the indices, the reballancing process with positions and indicators, and rolling computations of returns and drawdowns.

How to Read the Table

The a summary report for each of the 26 indices is given in a table. The header of the table contains

```
Input:
  PERIOD      Months        12   Length of stability probability window
  HORIZON     Months        36   Length of performance decision window
  LEVEL       Probability   0.3  Measure between 0 and 1
  METHOD      Integer       44   Internal code of the Algorithm used

Output:
  TRADESPA    Real               average number of rebalances per annum
  TRADELEN    Months             average length of rebalancing periods
```

The table itself has three columns. The first belongs to the equity index, the remaining two are those after the index has been stabilized. The second column lists the in-sample numbers, the third the out-of-sample stabilized values, The table list the following numbers:

```
Returns and Standard Deviations:
  MEAN.RETURN.MONTHLY              Monthly Means ofReturns
  STDEV.RETURN.MONTHLY             Monthly Standard Deviations
  MEAN.RETURN.ANNUALIZED           Annualized Mean Returns
  STDEV.RETURN.ANNUALIZED          Annualized Standard Deviation

Gain and Losses:
  MAX.LOSS.MONTHLY                 Largest Monthly Loss
  MAX.GAIN.MONTHLY                 Largest Monthly Gain

Rolling:
  MEAN.RETURN1Y.MONTHLY            12 Month Rolling Means of Returns
  STDEV.RETURN1Y.MONTHLY           12 Month Rolling Standard Deviations
  MEAN.DRAWDOWN1Y.MONTHLY          12 Month Rolling Mean of Drawdowns
  STDEV.DRAWDOWN1Y.MONTHLY         12 Month Rolling Standard Deviation
  MAX.DRAWDOWN1Y.MONTHLY           12 Month Rolling Maximum Drawdown
  QUANT95.DRAWDOWN1Y.MONTHLY       12 Month Rolling 5% Drawdown-at-Risk

Performance:
  SHARPE.RATIO                     Sample Sharpe Ratio
```

How to Read the Charts

There are four charts, the first shows the curves for the indices, the second shows the positions and rebalancing indicator curve (computed out-of-sample), and the third and fourth graphs show the 12 months rolling returns and drawdowns:

```
Chart 1:            Indices
  GREY CURVE          Equity Index
  BLACK CURVE         Stability Controlled Equity Index
  ORANGE CURVE        Cumulated Premium
  BROWN CURVE         Benchmark Curve

Chart 2:            Positions and Indicator
  BLACK CURVE         Rebalancing Indicator
  GREY/WHITE          Bacground of Index/HighRisk Positions

Chart 3:            Rolling 12 Months Returns
  GREY CURVE          Equity Index
  BLACK CURVE         Stability Controlled Equity Index
  ORANGE CURVE        Difference

Chart 4:            Rolling 12 Months Drawdowns
  GREY CURVE          Equity Index
  BLACK CURVE         Stability Controlled Equity Index
  ORANGE CURVE        Difference
```

The third chart also gives the information about the out-performance of negative 12 month rolling returns in the equity index by the satbility controlled index. The same information is given in the fourth chart for the out-performance of rolling 12 months drawdowns.

Stability Investment 01

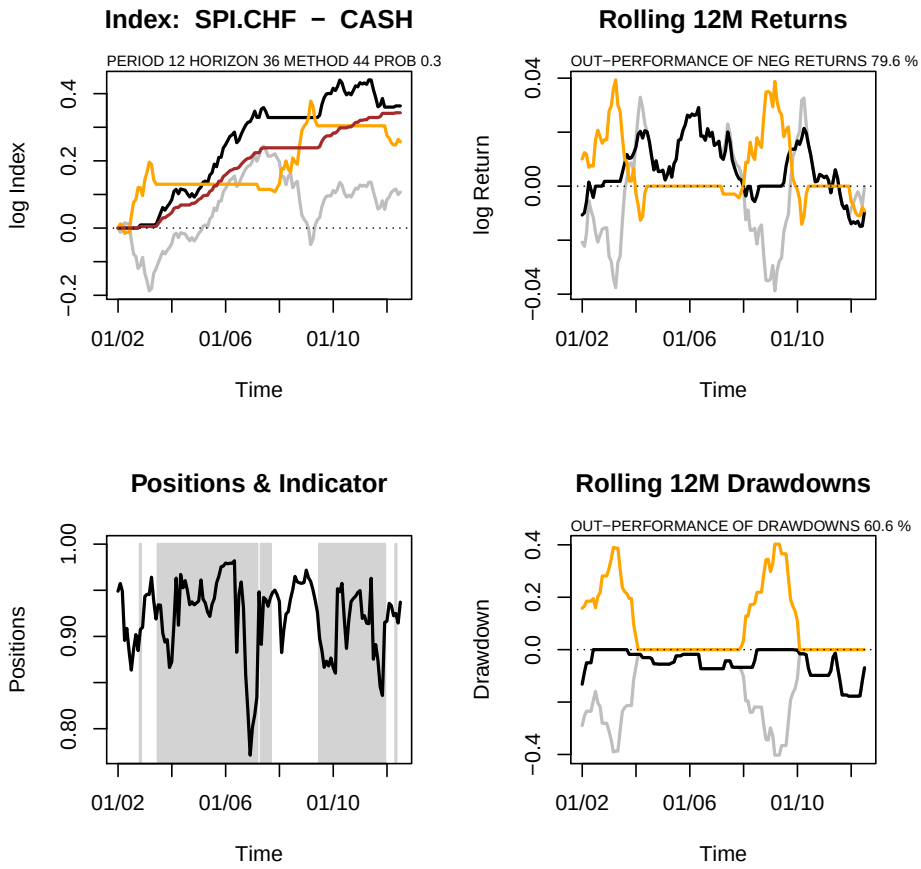


Figure 12: Swiss Performance TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 02

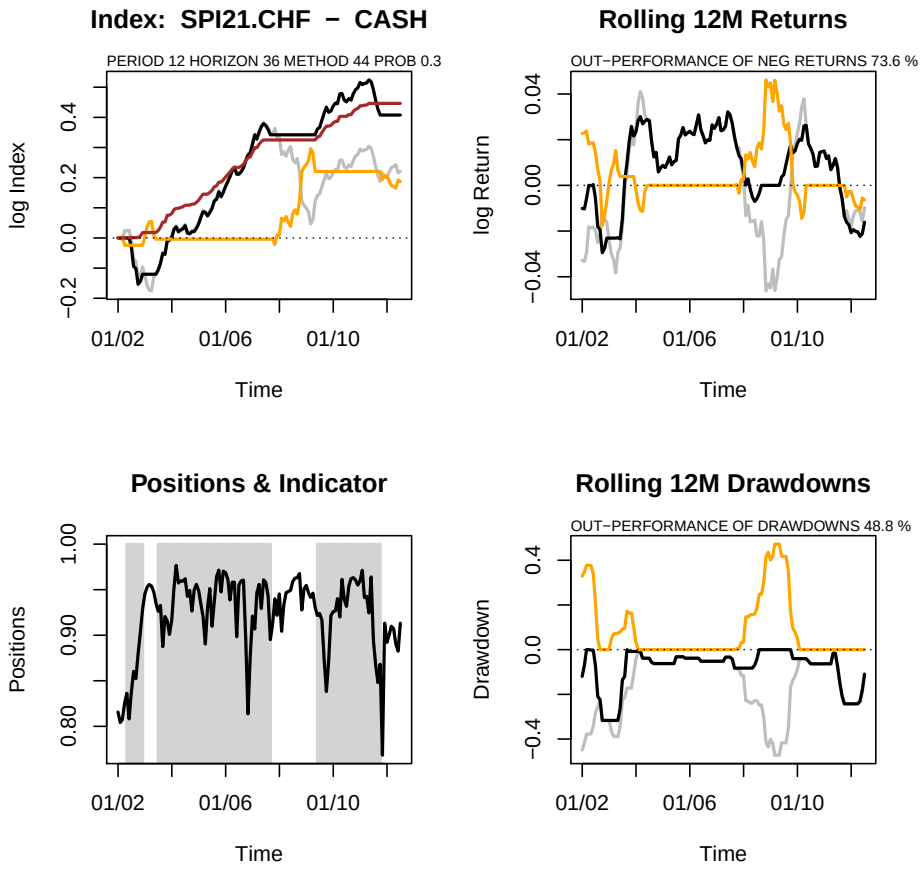


Figure 13: Large Cap Swiss Performance TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 03

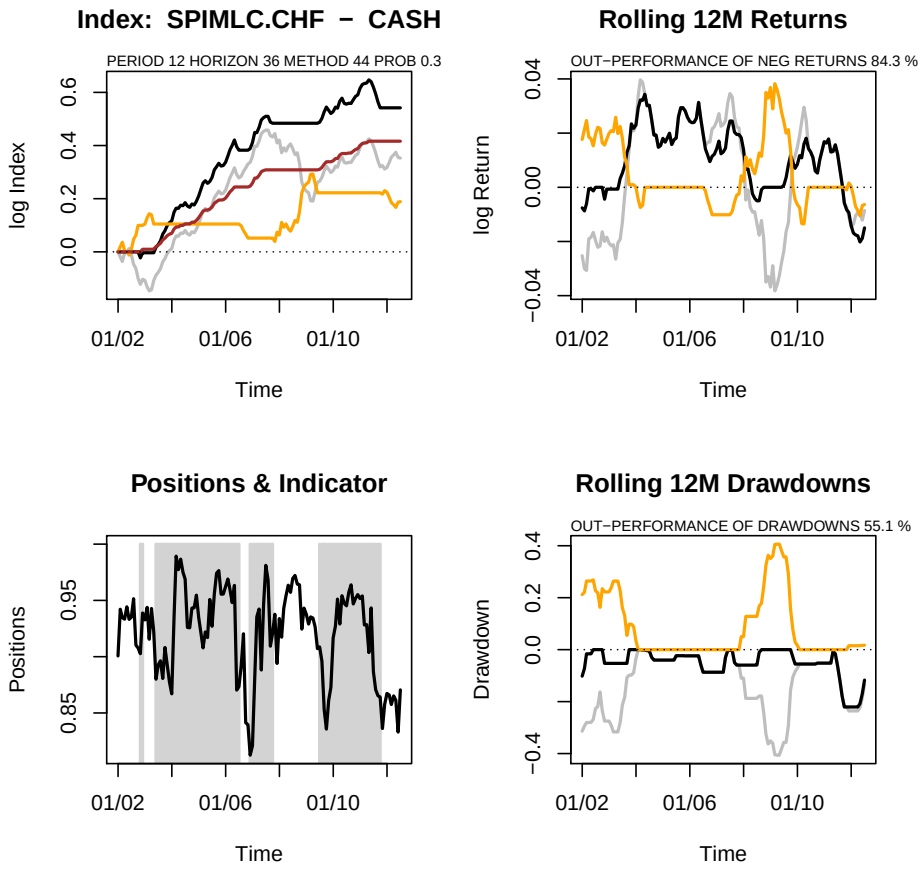


Figure 14: Mid Cap Swiss Performance Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 04

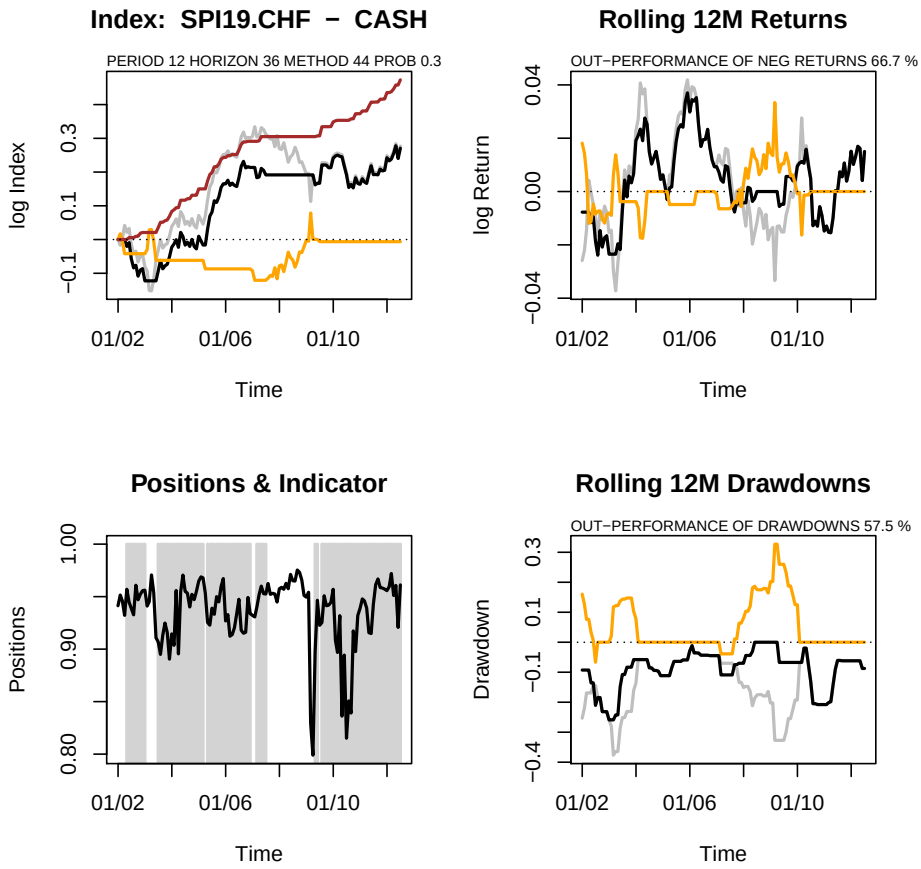


Figure 15: Small Cap Swiss Performance Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 05

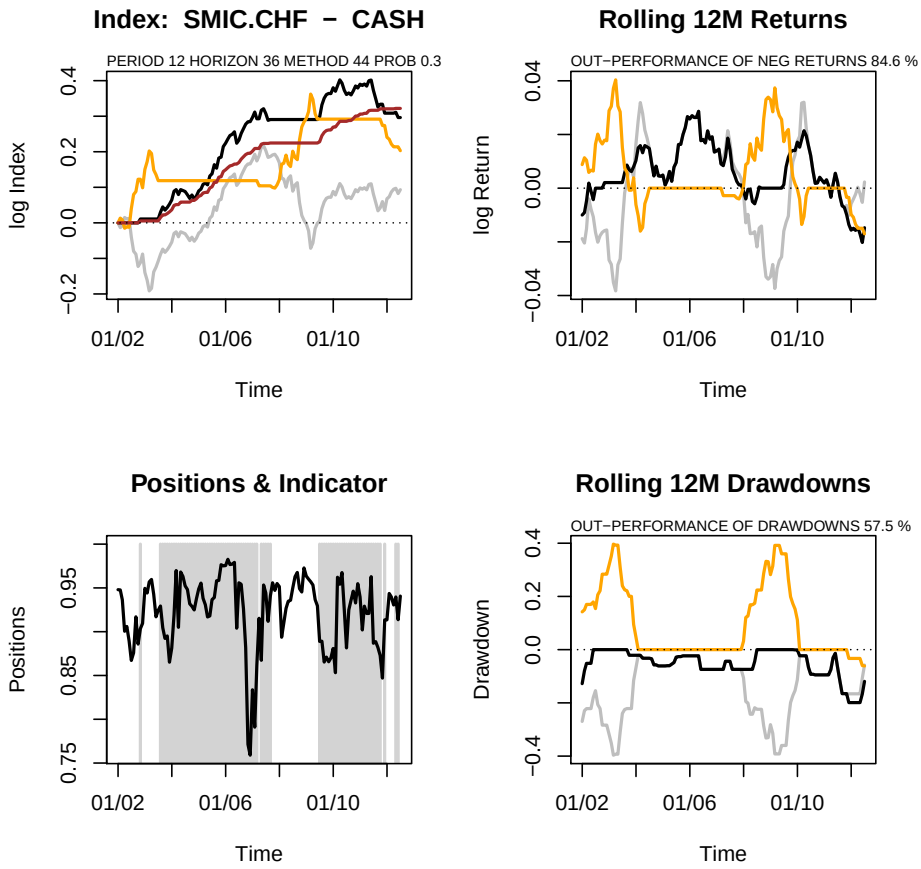


Figure 16: Swiss Market TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 06

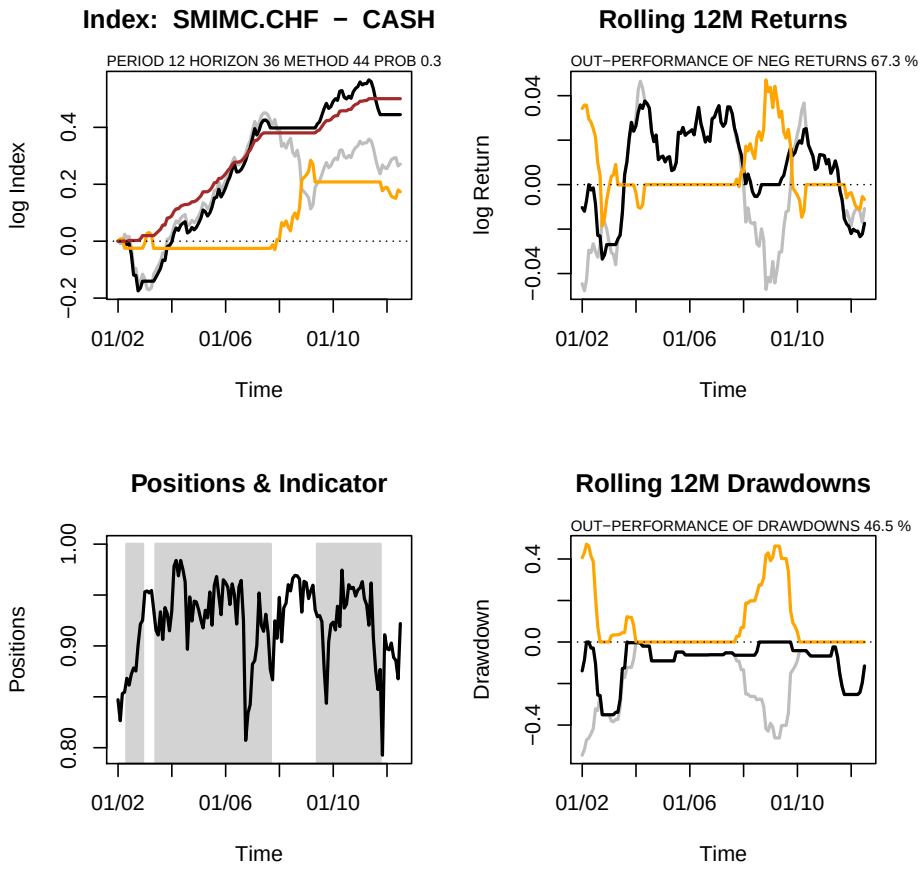


Figure 17: Mid Cap Swiss Market Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 07

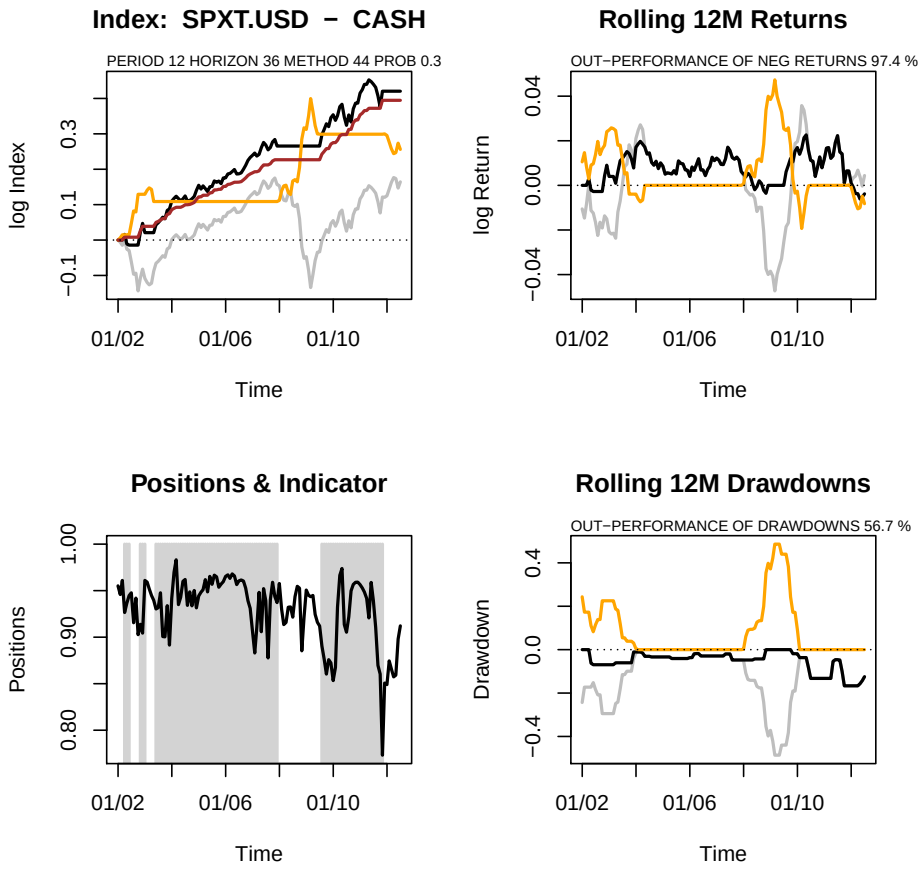


Figure 18: SP500 TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 08

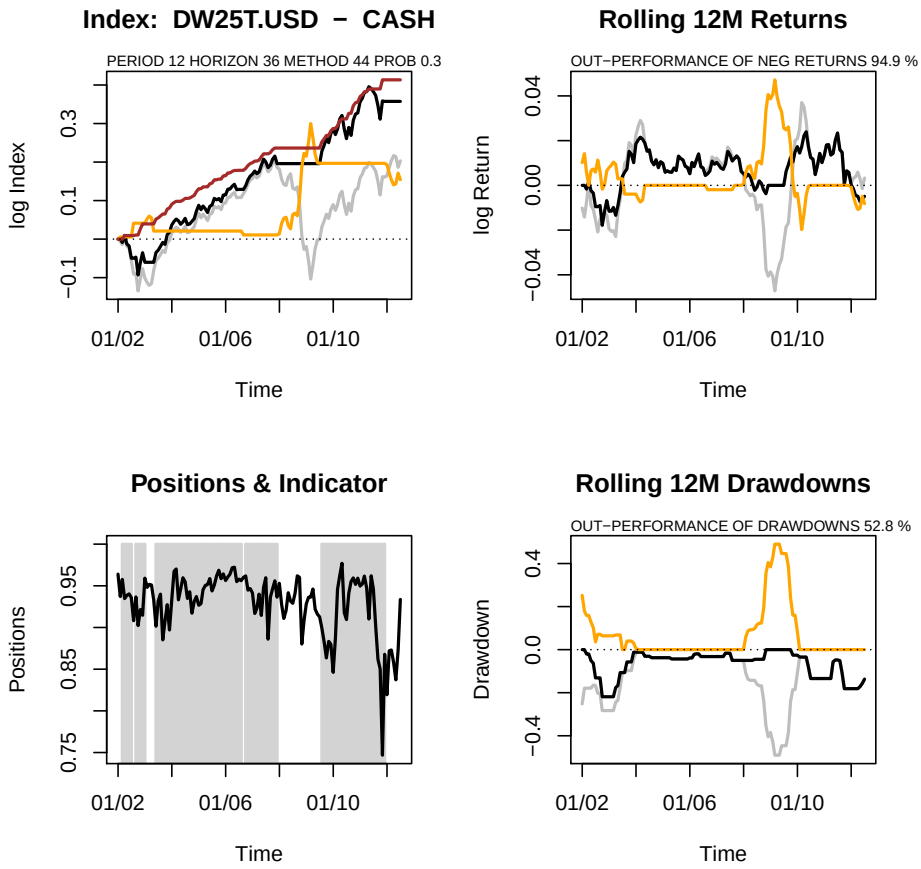


Figure 19: Dow Wilshire TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 09

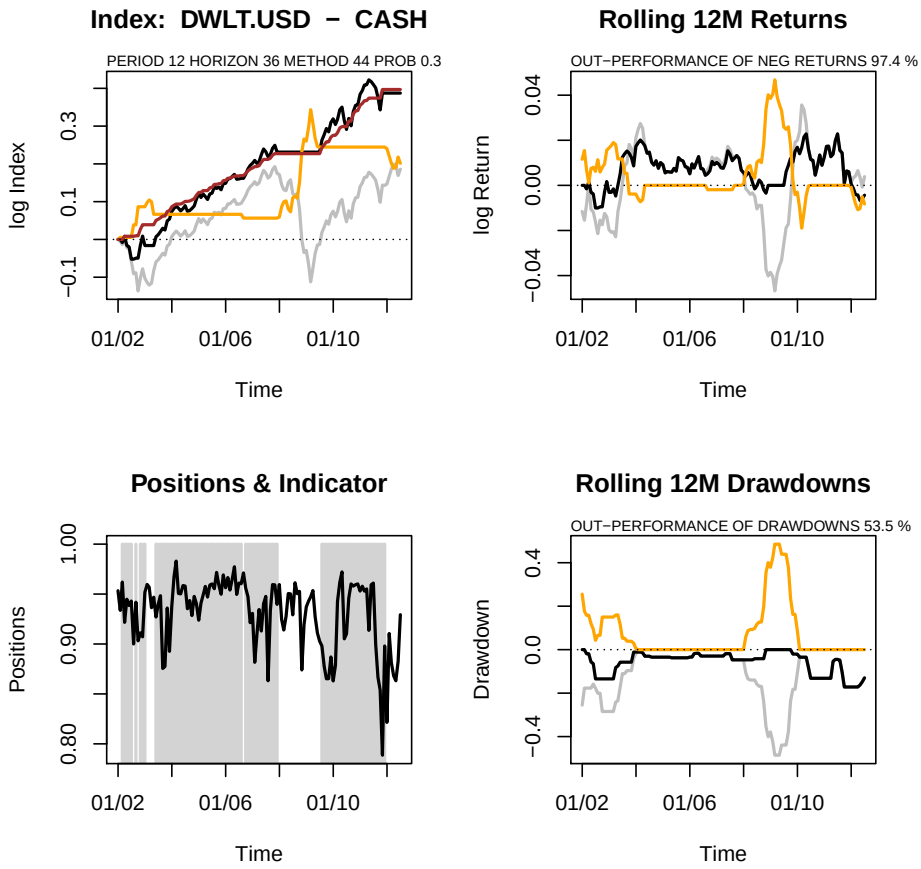


Figure 20: Large Cap Dow Wilshire TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 10

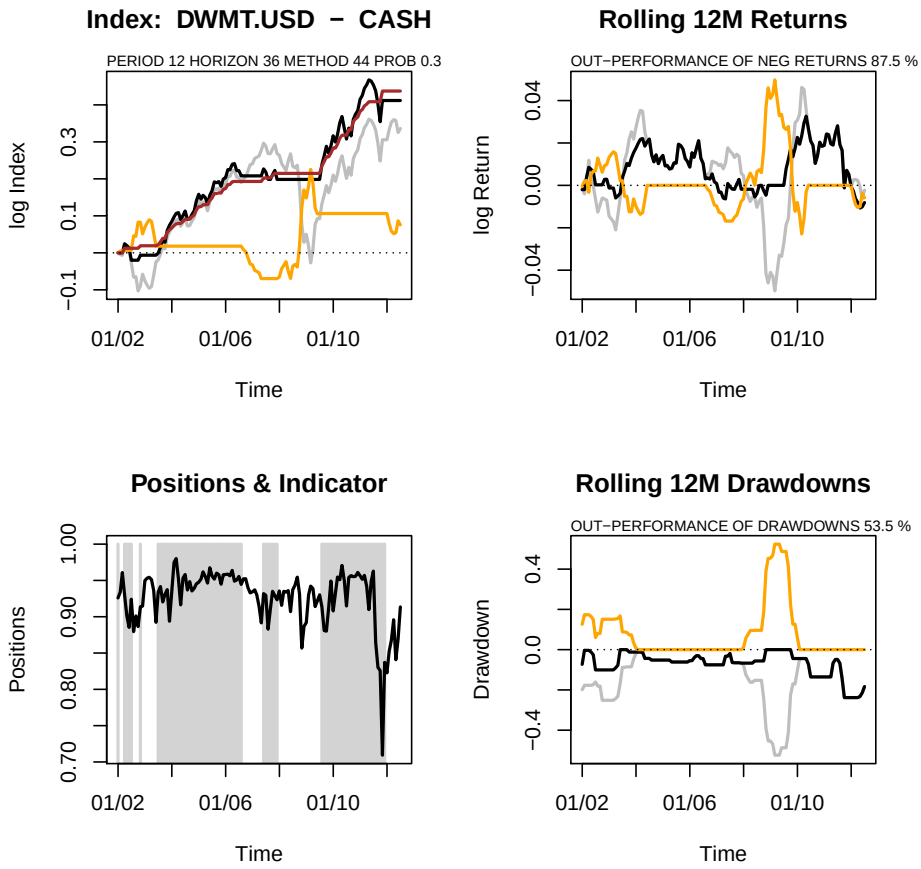


Figure 21: Mid Cap Dow Wilshire TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 11

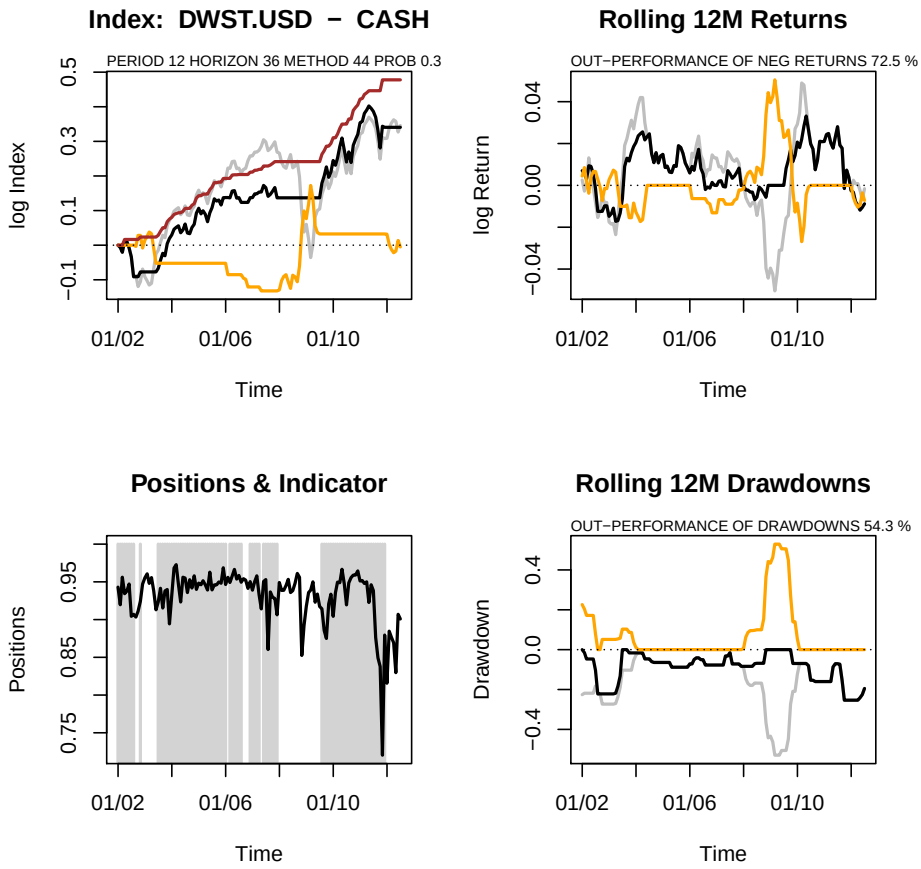


Figure 22: Small Cap Dow Wilshire TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 12

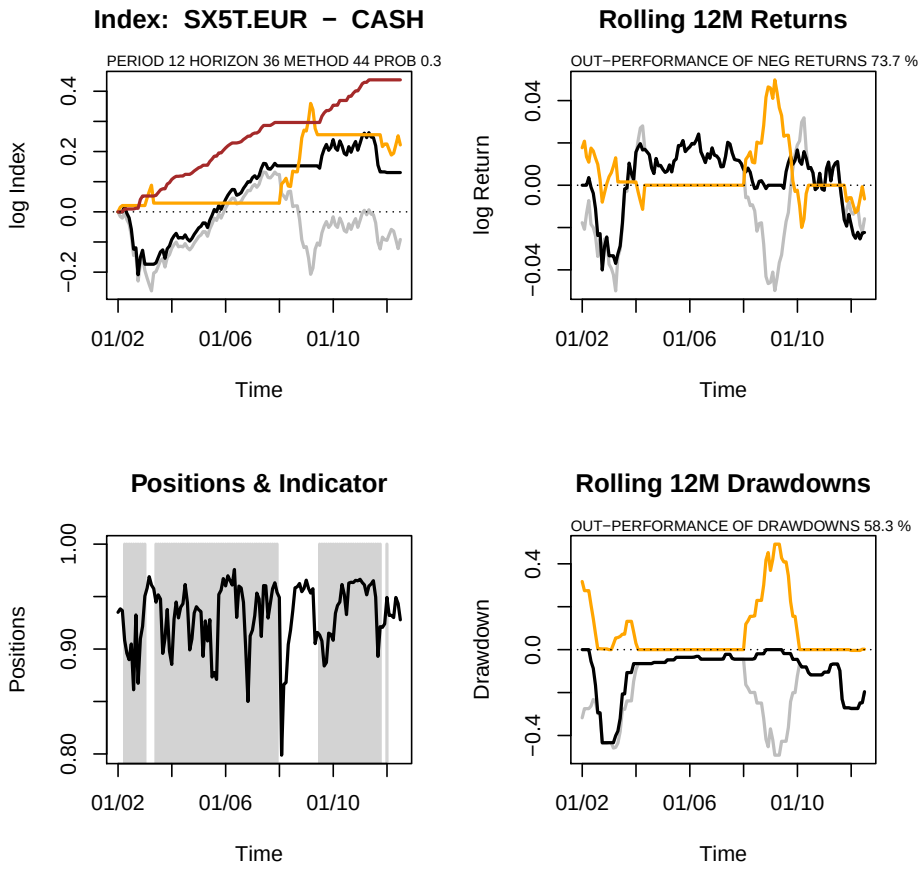


Figure 23: EUROSTOXX50 TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 13

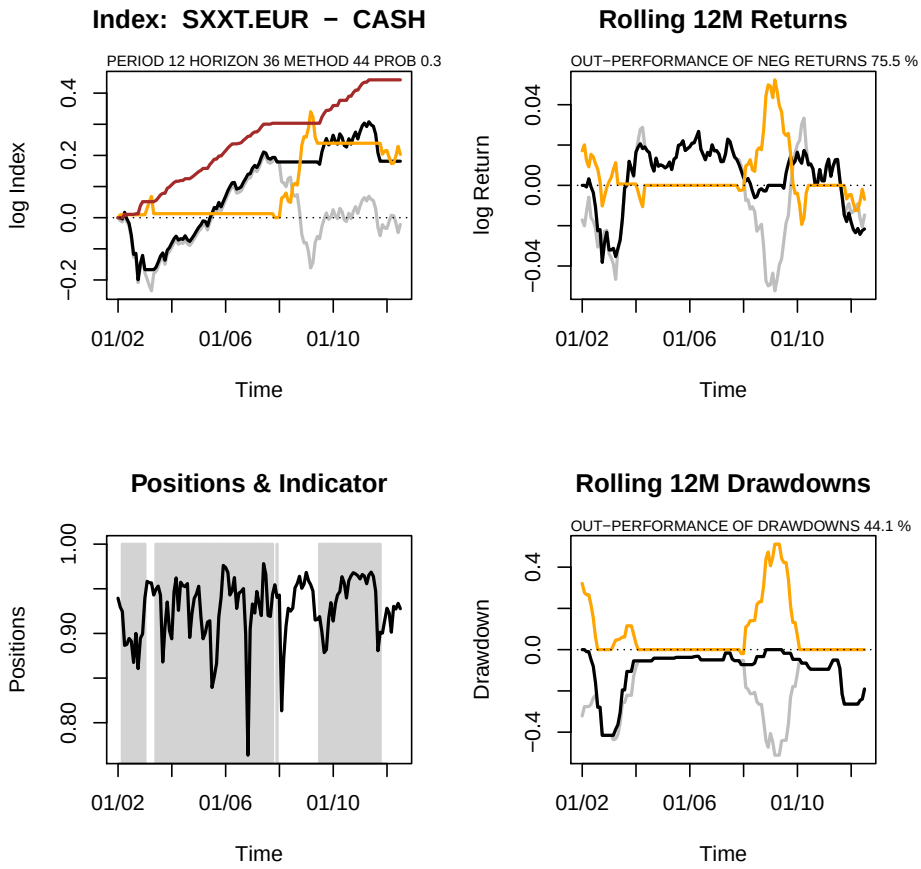


Figure 24: Stoxx Eurozone TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 14

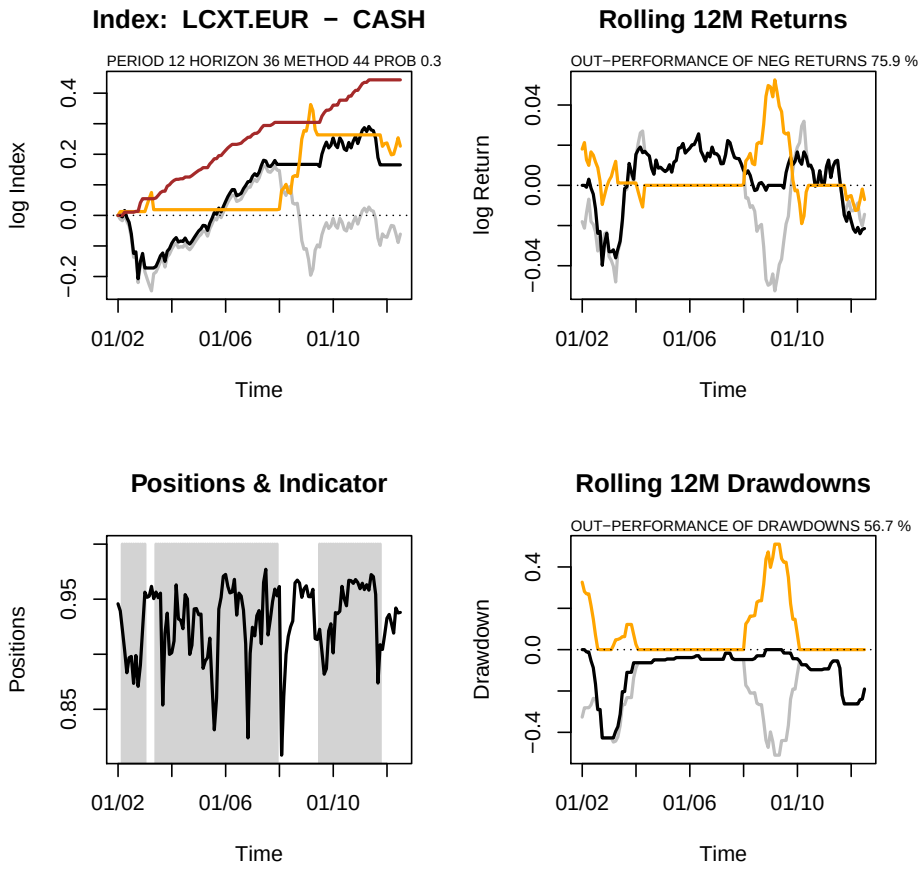


Figure 25: Large Cap Stoxx Eurozone TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 15

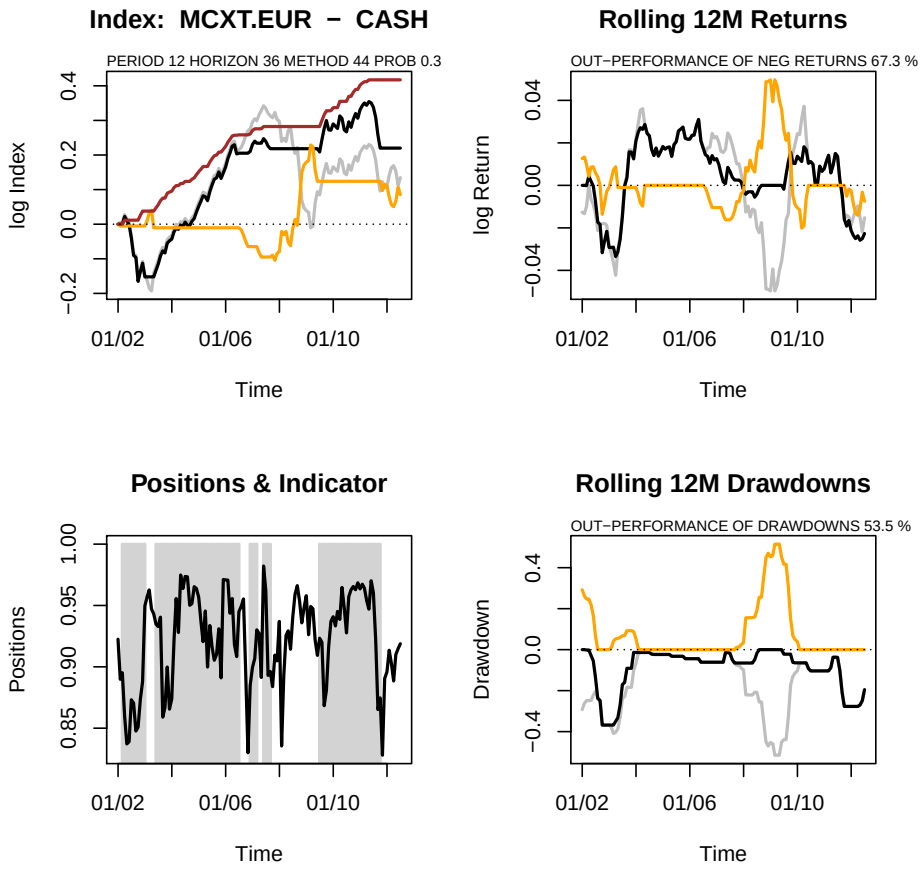


Figure 26: Mid Cap Stoxx Eurozone TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 16

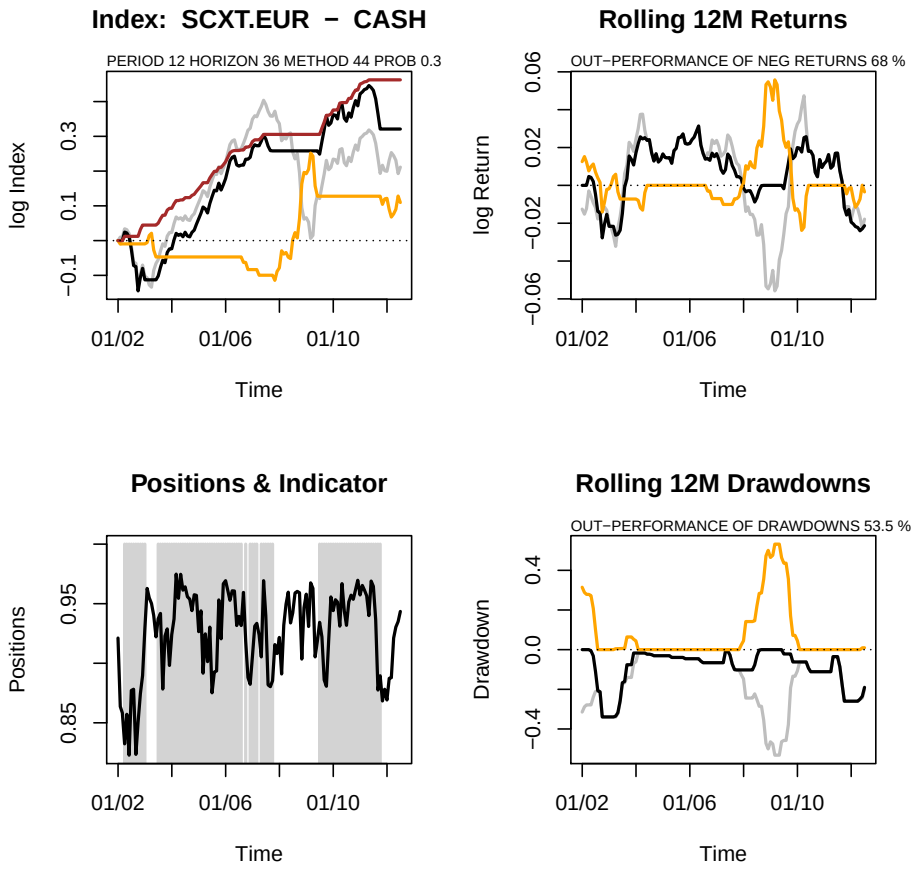


Figure 27: Small Cap Stoxx Eurozone TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 17

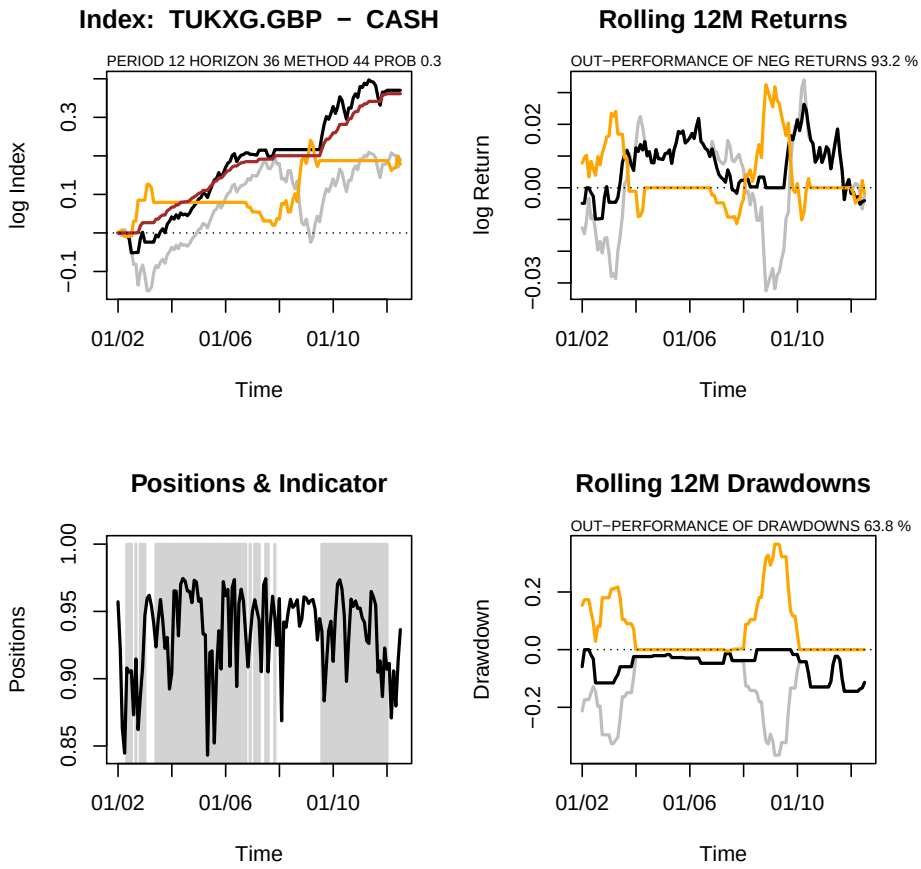


Figure 28: FTSE100 TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 18

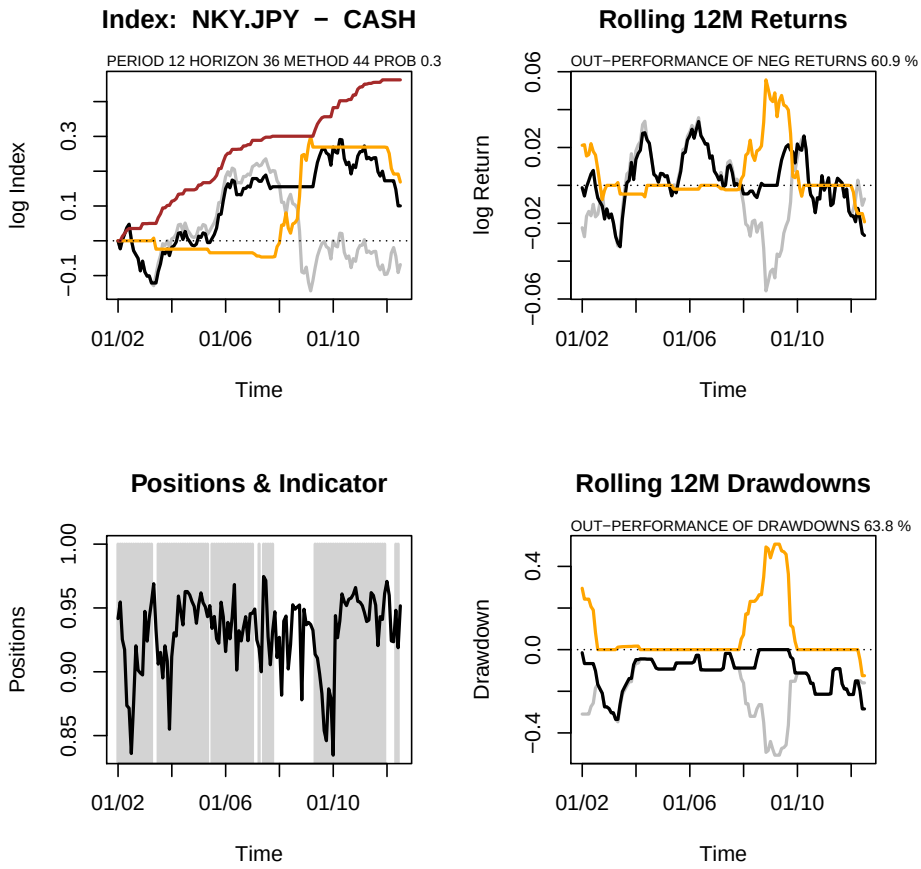


Figure 29: NIKKEI225 Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 19

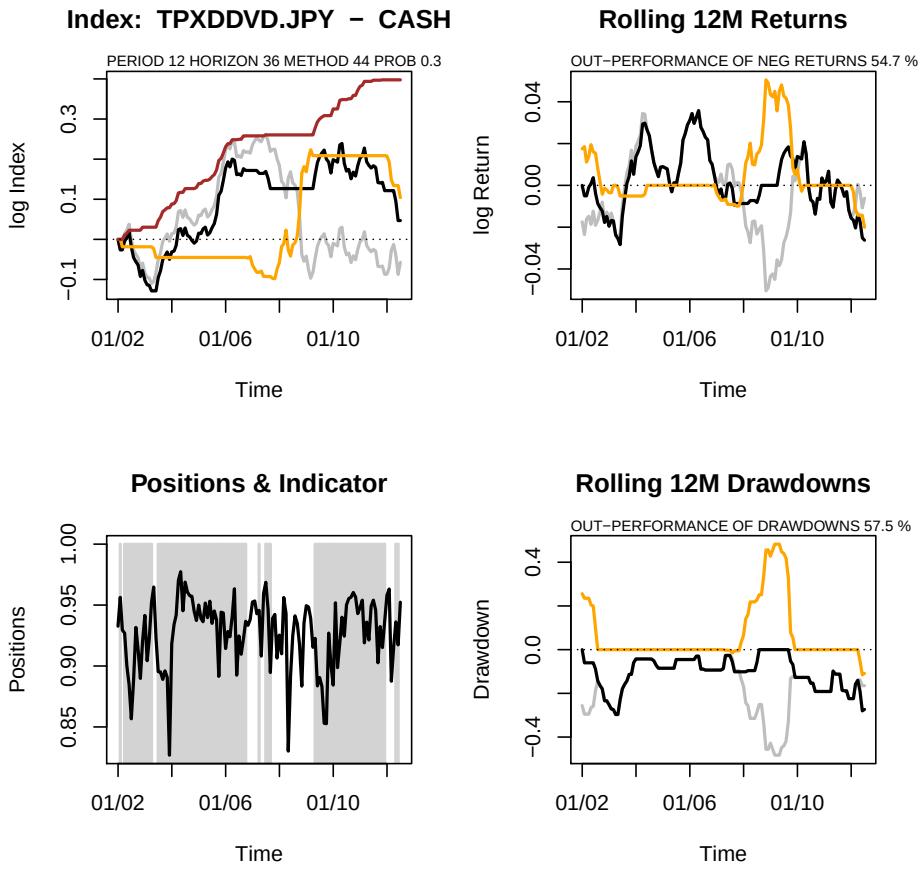


Figure 30: TOPIX TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 20

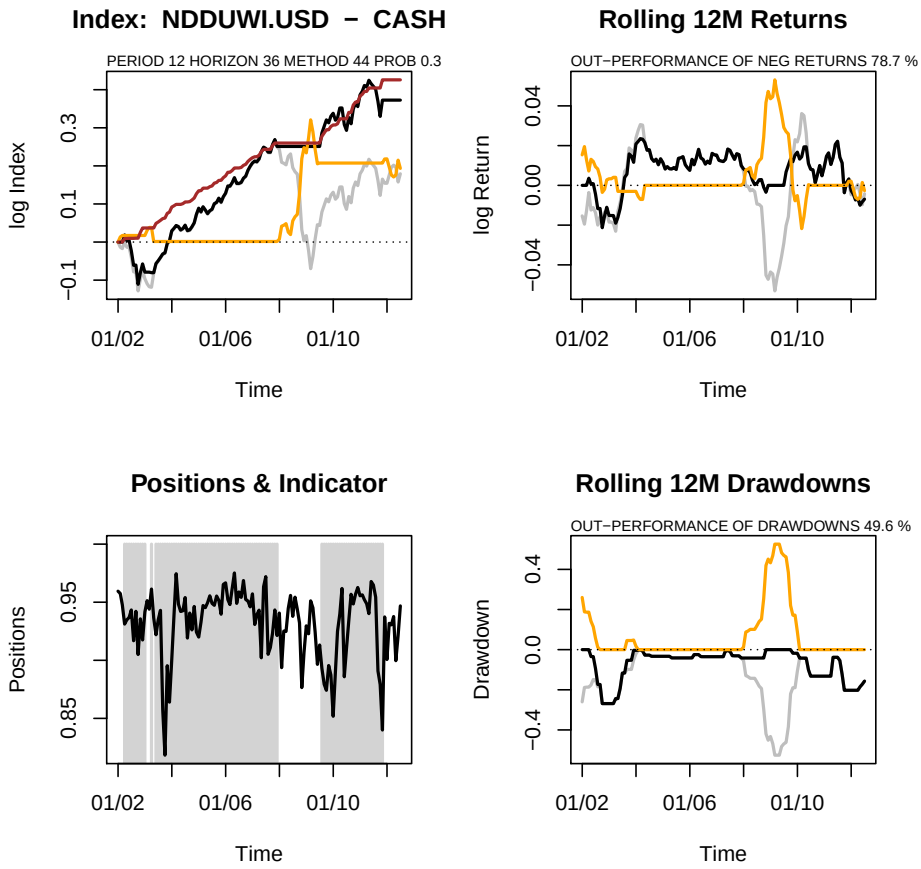


Figure 31: MSCI World TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 21

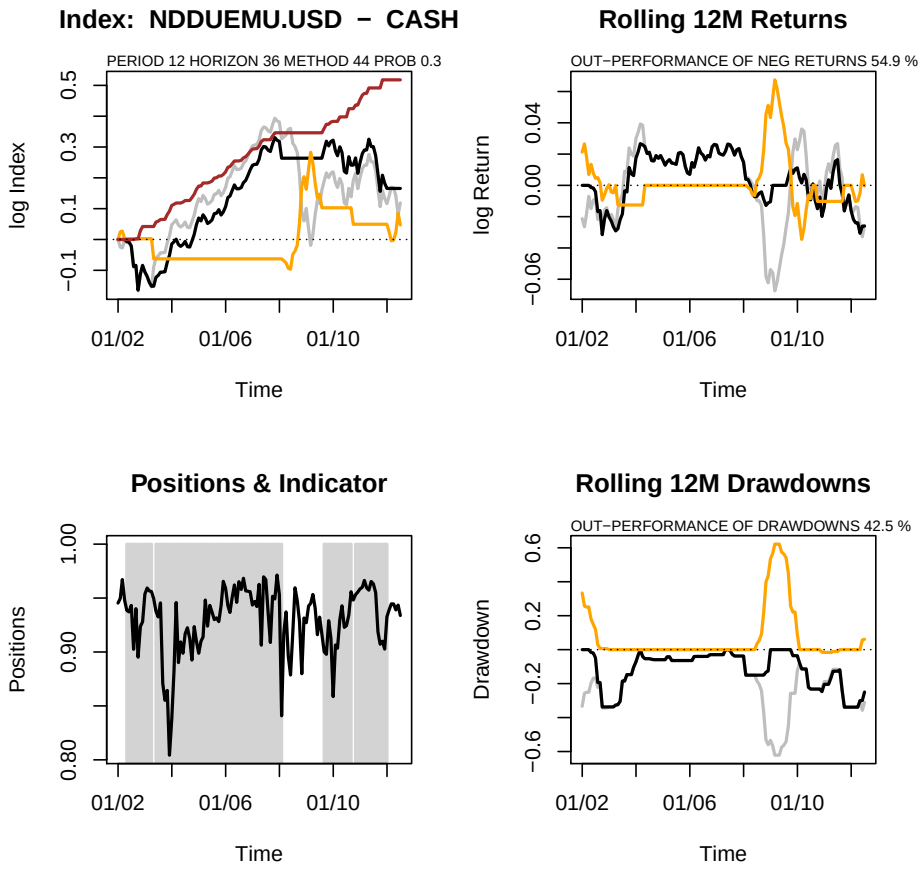


Figure 32: MSCI European Monetary Unit TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 22

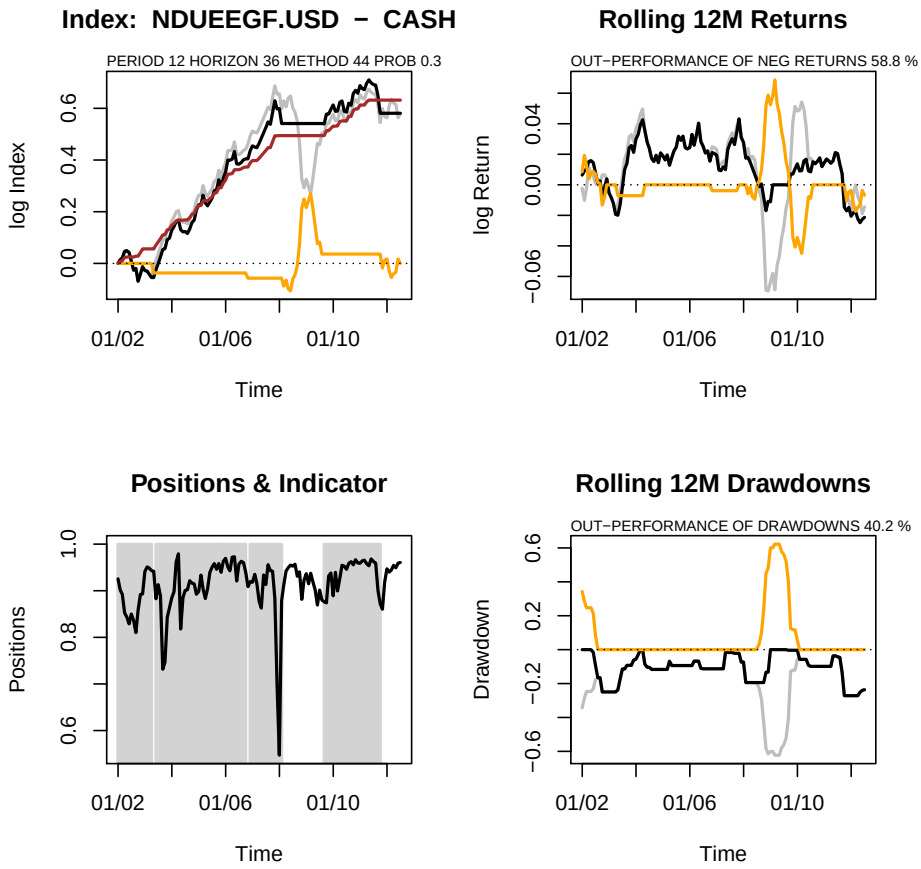


Figure 33: MSCI Emerging Markets TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 23

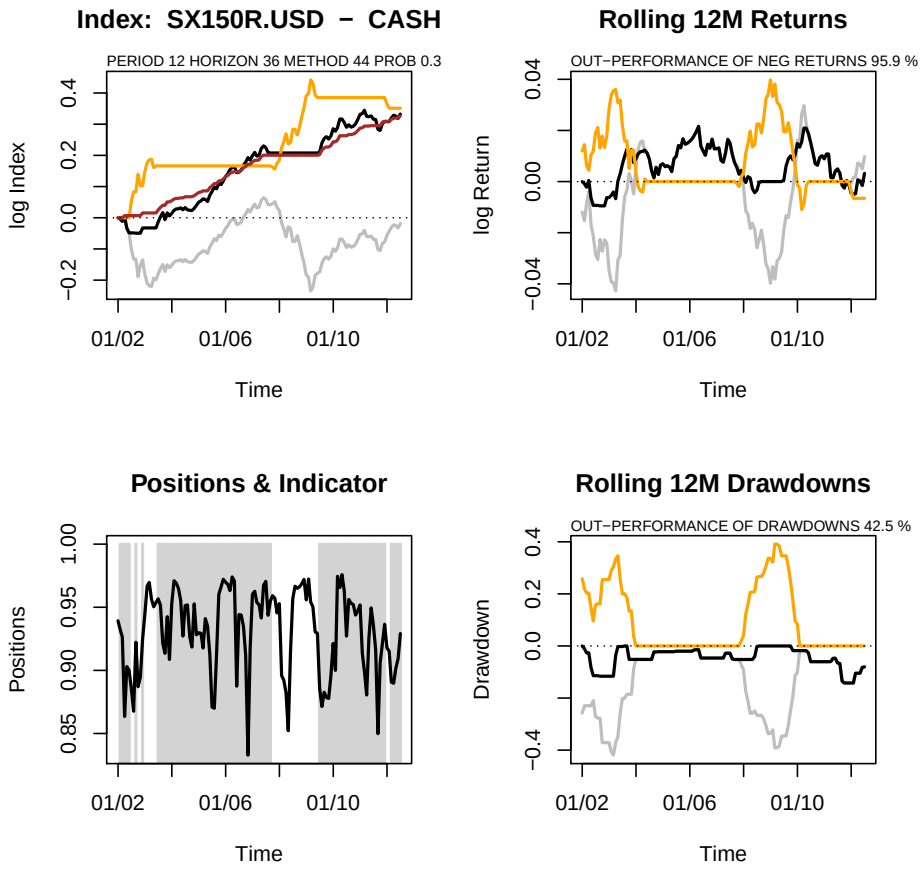


Figure 34: Stoxx GlOBAL150 TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 24

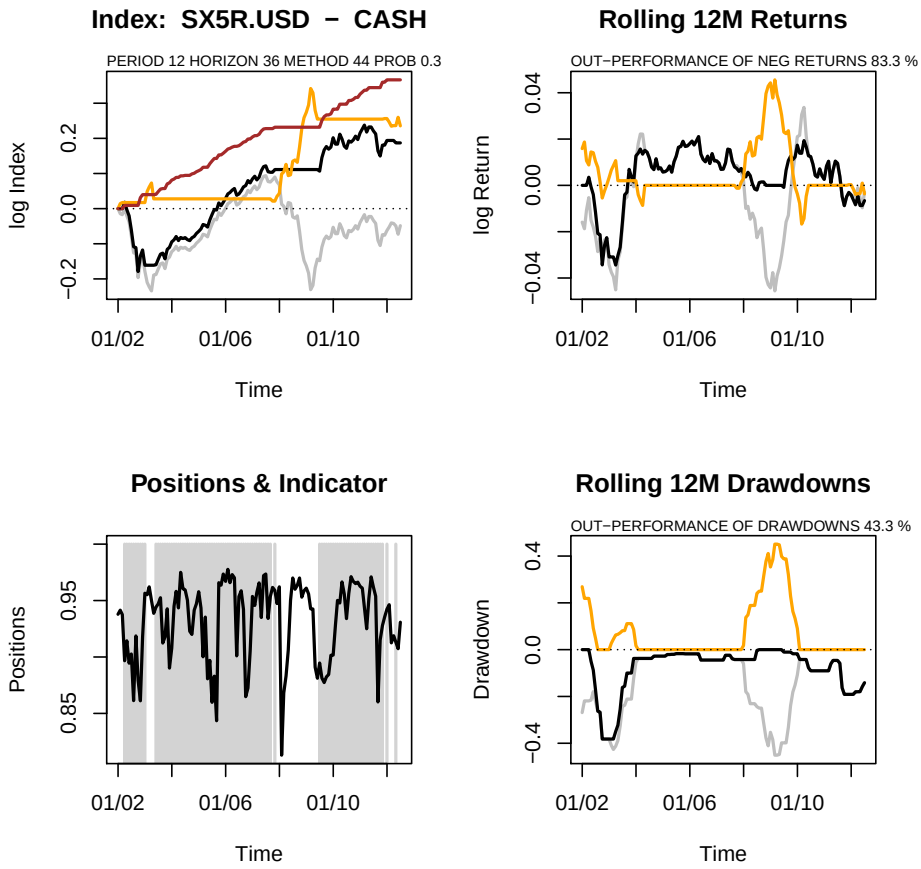


Figure 35: Stoxx GlOBAL150 Europe TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 25

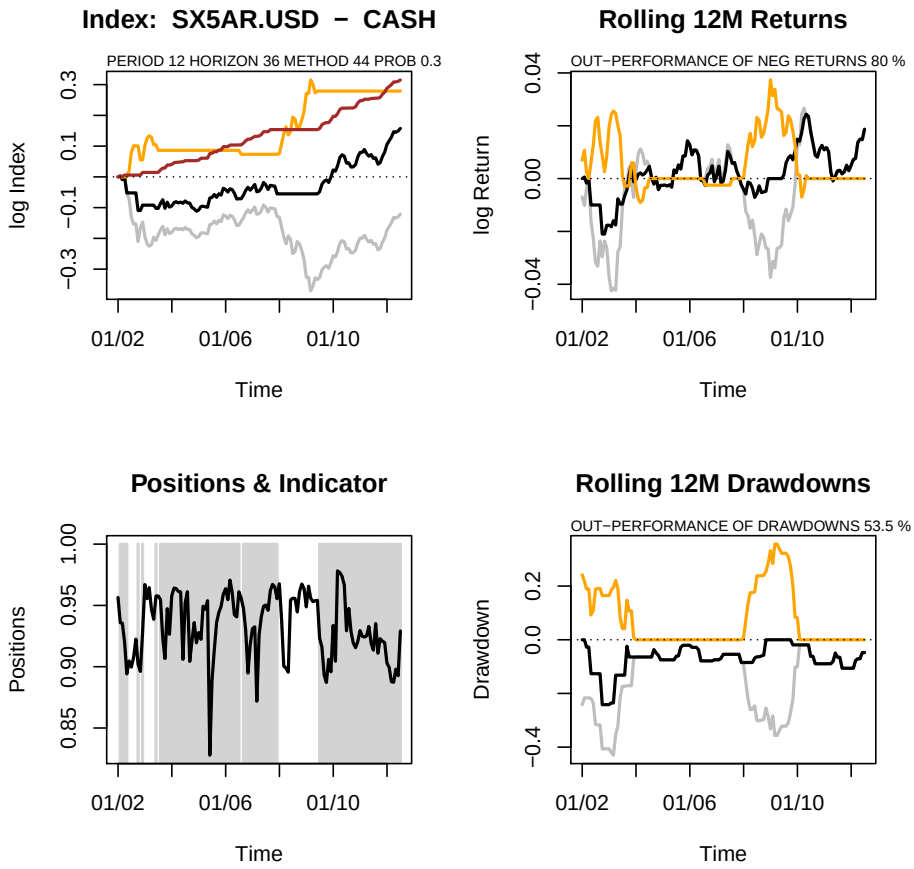


Figure 36: Stoxx GlOBAL150 North America TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

Stability Investment 26

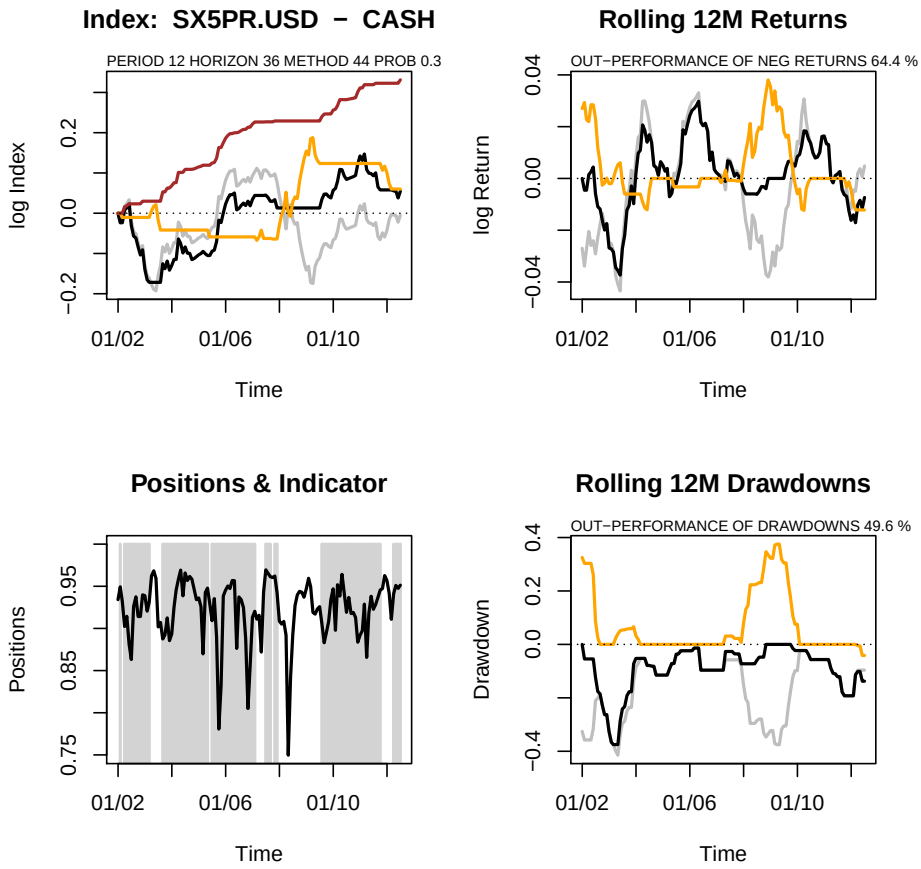


Figure 37: Stoxx GlOBAL150 Asia / Pacific TR Index: Chart 1 (upper left) displays the wealth series for the quity index (grey), for the risk controlled index (black), for the premium (orange), and for the benchmark series (brown). Chart 2 (lower left) shows the positions and the stability indicator trigger. Chart 3 (upper right) displays the 12 months rolling mean of the returns series for the equity index (gray), 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).

References

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

Bloomberg Symbols of Indixes, [2012], http://www.bloomberg.com/markets/indexes/.

Econophysics Group, ETH Zurich, 2012, Stability Analytics of Vulnerabilities in Financial Time Series, Working Paper, 15 pages.

Econophysics Group, ETH Zurich, 2012, Enhanced Risk Management by Stability Protective Investment Strategies, Working Paper, 27 pages.

MSCI [2012], Index Methodology: MSCI Risk Control Indices, www.msci.com, 8 pages.

SIX Group [2012], Guide Governing SMI Risk Control Indices, www.six-exchange.com, 4 pages.

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

Würtz D., et al., [2010], Proceedings of the Singapore R/Rmetrics Workshop 2010, Rmetrics Association and Finance Online Publishing, Zurich.

Würtz D., et al., [2011], Proceedings of the Meielisalp Summerschool and Workshop 2011, Rmetrics Association and Finance Online Publishing, Zurich.

Würtz D., et al., [2012], Advanced Portfolio Design with R/Rmetrics, Rmetrics Association and Finance Online Publishing, Zurich.

Disclaimer

This document is copyrighted and its content is confidential and may not be reproduced or provided to others without the express written permission of the authors. This material has been prepared solely for informational purposes only and it is not intended to be and should not be considered as an offer, or a solicitation of an offer, or an invitation or a personal recommendation to buy or sell any stocks and bonds, or any other fund, security or financial instrument, or to participate in any investment strategy, directly or indirectly. It is intended for use in research only by those recipients to whom it was made directly available by the authors of the document.

Data Sources and Software

Data are obtained from Bloomberg, CBOE, Federal Reserve, Swiss Exchange, Standard & Poors, and STOXX. All calculations were done with the R and Rmetrics statistical software environments. (Calculations are obtained from model strategy 44 with fixed quantile threshold.) For further information we refer to *www.rmetrics.org*.

CHAPTER 6

BAYESIAN SWITCHING STRATEGIES

Bayesian Stability Analytics: Indicators, Signal Strengths, and Position Thresholding
Tobias Setz and Diethelm Würtz
Econophysics Group, Swiss Federal Institute of Technology Zurich
Econophysics Working Paper, Unpublished, ETH Zurich, August 2012

Binary switching is a central concept in our approach of monitoring stability. Switching means that we have two states, the first state where we are invested in the market, and the second state where wealth has to be protected. In this research report we have investigated how a basic indicator that can be derived from a binary switching strategy could look like. We described in detail how the indicators can be calculated from Bayesian measures and how signals can be derived from them. Two central indications for rebalancing index/cash blends, the *indicator strength* and the adaptive *threshold lebels*, determine our view on the stability of an equity market.
In the Appendix we summarize the results for the total returns of the major large cap market indices: The Swiss market index SMIC, the German DAX, the Euro Stoxx 50, the U.S. S&P 500.

Bayesian Stability Analytics: Indicators, Signal Strengths, and Position Thresholding

Tobias Setz and Diethelm Würtz
Institute for Theoretical Physics - ETH Zurich
Econophysics Group

Abstract

In this report we describe financial indicators based on a Bayesian Stability approach. They are used to rebalance investments with the goal to achieve steady increases in the returns, and low drawdowns with short recovery times.

First Version: 4. September 2014

1 Introduction

The Bayesian Stability Analysis as introduced by Würtz et al. [2010] is an application that allows to analyze performance, risk, and stability issues of financial investments. We discuss in this report how one can apply the *Bayesian Change Point* (BCP) approach of Barry and Hartigan [1992, 1993] and how one can derive from it indicators and signals for decision taking. The major goal is to achieve investments with a steady increase in the wealth and with low drawdowns and short recovery times.

First we explain how to use the posterior mean, posterior variance and posterior probability. Then we describe the design of indicators for rebalancing investments and show how to derive measures for signal strengths and threshold levels.

The data in our study cover the total return index auf the Euro Stoxx 50. The frequency of the analysis is on a monthly base. We operate with end-of-month closing prices. Missing calendar dates due to holidays are replaced by their previous (daily recorded) values.

The concept behind investment stabilization is quite simple. The price series of an investment will be analyzed with the emphasis to take care on existing structural changes and breaks in the evolutionary dynamics of the price process of an index. We consider three major steps. In section 1 we show how to compute the BCP measures, in Section 2 we describe how to select appropriate indicators, and how to calculate the investment signals, and in section 3 we show the results.

1 BCP Measures

Within the framework of the *Bayesian Change Point Approach* and a *Markov Chain Monte Carlo Simulation* we calculate from the prior information of the financial returns describing the price process the posterior returns, their variances from the MCMC results, and the probability that we observe a structural change or break. We call the posterior mean, variance, and probability Bayesian *measures*. The simulations are done over a rolling window. We have to choose an appropriate value for the size of the window it may be either fixed or adaptive. From each window we get then the three measures. The result is shown in figure 1.

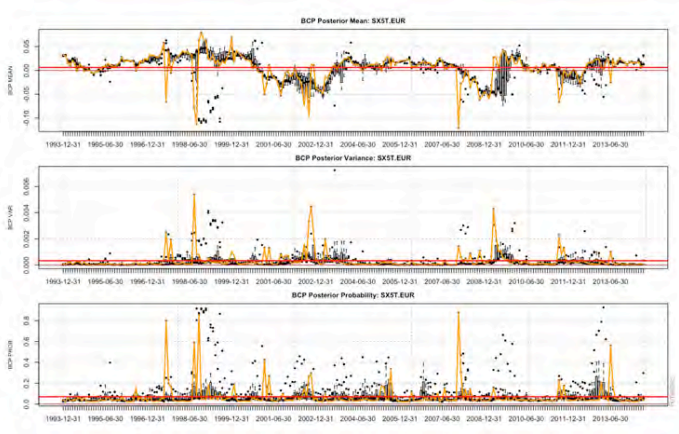


Figure 1: Posterior mean, posterior standard deviation and posterior probability for the logarithmic returns of the Euro Stoxx 50 Index.

Figure 1 shows the Bayesian measures from the posterior inference for the Euro Stoxx 50. From up to down: The posterior mean, the posterior variance and the posterior probability. Every end of month the results are presented for a rolling window of 12 months shifted by one month by a box plot. The orange curve is an average of the end-of-month measures, which are used to design indicators. The red curve is the long term mean.

2 Indicators, Signal Strengths and Threshold Levels

In the next step we derive an appropriate *indicator* from which we can calculate a probabilistic signal to determine the next investment decision in time. This signal should tell us if we should be invested in the market or if we have to protect our investment due to upcoming market instabilities.

Several variants of strategies can be applied to create such an appropriate indicator. Our standard strategy is the following:

Standard Investment Strategy:

We compute a Bayesian Sharpe Ratio over a rolling window of a given fixed size. The input numbers are the posterior mean, the posterior variances, and the one step ahead forecasted posterior probabilities as shown in Figure 1 by the orange lines. At each time step of a rolling window we calculate the ratio from the posterior mean and the square root of the posterior variance and weight it by the inverse posterior probability forecast. This is our indicator. We call it *Instantaneous Stability Weighted Sharpe Ratio Indicator*. The last value of the window will then be compared with a threshold quantile of the distribution of the indicator. This *threshold level* is adaptive and forecasted after each time step. If we cross the threshold we get the *signals* that tell us the positions for the next investment period. We call this process *position thresholding.*

For decision taking we consider the Bayesian indicator and the threshold levels. The upper chart in Figure 2 shows us the difference between the indicator and the adaptive threshold. We call this the *Signal Strength*. The signal strength allows for a simple interpretation. If the value crosses the zero line we get the timing point to rebalance our investment. Crossing from above indicates that we have to protect our investment, crossing from below means that the market is ready to get invested in.

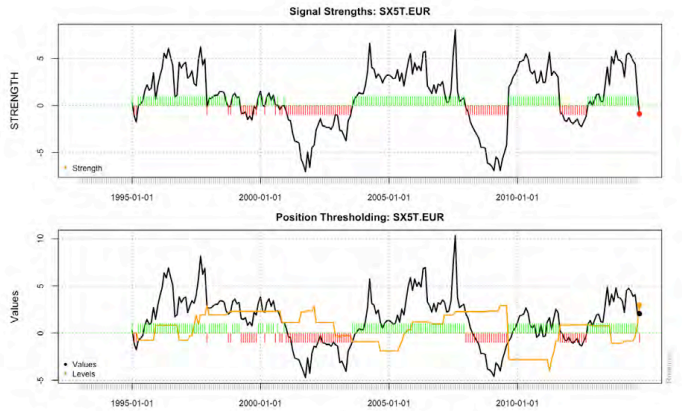


Figure 2: Signal Strengths (upper chart) and Position Thresholding (lower chart). Indicator (black) and threshold level (orange) for the Euro Stoxx 50 Index. Green and red rugs correspond to long and short positions.

The lower part of Figure 2 shows the indicator (black) itself and the threshold levels (orange) separately. When the market gets unstable we observe two complementary processes. When we are invested the signal strength gets weaker and at the same time the threshold level gets stronger. So the two curves are moving towards each other. The crossing happens much earlier than we would expect it from a fixed level. Thus the sensitivity of the signal is increased. This is a huge advantage of our indicator compared to others. We are not aware of any other financial indicator that shows such a behavior. In addition the size of the spread between the two curves can be considered as a measure for the reliability of the signal. That means if the signal strength comes very close to zero we can already start to rebalance partially our positions.

3 The Results

Was our strategy successful to rebalance an index/cash blend? To prove this, the last step in our stabilization process will be to compute the performance and the risk of the original index and to compare it with the stabilized index.

For the performance we take a look onto the logarithm of the wealth index: In the log plot we expect a straight line. The "least-squares" fitting process produces the r-squared test statistic. That is the square of the residuals of the data after the fit. It measures the fraction of the variance of the data that is explained by the fitted trend line. The statistical significance of the trend line is finally determined by its "t-Statistic" and can be compared with other strategies.

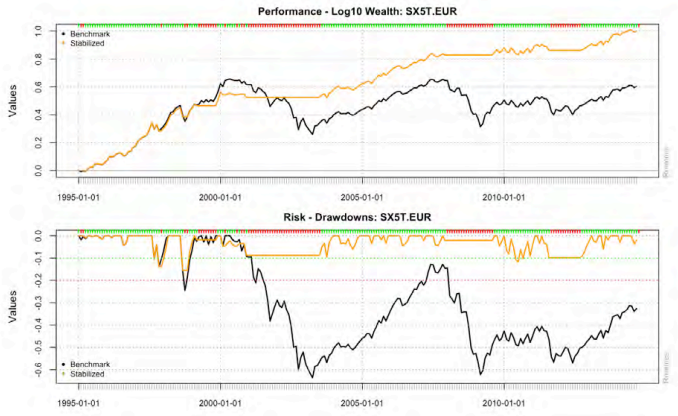


Figure 3: Wealth (upper chart) and Drawdowns (lower chart) for the Euro Stoxx 50 Index (black) and its stabilized counterpart (orange). Green and red rugs correspond to long and short positions.

For the risk measure we choose the drawdowns. In contrast to other risk measures like the volatility that has to be statistically estimated, the drawdowns can be directly measured. For the investor the drawdowns are easy to understand: It reports the depth of the losses from an initial investment and counts how long we have to wait until we are back to the original level.

Beside the historical view we are interested in rolling performance and risk numbers. This allows us to inspect the results independent of the starting and ending points of a fixed investment period. Depending on the investor's horizon one usually chooses a three, five, or ten years range as a typical holding period. Then the goal must be that for all possible periods over the whole series we achieve for every period a positive return and a drawdown that is always lower compared with the drawdowns of the original benchmark series.

The result is shown in figure 4 for the three years rolling log returns and drawdowns. The stabilized index exhibits almost everywhere positive returns, and the drawdowns have essentially lowered their values.

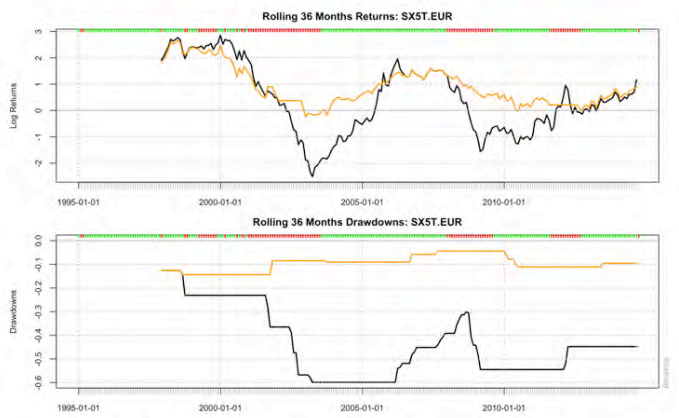


Figure 4: 36 Months rolling returns and drawdowns for the Euro Stoxx 50 Index (black) and its stabilized counterpart. Green and red rugs correspond to long and short positions.

4 Summary and Outlook

We have described the *Bayesian Instantaneous Stability Weighted Sharpe Ratio* as a new indicator for taking better investment decisions. Crossings of the indicator and an adaptive threshold level generate signals for rebalancing the investment. Thus the indicator can serve as a new measure to locate market instabilities and to protect the investors wealth against losses.

Of course, we can think of several modifications and improvements of our model and standard strategy. One of the interesting questions is: Can the instantaneous Sharpe Ratio replaced by other more efficient Reward/Risk measures? Yes, indeed. We believe that measures based on the expected shortfall risk or on the conditional drawdown at risk may be better candidates, Bacon [2006]. We are also most likely sure that on the level of the BCP algorithm itself further improvements are possible. Instead assuming a normal distribution for the returns we can use semi-fat distributions from the family of the hyperbolic distributions, Lillestol [1998]. The consequence of this will be that extreme values may not be considered as structural breaks but rather as a member of a fat tailed return distribution. Another improvement will be expected when we are not only looking at structural changes in the financial returns, but also taking structural changes in the variances, Loschi et al. [2001, 2003], and possibly even in higher moments into account. The last suggestion will be to consider adaptive window sizes, rather than fixed ones. In this context Bayesian online change point algorithms, Adams and MacKay [2007], may be of interest. We are working in some of these directions, results will be reported elsewhere.

Acknowledgement

This work was supported in financially by the Rmetrics Association in Zurich CH, and Record Currency Management in Windsor UK through a PhD Thesis Grant given to Tobias Setz.

References

Adams R. P. and MacKay D. J.C. [2007],
Bayesian Online Changepoint Detection, 7 p.
Machine Learning, arXiv:0710.3742.

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

Barry D. and Hartigan J. A. [1992],
Product Partition Models for Change Point Problems,
The Annals of Statistics 20, p. 260.

Barry D. and Hartigan J. A. [1993]
A Bayesian Analysis of Change Point Problems,
Journal of the American Statistical Association 88, 309,.

Erdman Ch. und Emerson J.W. [2008],
A Fast Bayesian Change Point Analysis for the Segmentation of Microarray Data,
Bioinformatics 24, 2143.

Loschi R.H. and Cruz F. R. B. [2001]
An analysis of the influence of some prior specifications in the identification of change points via product partition model,
Computational Statistics & Data Analysis.

Loschi R. H., Cruz F.R.B., Iglesias P.L., Arellano-Valle R.B. [2003],
A Gibbs sampling scheme to the product partition model: an application to change-point problems,
Computers & Operations Research 30, 463–482.

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

Würtz D., Y. Chalabi Y., Ellis A., Chen W., Theussl S.,
Proceedings of the Singapore Workshop on Computational Finance,
Editors: Diethelm Würtz, Mahendra Mehta, David Scott, and Juri Hinz,
Rmetrics Publishing, ISBN/EAN 9783906041087, www.rmetrics.org, 209 p.

Würtz D., Setz T., and Chalabi Y. [2011],
Stability Analytics of Vulnerabilities in Financial Time Series,
Econophysics ETH Zurich, Working Paper, 23 p.

Lillestol J. [1998],
Bayesian estimation of NIG-parameters by Markov Chain Monte Carlo methods
Working paper.

About the Authors

Tobias Setz has a Bachelor and Master degree in Computational Science from ETH Zurich. He is working in the field of risk and stability analysis of financial markets. He is a PhD Student in the Econophysics Research Group of Professor Diethelm Würtz.

Diethelm Würtz is Professor at the Institute for Theoretical Physics at ETH Zurich. He is working in the field of risk and stability analysis of financial markets. He is teaching computational finance and financial engineering at ETH Zurich. He is Senior Partner of the ETH Spin-Off Company Finance Online and President of the Rmetrics Association in Zurich.

Disclaimer

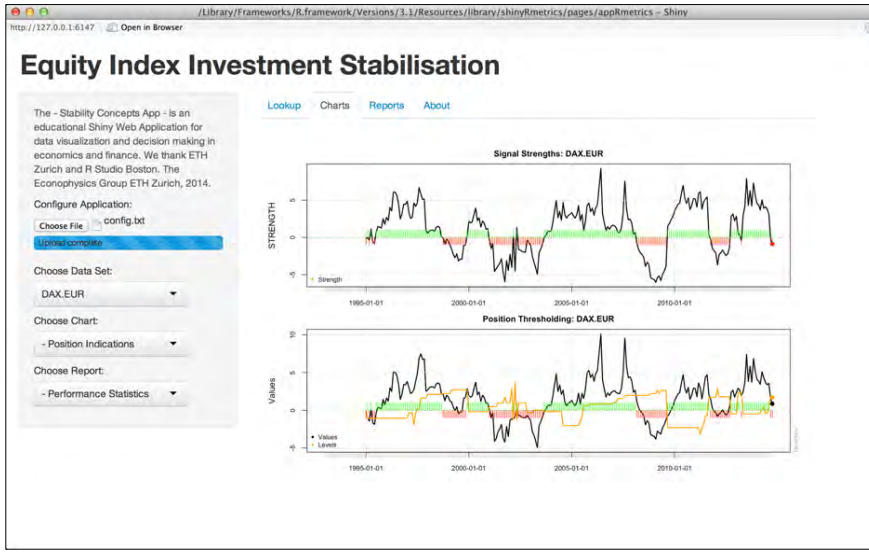
This document is copyrighted and reproduced or provided to others without the express written permission of the authors. This material has been prepared solely for informational purposes only and it is not intended to be and should not be considered as an offer, or a solicitation of an offer, or an invitation or a personal recommendation to buy or sell any stocks and bonds, or any other fund, security or financial instrument, or to participate in any investment strategy, directly or indirectly. It is intended for use in research only by those recipients to whom it was made directly available by the authors of the document.

Data Sources and Software

Data are obtained from the Internet sites of Stoxx and the Swiss Exchange. All calculations were done with the R and Rmetrics statistical software environments.

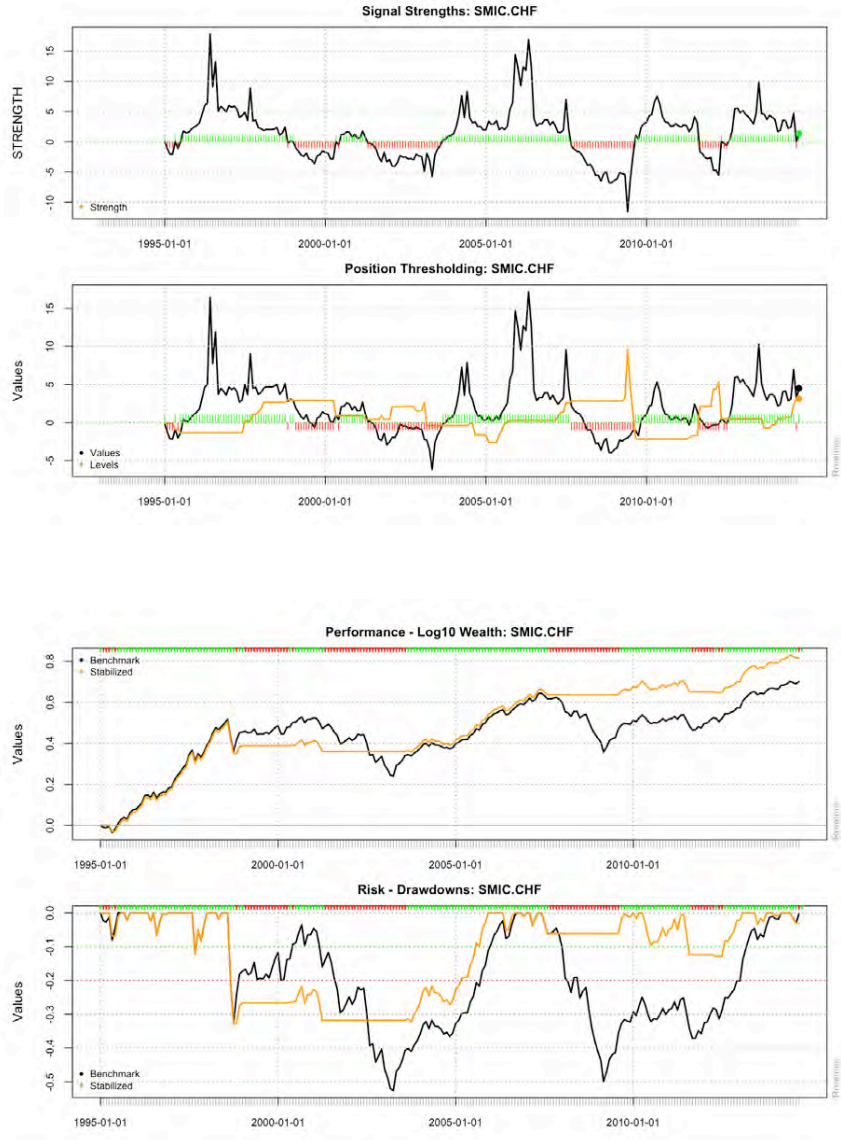
Appendix I

The figure shows a screenshot of the educational R Shiny application named *Equity Index Investment Stabilization.* The application can load data from a predefined set of stock market indices as listed in the "Lookup" Panel. A selected index can then be analyzed and monitored by "Charts" and "Reports".



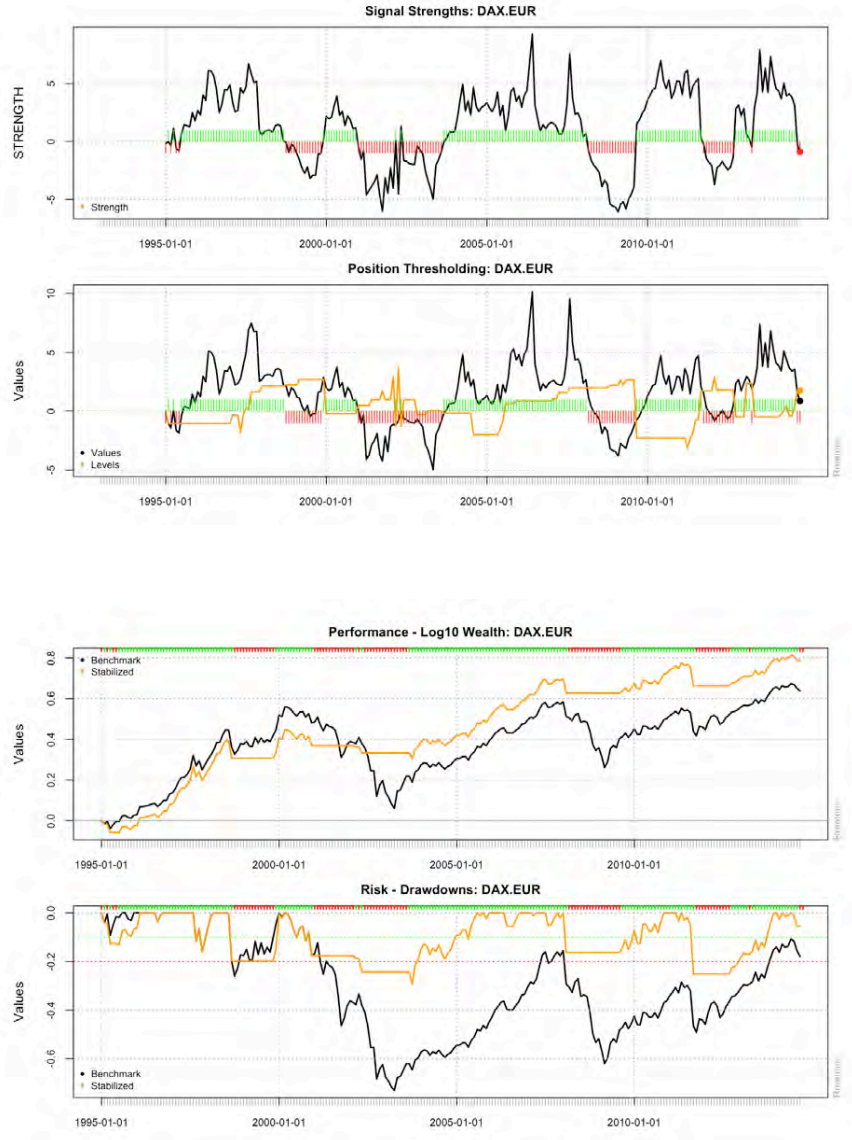
Source: Econophysics Group 2013

Appendix II Switzerland – Total Return Swiss Market Index as of August/September 2014



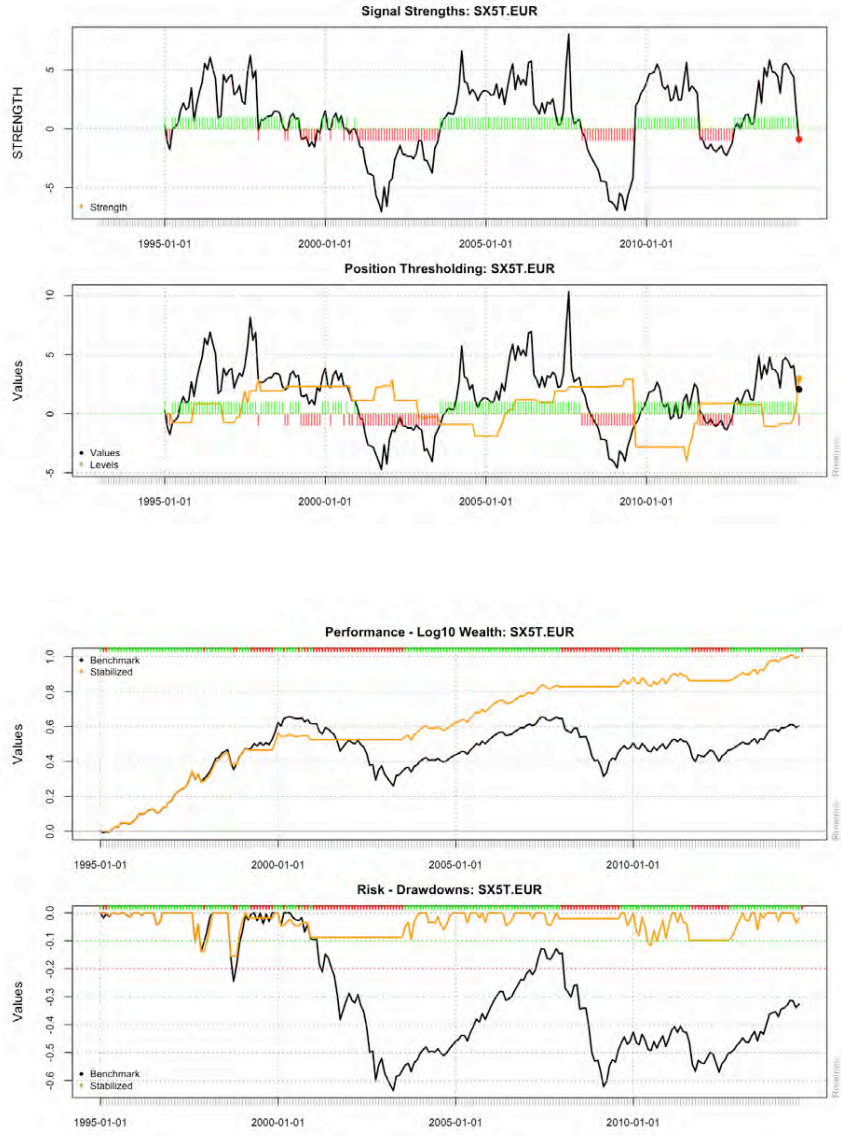
For the description of the charts we refer to the text.

Appendix III Germany – Total Return DAX Index as of August/September 2014



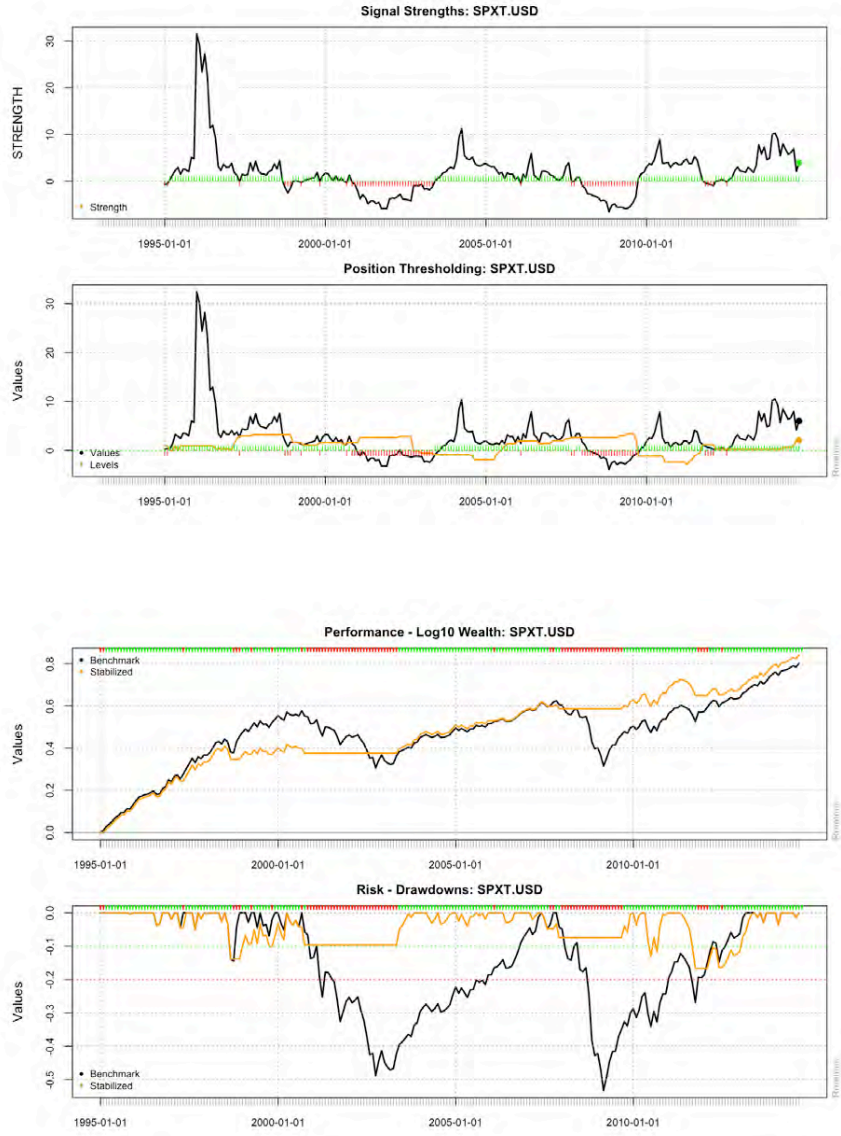
For the description of the charts we refer to the text.

Appendix IV Eurozone – Total Return Euro Stoxx 50 Index as of August/September 2014



For the description of the charts we refer to the text.

Appendix V United States – Total Return S&P 500 Index as of August/September 2014



For the description of the charts we refer to the text.

CHAPTER 7

STABILIZATION OF PORTFOLIOS

Performance and Risk Monitoring of Investments protected by Bayesian Stability Control Mechanisms
Tobias Setz and Diethelm Würtz
Econophysics Group, Swiss Federal Institute of Technology Zurich
Econophysics Working Paper, Unpublished, ETH Zurich, November 2012

The consequent use of the Bayesian binary switching strategy is to design stabilized portfolios. How this can be achieved is shown in the research paper describing the "Quadriga Market Analytics". The Quadriga is a portfolio composed of five components: Three risky ones, a less risky one, and cash. The three risky ones are an investable Blue Chip index, a Medimum or Small Cap Equity index, and an investable Real Estate index. The less risky asset is an investment in an intermediate Government bond. The strategy is to start with an investment of one quarter in each asset. If the risky assets get unstable rebalancing starts and the investment is shifted to bonds. If the bonds get unstable one shifts to cash. This is a very simple toy model which shows impressively how the Bayesian stabilization of an investment works and how it can be used for wealth protection in funds and portfolios.

Bayesian Ertragsanalyse von strukturbruchbereinigten dynamischen Prozessen am Beispiel von Kapitalmarktanlagen

Diethelm Würtz und Tobias Setz
ETH Zürich, Institut für Theoretische Physik
8032 Zürich, Hönggerberg HIT G32.3

First Version November 2012
This Version September 2013
mit Euro Factsheet von Dezember 2013

In der Zeit vom 1. September 2012 bis 31. August 2013 wurde im Rahmen eines Dissertationsvorhabens an der ETH Zurich zum Thema „Analyse von Strukturbrüchen in dynamischen Prozessen“ eine Fallstudie aus dem Bereich der Kapitalmarktanalyse durchgeführt. Das Projekt befasste sich mit dem Aufspüren und der Absicherung von strukturellen Veränderungen und den damit verbundenen Risiken in Zeitreihen von Finanzmarktindizes und Preisverläufen. Das Verfahren das in dieser Untersuchung angewendet wurde beruht auf einer statistischen Analyse nach der Methode von Bayes, die hierfür besonders prädestiniert erscheint. Neben der reinen Analyse von Kapitalanlagen wurde darüberhinaus gezeigt, wie die Algorithmen dazu benutzt werden können nachhaltig stabile Anlagen zu selektieren und zu steuern.

Als Beispiele wurden sechs Kapitalanlagen näher untersucht: Dies waren Kapitalanlagen in der jeweiligen Landeswährung auf dem schweizerischen Markt (CHF), in der Eurozone (EUR), und auf dem U.S. Markt (USD). Die Eurozone und der U.S. Markt wurden zusätzlich im Schweizer Franken analysiert. Eine Weltmarktkapitalanlage im USD rundete die Portfolios der betrachteten Kapitalanlagen ab. Die Komponenten des US, CH sowie des EU Portfolios setzten sich zur Diversifikation aus Aktienmarktanlagen des grossen und mittleren Kapitalisierungssegmentes (LCAP, MCAP) sowie aus Immobilienwerten (REITs) zusammen. Zur Stabilisierung dienten als Grundlage mittelfristige Staatsanleihen (GOVT). Der Kapitalschutz wurde durch Anlagen im Geldmarkt bzw. im Cash realisiert. Sämtliche Berechnungen basieren auf Monatsenddaten. Umschichtungen wurden, falls erforderlich, ausschliesslich zur nächsten Investitionsperiode am Monatsende durchgeführt. Die Ergebnisse aller Portfolios sind im Anhang zusammengefasst. Exemplarisch wollen wir uns im folgenden auf die Euro Kapitalmarktanlage konzentrieren.

Die Fallstudie untersucht das Design von Marktportfolios bei denen nicht die Optimierung des Ertrages und/oder der gängigen Risikomasse im Vordergrund steht. Vielmehr wird der Schwerpunkt auf eine stabilitätsgeschützte Vermehrung des Vermögens (Ertragsaspekt) bei möglichst kleinen Gewinneinbrüchen mit kurzen Erholungszeiten (Risikoaspekt) gelegt. Drei Designprinzipien finden hierbei besondere Beachtung: (i) Diversifikation, (ii) Stabilisierung, und (iii) Kapitalschutz.

Contact address: wuertz@phys.ethz.ch, www.rmetrics.org and www.phys.ethz.ch

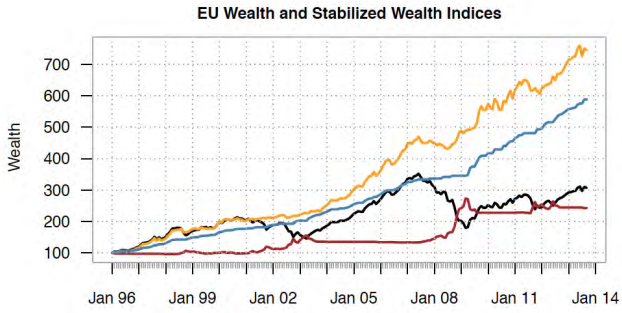


Abb 1: Aus 100 Euro werden nach 17 Jahren mehr als 700 Euros. Wachstumskurve (orange) einer 1m Libor stabilitätsgeschützten Euro Kapitalanlage aufgebaut aus vier Anlageklassen: Stoxx 50, MidCap Stoxx, Stoxx Reit Sector und 3-7 jährige Staatsanleihen. Zum Vergleich (schwarz) die gleichgewichtete Anlage. Die braune Kurve beschreibt das Premium dieser beiden Anlagen. Die blaue Kurve ist der Benchmark der "noLoss-halfGain" Anlage.

Eine Investition auf der Effizienzlinie eines Markowitz Portfolios stellt historisch gesehen eine in der Vergangenheit optimierte Kapitalanlage mit dem optimalen Satz an historischen Gewichten dar. Darüberhinaus werden die Schätzwerte für die Rendite und für das Kovarianzrisiko auf der Grundlage historischer Werte berechnet und sind somit mit einem Schätzfehler behaftet. Nicht zu unterschätzen ist auch die Tatsache dass auf der Effizienzlinie die notwendige Flexibilität verloren geht, die bei einer Umstrukturierung des Portfolios unter Stresssituationen erforderlich ist. Investitionen auf oder Nahe der Diversifikationslinie von Portfolios, das ist diejenige Linie im Rendite – Risiko Diagramm auf der die am besten diversifizierten Portfolios anzutreffen sind, sind deshalb immer vorzuziehen. Zu dieser Familie von Portfolios gehören das gleichgewichtete Portfolio, Portfolios mit paritätsgewichteten Kovarianz-Risikobudgets aber auch Tail-Risiko gewichtete Varianten. Es ist bekannt, dass Diversifikation in diesem Sinne wesentlich zur Stressresistenz von Kapitalanlagen beiträgt.

Diversifikation kann durch eine strategische Vorgehensweise leicht erreicht werden. Ein einfacher Fall ist das gleichgewichtete Portfolio, zum Beispiel aus LCAP, MCAP, REITS und GOVs. Entwickelt sich der Markt in den risikobehafteten Aktien- und Immobilienanlagen stabil, so wird jeweils 1/4 des Kapitals in diese 3 Anlagen (LCAP, MCAP, REITS) diversifiziert investiert. Das letzte Viertel wird zur weiteren Diversifikation in mittelfristige Staatsanleihen (GOVT) angelegt. Sobald eine der drei risikobehafteten Anlagen in eine kritische instabile Phase gelangt, wird die betroffene Komponente durch die Staatsanleihe ersetzt, aber nur solange sie selbst eine ausreichend hohe Stabilität ausweist. Ist dies nicht mehr der Fall erfolgt der Kapitalschutz durch die Verlagerung der Anlage in den Geldmarkt bzw. in Cash. In diesem Beispiel haben wir die Diversifizierung in gleichgewichtete Anteile durch eine taktische Stabilitätskomponente ergänzt. Der Kapitalschutz wird also dadurch erreicht, dass instabile Anlagekomponenten durch stabilere ersetzt werden. Diese Vorgehensweise ist in Abb. 2 illustriert.

Diese Ueberlegung mag erst einmal erstaunlich erscheinen, aber die zugrundeliegende Strategie kann mit Bayes'scher Statistik basierend auf Monte Carlo Markov Chain Simulationen durchaus erfolgreich realisiert werden. Das klingt erst einmal sehr technisch, was steht dahinter? In dieser Technologie werden anhand einer einzelnen historischen Marktreihe tausende von möglichen Markt Szenarien erzeugt und analysiert und mögliche strukturelle Veränderungen und Strukturbrüche im Marktgeschehen aufgespürt und lokalisiert. Diese werden mit einem Wahrscheinlichkeitsmass bewertet. Wahrscheinliche strukturelle Brüche helfen dann Indikatoren abzuleiten, die uns anzeigen wann und in welchem Masse die Komponenten im Portfolio abgesichert werden müssen.

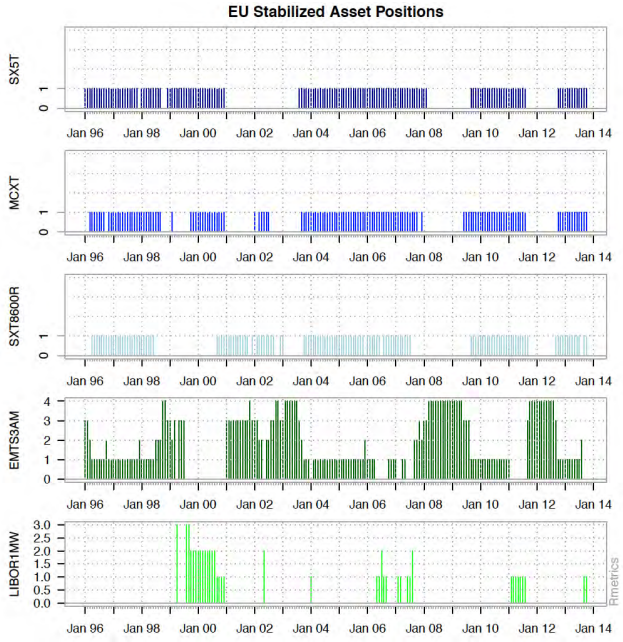


Abb 2: Gewichtung einer stabilitätsgeschützten Kapitalanlage aus drei risikobehafteten Aktienanteilen (Large CAP, Mid CAP, REITs) und einer mittelfristigen Staatsanleihe. Während instabilen Phasen werden die risikobehafteten Anteile in Staatsanleihen umgeschichtet. Sollten diese instabil werden, erfolgt eine Umschichtung in den 1 Monats Libor. Bemerkenswert sind die langreichenden Autokorrelationen der Umschichtungen, die zu einer mittleren Transaktionsdichte von lediglich 2.7 Umschichtungen im Jahresmittel führen.

Anstelle, dass wir nur über einen einzelnen Renditewert zu einem gegebenen Zeitpunkt verfügen und die Volatilität über zeitlich zurückliegende Renditewerten berechnen, verfügen wir nun über Verteilungen instantaner Schätzwerte aus denen wir stabilitätsgewichtete Indikatoren berechnen können. Erkennen wir einen positiven Trend mit hoher Stabilität vertrauen wir in das Fortbestehen des Trends, wohingegen eine Abnahme der Stabilität in der Regel eine Trendumkehr nach sich zieht. Entsprechendes gilt im Falle eines negativ verlaufenden Trends. Dies gestattet frühzeitig stabilitätserhaltende und kapitalschützende Massnahmen durch Umschichtungen in den einzelnen Assetklassen zu ergreifen.

Die stabilitätserhaltenden und kapitalschützenden Massnahmen wirken sich insbesondere auf eine signifikante Verringerung der Portfoliorisiken aus: Die Einbrüche an Verlusten fallen wesentlich weniger tief aus und die Erholungszeiten um auf das ursprüngliche Niveau zurückzukommen dauern erheblich kürzer. Dies ist eindrücklich in Abb. 3 dargestellt. Auch die Volatilitäten in Abb. 4 sind weniger hoch und befinden sich auf einem Niveau in der Grössenordnung von ca. 6%. Die Verringerung der Risiken drückt sich auch im Rückgang der Instabilitäten aus, Abb. 5, welche ein Mass für die Wahrscheinlichkeiten darstellen, dass der zukünftige Preis durch eine strukturelle Veränderung geprägt ist.

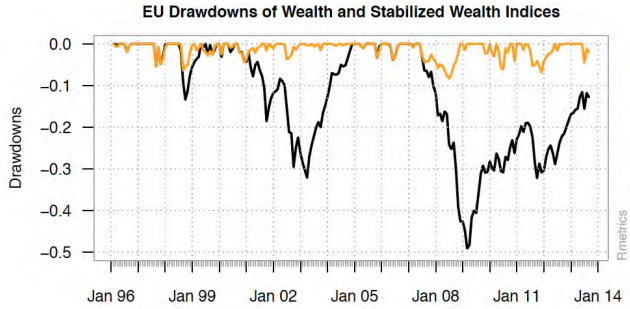


Abb 3: Vergleich der Gewinneinbrüche und den Erholungszeiten auf das ursprüngliche Niveau zurückzukehren für das gleichgewichtete Portfolio (schwarz) und das stabilitätsgesteuerte Portfolio (orange).

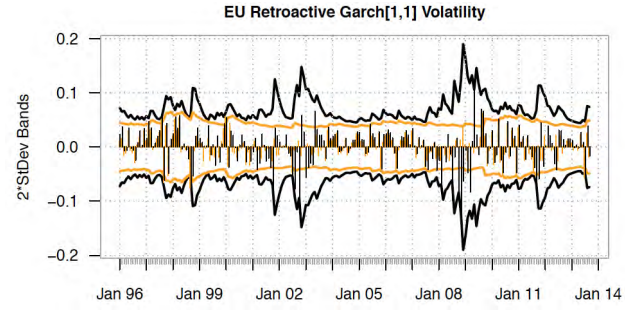


Abb 4: Vergleich der Garch(1,1) Volatilität ausgedrückt durch Bänder der Breite von 2 Standard Abweichungen für das gleichgewichtete Portfolio (schwarz) und das stabilitätsgesteuerte Portfolio (orange).

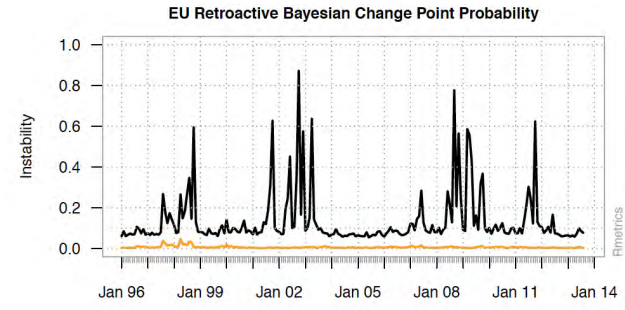


Abb 5: Vergleich der Instabilitäten ausgedrückt durch die Wahrscheinlichkeit, dass zum nächsten Zeitpunkt eine strukturelle Veränderung oder ein Strukturbruch in der Dynamik der Kapitalanlage auftritt für das gleichgewichtete Portfolio (schwarz) und das stabilitätsgesteuerte Portfolio (orange).

Die Studie hat sich auch darüber Gedanken gemacht, wie sich der Ertrag von herkömmlichen mit stabilitätsgesteuerten Portfolios vergleichen lässt. Hierzu haben wir zwei neue Benchmarks eingeführt: (i) den sogenannten monatlichen "noLoss-halfGain Benchmark" und den (ii) "beta-/beta+ Entflechtungs-Benchmark". Die Idee beim ersten Benchmark ist eine Ertragskurve zu erzielen, bei der keinerlei monatliche Verluste über den gesamten Investitionshorizont hinweg auftreten und man bereit ist, hierfür in Monaten mit positiven Renditen des gleichgewichteten Portfolios auf die Hälfte des Ertrages zu verzichten. Die blaue Ertragskurve in Abb. 1 beschreibt diesen Benchmark. Beachtenswert ist, dass dieser Benchmark, keine Verlustperioden mit Gewinneinbrüchen aufweist. Der "beta-/beta+ Entflechtungs-Benchmark" erlaubt den gleichen Sachverhalt etwas anders darzustellen: In einer Regressionsgraphik erwarten wir ein beta- von Null, und ein beta+ von ½.

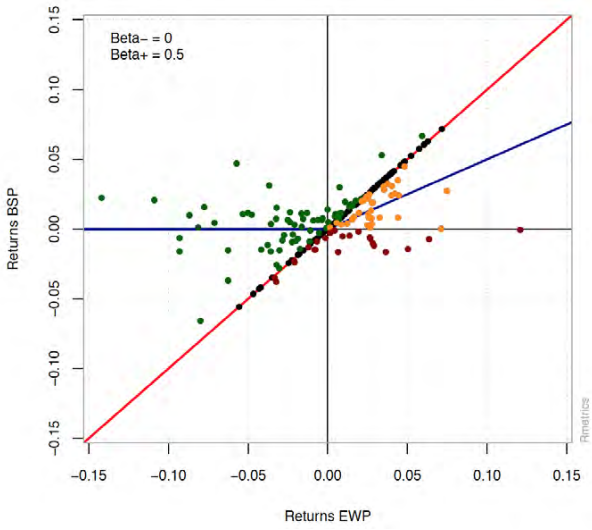


Abb. 6 beta-/beta+ Entflechtungs-Benchmark: Die Regressiongraphik zwischen den Renditen des stabilitätsgesteuerten (BSP) und des gleichgewichten (EWP) Portfolios zeigt, dass nach der Stabilisierung praktisch keine Monate mehr mit negativen Renditen verbleiben, und dass positive Perioden im Mittel den halben Gewinn auszeichnen.

Besonderes Gewicht legen wir auch auf den Punkt, dass eine nachhaltige Ertrags- und Risikokonstanz erzielt wird. Um konkreter zu sein, sollen bei einem Anlagehorizont über eine Periode von drei Jahren hinweg, unabhängig von der Einstiegszeit, keinerlei Verluste am Ende einer solchen Periode im Portfolio auftreten und eventuelle Gewinneinbrüche innerhalb der drei-Jahresperioden ca. 5 % nicht massgeblich übersteigen. Das sind harte Kriterien, die wir bei unseren Multi Asset Class Anlage (aus Stocks, Reits, Bonds, Money Market) durchaus erfüllen können. Solche Portfolios sind für Kapitalanleger interessant, denen es ein Anlegen ist, nachhaltig geschützte stabile Ertrags- und stabile Risikoentwicklungen zu erzielen. Hierzu zählen vorrangig Pensionskassen, Versicherungen, aber auch Kunden, die sich an einem kapitalgeschützten Wertsteigerungs-Management orientieren. Als Gegenleistung sind sie bereit in guten Zeiten auf singulär hohe Renditen zu verzichten und dafür kleine Gewinneinbrüche mit kurzen Erholungszeiten zu erhalten.

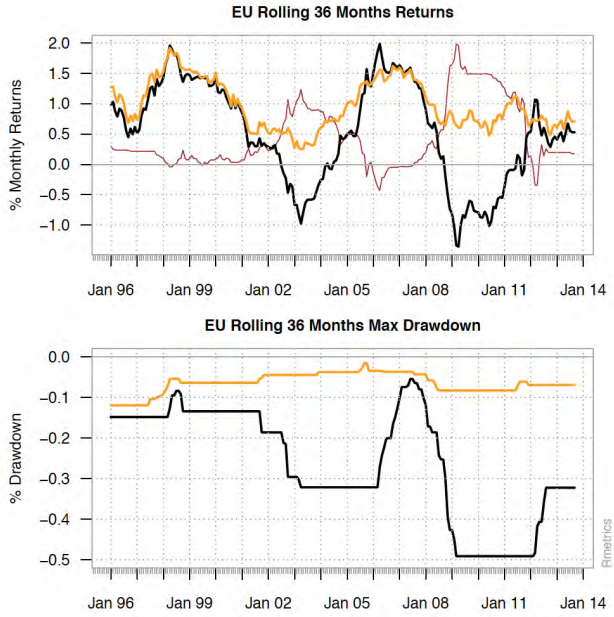


Abb. 7: Ertrags- und Risikokonstanz über drei Jahresperioden hinweg. Unabhängig vom Beginn der Periode erbrachten alle 3 Jahreszeiträume von 1996 bis heute eine positive Ertragsbilanz für stabilitätsgesteuerte Portfolios (orange) im Gegensatz zu den gleichgewichteten Portfolios (schwarz), welche erhebliche Ertragsverluste in den Jahren 2002 und 2008 ausweisen. Bei den Gewinneinbrüchen erkennen wir ein ähnliches Verhalten mit Werten bei über 30% und knapp 50%.

Stabilitätsgesteuerte und kapitalgeschützte Portfolios stellen eine neue Klasse von Anlageinstrumenten dar, deren Schwerpunkt auf eine nachhaltige Ertragsentwicklung und kleine Gewinneinbrüche mit kurzen Erholungszeiten ausgerichtet ist. Weitere Vorteile solcher Kapitalanlagen sind eine niedrige Volatilität, ein dynamischer Preisprozess mit wenig ausgeprägten strukturellen Veränderungen, sowie 3-Jahresperioden in denen sich das Investment durch praktisch keinerlei Verluste und nur geringe Gewinneinbrüche auszeichnet. Die hier aufgezeigten Benchmark Methodologie erlaubt uns auch erstmals zu beurteilen, inwieweit bestehende Funds und Portfolios dem Konzept der Stabilität genügen.

Disclaimer

This document is copyrighted and its content is confidential and may not be reproduced or provided to others without the express written permission of the authors. This material has been prepared solely for informational purposes only and it is not intended to be and should not be considered as an offer, or a solicitation of an offer, or an invitation or a personal recommendation to buy or sell any stocks and bonds, or any other fund, security or financial instrument, or to participate in any investment strategy, directly or indirectly. The document is intended for use in research only by those recipients to whom it was made directly available by the authors of the document.

Anhang – Letzter Stand Dezember 2013

Tabelle:

Uebersicht zu den Ertragswerten der untersuchten Kapitalanlagen, Stand Ende Dezember 2013.

Die ersten drei Spalten listen die Kennwerte der Schweizer, der Eurozone, und der U.S. Marktanlage jeweils in CHF ausgewiesen. Die vierte Spalte ist das daraus gebildete gleichgewichtete Marktportfolio.

Spalte 5 bis 7 listen die Marktportfolios Eurozone (EUR), U.S. (USD) und World (USD) in der jeweiligen Lokalwährung.

Die letzten drei Spalten listen ausgewählte Benchmarks: BVG40 von Pictet in CHF, SGI Harmonia Risk Parity Portfolio in EUR von Societé Generale und den Credit Suisse Hedge Fund Index in USD.

Der erste Block zeigt die Ertragswerte für die Jahre 2003 bis 2013, der zweite Block die Werte für die letzten 12 Monate (2013), und der dritte Block die Werte für die aktuelle Periode.

Summary Factsheet:

Das Uebersichts-Factsheet für den Euromarkt, Stand Ende Dezember 2013.

Zu sehen sind: Stabilitätsgeschützte Indexwerte, Ertragseinbrüche und Erholungszeiten, Retroaktive Volatilitätsanalyse, Retroaktive Bayes'sche Strukturbruchanalyse, beta+ und beta- Entflechtungsindikator, Rollende Erträge und Risikofaktoren, Trendindikator, Anzahl von Portfolioumschichtungen, Tabellen von Ertrags- und Risikokennziffern.

Rmetrics

Stability Benchmark Indices

End of December 2013

This factsheet summarizes a new family of Multi Asset Class Benchmarks composed from Large and MidCap Equities, Real Estate and Government Bond Investments.
The new indices are wealth protected and weighted by stability concepts derived from a Bayesian statistical approach.
Four Indices are listed, a World Index, with Swiss Market, Eurozone, and US subindices in CHF, and three indices, for the Eurozone in EUR, and U.S. and World in USD.
These Benchnmarks can be compared to three Investments: The Pictet LPP 40 in CHF, the SGI Risk Parity Fund in EUR, and the Credit Swiss Hedge fun in USD.

Performance | **CHF: Monthly Performance Analysis** Bayesian Stability Analytics | **Local Currency Analysis** Bayesian Stability Analytics | **Benchmark Funds**

YEAR:	Swiss Market Portfolio in CHF *1 CH/CHF	Eurozone Market Portfolio in CHF *2 EMU/CHF	U.S. Market Portfolio in CHF *3 US/CHF	*World Market Portfolio in CHF* *MEAN/CHF*	Eurozone Market Portfolio in EUR *2 EMU/EUR	U.S. Market Portfolio in USD *3 US/USD	World Market Portfolio in USD *4 WORLD/USD	World Pictet LPP 40 in CHF *A WORLD/CHF	World SGI Risk Parity in EUR *B WORLD/EUR	World CreditSuisse CSLAB Hedge in USD *C WORLD/USD
2003*	12.8	12.6	2.5	*9.3*	12.9	17.8	24.4	11.2	14.0	12.1
2004	7.7	16.7	6.6	*10.3*	18.5	14.7	15.0	6.5	13.2	8.9
2005	15.7	18.7	17.5	*17.3*	17.9	7.1	13.7	13.3	16.9	8.3
2006	14.5	22.1	7.4	*14.7*	21.0	12.9	15.3	7.0	7.4	15.0
2007	3.7	2.0	-2.3	*1.1*	0.6	5.0	14.5	-0.2	2.2	11.9
2008	6.8	3.2	8.0	*6.0*	8.4	1.4	3.1	-22.3	-0.6	-12.1
2009	14.9	13.8	16.8	*15.2*	16.2	-0.8	7.7	16.9	13.2	12.6
2010	6.5	-6.5	9.4	*3.1*	7.3	17.2	14.2	5.5	5.0	8.1
2011	-1.8	-5.6	4.0	*-1.1*	0.9	3.5	-1.9	-0.8	-1.1	0.2
2012	6.1	10.8	8.4	*8.4*	13.5	7.2	7.8	9.6	8.5	3.3
2013	10.6	14.5	11.6	*12.2*	12.3	13.4	11.5	7.7	13.8	7.4
mean p.a.	8.9	9.3	8.2	*8.8*	11.8	9.0	11.4	4.9	8.4	6.9
	* sum of monthly returns		best Portfolio							

MONTH:	CHF	CHF	CHF	*CHF*	EUR	USD	USD	CHF	EUR	USD
2013 Jan	2.9	2.4	3.2	*2.8*	0.4	3.4	2.5	1.8	2.2	1.1
2013 Feb	0.9	-0.3	2.3	*1.0*	0.9	0.9	0.2	1.5	1.0	-0.2
2013 Mar	1.4	0.0	4.7	*2.0*	0.4	2.8	1.0	1.6	2.8	1.2
2013 Apr	1.6	3.4	1.1	*2.0*	3.2	2.7	1.8	1.3	3.9	1.1
2013 May	0.8	2.6	0.6	*1.3*	1.4	-1.4	-1.2	0.1	-0.8	0.0
2013 Jun	-2.2	-4.9	-2.0	*-3.0*	-4.7	-1.2	-3.0	-2.5	-1.9	-1.1
2013 Jul	1.2	4.0	1.2	*2.1*	3.5	2.8	2.7	1.3	0.7	1.7
2013 Aug	0.2	-0.9	-3.1	*-1.3*	-0.9	-1.7	-1.1	-0.9	-1.5	-1.0
2013 Sep	1.3	3.4	0.7	*1.8*	4.0	2.0	4.5	1.4	2.2	1.4
2013 Oct	1.7	4.3	2.5	*2.8*	3.7	2.9	2.9	1.8	2.5	1.7
2013 Nov	0.8	0.6	0.1	*0.5*	0.7	-0.4	0.4	0.4	1.5	0.8
2013 Dec	0.0	-0.3	0.3	*0.0*	-0.1	1.4	0.7	-0.3	0.5	0.5

PERIOD:	CHF	CHF	CHF	*CHF*	EUR	USD	USD	CHF	EUR	USD
Last 12 Months	10.6	14.3	11.6	12.2	12.5	14.2	11.4	7.5	13.1	7.2
YTM	10.6	14.3	11.6	12.2	12.5	14.2	11.4	7.5	13.1	7.2
Last 6 Months	5.2	11.1	1.7	6.0	10.9	7.0	10.1	3.7	6.0	5.0
Last 3 Months	2.5	4.6	2.9	3.3	4.3	3.9	4.0	1.9	4.5	2.9
Last Month	0.0	-0.3	0.3	0.0	-0.1	1.4	0.7	-0.3	0.5	0.5

Assets | **Multi Asset Class Portfolio Composition**

No	Large Cap	Mid Cap	Reits	Govt Bonds	MoneyMarket
*1	SMI	SMI MCap	SWIIT	CH Govt 3-7Y	1M Libor CHF
*2	EuroStoxx50	Mid Cap	Reits	EU Govt 3-7Y	1M Libor EUR
*3	SP500	Russell MCap	Steer&Cohens	US Govt 3-7Y	1M Libor USD

No	Developed Mkts	AllCountry MCap	Emerging Mkts	Govt Bonds	MoneyMarket
*4	MSCI World	ACWI MCap	MSCI EM	US Govt 3-7Y	1M Libor USD

No	Benchmark:	Bloomberg Ticker:	Web Link:
*A	Pictet LPP 40 Index	LPP40	*http://www.pictet.com/content/corporate/en/home/institutional_investors/lpp_indices/lpp2005.html*
*B	SGI Risk Parity Index	SGIXHETR	*https://www.sgindex.com/indexdetail/bbg/SGIXHETR/*
*C	CS Inv. Hedge Fund Index	CSLAB	*https://secure-alternativebeta.credit-suisse.com/altbeta/secure/en/ab_data.aspx?cy=USD*

Notes

In the Rmetrics Analytics we use monthly log Returns

Forecasts	LCAP	MCAP	REIT/EM	GOVT	Positions & Forecsats		Average Number of Trades p.a
CH / CHF	1	1	0	2	Positions	December	3.0
	1	1	0	0	Forecast	January	
EU / CHF	1	1	1	1	Positions	December	2.6
	1	1	1	0	Forecast	January	
US /CHF	1	1	0	2	Positions	December	2.9
	1	1	0	0	Forecast	January	
EU / EUR	1	1	1	1	Positions	December	2.8
	1	1	1	0	Forecast	January	
US / USD	1	1	0	0	Positions	December	3.6
	1	1	0	0	Forecast	January	
WORLD / USD	1	1	1	0	Positions	December	3.7
	1	1	0	0	Forecast	January	

as of 2013-12-31

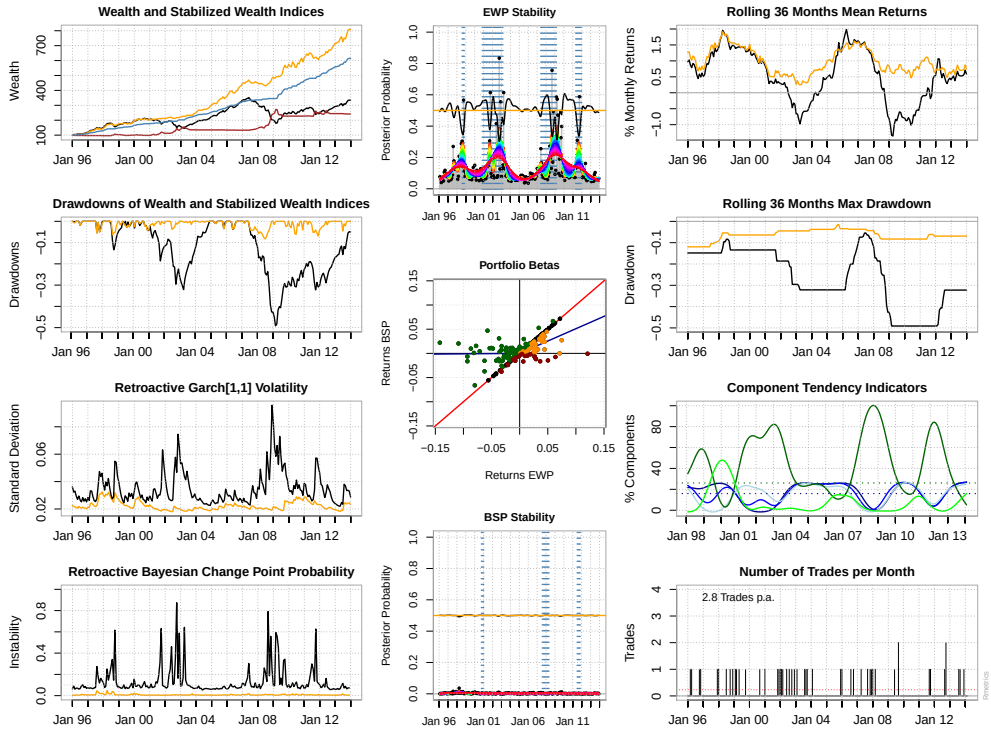
Disclaimer:

This document is copyrighted and its content is confidential and may not be reproduced or provided to others without the express written permission of the authors. This material has been prepared solely for informational purposes only and it is not intended to be and should not be considered as an offer, or a solicitation of an offer, or an invitation or a personal recommendation to buy or sell any stocks and bonds, or any other fund, security or financial instrument, or to participate in any investment strategy, directly or indirectly. It is intended for use in research only by those recipients to whom it was made directly available by the authors of the document.

Euro Multi Asset Portfolio

STOXX EUR EuroStoxx50 TR Index (SX5T)	[1|1]
STOXX EUR Eurozone MCap TR Ind (MCXT)	[1|1]
STOXX EUR Reits Sector Index (SXT8600R)	[1|1]
EMTS EUR 3-7Y MEAN TR Bond Idx (EMTS3AM)	[1|0]
BBA EUR 1M Libor Wealth (LIBOR1MW)	[0|1]

Parameter Settings:
Last Update: Dez 2013
BCP Flexible: 24 Months
Transaction Throttle: On
Independent Averaging: Off
Leverage Factor: 1



Monthly Performance of Equal Weigths Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	EWP	#M>0	HIT%	G/L	MIN	MAX
2001	2.1	-3.6	-2.4	2.9	0.8	-2.1	-1.5	-3.2	-9.3	4.0	2.6	1.4	-8.2	6	50	0.6	-9.3	4.0
2002	0.5	0.6	2.7	-0.6	-1.1	-6.3	-7.1	-0.4	-10.9	6.4	3.3	-5.0	-17.9	5	42	0.4	-10.9	6.4
2003	-3.2	-2.4	-2.7	7.1	3.8	2.7	2.8	1.6	-1.5	4.2	2.1	2.5	16.8	8	67	2.7	-3.2	7.1
2004	2.8	3.5	-0.3	-0.1	0.4	2.1	-0.4	0.4	1.7	1.8	3.3	3.2	18.5	9	75	22.5	-0.4	3.5
2005	1.9	1.8	-0.6	-0.4	4.8	2.9	2.3	0.6	3.4	-3.5	2.8	3.0	18.8	9	75	5.2	-3.5	4.8
2006	3.7	3.1	2.2	-0.5	-3.3	0.6	2.4	2.3	3.6	2.7	1.0	3.9	21.5	10	83	6.5	-3.3	3.9
2007	0.7	-0.7	2.2	0.8	1.7	-3.0	-3.6	-0.1	-1.6	1.4	-3.8	-1.9	-7.8	5	42	0.5	-3.8	2.2
2008	-6.3	0.4	-2.2	2.8	-0.8	-9.3	-1.3	2.1	-8.7	-14.2	-5.7	0.0	-43.0	3	25	0.1	-14.2	2.8
2009	-4.2	-7.8	1.5	12.1	2.7	-0.9	7.5	7.2	2.9	-2.5	0.3	3.5	22.4	8	67	2.5	-7.8	12.1
2010	-2.2	-0.8	5.7	-1.8	-4.2	-0.3	5.2	-1.1	4.0	2.5	-4.2	4.6	7.3	5	42	1.5	-4.2	5.7
2011	1.5	2.4	-1.7	2.6	0.2	-1.2	-3.2	-8.1	-5.3	5.0	-3.0	0.7	-10.3	6	50	0.5	-8.1	5.0
2012	4.4	2.6	1.2	-2.5	-3.7	3.6	3.5	1.9	0.8	2.0	2.0	1.7	17.6	10	83	3.9	-3.7	4.4
2013	0.4	0.9	0.4	3.2	1.4	-4.7	4.4	-1.1	4.2	3.9	0.7	-0.1	13.5	9	75	3.3	-4.7	4.4

Performance and Risk Statistics

	BSP	EWP
Mean Monhtly Return %	0.97	0.57
Mean Monthly Standard Dev %	2.26	3.56
Average Annualized Return %	12.37	7.07
Average Ann. Volatility %	7.83	12.33
Sharpe Ratio	0.43	0.16
Maximum Drawdown %	-8.29	-49.11
No of Positive Months	151.00	137.00
Pos/Neg No of Month Ratio	2.29	1.71
Monthly Gain/Loss Ratio	3.08	1.51
Semi Deviation	0.02	0.03
Historical VaR (95%)	-0.03	-0.06
Historical ES (95%)	-0.04	-0.09
Kurtosis Monthly Returns	0.60	1.69

Monthly Performance of Binary Stability Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	BSP	#M>0	HIT%	G/L	MIN	MAX
2001	2.0	0.3	0.5	-1.2	1.1	0.3	0.7	0.7	-1.6	2.4	-0.6	-0.5	4.2	8	67	2.1	-1.6	2.4
2002	1.0	1.1	1.3	0.6	-0.1	-3.7	0.4	0.7	2.0	-0.7	0.8	1.1	4.6	9	75	2.0	-3.7	2.0
2003	1.5	1.2	-0.4	0.0	3.3	-0.7	0.4	0.9	-1.5	4.2	2.1	2.2	12.9	9	75	5.9	-1.5	4.2
2004	2.8	3.5	-0.3	-0.1	0.4	2.1	-0.4	0.4	1.7	1.8	3.3	3.2	18.5	9	75	22.5	-0.4	3.5
2005	1.9	1.8	-0.6	-0.4	4.8	2.9	2.3	0.6	3.4	-3.5	1.9	3.0	17.9	9	75	5.0	-3.5	4.8
2006	3.7	3.1	2.2	-0.3	-3.5	0.4	2.2	2.1	3.6	2.7	1.0	3.9	21.0	10	83	6.6	-3.5	3.9
2007	0.9	-0.9	2.2	0.8	2.0	-2.8	-1.6	0.1	0.2	1.6	-1.1	-0.7	0.6	7	58	1.1	-2.8	2.2
2008	-1.5	0.9	-0.4	-1.0	-1.5	-0.6	1.1	2.2	1.0	2.2	4.7	1.4	8.4	7	58	2.6	-1.5	4.7
2009	-1.5	1.5	0.7	-0.1	0.8	0.6	2.7	7.2	2.9	-2.5	0.3	3.5	16.2	9	75	5.0	-2.5	7.2
2010	-2.2	-0.8	5.7	-1.8	-4.2	-0.3	5.2	-1.1	4.0	2.5	-4.2	4.6	7.3	5	42	1.5	-4.2	5.7
2011	1.8	2.3	-1.5	2.5	-0.3	-1.3	-3.8	0.1	1.1	-1.5	-1.5	3.0	0.9	6	50	1.1	-3.8	3.0
2012	0.8	0.8	0.4	0.7	3.1	-1.6	3.0	-0.2	0.8	2.0	2.0	1.7	13.5	10	83	8.5	-1.6	3.1
2013	0.4	0.9	0.4	3.2	1.4	-4.7	3.5	-0.9	4.0	3.7	0.7	-0.1	12.3	9	75	3.2	-4.7	4.0

Benchmark Statistics

	BSP to EWP
Alpha	0.01
Beta	0.38
Beta+	0.51
Beta-	0.01
R-squared	0.35
Annualized Alpha	0.09
Correlation	0.59
Correlation p-value	0.00
Tracking Error	0.10
Active Premium	0.06
Information Ratio	0.58
Treynor Ratio	0.32

SWISS MULTI ASSET PORTFOLIO

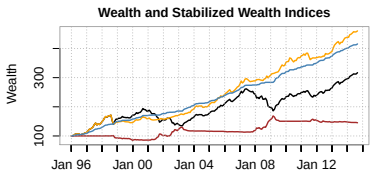
In the following some selected pages from the Swiss Multi Asset Portfolio factsheet are shown:

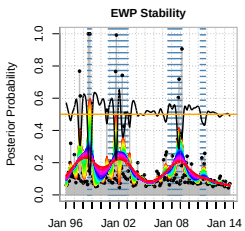
- The Summary Page
- The Index of the Benchmark and Stabilized Market Components
- The Drawdowns of the Benchmark and Stabilized Market Components
- The Positions of the Stabilized Market Components
- The Bayesian change point analytics of the Equal Weighted and the Stabilized Portfolio

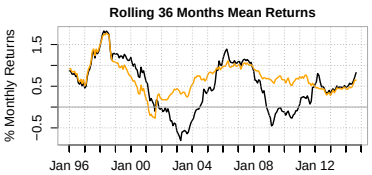
Swiss Multi Asset Portfolio

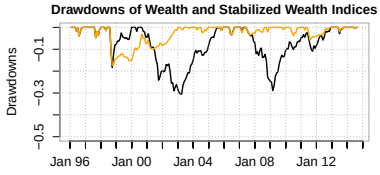
SIX CHF Swiss Market Index (SMIC)	[0 1]
SIX CHF SMI MCap TR Index (SMIMC)	[1 1]
SIX CHF SWIIT TR Reits Fund (SWIIT)	[1 1]
SIX CHF SBGM 3-7Y TR Bond Idx (SBGM3T)	[2 1]
BBA CHF 1M Libor Wealth (LIBOR1MW)	[0 0]

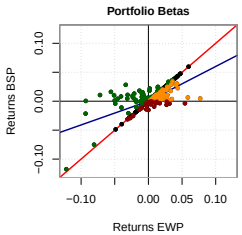
Parameter Settings:
Last Update: Aug 2014
BCP Flexible: 24 Months
Transaction Throttle: Off
Independent Averaging: Off
Leverage Factor: 1

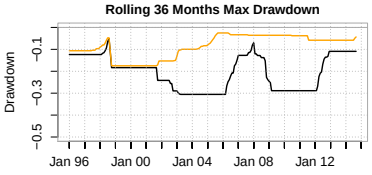


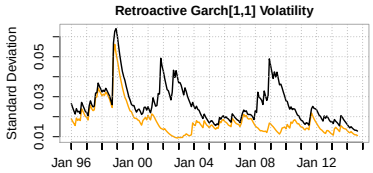


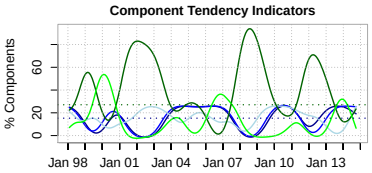


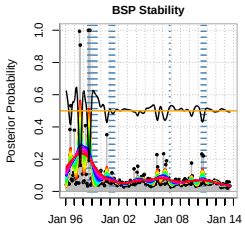


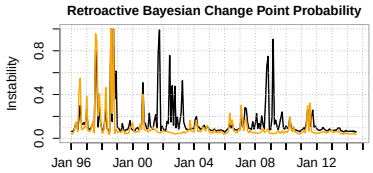


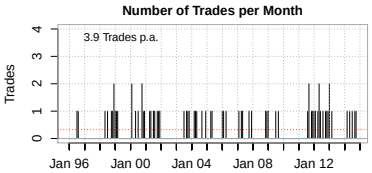












Monthly Performance of Equal Weigths Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	EWP	#M>0	HIT%	G/L	MIN	MAX
2002	-0.9	0.7	3.5	-0.7	1.0	-4.1	-7.2	0.5	-5.1	2.3	1.7	-3.1	-11.4	6	50	0.5	-7.2	3.5
2003	-2.1	-0.8	-0.3	5.4	2.5	1.3	2.1	2.0	-0.3	4.1	1.0	2.1	17.1	8	67	6.0	-2.1	5.4
2004	3.6	1.5	-1.3	1.1	-0.1	0.1	-2.3	0.1	1.4	0.0	1.1	2.6	7.7	9	75	3.1	-2.3	3.6
2005	2.3	1.2	0.4	-0.2	2.4	1.6	3.7	-0.3	3.0	-1.4	1.4	2.7	16.8	9	75	9.6	-1.4	3.7
2006	1.8	2.0	1.5	1.4	-2.9	-0.6	1.7	1.8	1.8	1.9	1.0	3.4	14.8	10	83	5.2	-2.9	3.4
2007	3.5	-2.3	2.2	2.9	0.4	-1.2	-1.3	-1.0	-0.5	0.7	-3.1	-0.8	-0.5	5	42	0.9	-3.1	3.5
2008	-5.6	1.0	-1.9	2.7	1.1	-4.9	0.2	1.5	-3.4	-9.3	-1.3	-1.0	-20.9	5	42	0.2	-9.3	2.7
2009	-0.9	-5.0	2.8	5.9	2.0	0.7	4.3	2.7	2.0	-1.0	0.5	3.1	17.1	9	75	3.5	-5.0	5.9
2010	0.7	0.0	3.5	-0.6	-1.9	-1.4	1.4	0.0	2.2	0.6	-0.2	1.9	6.2	6	50	2.5	-1.9	3.5
2011	0.1	1.3	-1.3	1.8	0.5	-2.7	-3.1	-2.4	-1.0	2.7	-1.2	1.6	-3.7	6	50	0.7	-3.1	2.7
2012	1.3	2.1	1.1	0.3	-2.3	1.2	3.0	-0.4	0.5	-0.2	2.2	0.7	9.5	9	75	4.2	-2.3	3.0
2013	3.1	1.4	1.6	1.2	0.7	-3.0	2.0	0.2	1.4	1.3	1.0	0.4	11.3	11	92	4.8	-3.0	3.1
2014	0.6	2.1	0.9	0.9	1.1	-0.3	0.2	1.4					6.9	7	88	25.4	-0.3	2.1

Performance and Risk Statistics

	BSP	EWP
Mean Monhtly Return %	0.68	0.52
Mean Monthly Standard Dev %	1.89	2.64
Average Annualized Return %	8.53	6.39
Average Ann. Volatility %	6.55	9.15
Sharpe Ratio	0.36	0.20
Maximum Drawdown %	-17.50	-30.55
No of Positive Months	161.00	150.00
Pos/Neg No of Month Ratio	2.52	2.00
Monthly Gain/Loss Ratio	2.79	1.69
Semi Deviation	0.01	0.02
Historical VaR (95%)	-0.02	-0.04
Historical ES (95%)	-0.04	-0.07
Kurtosis Monthly Returns	8.85	3.53

Monthly Performance of Binary Stability Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	BSP	#M>0	HIT%	G/L	MIN	MAX
2002	0.3	0.6	0.4	0.8	0.9	0.8	1.1	0.7	1.0	1.0	-0.3	1.1	8.3	11	92	25.4	-0.3	1.1
2003	1.3	1.2	-0.8	-0.4	1.9	0.2	0.7	1.5	-0.6	4.1	1.1	1.8	12.2	9	75	8.3	-0.8	4.1
2004	3.4	1.5	-1.2	1.1	-0.1	0.3	-2.6	0.3	1.1	-0.5	1.1	2.6	7.0	8	67	2.6	-2.6	3.4
2005	2.3	1.2	0.0	-0.2	2.4	1.6	3.7	-0.3	3.0	-1.4	1.4	2.0	15.7	8	67	9.0	-1.4	3.7
2006	1.8	1.2	1.8	1.6	-2.9	-0.5	1.4	1.6	1.9	2.0	0.8	2.9	13.7	10	83	5.0	-2.9	2.9
2007	3.6	-2.4	1.6	3.0	0.7	-1.0	-1.4	-1.2	0.4	0.2	0.5	-0.3	3.6	7	58	1.6	-2.4	3.6
2008	1.6	0.1	0.2	-0.6	-0.3	-0.4	1.8	0.6	2.8	-2.1	1.8	1.4	6.8	8	67	2.9	-2.1	2.8
2009	1.5	0.1	0.5	0.6	0.3	0.5	2.3	2.7	2.0	-1.0	0.5	3.1	13.2	11	92	14.5	-1.0	3.1
2010	0.7	0.0	3.5	-0.6	-1.9	-1.4	1.4	0.0	2.2	0.6	-0.2	1.9	6.2	6	50	2.5	-1.9	3.5
2011	0.3	1.3	-1.2	1.8	0.1	-2.9	-3.1	0.9	0.7	-0.1	-0.1	0.4	-1.7	7	58	0.8	-3.1	1.8
2012	0.3	0.5	-0.3	0.2	0.7	-0.1	2.5	-0.5	0.1	0.5	1.0	0.7	5.5	9	75	7.3	-0.5	2.5
2013	3.1	2.3	1.2	1.1	0.6	-2.1	1.5	-0.1	1.7	1.7	0.4	0.3	11.9	10	83	6.5	-2.1	3.1
2014	-0.1	2.0	0.4	0.9	1.1	-0.3	0.2	0.7					4.8	6	75	13.7	-0.3	2.0

Benchmark Statistics

	BSP to EWP
Alpha	0.00
Beta	0.50
Beta+	0.60
Beta-	0.41
R-squared	0.49
Annualized Alpha	0.05
Correlation	0.70
Correlation p-value	0.00
Tracking Error	0.07
Active Premium	0.02
Information Ratio	0.36
Treynor Ratio	0.16

Market Components

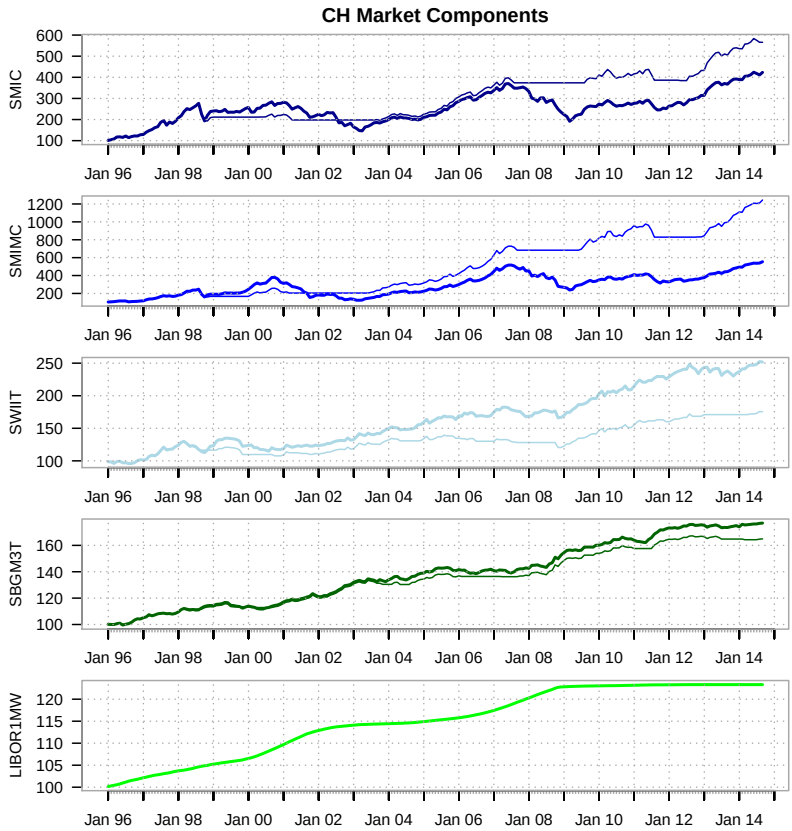


Figure 10: The charts show the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SMIC (darkblue), SMIMC (blue) and SWIIT (lightblue) and the lower charts the less risky asset, SBGM3T (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

Component Drawdowns

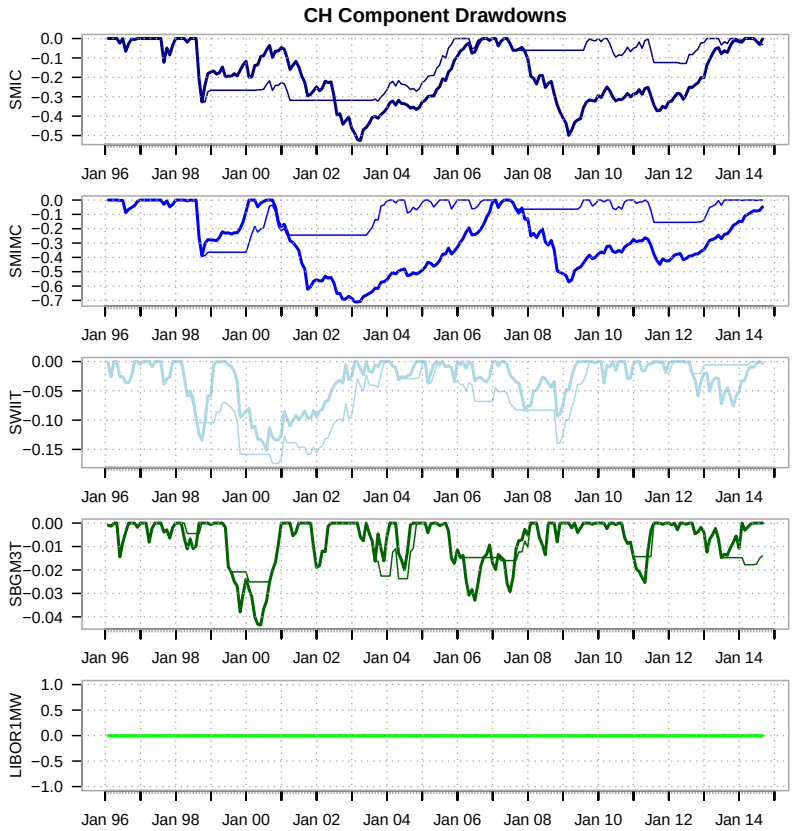


Figure 11: The charts show the drawdowns of the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SMIC (darkblue), SMIMC (blue) and SWIIT (lightblue) and the lower charts the less risky asset, SBGM3T (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

Stabilized Asset Positions

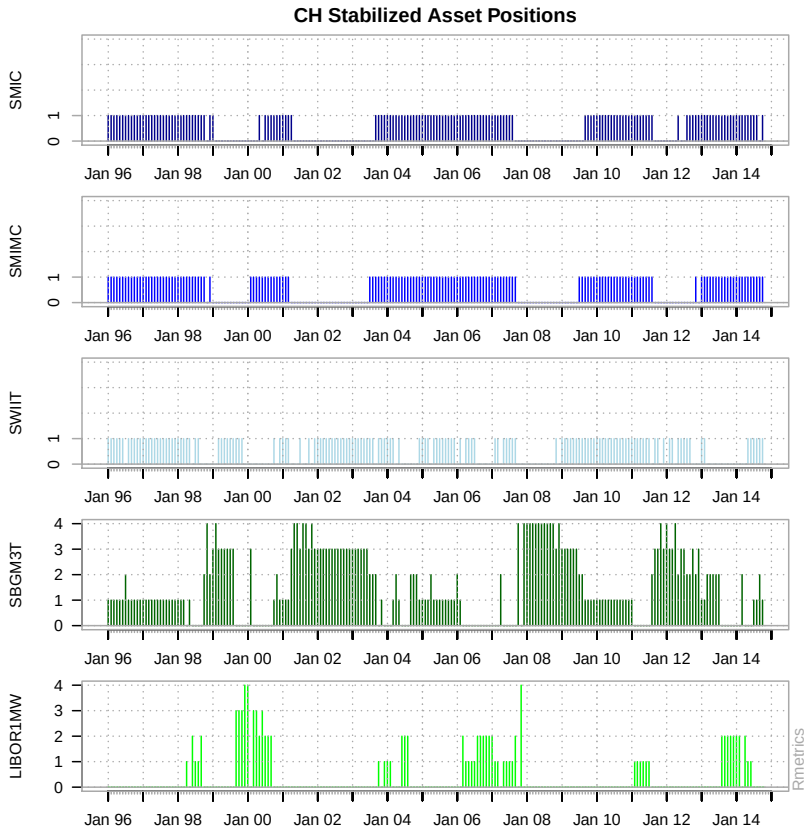


Figure 12: The graph shows the market positions as realized in the Binary Stability Portfolio. The positions can range between zero and four units (the total capital). The risky assets (SMIC, SMIMC, and SWIIT) are limited to one unit (25%), the less and no risk assets (SBGM3T, LIBOR1MW) are allowed to fill the whole range between zero and four units (100%).

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

Structural Change and Break Points Indicator

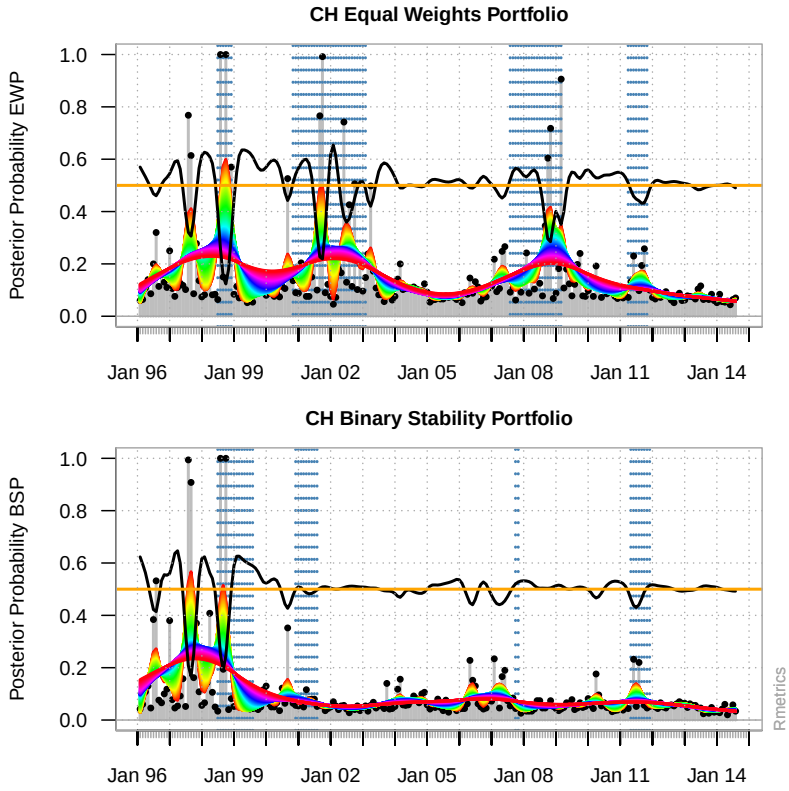


Figure 16: The two charts display the results from the retroactive Bayesian change point analytics. The grey bars with a black dot on top mark the stability probabilities for each month of the financial return series. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colours. From their ranges, 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. The end of the curves can be extrapolated and can serve for forecasting market stability. The upper chart belongs to the Equal Weights Portfolio, the lower chart to the Binary Stability Portfolio.

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

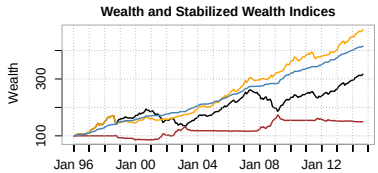
THROTTLED SWISS MULTI ASSET PORTFOLIO

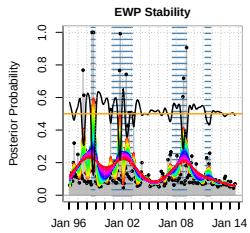
The only difference of the portfolio presented in the following factsheet is the addition of a transaction throttle. This is a parameterless mechanism that prevents the algorithm from leaving the market if the actual drawdown is still very low compared to the actual variance.

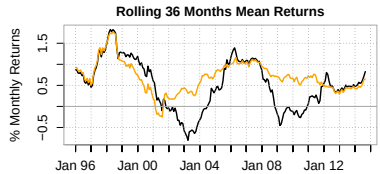
Swiss Multi Asset Portfolio

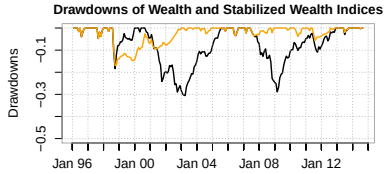
SIX CHF Swiss Market Index (SMIC)	[1 1]
SIX CHF SMI MCap TR Index (SMIMC)	[1 1]
SIX CHF SWIIT TR Reits Fund (SWIIT)	[1 1]
SIX CHF SBGM 3-7Y TR Bond Idx (SBGM3T)	[1 1]
BBA CHF 1M Libor Wealth (LIBOR1MW)	[0 0]

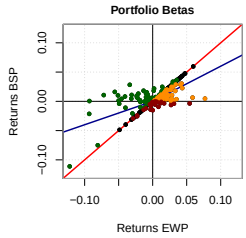
Parameter Settings:
Last Update: Aug 2014
BCP Flexible: 24 Months
Transaction Throttle: On
Independent Averaging: Off
Leverage Factor: 1

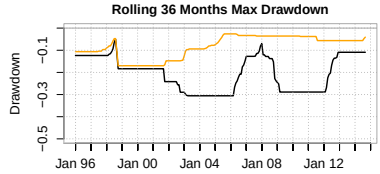


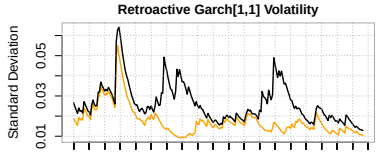


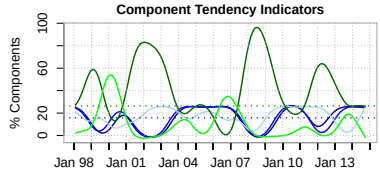


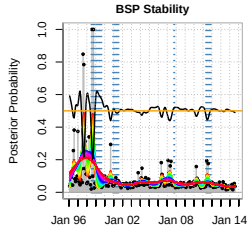


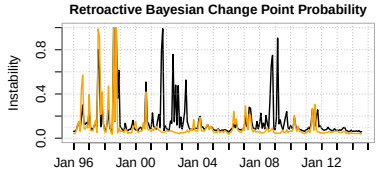


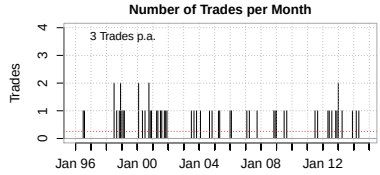












Monthly Performance of Equal Weigths Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	EWP	#M>0	HIT%	G/L	MIN	MAX
2002	-0.9	0.7	3.5	-0.7	1.0	-4.1	-7.2	0.5	-5.1	2.3	1.7	-3.1	-11.4	6	50	0.5	-7.2	3.5
2003	-2.1	-0.8	-0.3	5.4	2.5	1.3	2.1	2.0	-0.3	4.1	1.0	2.1	17.1	8	67	6.0	-2.1	5.4
2004	3.6	1.5	-1.3	1.1	-0.1	0.1	-2.3	0.1	1.4	0.0	1.1	2.6	7.7	9	75	3.1	-2.3	3.6
2005	2.3	1.2	0.4	-0.2	2.4	1.6	3.7	-0.3	3.0	-1.4	1.4	2.7	16.8	9	75	9.6	-1.4	3.7
2006	1.8	2.0	1.5	1.4	-2.9	-0.6	1.7	1.8	1.8	1.9	1.0	3.4	14.8	10	83	5.2	-2.9	3.4
2007	3.5	-2.3	2.2	2.9	0.4	-1.2	-1.3	-1.0	-0.5	0.7	-3.1	-0.8	-0.5	5	42	0.9	-3.1	3.5
2008	-5.6	1.0	-1.9	2.7	1.1	-4.9	0.2	1.5	-3.4	-9.3	-1.3	-1.0	-20.9	5	42	0.2	-9.3	2.7
2009	-0.9	-5.0	2.8	5.9	2.0	0.7	4.3	2.7	2.0	-1.0	0.5	3.1	17.1	9	75	3.5	-5.0	5.9
2010	0.7	0.0	3.5	-0.6	-1.9	-1.4	1.4	0.0	2.2	0.6	-0.2	1.9	6.2	6	50	2.5	-1.9	3.5
2011	0.1	1.3	-1.3	1.8	0.5	-2.7	-3.1	-2.4	-1.0	2.7	-1.2	1.6	-3.7	6	50	0.7	-3.1	2.7
2012	1.3	2.1	1.1	0.3	-2.3	1.2	3.0	-0.4	0.5	-0.2	2.2	0.7	9.5	9	75	4.2	-2.3	3.0
2013	3.1	1.4	1.6	1.2	0.7	-3.0	2.0	0.2	1.4	1.3	1.0	0.4	11.3	11	92	4.8	-3.0	3.1
2014	0.6	2.1	0.9	0.9	1.1	-0.3	0.2	1.4					6.9	7	88	25.4	-0.3	2.1

Performance and Risk Statistics

	BSP	EWP
Mean Monhtly Return %	0.70	0.52
Mean Monthly Standard Dev %	1.87	2.64
Average Annualized Return %	8.70	6.39
Average Ann. Volatility %	6.49	9.15
Sharpe Ratio	0.37	0.20
Maximum Drawdown %	-16.98	-30.55
No of Positive Months	163.00	150.00
Pos/Neg No of Month Ratio	2.63	2.00
Monthly Gain/Loss Ratio	2.86	1.69
Semi Deviation	0.01	0.02
Historical VaR (95%)	-0.02	-0.04
Historical ES (95%)	-0.04	-0.07
Kurtosis Monthly Returns	7.73	3.53

Monthly Performance of Binary Stability Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	BSP	#M>0	HIT%	G/L	MIN	MAX
2002	0.3	0.6	0.4	0.8	0.9	0.8	1.1	0.7	1.0	1.0	-0.3	1.1	8.3	11	92	25.4	-0.3	1.1
2003	1.3	1.2	-0.8	-0.4	1.9	0.2	0.7	2.0	-0.6	4.1	1.1	1.8	12.8	9	75	8.6	-0.8	4.1
2004	3.6	1.5	-1.3	1.1	-0.1	0.3	-2.6	0.3	1.1	0.0	1.1	2.6	7.5	9	75	2.9	-2.6	3.6
2005	2.3	1.2	0.0	-0.2	2.4	1.6	3.7	-0.3	3.0	-1.4	1.4	2.0	15.7	8	67	9.0	-1.4	3.7
2006	1.8	2.0	1.8	1.6	-2.9	-0.5	1.4	1.6	1.9	2.0	0.8	2.9	14.4	10	83	5.3	-2.9	2.9
2007	3.6	-2.4	2.2	3.0	0.7	-1.0	-1.4	-1.2	0.4	0.0	0.5	-0.3	4.1	7	58	1.6	-2.4	3.6
2008	1.6	0.1	0.2	-0.6	-0.3	-0.4	1.8	0.6	2.8	-2.1	1.8	1.4	6.8	8	67	2.9	-2.1	2.8
2009	1.5	0.1	0.5	0.6	0.3	0.5	2.3	2.7	2.0	-1.0	0.5	3.1	13.2	11	92	14.5	-1.0	3.1
2010	0.7	0.0	3.5	-0.6	-1.9	-1.4	1.4	0.0	2.2	0.6	-0.2	1.9	6.2	6	50	2.5	-1.9	3.5
2011	0.1	1.3	-1.2	1.8	0.1	-2.7	-3.1	0.9	0.7	0.0	-0.1	0.7	-1.3	8	67	0.8	-3.1	1.8
2012	0.3	0.5	0.0	0.2	0.7	-0.1	2.5	-0.5	-0.1	0.5	1.0	0.7	5.7	9	75	9.6	-0.5	2.5
2013	3.1	1.4	1.2	1.1	0.6	-2.1	1.5	-0.1	1.7	1.7	0.6	0.0	10.8	10	83	6.0	-2.1	3.1
2014	-0.1	2.0	0.5	0.9	1.1	-0.3	0.2	1.4					5.6	6	75	16.0	-0.3	2.0

Benchmark Statistics

	BSP to EWP
Alpha	0.00
Beta	0.50
Beta+	0.60
Beta-	0.40
R-squared	0.50
Annualized Alpha	0.05
Correlation	0.70
Correlation p-value	0.00
Tracking Error	0.06
Active Premium	0.03
Information Ratio	0.39
Treynor Ratio	0.17

Market Components

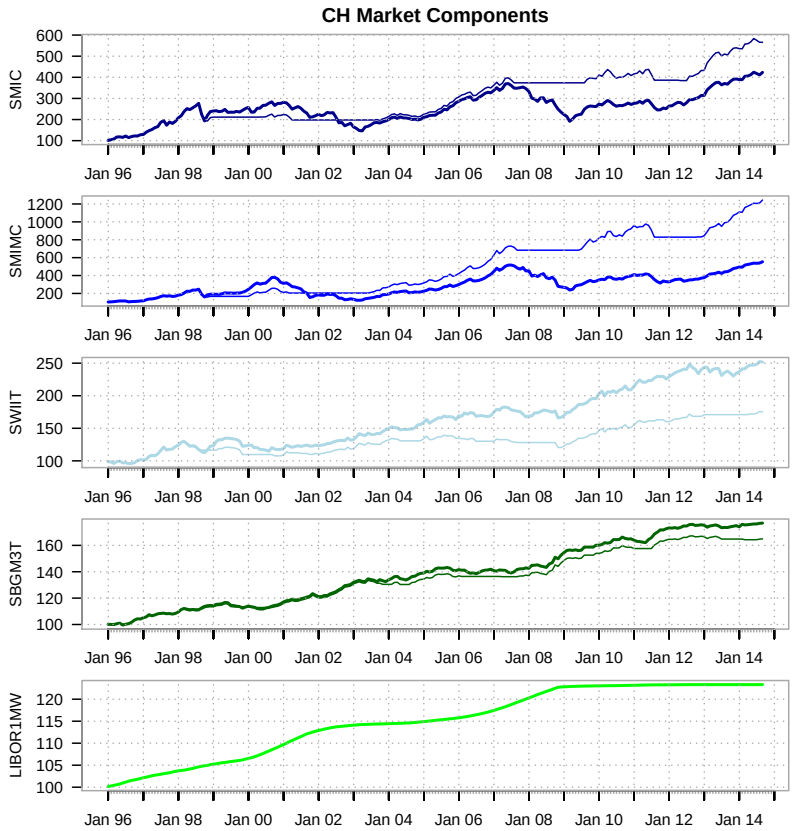


Figure 10: The charts show the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SMIC (darkblue), SMIMC (blue) and SWIIT (lightblue) and the lower charts the less risky asset, SBGM3T (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

Component Drawdowns

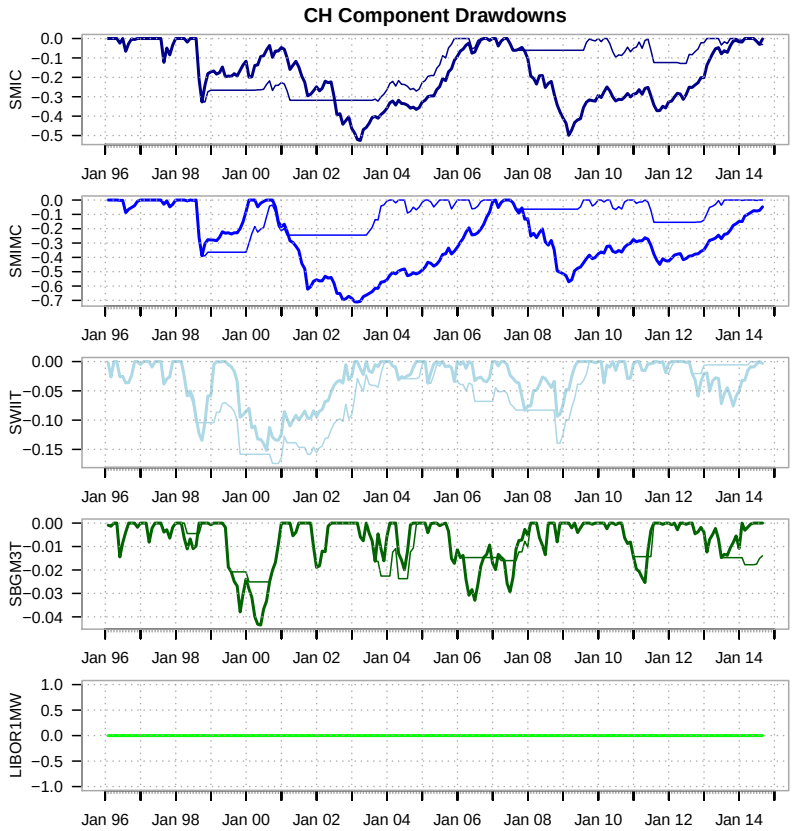


Figure 11: The charts show the drawdowns of the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SMIC (darkblue), SMIMC (blue) and SWIIT (lightblue) and the lower charts the less risky asset, SBGM3T (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

Stabilized Asset Positions

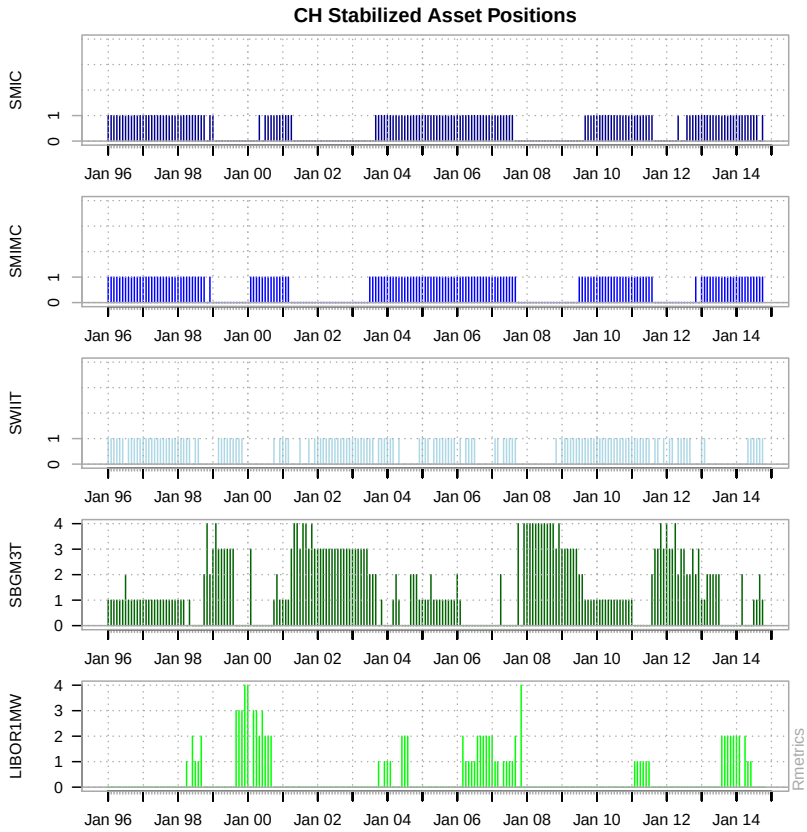


Figure 12: The graph shows the market positions as realized in the Binary Stability Portfolio. The positions can range between zero and four units (the total capital). The risky assets (SMIC, SMIMC, and SWIIT) are limited to one unit (25%), the less and no risk assets (SBGM3T, LIBOR1MW) are allowed to fill the whole range between zero and four units (100%).

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

Structural Change and Break Points Indicator

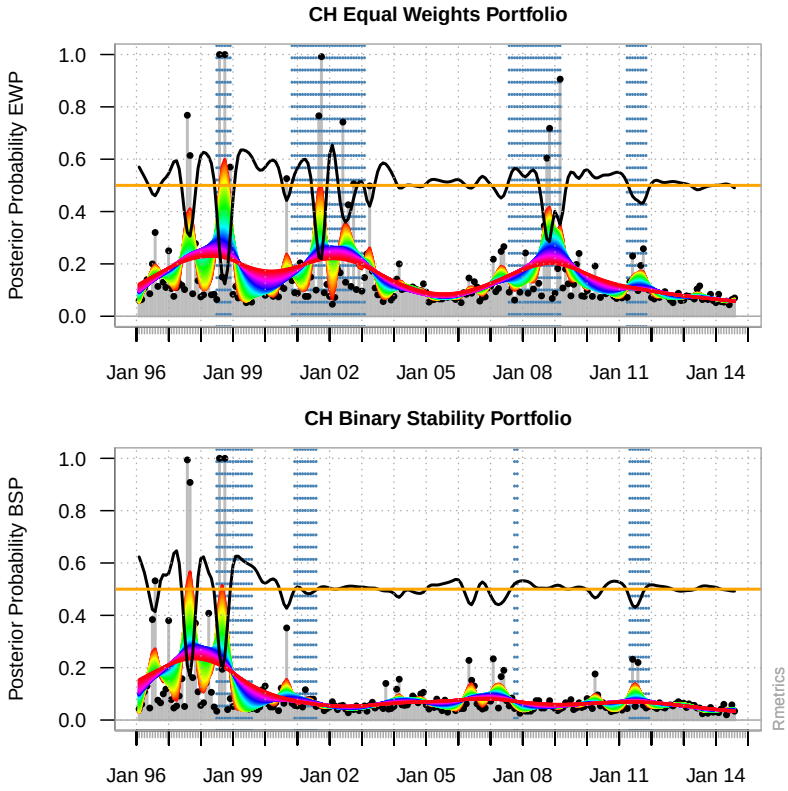


Figure 16: The two charts display the results from the retroactive Bayesian change point analytics. The grey bars with a black dot on top mark the stability probabilities for each month of the financial return series. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colours. From their ranges, 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. The end of the curves can be extrapolated and can serve for forecasting market stability. The upper chart belongs to the Equal Weights Portfolio, the lower chart to the Binary Stability Portfolio.

SMIC | SMIMC | SWIIT | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: Off | Independent Average: Off | Leverage: 1

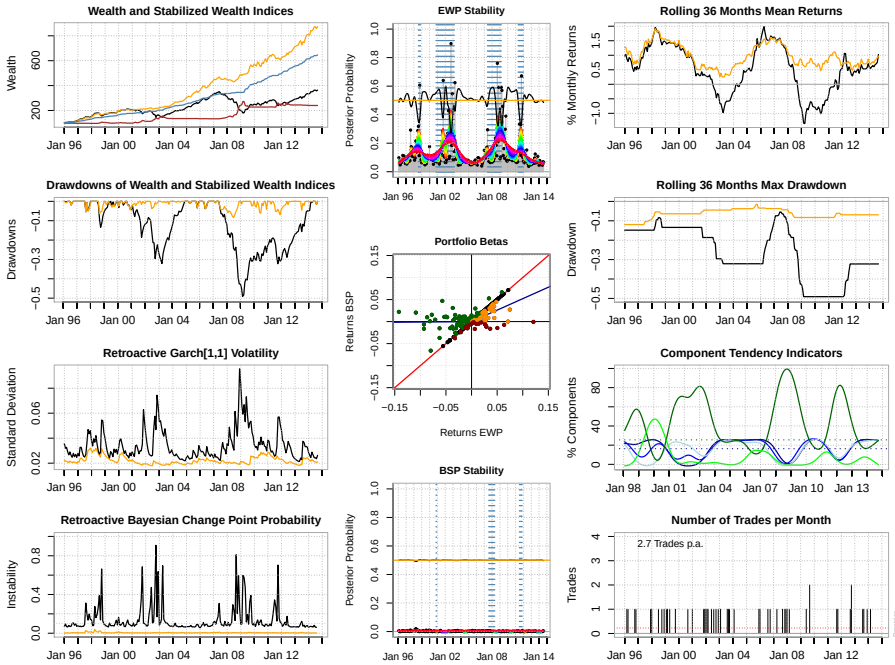
THROTTLED EUROZONE MULTI ASSET PORTFOLIO

Same as for the Throttled Swiss Multi Asset Portfolio.

Euro Multi Asset Portfolio

STOXX EUR EuroStoxx50 TR Index (SX5T)	[1|1]
STOXX EUR Eurozone MCap TR Index (MCXT)	[1|1]
STOXX EUR Reits Sector Index (SXT8600R)	[1|1]
EMTS EUR 3-7Y MEAN TR Bond Idx (EMTS3AM)	[1|1]
BBA EUR 1M Libor Wealth (LIBOR1MW)	[0|0]

Parameter Settings:
Last Update: Aug 2014
BCP Flexible: 24 Months
Transaction Throttle: On
Independent Averaging: Off
Leverage Factor: 1



Monthly Performance of Equal Weigths Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	EWP	#M>0	HIT%	G/L	MIN	MAX
2002	0.5	0.6	2.7	-0.6	-1.1	-6.3	-7.1	-0.4	-10.9	6.4	3.3	-5.0	-17.9	5	42	0.4	-10.9	6.4
2003	-3.2	-2.4	-2.7	7.1	3.8	2.7	2.8	1.6	-1.5	4.2	2.1	2.5	16.8	8	67	2.7	-3.2	7.1
2004	2.8	3.5	-0.3	-0.1	0.4	2.1	-0.4	0.4	1.7	1.8	3.3	3.2	18.5	9	75	22.5	-0.4	3.5
2005	1.9	1.8	-0.6	-0.4	4.8	2.9	2.3	0.6	3.4	-3.5	2.8	3.0	18.8	9	75	5.2	-3.5	4.8
2006	3.7	3.1	2.2	-0.5	-3.3	0.6	2.4	2.3	3.6	2.7	1.0	3.9	21.5	10	83	6.5	-3.3	3.9
2007	0.7	-0.7	2.2	0.8	1.7	-3.0	-3.6	-0.1	-1.6	1.4	-3.8	-1.9	-7.8	5	42	0.5	-3.8	2.2
2008	-6.3	0.4	-2.2	2.8	-0.8	-9.3	-1.3	2.1	-8.7	-14.2	-5.7	0.0	-43.0	3	25	0.1	-14.2	2.8
2009	-4.2	-7.8	1.5	12.1	2.7	-0.9	7.5	7.2	2.9	-2.5	0.3	3.5	22.4	8	67	2.5	-7.8	12.1
2010	-2.2	-0.8	5.7	-1.8	-4.2	-0.3	5.2	-1.1	4.0	2.5	-4.2	4.6	7.3	5	42	1.5	-4.2	5.7
2011	1.5	2.4	-1.7	2.6	0.2	-1.2	-3.2	-8.1	-5.3	5.0	-3.0	0.7	-10.3	6	50	0.5	-8.1	5.0
2012	4.4	2.6	1.2	-2.5	-3.7	3.6	3.5	1.9	0.8	2.0	2.0	1.7	17.6	10	83	3.9	-3.7	4.4
2013	0.4	0.9	0.4	3.2	1.4	-4.7	4.4	-1.1	4.2	3.9	0.7	-0.1	13.5	9	75	3.3	-4.7	4.4
2014	0.4	4.3	-0.2	1.2	2.6	0.0	-1.5	1.8					8.5	5	62	5.9	-1.5	4.3

Performance and Risk Statistics

	BSP	EWP
Mean Monhtly Return %	0.97	0.59
Mean Monthly Standard Dev %	2.24	3.51
Average Annualized Return %	12.37	7.29
Average Ann. Volatility %	7.77	12.17
Sharpe Ratio	0.43	0.17
Maximum Drawdown %	-8.29	-49.11
No of Positive Months	155.00	142.00
Pos/Neg No of Month Ratio	2.21	1.71
Monthly Gain/Loss Ratio	3.12	1.54
Semi Deviation	0.02	0.03
Historical VaR (95%)	-0.03	-0.06
Historical ES (95%)	-0.04	-0.08
Kurtosis Monthly Returns	0.61	1.80

Monthly Performance of Binary Stability Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	BSP	#M>0	HIT%	G/L	MIN	MAX
2002	1.0	1.1	1.3	0.6	-0.1	-3.7	0.4	0.7	2.0	-0.7	0.8	1.1	4.6	9	75	2.0	-3.7	2.0
2003	1.5	1.2	-0.4	0.0	3.3	-0.7	0.4	0.9	-1.5	4.2	2.1	2.2	12.9	9	75	5.9	-1.5	4.2
2004	2.8	3.5	-0.3	-0.1	0.4	2.1	-0.4	0.4	1.7	1.8	3.3	3.2	18.5	9	75	22.5	-0.4	3.5
2005	1.9	1.8	-0.6	-0.4	4.8	2.9	2.3	0.6	3.4	-3.5	1.9	3.0	17.9	9	75	5.0	-3.5	4.8
2006	3.7	3.1	2.2	-0.3	-3.5	0.4	2.2	2.1	3.6	2.7	1.0	3.9	21.0	10	83	6.6	-3.5	3.9
2007	0.9	-0.9	2.2	0.8	2.0	-2.8	-1.6	0.1	0.2	1.6	-1.1	-0.7	0.6	7	58	1.1	-2.8	2.2
2008	-1.5	0.9	-0.4	-1.0	-1.5	-0.6	1.1	2.2	1.0	2.2	4.7	1.4	8.4	7	58	2.6	-1.5	4.7
2009	-1.5	1.5	0.7	-0.1	0.8	0.6	2.7	7.2	2.9	-2.5	0.3	3.5	16.2	9	75	5.0	-2.5	7.2
2010	-2.2	-0.8	5.7	-1.8	-4.2	-0.3	5.2	-1.1	4.0	2.5	-4.2	4.6	7.3	5	42	1.5	-4.2	5.7
2011	1.8	2.3	-1.5	2.5	-0.3	-1.3	-3.8	0.1	1.1	-1.5	-1.5	3.0	0.9	6	50	1.1	-3.8	3.0
2012	0.8	0.8	0.4	0.7	3.1	-1.6	3.0	-0.2	0.8	2.0	2.0	1.7	13.5	10	83	8.5	-1.6	3.1
2013	0.4	0.9	0.4	3.2	1.4	-4.7	3.5	-0.9	4.0	3.7	0.7	-0.1	12.3	9	75	3.2	-4.7	4.0
2014	-0.2	4.3	-0.2	1.2	2.6	0.0	-1.5	1.8					7.9	4	50	5.1	-1.5	4.3

Benchmark Statistics

	BSP to EWP
Alpha	0.01
Beta	0.38
Beta+	0.52
Beta-	0.01
R-squared	0.35
Annualized Alpha	0.09
Correlation	0.60
Correlation p-value	0.00
Tracking Error	0.10
Active Premium	0.06
Information Ratio	0.56
Treynor Ratio	0.32

Market Components

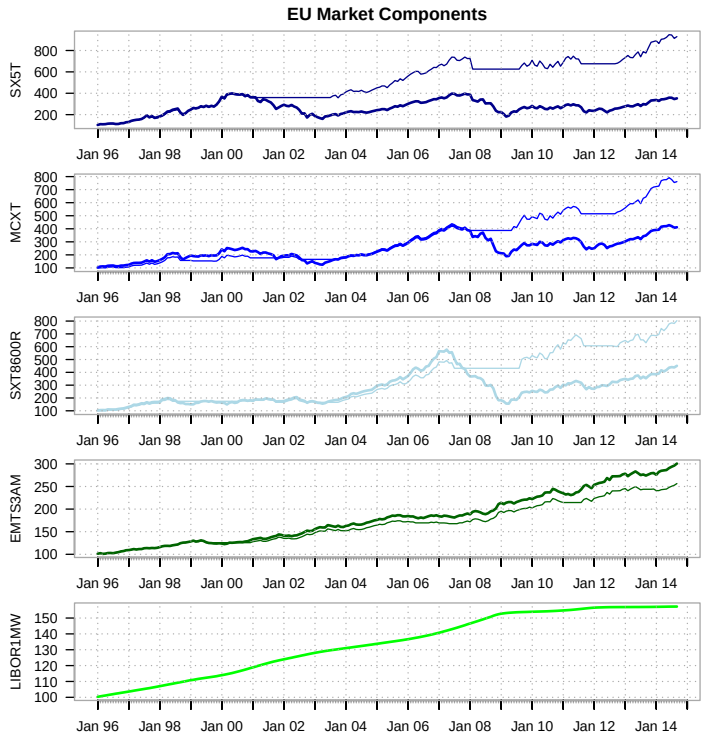


Figure 10: The charts show the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SX5T (darkblue), MCXT (blue) and SXT8600R (lightblue) and the lower charts the less risky asset, EMTS3AM (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SX5T | MCXT | SXT8600R | EMTS3AM | LIBOR1MW
Aug 2014 | EUR | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

Component Drawdowns

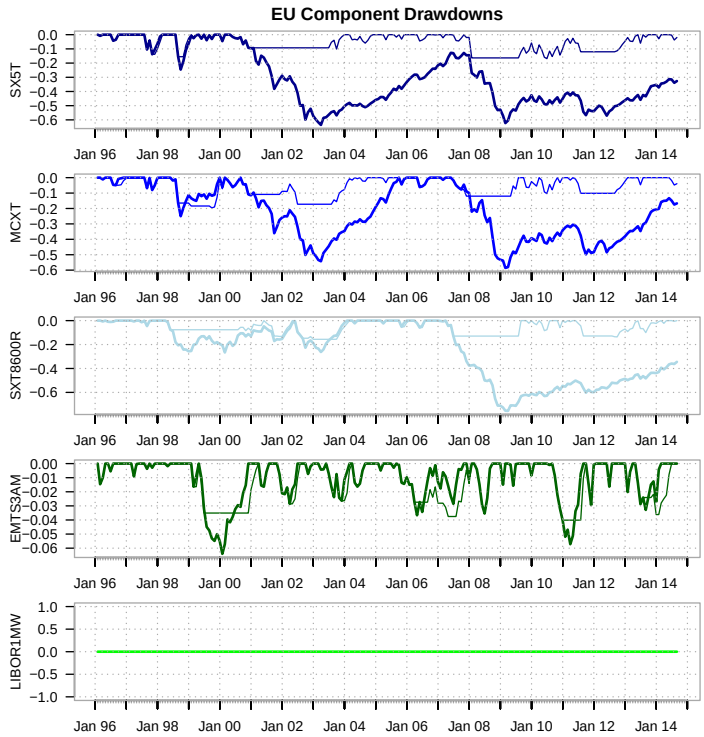


Figure 11: The charts show the drawdowns of the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SX5T (darkblue), MCXT (blue) and SXT8600R (lightblue) and the lower charts the less risky asset, EMTS3AM (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SX5T | MCXT | SXT8600R | EMTS3AM | LIBOR1MW
Aug 2014 | EUR | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

Stabilized Asset Positions

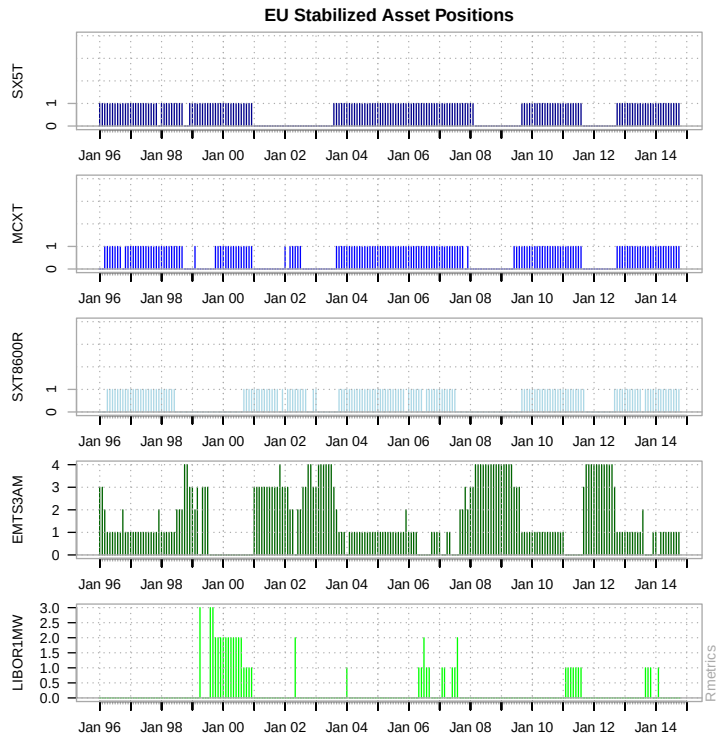


Figure 12: The graph shows the market positions as realized in the Binary Stability Portfolio. The positions can range between zero and four units (the total capital). The risky assets (SX5T, MCXT, and SXT8600R) are limited to one unit (25%), the less and no risk assets (EMTS3AM, LIBOR1MW) are allowed to fill the whole range between zero and four units (100%).

SX5T | MCXT | SXT8600R | EMTS3AM | LIBOR1MW
Aug 2014 | EUR | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

Structural Change and Break Points Indicator

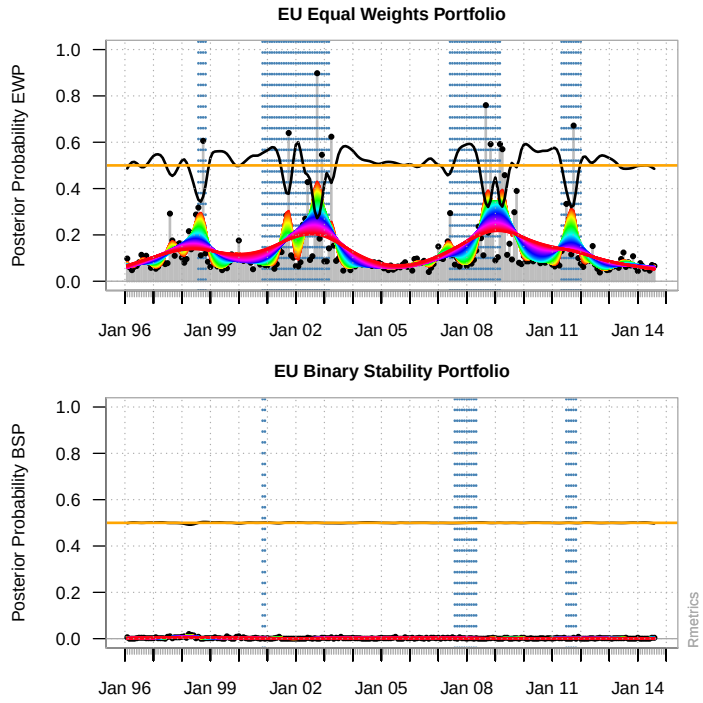


Figure 16: The two charts display the results from the retroactive Bayesian change point analytics. The grey bars with a black dot on top mark the stability probabilities for each month of the financial return series. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colours. From their ranges, 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. The end of the curves can be extrapolated and can serve for forecasting market stability. The upper chart belongs to the Equal Weights Portfolio, the lower chart to the Binary Stability Portfolio.

SX5T | MCXT | SXT8600R | EMTS3AM | LIBOR1MW
Aug 2014 | EUR | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

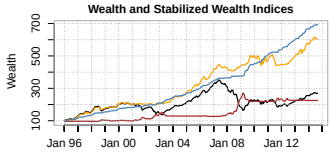
THROTTLED EUROZONE MULTI ASSET PORTFOLIO IN SWISS FRANC

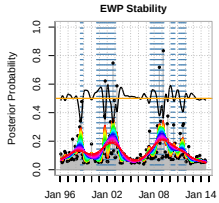
Same as for the Throttled Eurozone Multi Asset Portfolio. With the difference that the portfolios currency is in Swiss Francs (CHF).

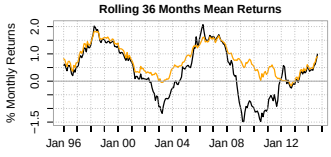
Euro-Swiss Multi Asset Portfolio

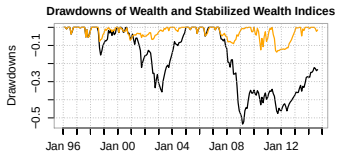
STOXX CHF EuroStoxx50 TR Index (SX5T)	[1|1]
STOXX CHF Eurozone MCap TR Index (MCXT)	[1|1]
STOXX EUR Reits Sector Index (SXT8600R)	[1|1]
SIX CHF SBGM 3-7Y TR Bond Idx (SBGM3T)	[1|1]
BBA CHF 1M Libor Wealth (LIBOR1MW)	[0|0]

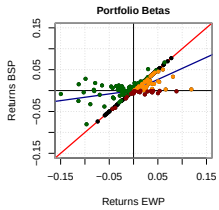
Parameter Settings:
Last Update: Aug 2014
BCP Flexible: 24 Months
Transaction Throttle: On
Independent Averaging: Off
Leverage Factor: 1

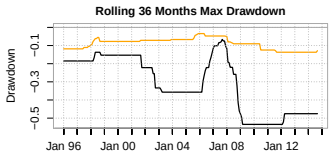


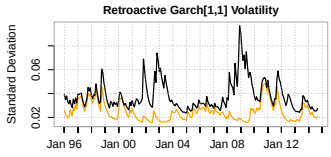


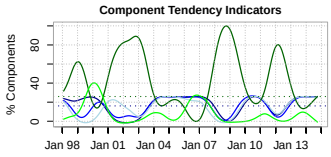


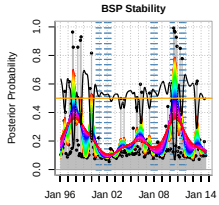


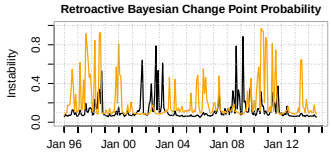


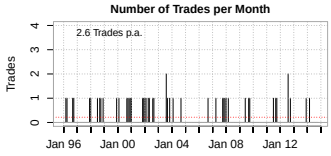












Monthly Performance of Equal Weigths Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	EWP	#M>0	HIT%	G/L	MIN	MAX
2002	0.2	0.8	2.4	-0.7	-1.0	-6.0	-8.1	0.1	-11.3	6.6	3.8	-6.5	-19.7	6	50	0.4	-11.3	6.6
2003	-2.7	-2.8	-2.1	8.8	4.2	3.8	2.7	1.1	-1.6	4.4	2.5	2.9	21.4	8	67	3.3	-2.8	8.8
2004	3.0	4.1	-1.3	-0.4	-0.7	1.9	0.1	0.4	2.1	1.8	1.3	4.5	16.7	9	75	7.9	-1.3	4.5
2005	2.2	1.3	-0.2	-1.1	4.9	2.9	2.9	0.0	3.6	-3.5	2.4	3.4	18.7	8	67	4.9	-3.5	4.9
2006	3.6	3.7	2.9	-0.7	-4.3	1.1	2.6	2.4	4.0	2.8	1.1	4.6	23.7	10	83	5.7	-4.3	4.6
2007	1.6	-1.3	2.8	1.8	1.8	-2.6	-4.1	-0.2	-0.9	1.1	-4.2	-1.5	-5.7	5	42	0.6	-4.2	2.8
2008	-8.9	-0.3	-3.2	5.0	0.1	-10.3	0.2	0.7	-9.9	-14.9	-7.9	-3.0	-52.3	4	33	0.1	-14.9	5.0
2009	-3.6	-8.2	2.8	11.9	3.1	-0.7	8.1	6.0	2.5	-2.5	0.1	2.6	22.2	8	67	2.5	-8.2	11.9
2010	-3.3	-1.1	3.9	-1.7	-5.2	-5.9	7.0	-5.0	6.1	2.7	-5.7	1.7	-6.4	5	42	0.8	-5.9	7.0
2011	3.7	2.0	-0.5	1.9	-3.8	-2.2	-7.4	-7.0	-2.4	5.4	-2.1	-0.5	-12.9	4	33	0.5	-7.4	5.4
2012	3.6	2.4	1.0	-2.8	-4.3	4.0	2.9	1.9	1.2	1.9	1.5	1.7	15.1	10	83	3.1	-4.3	4.0
2013	2.4	-0.3	0.0	3.4	2.6	-4.9	4.1	-0.9	3.5	4.4	0.6	-0.3	14.7	8	67	3.3	-4.9	4.4
2014	-0.1	3.6	0.0	1.1	2.3	-0.6	-1.6	0.8					5.5	5	62	3.3	-1.6	3.6

Performance and Risk Statistics

	BSP	EWP
Mean Monhtly Return %	0.81	0.45
Mean Monthly Standard Dev %	2.54	3.88
Average Annualized Return %	10.15	5.55
Average Ann. Volatility %	8.80	13.45
Sharpe Ratio	0.32	0.12
Maximum Drawdown %	-13.69	-53.45
No of Positive Months	147.00	140.00
Pos/Neg No of Month Ratio	1.88	1.65
Monthly Gain/Loss Ratio	2.39	1.35
Semi Deviation	0.02	0.03
Historical VaR (95%)	-0.04	-0.07
Historical ES (95%)	-0.05	-0.10
Kurtosis Monthly Returns	1.01	1.39

Monthly Performance of Binary Stability Portfolio

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	BSP	#M>0	HIT%	G/L	MIN	MAX
2002	0.1	0.6	0.4	1.0	0.0	-3.8	-0.1	0.9	1.5	0.3	0.4	1.2	2.5	9	75	1.6	-3.8	1.5
2003	0.6	0.5	-0.6	-0.2	1.6	-0.4	2.1	1.1	-1.9	4.4	2.6	2.6	12.6	8	67	5.1	-1.9	4.4
2004	3.0	4.1	-1.3	-0.4	-0.6	2.0	-0.1	0.4	2.1	1.8	1.3	4.5	16.7	8	67	7.9	-1.3	4.5
2005	2.2	1.3	-0.2	-1.1	4.9	2.9	2.9	0.0	3.6	-3.5	2.4	3.4	18.7	8	67	4.9	-3.5	4.9
2006	3.6	3.7	3.2	-0.5	-4.4	0.7	0.9	2.2	3.9	2.8	1.0	4.9	22.1	10	83	5.5	-4.4	4.9
2007	1.8	-1.5	2.8	1.9	2.1	-2.4	-1.9	-0.5	0.8	0.6	-1.6	-0.1	2.0	6	50	1.3	-2.4	2.8
2008	-3.2	0.1	0.2	-0.6	-0.3	-0.4	1.8	0.6	2.8	-0.8	1.8	1.2	3.2	7	58	1.6	-3.2	2.8
2009	1.1	0.2	-0.2	0.3	1.6	-0.2	3.3	5.0	2.5	-2.5	0.1	2.6	13.8	9	75	5.7	-2.5	5.0
2010	-3.3	-1.1	3.9	-1.7	-5.2	-5.9	7.0	-5.0	6.1	2.7	-5.7	1.7	-6.4	5	42	0.8	-5.9	7.0
2011	3.7	2.0	-0.4	1.9	-4.1	-2.2	-7.4	-1.0	1.0	-0.1	0.5	0.4	-5.6	6	50	0.6	-7.4	3.7
2012	-0.1	0.2	-0.3	0.4	0.6	-0.1	2.7	1.1	1.2	1.9	1.5	1.7	10.8	9	75	27.5	-0.3	2.7
2013	2.4	-0.3	0.0	3.4	2.6	-4.9	4.0	-0.9	3.4	4.3	0.6	-0.3	14.5	8	67	3.3	-4.9	4.3
2014	-0.4	3.6	0.0	1.1	2.3	-0.6	-1.6	0.8					5.2	5	62	2.9	-1.6	3.6

Benchmark Statistics

	BSP to EWP
Alpha	0.01
Beta	0.45
Beta+	0.53
Beta-	0.16
R-squared	0.47
Annualized Alpha	0.07
Correlation	0.69
Correlation p-value	0.00
Tracking Error	0.10
Active Premium	0.05
Information Ratio	0.52
Treynor Ratio	0.22

Market Components

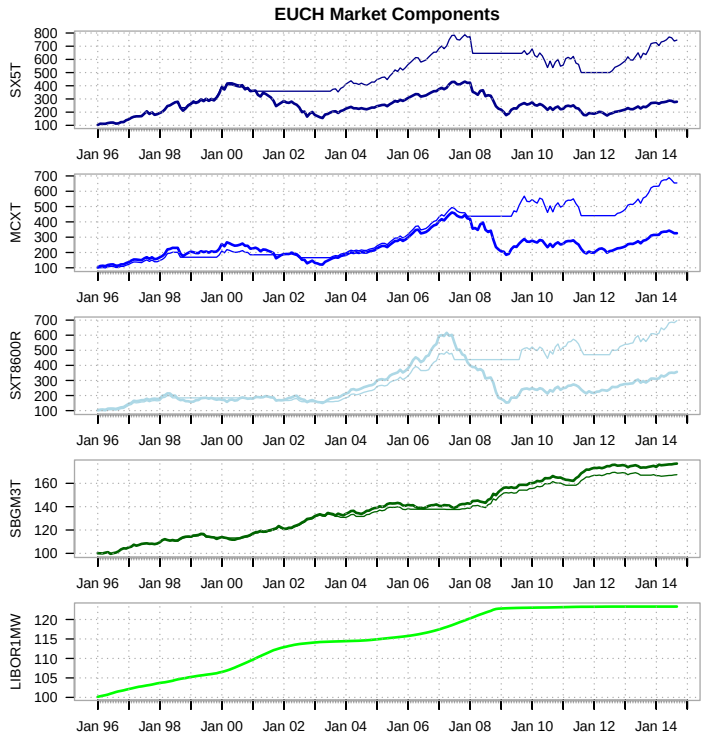


Figure 10: The charts show the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SX5T (darkblue), MCXT (blue) and SXT8600R (lightblue) and the lower charts the less risky asset, SBGM3T (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SX5T | MCXT | SXT8600R | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

Component Drawdowns

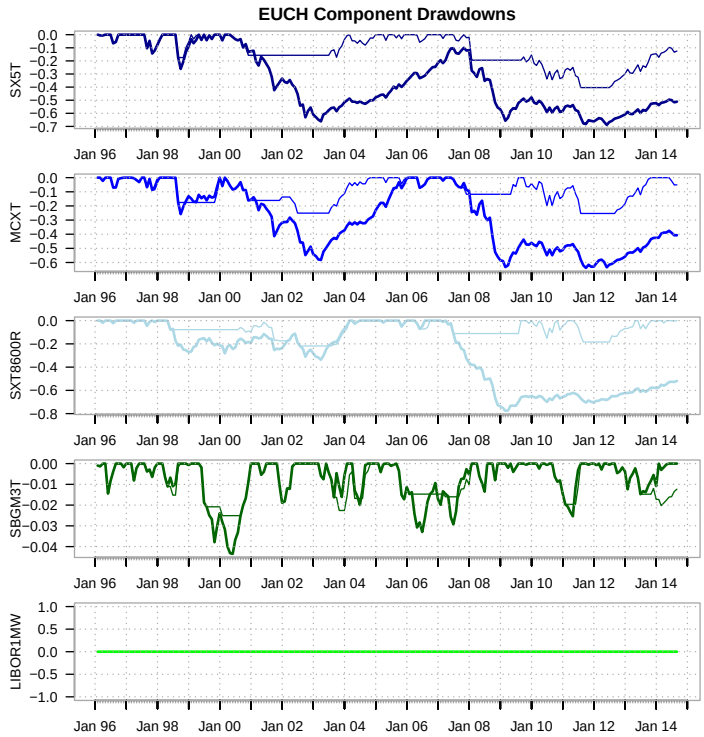


Figure 11: The charts show the drawdowns of the market indices from which we composed the Equal Weights and the Binary Stability Portfolios. The upper charts visualize the risky assets, SX5T (darkblue), MCXT (blue) and SXT8600R (lightblue) and the lower charts the less risky asset, SBGM3T (darkgreen) as well as the no risk asset, LIBOR1MW (green). The bold curves belong to the original indices and the thin curves to the stabilized indices. Note that the stabilized indices are shown including additional parameters like the leverage or the transaction throttle.

SX5T | MCXT | SXT8600R | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

Stabilized Asset Positions

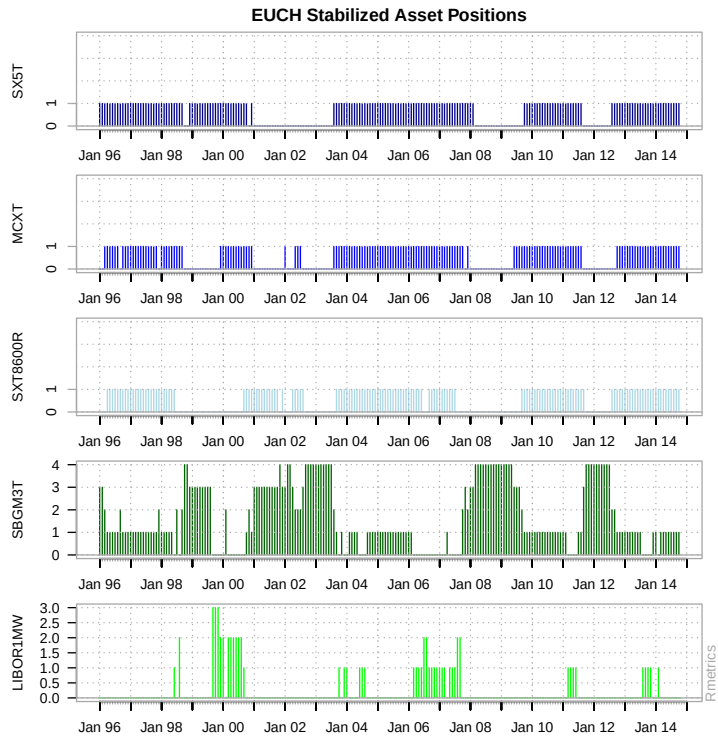


Figure 12: The graph shows the market positions as realized in the Binary Stability Portfolio. The positions can range between zero and four units (the total capital). The risky assets (SX5T, MCXT, and SXT8600R) are limited to one unit (25%), the less and no risk assets (SBGM3T, LIBOR1MW) are allowed to fill the whole range between zero and four units (100%).

SX5T | MCXT | SXT8600R | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

Structural Change and Break Points Indicator

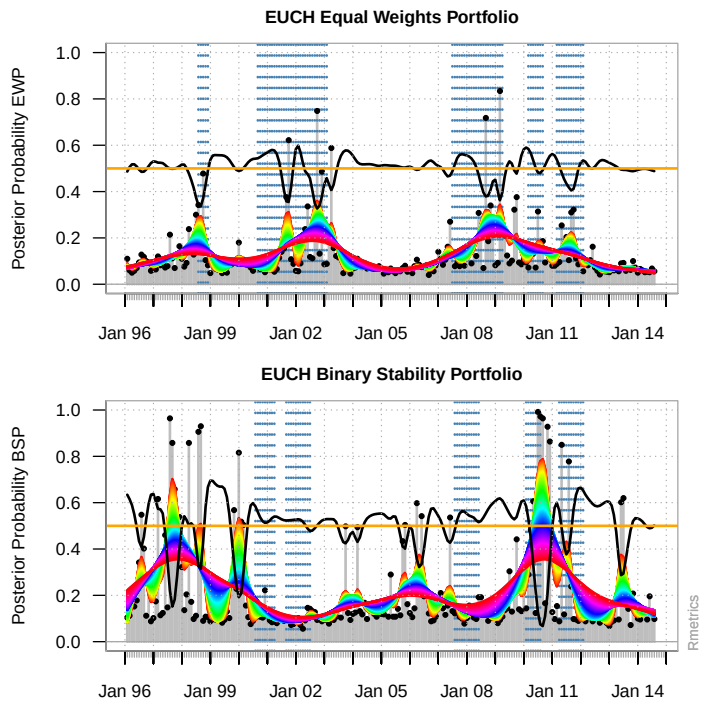


Figure 16: The two charts display the results from the retroactive Bayesian change point analytics. The grey bars with a black dot on top mark the stability probabilities for each month of the financial return series. These probabilities are smoothed on a whole bundle of curves with different degrees of smoothness dyed by rainbows colours. From their ranges, 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. The end of the curves can be extrapolated and can serve for forecasting market stability. The upper chart belongs to the Equal Weights Portfolio, the lower chart to the Binary Stability Portfolio.

SX5T | MCXT | SXT8600R | SBGM3T | LIBOR1MW
Aug 2014 | CHF | BCP Flexible: 24 Month | Throttle: On | Independent Average: Off | Leverage: 1

CHAPTER 8

SECTOR ROTATION AND EQUITIES

Bayes'sche Investment Strategie: Stabilitätsanalyse des Swiss Performance Indexes

Tobias Setz[1], Diethelm Würtz[1], Cyril Bachelard[2] und Lorenz Beyeler[2]
[1] Institut für Theoretische Physik, ETH Zürich
[2] OLZ Management AG Berne
Preprint, 2014

How to apply the Bayesian Stability Control to Sector indices and to equities was investigated in a research report funded through a student internship by OLZ in Berne. The work presented consists of three parts: (i) stabilization of the SPI index, (ii) stabilization of each industry sector index to use them for an equally weighted portfolio, (iii) stabilization of tradition companies that are at least 10 years on the market to use them for an equaly weighted portfolio.

Our study shows that both, the equally weighted sector rotated portfolio and the equally weighted portfolio of tradition companies perform better with lower risk after stabilization.

The results were presented at the Rmetrics Workshop in Paris, June 2014.

Bayes'sche Investment Strategie: Stabilitätsanalyse des Swiss Performance Indexes

Tobias Setz[1], Diethelm Würtz[1], Cyril Bachelard[2] und Lorenz Beyeler[2]
[1]Institut für Theoretische Physik, ETH Zürich
[2]OLZ Management AG Berne

12. Mai 2014
Diese Version: 13. Juni 2014

Zusammenfassung

"Bayes'sche Statistik" und "Markov Chain Monte Carlo" Methoden sind zwei mächtige Verfahren, die es uns erlauben strukturelle Veränderungen in dynamischen Systemen aufzuspüren und zu quantifizieren. Würtz et al. [2010] haben damit begonnen diese Verfahren zu benutzen und weiterzuentwickeln um strukturelle Stabilität als neues zentrales Mass für die Beurteilung von Ertrag und Risiko von Investmentanlagen zu definieren.

In diesem Bericht benutzen wir die "Produkt Partitions Methode" von Barry und Hartigan [1992, 1993] in der Implementation von Erdman und Emerson [2008]. Wir stellen einen neuen Investment Indikator und ein neues stabilitätsgewichtetes Umschichtungsverfahren vor, das wir am SPI erproben. Ziel ist es, das in den SPI investierte Kapital besser zu schützen.

Unsere Bayes'sche Investment Strategie wenden wir auf den SPI Index an, dessen Sektorenindizes, und auf über 100 im Index gelistete Einzeltitel. Das Resultat is ein kapitalgeschütztes Investment mit einem stabilen positiven Trend in den Erträgen, mit signifikant tiefen Ertragseinbrüchen, mit kurzen Erholungsphasen bei Gewinneinbrüchen sowie mit niedrigen und wenig fluktuierenden Volatilitäten.

Inhaltsverzeichnis

1 Einleitung **2**

2 Schweizer Aktienindex seit 1925 **3**

3 SPI Sektorenindizes seit 1999 **6**

4 SPI Traditionsunternehmen seit 2004 **12**

5 Zusammenfassung **16**

1 Einleitung

Dieser Bericht befasst sich mit der Ertrags- und Risikoanalyse des Swiss Performance Indexes (SPI), seiner Sektorenindizes, sowie mit der Analyse von 131 traditionsreichen Einzeltiteln die eine Kurshistorie von mehr als zehn Jahren besitzen.

Der SPI ist der Gesamtmarktindex für den Schweizer Aktienmarkt. Er enthält fast alle an der *Swiss Exchange* [2014] gehandelten Beteiligungspapiere von schweizerischen Firmen. Nicht enthalten sind Papiere deren "Free Float" kleiner als 20% ist, sowie Investmentgesellschaften. Der SPI ist nach Sektoren wirtschaftlicher Tätigkeit eingeteilt. Der SPI ist ein *Total Return Index* oder *Performance Index*, d.h. die Auszahlungen von Dividenden werden bei der Indexberechnung mit berücksichtigt. Der Index wurde am 1. Juni 1987 eingeführt und auf einen Indexstand von 1000 Punkten festgelegt. Für historische Werte vor 1987 haben wir die Kurse des *Swiss Banking Corporation* Indexes [2007] verwendet, und davor Kurse von der *Schweizerischen Nationalbank* [2007].

Bei der Untersuchung kommt die *Produkt Partitions Methode*, PPM, zur Anwendung die strukturelle Veränderungen in Zeitreihen mit der *Bayes'schen Strukturbruchmethode*, BCP, und mit einer *Markov Chain Monte Carlo*, MCMCM, Methode analysiert. Dabei bauen wir auf das Verfahren von Barry und Hartigan [1992, 1993] in der Implementierung von Erdman und Emerson [2008] auf. Die grundlegende Idee die wir dabei verfolgen ist ähnlich wie bei Volatilitätsindikatoren. Das PPM Verfahren partitioniert zunächst zur Lokalisierung und zur Messung der Stärke von strukturellen Veränderungen die Zeitreihe in Cluster. Innerhalb eines Clusters nehmen wir an, dass die Modellparameter unverändert gleich bleiben und sich an den Partitionsgrenzen verändern. Die Verteilung der Parameter innerhalb eines Clusters nimmt unabhängig und identisch verteilte Grössen an. Die Verteilung aller Cluster lässt sich dann als *Produkt* der Einzelverteilungen beschreiben.

Bei einem Kurseinbruch erwarten wir an den Partitionsgrenzen, ähnlich wie beim plötzlichen Ansteigen der Volatilität, dass sich in der Dynamik des Prozesses strukturelle Veränderungen abspielen oder sich eventuell sogar Strukturbrüche manifestieren. Da sich in der Regel solche Stressszenarien über endlich lange Zeitperioden hinweg aufbauen, erwarten wir, dass diese sich in messbaren Grössen äussern.

Der Stabilitätsindikator der die Portfoliogewichte und die Umschichtung der Positionen letztendlich bestimmt wird aus dem Erwartungswert aus Rendite (aposteriori BCP Mittelwerte) und deren Variabilitäten (aposteriori BCP Varianzen) berechnet, wobei die zugrundeliegende Dichte durch das Stabilitätsmass (aposterioriori Wahrscheinlichkeit, dass zum nächsten Zeitpunkt ein Strukturbruch vorliegt) gegeben wird. Die prognostizierte Stärke des Indikators in Bezug auf eine adaptive Schwelle bestimmt dann ob das Investment getätigt wird oder nicht. Die Konstruktion verschiedener massgeschneiderter Stabilitätsindikatoren ist denkbar, der hier zur Anwendung gebrachte lässt sich folgendermassen interpretieren: Solange ein Aufwärts- oder Abwärtstrend vorherrscht und die Stabilität ihn weiterführt, gehen wir davon aus, dass der Trend auch in der Zukunft weiterbesteht. Ist dies nicht der Fall gehen wir davon aus, dass eine Kurswende erfolgt. Auf der Basis dieser Analyse wird eine neuartige Investmentstrategie aufgezeigt, bei der die einzelnen Portfoliokomponenten, Sektoren oder auch Einzeltitel, nach den Signalen der stabilitätsgewichteten Indikatoren ausgewählt werden.

Es sei anzumerken, dass der BCP Algorithmus von Barry und Hartigan [1992, 1993] in verschiedene Richtungen erweitert werden kann. Für die Verteilung der Renditen kann anstelle einer Normalverteilung eine "fat tailed" Verteilung in Betracht gezogen werden, z.B. die NIG Verteilung, welche extreme Werte in den Ausläufern der Renditeverteilung und die Leptokurtosis im Zentrum der Verteilung besser beschreibt. Desweiteren können höhere Momente mit in die BCP Analyse mit eingebunden werden, d.h. z.B. Strukturbrüche in der Volatilität, in der Schiefe, oder in der Kurtosis der Verteilung. Es können aber auch die rollenden BCP Zeitfenster die wir hier benutzen durch

einen BCP Online Algorithmus ersetzt werden, der die Fensterlängen dann adaptiv anpasst. Für die Wahl der Schwellen welche die Signale und Positionen bestimmen lassen sich ebenfalls diverse alternative Optionen vorstellen. Somit lässt sich eine ganze Familie von BCP Indikatoren und Investment Strategien erzeugen, die auf bestimmte Bedürfnisse hin entworfen und massgeschneidert werden können. Einige dieser Erweiterungen befinden sich derzeit in Bearbeitung.

Der Bericht ist folgendermassen aufgebaut: Abschnitt 2 befasst sich mit der Analyse von Strukturbrüchen im SPI Langzeit-Index bis zurück ins Jahr 1925. Danach untersuchen wir im dritten Abschnitt die SPI Sektoren, deren Kurse seit Dezember 1999 ermittelt werden. in Abschnitt 4 führen wir dann die Analyse von Strukturbrüchen an 131 an der SIX gehandelten SPI Einzeltiteln durch.

2 Schweizer Aktienindex seit 1925

Wir starten mit der Analyse des schweizerischen Langzeit-Aktienindexes. Wir wollen wissen wie stabil sich die Dynamik dieses Indexes über fast ein Jahrhundert hinweg verhalten hat. Am besten kann man die Veränderungen in der Dynamik erkennen und beurteilen wenn man sich das Ergebnis der "Bayes'schen Statistik" und der "Markov Chain Monte Carlo" Methode vor Augen führt.

Den Kern dieser Kennzahlen bilden die Masszahlen für den (i) Index, für die (ii) Ertragseinbrüche (Drawdowns), für den (iii) Strukturbruch-Stabilitätsindikator und für die (iv) prognostizierten Signale und Positionen. Diese Kennzahlen sind in einer retroaktiven BCP Analyse entnommen und in Abbildung 1 dargestellt.

Stabile Renditen und Ertragseinbrüche für den Langzeit Index

Wir wollen nun eine zeitlich rollende Out-of-Sample Analyse durchführen. Die Ergebnisse für die Renditen und die Ertragseinbrüche sind in Abbildung 2 dargestellt. Das oberste Bild zeigt den logarithmierten Index des kapitalgewichteten Langzeit-Indexes (schwarz). Im Vergleich dazu sehen wir den stabilisierten Index (orange). Dieser Index ist investiert wenn die prognostizierte Position 1 ist und nicht investiert wenn die Position 0 ist. Die Position wird aus einem Signal ermittelt, das sich aus dem Stabilitätsindikator berechnet. Die Kurshistorie für den Langzeit-Index beginnt am 31 Dezember 1925. Unsere Berechnung der Bayes'schen Statistik benötigt einen Vorlauf von 36 Monaten, so dass unsere Kurshistorie explizit am 31. Dezember 1928 beginnt. Wir haben zu diesem Zeitpunkt den Index auf 1 normiert. Das heisst, eine Investition von 1 CHF hat am 30. April 2014 einen Ertrag von 12'001 CHF erbracht. Wenn wir nun nur zu wirtschaftlich stabilen Zeiten über die gleiche Zeitperiode investieren wächst der Gesamtbetrag hingegen auf 86'524 CHF an. Das ist ein Faktor 7 mehr.

Die Ursache dafür wird aus den Ertragseinbrüchen (Drawdowns) ersichtlich. Der SPI zeigt 4 Perioden mit Verlusten in der Grössenordnung von 50%. Bleibt man jedoch dem Markt zu instabilen Zeiten fern oder sichert sich entsprechend gegen die Verluste ab, beobachtet man nur noch 2 Perioden mit Ertragseinbrüchen von ca. 20%.

Stabilitätsindikator und Positionen

Der Stabilitätsindikator ist das Mass, das darüber entscheidet, ob die Renditen aus einer stabilen Dynamik heraus entstanden sind, oder ob wir uns in einer fragilen Phase mit Turbulenzen befinden. Rollen wir den Indikator über ein Zeitfenster hinweg und bewerten seine zeitliche Entwicklung in Bezug auf eine aktuelle Schwelle in den Quantilen der Verteilung so erhalten wir Signale oder Positionswerte von 1 (oberhalb der Schwelle) bzw. von 0 (unterhalb). Dieser Schwellenwert unterteilt

dann die Marktsituation in “stabil” bzw. “instabil”. Indikator und Positionen sind in den unteren beiden Bildern von Abbildung 2 dargestellt. Es ist klar zu erkennen dass die (instabilen) Positionen mit den Ertragseinbrüchen korrelliert sind.

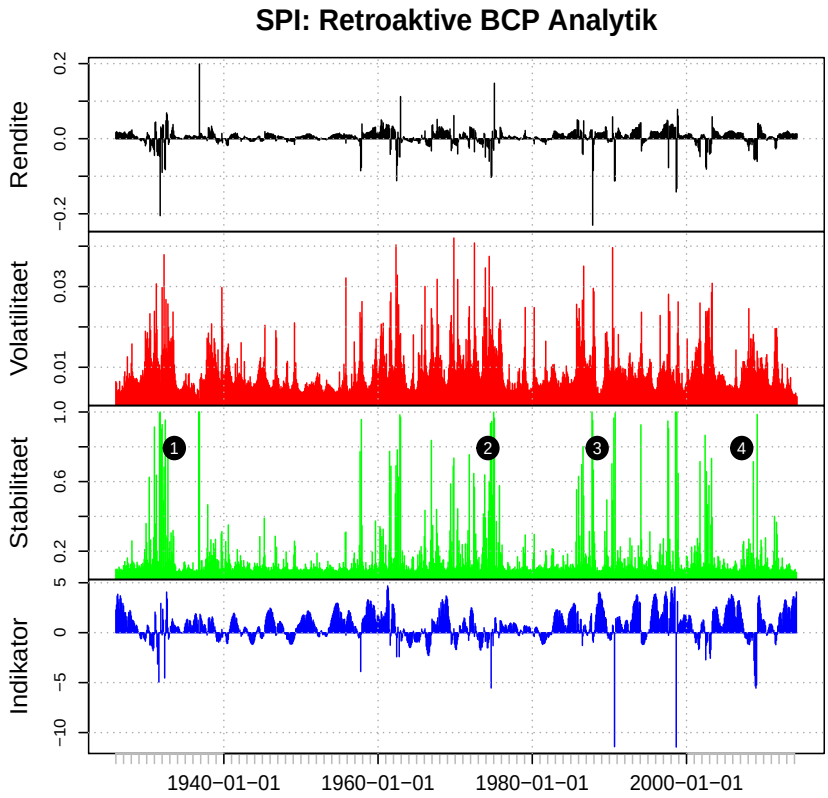


Abbildung 1: Monatliche Out-of-Sample Strukturbruchanalyse nach dem Bayes’schen Verfahren für logarithmierte Renditen. Der Gesamtindex der schweizerischen Aktien started im Dezember 1925 und endet im Mai 2014. Von oben nach unten: (i) Die posterior BCP Renditen, (ii) deren posterior BCP Variabilitäten (Standardabweichung), (iii) die posterior Wahrscheinlichket, dass der nächste Zeitpunkt ein Strukturbruch aufzeigt, und (iv) der gemittelte stabilitätsgewichtete Indikator. Die vier Punkte markieren den (1) schwarzen Donnerstag 1929, den (2) Oel Schock und die Aktienmarktkrise 1973/1974, den (3) schwarzen Montag 1987, und den (4) Zusammenbruch von Lehman Brothers 2008.

Fragmentierung der Positionen und stabilisierte Renditen

Die SPI Daten umfassen einen Zeitraum von 1026 Monaten (85.5 Jahre). Der Index wurde an 617 Monaten stabil bewertet, das sind 60.1% der Zeit. Die mittlere logarithmische Rendite des Indexes betrug 5.61% monatlich, die des stabilisierten Indexes betrug dagegen 7.91%.

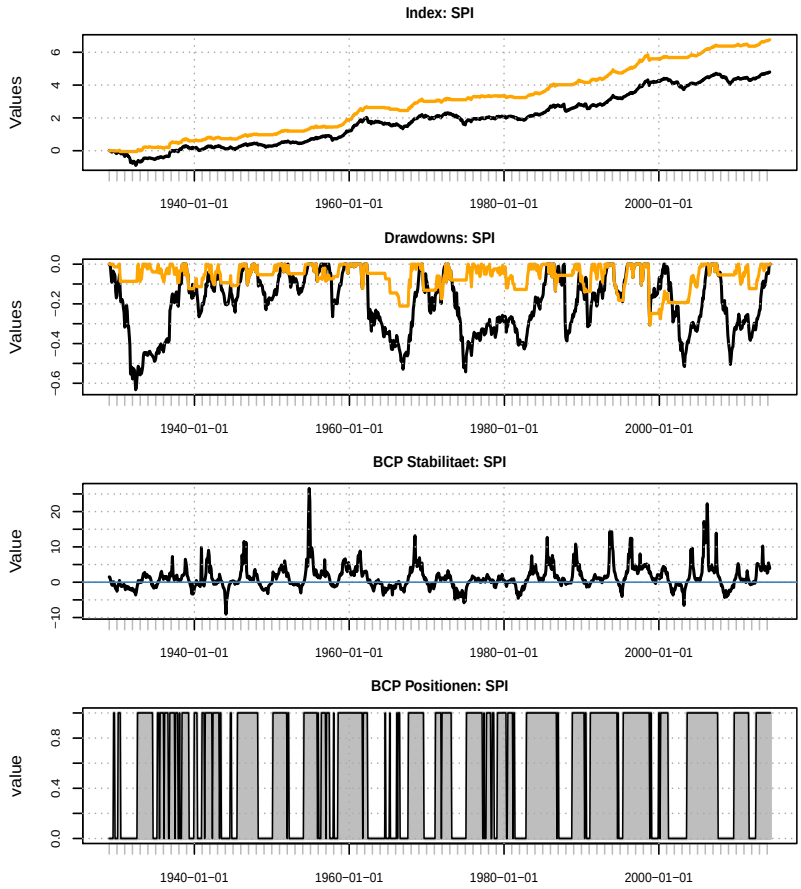


Abbildung 2: Von oben nach unten: (i) Kapital- (schwarz) und stabilitätskorrigierter (orange) Langzeit-Index, (ii) Ertragseinbrüche (Drawdowns), (iii) Stabilitätsindikator, (iv) Stabilitätsgewichtung des Langzeit-Indexes.

3 SPI Sektorenindizes seit 1999

Die gleichen Stabilitätskennzahlen haben wir für die SPI Sektorenindizes berechnet. Diese können zur Konstruktion eines stabilitätsgewichteten Sektor Portfolios herangezogen werden.

SPI Sektorindex Daten

Die SPI Sektorenindizes werden von der Swiss Exchange nach dem ICB Klassifizierungsstandard ICB (Industry Classification Benchmark) zusammengestellt. Die 10 Sektoren sind:

CH0022635152	2263515	SWX ID OIL&GAS TR	C0001T
CH0022635194	2263519	SWX ID BASICMAT TR	C1000T
CH0022635210	2263521	SWX ID INDUSTRY TR	C2000T
CH0022635301	2263530	SWX ID CONGOODS TR	C3000T
CH0022647017	2264701	SWX ID HLTHCARE TR	C4000T
CH0022647256	2264725	SWX ID CONSERV TR	C5000T
CH0022647405	2264740	SWX ID TELECOM TR	C6000T
CH0022647835	2264783	SWX ID UTILITIES TR	C7000T
CH0022647934	2264793	SWX ID FINANCE TR	C8000T
CH0022652785	2265278	SWX ID TECH TR	C9000T

Abbildung 3: Sektoren des SPI Indexes. Von links nach rechts: ISIN, Valorennummer, Beschreibung, SIX Code.

Bis auf den Oel und Gassektor (Kurse erst seit 3. Januar 2007 verfügbar) wurden die Sektoren mit einem Basiswert von 1000 am 30. Dezember 1999 eingeführt. Im folgenden werden wir den Oel und Gassektor (mangels Daten) von unserer Analyse ausschliessen.

Stabilitätsindikatoren für die SPI Sektorenindizes

Wie wir bereits beim SPI Gesamtindex gesehen haben, führt auch der stabilitätsgewichtete SPI Sektorenindex zu einem markant höheren Ertrag und gleichzeitig zu weniger tiefen Ertragseinbrüchen wenn man die Ergebnisse mit den originären nicht stabilitätsgewichteten Indizes vergleicht.

Gemittelte Stabilität und gemittelte Position zeigen jeweils drei Perioden auf, an denen der Markt als instabil eingeschätzt wurde. Die Minimalwerte wurden im Septemer 2008 und im August 2011 erreicht.

Stabilisierung des Gleichgewichteten Sektorenindexes

Es stellt sich nun natürlich die Frage, ob es nicht ausreichend gewesen wäre die Stabilisierung direkt auf den SPI Index anzuwenden und sich die Stabilisierung der einzelnen Sektoren zu ersparen. In der Tat beobachtet man bereits bei dieser vereinfachten Vorgehensweise nur eine geringe Verschlechterung der Ergebnisse. Der Index und die Ertragseinbrüche sind bei der direkten Stabilisierung etwas tiefer und die Varianzen der Renditen und der Ertragseinbrüche etwas grösser. Der essentielle Punkt wird aber in Abbildung 5 ersichtlich. Der stabilisierte SPI Gesamtindex hat wesentlich ausgeprägtere Instabilitätspitzen im Vergleich zum Portfolio das aus den stabilitätsgewichteten Sektorenindizes gebildet wurde.

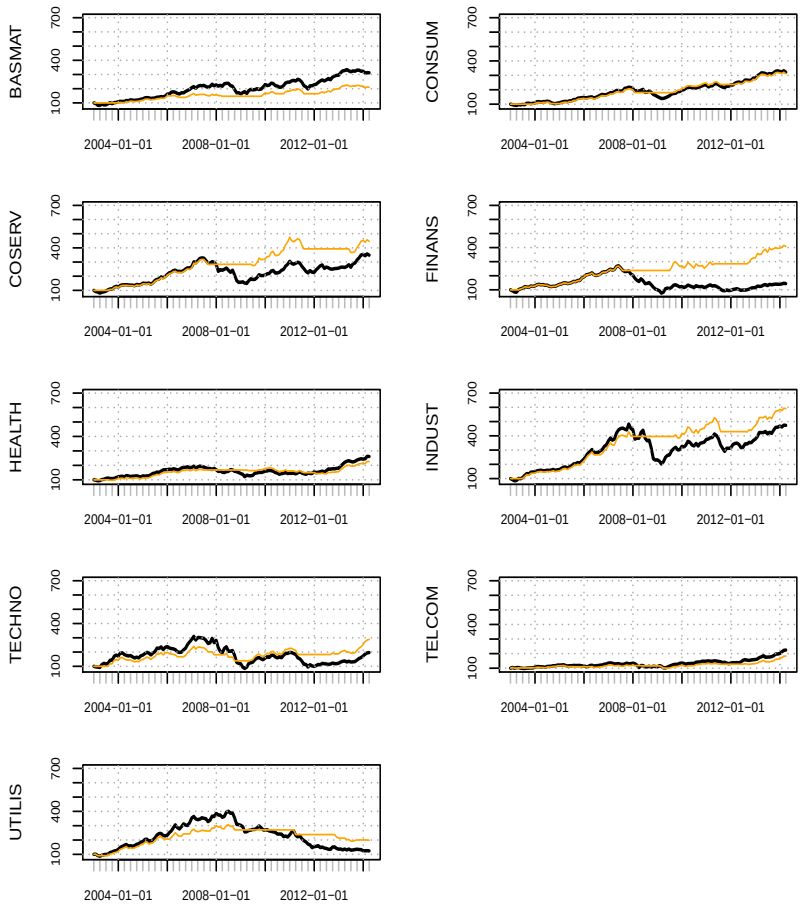


Abbildung 4: Kapital- (schwarz) und stabilitätsgewichtete (orange) SPI Sektoren Indizes. Alle Indizes sind auf 100 indexiert. Die Skalen sind für eine bessere Vergleichbarkeit in allen neun Graphiken gleich justiert. Nach der Stabilisierung wurden die höchsten Erträge im Industrie- und Finanzsektor erzielt.

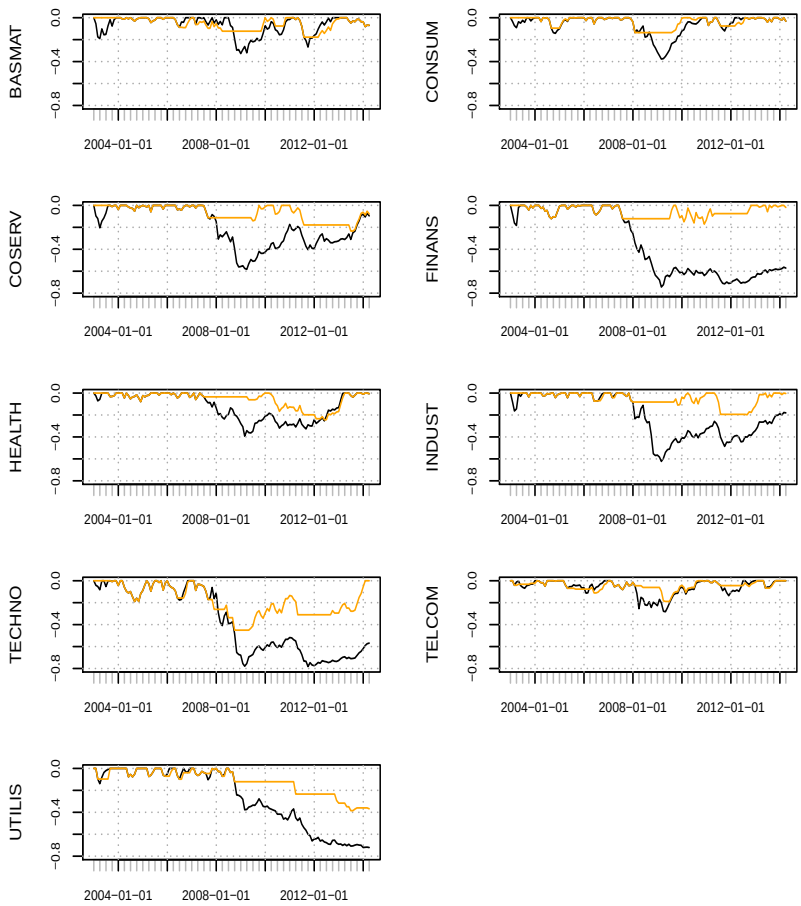


Abbildung 5: Ertragseinbrüche für kapital- (schwarz) und stabilitätsgewichtete (orange) SPI Sektoren Indizes. Die Skalen sind für eine bessere Vergleichbarkeit in allen neun Graphiken gleich (auf 80%) justiert. Die Kapitalsicherung hat für den Finanz-, den Industrie- und den Technologiesektor die besten Ergebniss erzielt. Der tiefste Ertragseinbruch ist beim Technologiesektor mit ca. 40% festzustellen, was allerdings immer noch eine Verbesserung um ca. einen Faktor zwei im Vergleich mit der nicht-stabilisierten Kurve darstellt.

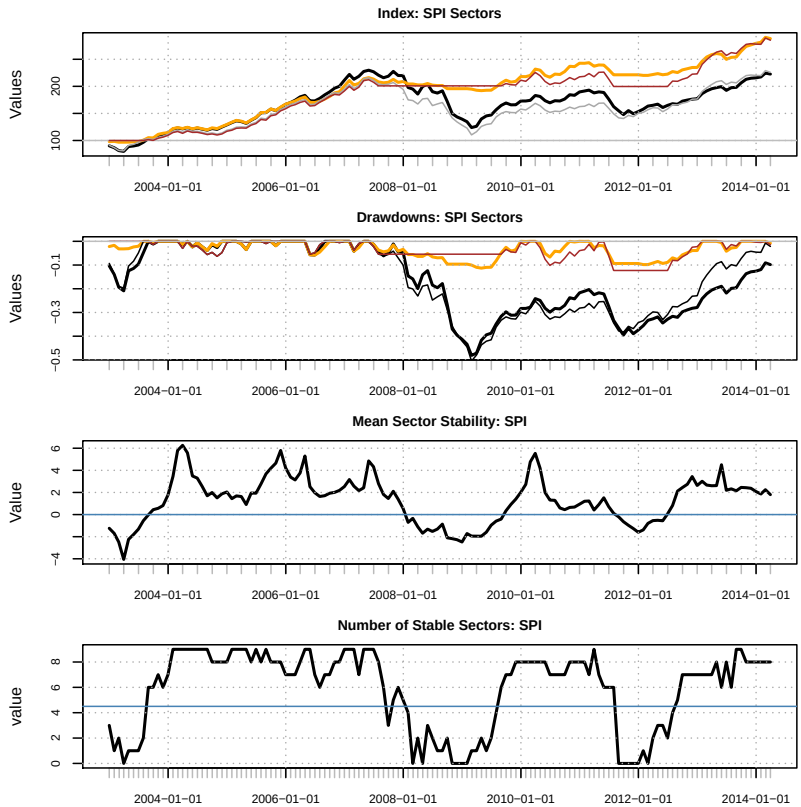


Abbildung 6: Von oben nach unten: (i) Gleich- (schwarz) und stabilitätsgewichteter (orange) SPI Sektoren Index, (ii) Ertragseinbrüche (Drawdowns), (iii) Gemittelter Stabilitätsindex, (iv) Anzahl der stabilen Sektoren aus insgesamt 9 Sektoren. In den Abbildungen für den Index und die Drawdowns sind auch die Ergebnisse für den kapitalgewichteten SPI Index und dessen stabilisierte Variante aufgezeigt.

Als Ergebnis dürfen wir festhalten, dass ein nach Stabilitätsprinzipien gewichtetes Sektoren Portfolio im Vergleich zu einem gleichgewichten Sektoren Portfolio zu einem an Ertrag reicheren, an Risiko aversierteren und somit insgesamt zu einem weniger fragilen Portfolio geführt hat. Dies ist die Grundlage zum Design von kapitalgeschützten Portfolios mit Hilfe der BCP Analyse.

Positionen für die Einzelsektoren

Abbildung 8 listed die Sequenzen der Positionen für jeden der neun Sektorenindizes sowie für die aggregierten Werte des stabilisierten Portfolios. In der Tabelle sind die letzten 5 Jahre aufgelisted.

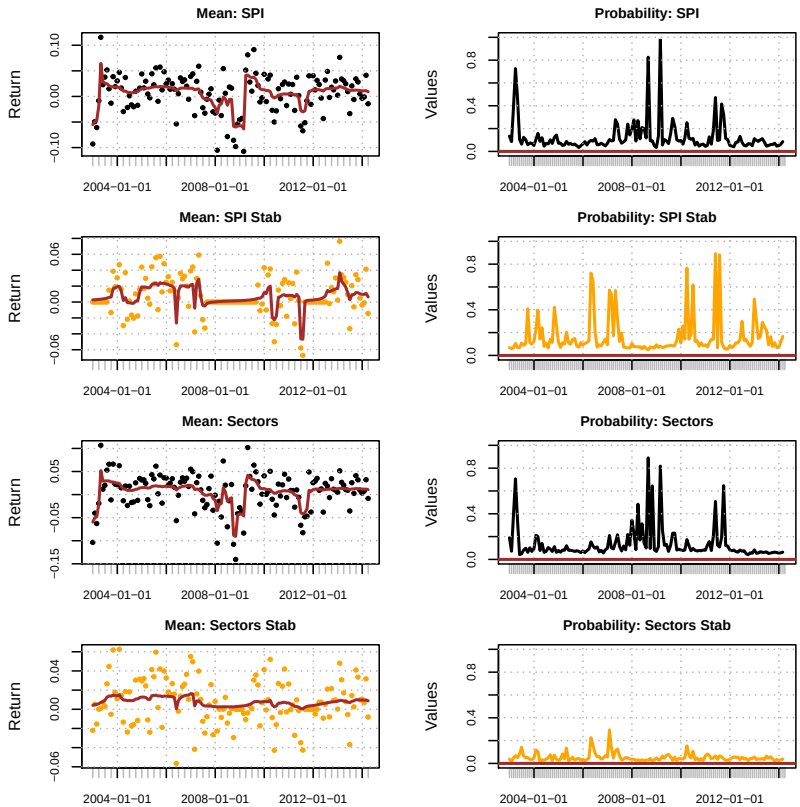


Abbildung 7: Von oben nach unten: Mittelwerte der Renditen (Punkte) und Bayesian Posterior Mean (brown) sowie rechts die Wahrscheinlichkeit, dass zum nächsten Zeitpunkt ein Strukturbruch auftritt. Erste Reihe: Für den SPI Index. Zweite Reihe: Für den stabilitätsgeschützten SPI. Dritte Reihe: Für den gleichgewichteten SPI Sektorenindex. Vierte Reihe: Für den satbiltätsgewichteten SPI Sektorenindex.

Es ist bemerkenswert, dass die Sequenzen für die Positionen nur wenig fragmentiert sind. Dies steht in der Regel im Gegensatz zu den Ergebissen wie man sie von klassischen *Moving Average* Trading Indikatoren erwartet.

Um die Fragmentierung zu quantifizieren und eine Ordnung für die einzelnen Indizes herzustellen haben wir die Autokorrelationsfunktion berechnet, siehe Abbildung 9. Die höchste Fragmentierung zeigt der Utilities Index auf, die niedrigste der Finanzsektor. Das stabilisierte Sektoren Portfolio selbst ist noch weniger fragmentiert als der Finanzindex.

	BASMAT	CONSUM	COSERV	FINANS	HEALTH	INDUST	TECHNO	TELCOM	UTILIS	SUM
2014-03-31	0	1	1	1	1	1	1	1	1	8
2014-02-28	1	1	1	1	1	1	1	1	0	8
2014-01-31	1	1	1	1	1	1	1	1	0	8
2013-12-31	1	1	1	1	1	1	1	1	0	8
2013-11-30	1	1	1	1	1	1	1	1	0	8
2013-10-31	1	1	1	1	1	1	1	1	0	8
2013-09-30	1	1	1	1	1	1	1	1	1	9
2013-08-31	1	1	1	1	1	1	1	1	1	9
2013-07-31	1	1	0	1	1	1	0	1	0	6
2013-06-30	1	1	1	1	1	1	1	0	1	8
2013-05-31	1	1	0	1	1	1	0	1	0	6
2013-04-30	1	1	0	1	1	1	1	1	1	8
2013-03-31	1	1	0	1	1	1	1	1	0	7
2013-02-28	1	1	0	1	1	1	1	1	0	7
2013-01-31	1	1	0	1	1	1	1	1	0	7
2012-12-31	1	1	0	1	1	1	0	1	1	7
2012-11-30	1	1	0	1	1	1	0	1	1	7
2012-10-31	1	1	0	1	1	1	1	1	0	7
2012-09-30	1	1	0	1	1	1	1	1	0	7
2012-08-31	1	1	0	0	1	1	0	1	0	5
2012-07-31	1	1	0	0	1	0	0	1	0	4
2012-06-30	1	1	0	0	0	0	0	0	0	2
2012-05-31	1	1	0	0	1	0	0	0	0	3
2012-04-30	1	1	0	0	1	0	0	0	0	3
2012-03-31	1	1	0	0	0	0	0	0	0	2
2012-02-29	0	0	0	0	0	0	0	0	0	0
2012-01-31	0	0	0	0	1	0	0	0	0	1
2011-12-31	0	0	0	0	0	0	0	0	0	0
2011-11-30	0	0	0	0	0	0	0	0	0	0
2011-10-31	0	0	0	0	0	0	0	0	0	0
2011-09-30	0	0	0	0	0	0	0	0	0	0
2011-08-31	0	0	0	0	0	0	0	0	0	0
2011-07-31	1	1	1	0	1	1	0	1	0	6
2011-06-30	1	1	1	0	1	1	0	1	0	6
2011-05-31	1	1	1	0	1	1	0	1	0	6
2011-04-30	1	1	1	1	0	1	1	1	0	7
2011-03-31	1	1	1	1	1	1	1	1	1	9
2011-02-28	1	1	1	1	0	1	1	1	0	7
2011-01-31	1	1	1	1	1	1	1	1	0	8
2010-12-31	1	1	1	1	1	1	1	1	0	8
2010-11-30	1	1	1	1	1	1	1	1	0	8
2010-10-31	1	1	1	1	1	1	1	1	0	8
2010-09-30	0	1	1	1	1	1	1	1	0	7
2010-08-31	0	1	1	1	1	1	1	1	0	7
2010-07-31	0	1	1	1	1	1	1	1	0	7
2010-06-30	0	1	1	1	1	1	1	1	0	7
2010-05-31	1	1	1	1	1	1	1	1	0	8
2010-04-30	1	1	1	1	1	1	1	1	0	8
2010-03-31	1	1	1	1	1	1	1	1	0	8
2010-02-28	1	1	1	1	1	1	1	1	0	8
2010-01-31	1	1	1	1	1	1	1	1	0	8
2009-12-31	1	1	1	1	1	1	1	1	0	8
2009-11-30	1	1	1	1	1	1	1	1	0	8
2009-10-31	0	1	1	1	1	1	1	1	0	7
2009-09-30	0	1	1	1	1	1	1	1	0	7
2009-08-31	0	1	1	1	1	0	1	1	0	6
2009-07-31	0	0	1	1	0	0	1	1	0	4
2009-06-30	0	0	1	0	0	0	1	0	0	2
2009-05-31	0	0	0	0	0	0	1	0	0	1
2009-04-30	0	0	0	0	1	0	0	1	0	2

Abbildung 8: Prognostizierte Erwartungswerte der 9 SPI Sektorenindizes füer Positionen der letzten 5 Jahre. Die letzte Kolonne gibt die Anzahl der investierten Sektorenindizes an.

UTILIS	HEALTH	TECHNO	TELCOM	BASMAT	CONSUM	COSERV	INDUST	FINANS	SUM
0.151	0.406	0.650	0.715	0.733	0.794	0.811	0.853	0.863	0.874

Abbildung 9: Fragmentation der Sequenzen der Positionen ausgedrückt durch den Autokorrelationskoeffizienten.

4 SPI Traditionsunternehmen seit 2004

Aus den ca. 220 Einzeltiteln des Swiss Performance Index Universums (Stand Mai 2014) haben wir ein Portfolio aus schweizerischen Traditionsunternehmen konstruiert. Das Portfolio ist aus Einzeltiteln zusammengesetzt, die eine Markthistorie von mindestens 10 Jahren vorweisen können.

Symbol	Description	ISIN	Symbol	Description	ISIN
ABBN	ABB N	CH0012221716	LEHN	LEM Hldg N	CH0022427626
ACUN	Accu Hldg N	CH0001366332	LLB	Liechtenst Landesbk	LI0030195247
ADEN	Adecco N	CH0012138605	LIFE	LifeWatch N	CH0012815459
AFGN	AFG Arbonia N	CH0110240600	LISN	Lindt & Spruengli N	CH0010570759
AIRN	Air Tech Group N	CH0242606942	LISP	Lindt&Spruengli PS	CH0010570767
AIRE	AIRESIS N	CH0010947627	LOEP	Loeb Holding BE PS	CH0002045497
ALLN	Allreal Hldg N	CH0008837566	LONN	Lonza Grp N	CH0013841017
ALSN	ALSO Holding N	CH0024590272	LUKN	Luzerner KB N	CH0011693600
APGN	APG SGA N	CH0019107025	METN	METALL ZUG N -B-	CH0039821084
ARYN	Aryzta N	CH0043238366	MASN	Micronas Semicond N	CH0012337421
ASCN	Ascom Hldg N	CH0011339204	MIKN	Mikron Hldg N	CH0003390066
BALN	Baloise Hldg N	CH0012410517	NESN	Nestle N	CH0038863350
BARN	Barry Callebaut N	CH0009002962	NOBN	Nobel Biocare N	CH0037851646
BSLN	Basilea Pharmaceu N	CH0011432447	OFN	Orell Fuessli Hld N	CH0003420806
BCJ	BC Jura	CH0032991348	PARG	Pargesa Hldg	CH0021783391
BCVN	BCV N	CH0015251710	PAXN	PAX Anlage N	CH0002178348
BEKN	BEKB / BCBE N	CH0009691608	PEDP	Perrot Duval BP	CH0002906938
BELL	Bell N	CH0004410418	PED	Perrot Duval Hldg	CH0002906912
BBN	Bellevue Grp N	CH0028422100	PM	Phoenix Mecano	CH0002187810
BC	Bk Coop	CH0018116472	PSPN	PSP Swiss Propert N	CH0018294154
LINN	Bk Linth N LLB	CH0001307757	REPP	Repower PS	CH0016405844
BOBNN	Bobst Grp N	CH0012684657	CFR	Richemont N	CH0210483332
BON	Bondpartners	CH0006227414	ROG	Roche Hldg G	CH0012032048
BOSN	Bossard Hldg N	CH0238627142	HREN	Romande Energie N	CH0025607331
BPDG	Bq Prof Gestion	CH0002492293	SCHN	Schindler Hldg N	CH0024638212
BCGE	Bque Cant Geneve	CH0001642682	SCHP	Schindler Hldg PS	CH0024638196
BVZN	BVZ Hldg N	CH0008207356	STRN	Schlatter Industr N	CH0002277314
CALN	Calida Hldg N	CH0126639464	NATN	Schw Natl Vers N	CH0100699641
GAV	Carlo Gavazzi	CH0011003594	SWTQ	Schweiter Technolog	CH0010754924
CPGN	Cham Paper Grp N	CH0001931853	SGSN	SGS N	CH0002497458
VCH	Charles Voegele Hld	CH0006937772	SHLTN	SHL Telemedicine R	IL0010855885
CIE	CI COM Pr	CH0001625810	SFZN	Siegfried Hldg N	CH0014284498
CICN	Cicor Technologie N	CH0008702190	SIK	Sika	CH0000587979
CLN	Clariant N	CH0012142631	SOON	Sonova Hldg N	CH0012549785
CZH	Conzzeta	CH0002657986	SXGE	SPI	CH0009987501
CPHN	CPH Chem&Pap H N-A-	CH0001624714	SGKN	St.Galler KB N	CH0011484067
CLXN	Crealogix Hldg N	CH0011115703	STGN	Starrag Group Hd N	CH0002361068
CSGN	CS Group N	CH0012138530	STMN	Straumann Hldg N	CH0012280076
CYTN	Cytos Biotechnolo N	CH0011025217	SUN	Sulzer N	CH0038388911
DAE	Daetwyler Hldg	CH0030486770	SLHN	Swiss Life Hldg N	CH0014852781
FTON	Feintool Intl N	CH0009320091	SPSN	Swiss Prime Site N	CH0008038389
FHZN	Flughafen Zuerich N	CH0010567961	SREN	Swiss Re N	CH0126881561
FORN	Forbo Hldg N	CH0003541510	SCMN	Swisscom N	CH0008742519
GALN	Galenica N	CH0015536466	SLOG	Swisslog Hldg N	CH0012324627
FI-N	Georg Fischer N	CH0001752309	SQN	Swissquote Grp Hl N	CH0010675863
GRKP	Graubuendner KB PS	CH0001340204	SMET	Swmtl Holding	CH0002572268
GMI	Groupe Minoteries N	CH0012949464	SYNN	Syngenta N	CH0011037469
GUR	Gurit Hldg	CH0008012236	TAMN	Tamedia N	CH0011178255
HELN	Helvetia Hldg N	CH0012271687	TECN	Tecan Grp N	CH0012100191
HLEE	Highlight Ev&En	CH0003583256	TEMN	Temenos Grp N	CH0012453913
HOLN	Holcim N	CH0012214059	TOHN	Tornos Hldg N	CH0011607683

Abbildung 10: Liste der SPI Traditionsunternehmen, Teil I

HUE	Huegli Hldg	CH0004647951	UBSN	UBS N	CH0024899483
HBLN	Hyp Bk Lenzburg N	CH0001341608	USIN	USI Grp N	CH0002271010
IFCN	INFICON HLDG N	CH0011029946	VLRT	Valartis Group	CH0001840450
INI	Infranor Inter	CH0007249102	VATN	Valiant Hldg N	CH0014786500
IS	Intershop Hldg	CH0017313948	VALN	Valora Hldg N	CH0002088976
VBSN	IVF HARTMANN Hldg N	CH0187624256	VAHN	VD Assur Hldg N -B-	CH0021545667
JFN	Jungfraubahn Hld N	CH0017875789	VET	Vetropack	CH0006227612
KABN	Kaba Hldg N	CH0011795959	VILN	Villars Hldg N	CH0002609656
KARN	Kardex N	CH0100837282	ROL	Von Roll Hldg	CH0003245351
BSKP	KB Basel PS	CH0009236461	VONN	Vontobel Hldg N	CH0012335540
WKB	KB Wallis	CH0000288735	WARN	Warteck Invest N	CH0002619481
KOMN	Komax Hldg N	CH0010702154	ZEH	Zehnder Grp	CH0132557338
KUD	Kudelski	CH0012268360	ZUBN	Zueblin Imm Hldg N	CH0021831182
KNIN	Kuehne+Nagel Int N	CH0025238863	ZURN	Zurich Insur Grp N	CH0011075394
KUNN	Kuoni R Hldg N -B-	CH0003504856	ZWM	Zwahlen&Mayr Aigle	CH0002661731

Abbildung 11: Liste der SPI Traditionsunternehmen, Teil II

Eine traditionsreiche Firma ist nach dieser Definition ein Unternehmen, das an der Schweizer Börse seit mehr als zehn Jahren vertreten ist.

Stabilität Schweizer Traditionsunternehmen

Die Ergebnisse sind in Abbildung 11 dargestellt. Unser SPI Traditionsindex weist eine geringere Performance aus als der SPI Gesamtindex. Ein Grossteil der Performance wurde also von denjenigen Aktien erzielt, die eine jüngere Firmengeschichte aufweisen. In den letzten zehn Jahren konnte also bei einem Investment in die traditionsreichen Firmen kein Gewinn erzielt werden. Für die 131 Einzeltitel haben wir dann die Stabilitätskennzahlen berechnet. Eine Beschränkung in Investments der stabilen Aktien führt zu einer positiven Rendite und die Ertragseinbrüche der letzten 10 Jahre reduzieren sich auf weniger als 20%.

Im September/October 2008 und im August 2011 brachen die Aktienmärkte massiv ein, der Grund dafür waren die *Sub Prime* Krise und die *Credit Debt* Krise. Obgleich der Verfall der Kurse sich über einen gewissen Zeitraum hinzog seien der 16. September 2008 mit dem Fall von AIG und der 8. August 2011 mit der Herabstufung der Keditwürdigkeit der USA durch Standard and Poors von AAA auf AA+ als markante Ereignisse genannt. Beide Gefahren wurden rechtzeitig als instabile Perioden vom Stabilitätsindikator erkannt.

Die Nulllinie des Stabilitätsindikators und die 50% Linie der Anzahl der stabilen Assets in Abbildung 11 trennen die Bereiche in denen wir stabile Investment Perioden erwarten durften, bzw. wir ein Investment nicht in Betracht ziehen sollten. Die beiden Indikatoren haben in der Tat eine verlässliche Indikationen für aufkommende Verluste im Index aufgezeigt.

Stabilitätspositionen der Traditionsunternehmen

In Abbildung 12 sind seit Dezember 2010 für alle 131 traditionsreichen Unternehumungen der Schweiz die stabilen (1) und instabilen (0) Perioden verzeichnet. Die Werte in der Tabelle können dazu dienen ein vorhandenes Portfolio zu stabilisieren, in dem zu instabilen Zeiten auf ein Investment der entsprechenden Aktien verzichtet wird.

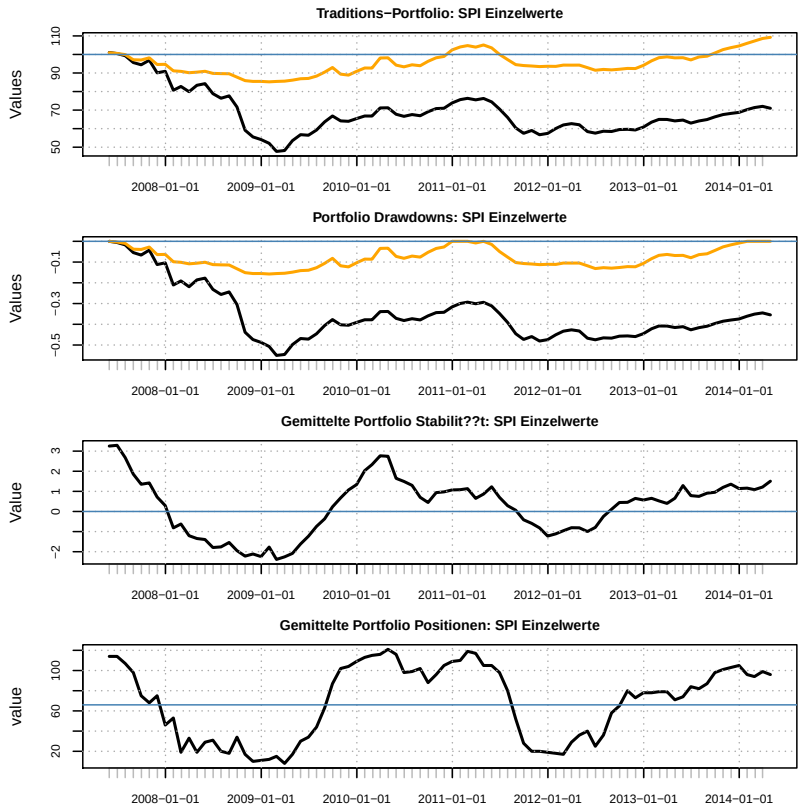


Abbildung 12: Von oben nach unten: (i) Gleich- (schwarz) und stabilitätsgewichteter (orange) SPI Traditions Index, (ii) Portfolio Ertragseinbrüche (Drawdowns), (iii) Gemittelter Stabilitätsindex, (iv) Anzahl der stabilen Titel aus insgesamt 132 Aktien.

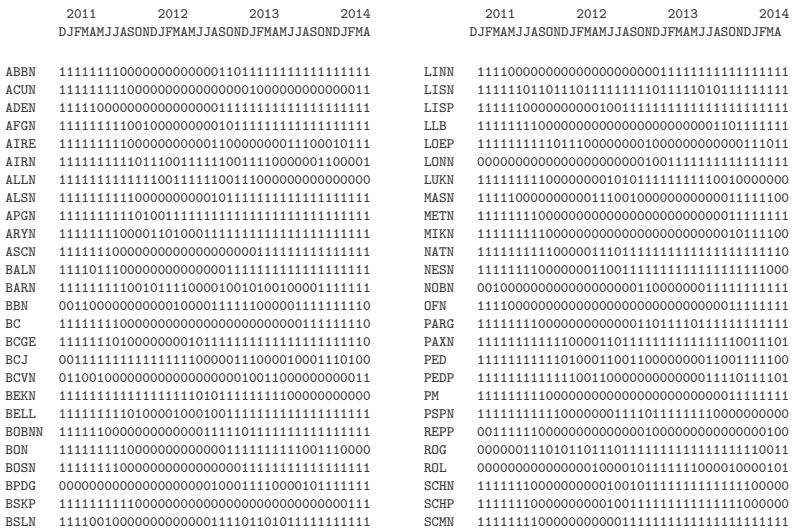


Abbildung 13: Prognostizierte Erwartungswerte füer die Positionen seit Dezember 2010.

5 Zusammenfassung

"Bayes'sche Strukturbruchanalysen" sind eine neue Methode mit der kapitalgeschützte Investitionen erfolgreich getätigt werden können. Das Verfahren ermöglicht einen vertieften Einblick in die Struktur und Dynamik von Finanzmärkten und Investments aus der Sicht von Instabilitäten und Stressszenarien. Der von uns vorgestellte Stabilitätsindikator für den "Swiss Performance Index" erlaubt Portfolios nach Sektoren sowie Einzeltiteln zu strukturieren, und dabei die Risikokennzahlen wesentlich zu verbessern.

Ebenfalls kann auch in bestehende Portfoliostrategien eingegriffen werden, um Ertrags- und Risikokennzahlen gezielt zu verbessern. Die Gewichtung von Sektorn oder Einzeltiteln die Stress und Turbulenzen ausgesetzt sind kann im Portfolio reduziert werden, und damit das eingesetzte Kapital besser geschützt werden.

Das BCP Verfahren hilft uns Gefahren und Risiken besser einzuschätzen und unterstützt uns dabei die richtigen Entscheidungen rechtzeitig zu treffen.

Dank

Die vorliegenden Untersuchungen wurden in der "Econophysik Gruppe" von Professor Diethelm Würtz an der ETH Zürich durchgeführt und sind Teil des Dissertationsvorhabens von Tobias Setz. Wir bedanken uns bei der Rmetrics Association Zürich und der OLZ Management AG in Bern, die durch ein Grant zur Durchführung dieser Studie beigetragen haben.

Ueber die Autoren

Diethelm Würtz ist Professor am Institut für Theoretische Physik an der ETH Zürich. In seinem Forschungsgebiet befasst er sich mit Risiko und Stabilitätsanalysen von Finanzmärkten. Er unterrichtet im Bereich "Computational Science and Financial Engineering". Er ist Senior Partner der ETH spin-off Firma Finance Online GmbH und Präsident der Rmetrics Association in Zürich.

Tobias Setz hat einen Bachelor und Master Abschluss in Computational Science von der ETH Zürich. Sein Arbeitsgebiet umfasst Risiko und Stabilitätsmanagement mit "Wavelet" und "Bayesian Change Point" Verfahren. Er ist PhD Student in der Econophysik Gruppe von Professor Diethelm Würtz.

Cyril Bachelard ist "Research Analyst" bei der OLZ Management AG in Bern. Er studierte Wirtschaftswissenschaften an der Universität Bern und an der Singapore Management University (SMU). Seine Spezialgebiete sind Finanzökonometrie und Finanzmarkttheorie.

Lorenz Beyeler ist "Senior Research Analyst" bei der OLZ Management AG in Bern. Er studierte Wirtschaftswissenschaften an der Universität Bern. Seine Spezialgebiete sind Oekonometrie und Finanzmarkttheorie.

Literatur

[1] D. Würtz, Y. Chalabi, A Ellis, W. Chen, S. Theussl,
Proceedings of the Singapore Workshop on Computational Finance,
Editors: Diethelm Würtz, Mahendra Mehta, David Scott, and Juri Hinz,
Rmetrics Publishing, ISBN/EAN 9783906041087, www.rmetrics.org, p. 209, 2010.

[2] Swiss Exchange,
Swiss Performance Index, 2007.

[3] Swiss Bank Corporation Index,
Swiss Bank Corporation Index,
in: Swiss National Bank, Capital and Stock Markets, 2007.

[4] Swiss National Bank,
Historical Time Series: Capital and Stock Markets, 2007
http://www.snb.ch/en/mmr/reference/histz_kapitalmarkt_book/source

[5] Industry Classification Benchmark,
ICB Brochure: http://www.icbenchmark.com/ICBDocs/FTSE_ICB_Corporate_Brochure.pdf

[6] Barry und Hartigan,
Product Partition Models for Change Point Problems,
The Annals of Statistics 20, 260, 1992.

[7] Barry und Hartigan,
A Bayesian Analysis of Change Point Problems,
Journal of the American Statistical Association 88, 309, 1993.

[8] Ch. Erdman und J.W. Emerson,
A Fast Bayesian Change Point Analysis for the Segmentation of Microarray Data,
Bioinformatics 24, 2143, 2008.

CHAPTER 9

FORWARD AND SPOT FX MARKETS

Forward and Spot FX Markets
Tobias Setz[1], Diethelm Würtz[1] and Jan Witte[2]
[1] Swiss Federal Institute of Technology, Zurich
[2] Record Currency Management, Windsor

Our most challenging research project is funded (since February 2012) by FX Record in Windsor UK. The topic is to apply Bayesian stability strategies to the management of foreign currencies.

The results were presented at the R-in-Finance Conference in Chicago in May 2014, at the Rmetrics Paris Workshop in June 2014, and at the UseR! Meeting in Los Angeles in July 2014.

BCP Stability Analytics
New Directions in Tactical Asset Management

Tobias Setz[1], Venetia Christodoulopoulou [1], Jan Hendrik Witte[2], Diethelm Würtz[1]
[1]Swiss Federal Institute of Technology, Zurich, [2] Record Currency Management, Windsor

Chicago, R-in-Finance Conference, May 2014

Modern Portfolio Theory goes back to Harry Markowitz [1952]. When he published his article *Portfolio Selection* more than half a century ago, our knowledge of mathematical finance, econometrics, and statistics, as well as computer science, was much less developed than the options and the tools we have available today. In this presentation, we would like to share new ideas based on modern concepts of stability analytics, which allow for an alternative view on performance and risk in funds and portfolios and their impact on indexation techniques and tactical asset management. The main topics we would like to address are based on statistical methods for the identification of instabilities. We would like to detect and explore vulnerabilities in the dynamics behind financial markets. With our new approach, we would like to reinvestigate and to contribute to a better understanding of performance and risk. The indicators and measures we use allow us to create a distinct view of the weaknesses of classical allocation methods and modern portfolio theory and to venture into alternative and new directions.

We have introduced (Würtz et al. [2010]) a method to identify and locate change points and structural breaks in financial and economic time series. We named this method BCP (Bayesian change point) Stability Analytics, an approach based on the work of Barry and Hartigan [1993] on the partitioning of a time series in strings with different parameter settings. The parameters are the same within each partition, but change from one to the next. The method makes use of Bayesian Statistics and a Monte Carlo Markov Chain approach (implemented by Erdman and Emerson [2008]). The analytics can be used to explore financial markets and financial investments before, during, and after critical financial and economic periods, which include, for example, the recent sub-prime crisis, or the European debt crisis.

From a „stabilization" of a financial time series, we expect a steady increase in the cumulative returns that go with low volatility, small drawdowns, and short recovery times. We show that BCP Stability analytics can detect, analyse, quantify, and even predict vulnerabilities to external forces of a time series process. Thus, we can define figures to measure the structure and strength of instabilities appearing over time.

As a practical example, we assess the fragility of different currencies in spot and forward FX markets. We show how wealth protected FX indices can be constructed, and how they can be combined in an FX portfolio. As a valuable tool to visualize the results we additionally present an R Shiny app.

References

Markowitz Harry, [1952], Portfolio Selection, Journal of Finance Vol. 7 No. 1, pp. 77 - 91

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

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

Würtz Diethelm, Chalabi Yohan, Ellis Andrew, and Theussl Stefan [2010], Proceedings of the Singapore Conference on "Computational Finance and Financial Engineering, pp. 205 - 213, Finance Online Publishing, Zurich

Note: All calculations were done in the R, R Shiny and Rmerics Software Environments.

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

PART III

APPENDIX

CHAPTER 10

RMETRICS ASSOCIATION

Rmetrics is a non-profit taking association founded in 2007 in Zurich working in the public interest. Regional bodies include the Rmetrics Asia Chapter. Rmetrics provides support for innovations in statistical computing. Starting with the Rmetrics Open Source code libraries which have become a valuable tool for education and business Rmetrics has developed a wide variety of activities.

- **Rmetrics Research:** supporting research activities done by the Econophysics group at the Institute for Theoretical Physics at ETH Zurich.
- **Rmetrics Software:** maintaining high quality open source code libraries.
- **Rmetrics Publishing:** publication of various Rmetrics books as well as from contributed authors.
- **Rmetrics Events:** organizing lectures, trainings and workshops on various topics.
- **Rmetrics Juniors:** helping companies to find students for interim jobs such as reviewing and checking code for higher quality or statistical analyses of various problems.
- **Rmetrics Stability:** licensing of stability signals and indicators to describe changing environments.

RMETRICS RESEARCH

The Rmetrics Association is mainly run by the researchers working at the Econophysics group at the Institute for Theoretical Physics at ETH Zurich. Research activities include:

- PhD, Master, Bachelor and Semester Theses

- Papers and Articles
- Presentations on international conferences
- Sponsored and tailored theses for companies
- Paid student internships at ETH Zurich

RMETRICS SOFTWARE

Without the Rmetrics Open Source Software Project it wouldn't be possible to realize all the research projects done in the Econophysics Group at ETH in such a short time . But it is not only the Econophysics group who has profited from the Open Source Rmetrics Software, there are worldwide many other research institutes and companies that are using Rmetrics Software.

The Rmetrics Software environment provides currently more than 40 R packages authored and maintained by 22 developers from all over the world. Amongst others it includes topics about basic statistics, portfolio optimization, option pricing as well as ARMA and GARCH processes.

An "ohloh" evaluation in 2012 of the Rmetrics Software concluded with the following results:

- Mature, well-established codebase
- Large, active development team
- Extremly well-documented source
- Cocomo project cost estimation
  - Codebase: 367'477 Lines
  - Effort: 97 Person Years
  - Estimated Cost: USD 5'354'262

This powerful software environment is freely available for scientific research and even for commerical applications.

RMETRICS PUBLISHING

Rmetrics Publishing is an electronic publishing project with a bookstore [1] offering textbooks, handbooks, conference proceedings, software user guides and manuals related to R in finance and insurance. Most of the

[1] http://finance.e-bookshelf.ch/

books can be ordered and downloaded for free. The bookstore is sponsored by the Rmetrics Association and the ETH spin-off company Finance Online. For contributed authors our bookstore offers a peer-reviewing process and a free platform to publish and to distribute books without transfering their copyright to the publisher. You can find a list of our books on page ii.

RMETRICS EVENTS

Trainings and Seminars are offered by Rmetrics for the most recent developments in R. Topics include all levels of knowledge:

- Basic R programming
- Advanced R project management
- Efficiently debugging code
- Speeding up code by e.g. byte compiling or using foreign language interfaces
- Managing big data
- Professional reporting by e.g. using R Sweave, knitr, Markdown or interactive R Shiny web applications and presentations

There also exists an Rmetrics Asia Chapter for teaching and training R with its home in Mumbai, India.
Besides that Rmetrics organizes a yearly international summer school together with a workshop for users and developers.

RMETRICS JUNIORS

The Rmetrics Juniors initiative helps companies to find students for interim jobs. This ranges from reviewing and checking code for higher quality, to building R projects from scratch, to statistical analyses of inhouse problems and questions. The work is done by experienced Rmetrics Juniors members, usually Master or PhD thesis students. This is an advisory concept quite similar to that offered by ETH Juniors.

RMETRICS STABILITY

Analyzing and enhancing the research results from the Econophysics Group at ETH Zurich and other research institutions worldwide, the Rmetrics Association implements stability and thresholding indicators. These indicators can then be licensed by industry.

In this context it is important to keep in mind that Rmetrics is an independent non-profit taking association. With the money we earn from the stability project, we support open source software projects, student internships, summer schools, and PhD student projects.

CHAPTER 11

RMETRICS TERMS OF LEGAL USE

Grant of License

Rmetrics Association (Zurich) and *Finance Online* (Zurich) have authorized you to download one copy of this electronic book (eBook). The service includes free updates for the period of one year. *Rmetrics Association* (Zurich) and *Finance Online* (Zurich) grant you a nonexclusive, nontransferable license to use this eBook according to the terms and conditions specified in the following. This License Agreement permits you to install and use the eBook for your personal use only.

Restrictions

You shall not resell, rent, assign, timeshare, distribute, or transfer all or any part of this eBook (including code snippets and functions) or any rights granted hereunder to any other person.
You shall not duplicate this eBook, except for a single backup or archival copy. You shall not remove any proprietary notices, labels, or marks from this eBook and transfer to any other party.
The code snippets and functions provided in this book are for teaching and educational research, i.e. for non commercial use. It is not allowed to use the provided code snippets and functions for any commercial use. This includes workshops, seminars, courses, lectures, or any other events.
The unauthorized use or distribution of copyrighted or other proprietary content from this eBook is illegal.

Intellectual Property Protection

This eBook is owned by the *Rmetrics Association* (Zurich) and *Finance Online* (Zurich) and is protected by international copyright and other intellectual property laws.

Rmetrics Association (Zurich) and *Finance Online* (Zurich) reserve all rights in this eBook not expressly granted herein. This license and your right to use this eBook terminates automatically if you violate any part of this agreement. In the event of termination, you must destroy the original and all copies of this eBook.

General

This agreement constitutes the entire agreement between you and *Rmetrics Association* (Zurich) and *Finance Online* (Zurich) and supersedes any prior agreement concerning this eBook. This Agreement is governed by the laws of Switzerland.

(C) 2007-2015 Rmetrics Association Zurich. All rights reserved.

About the Authors

Diethelm Würtz is professor at the Institute for Theoretical Physics, ITP, and for the Curriculum Computational Science and Engineering, CSE, at the Swiss Federal Institute of Technology in Zurich. He teaches Econophysics at ITP and supervises seminars in Financial Engineering at CSE. Diethelm is senior partner of Finance Online, an ETH spin-off company in Zurich, and co-founder of the Rmetrics Association.

Tobias Setz has a Bachelor and Master degree in Computational Science and Engineering from ETH in Zurich and has contributed with his thesis projects on wavelet and Bayesian change point analytics to this ebook. He is now a PhD student in the Econophysics group at ETH Zurich at the Institute for Theoretical Physics and maintainer of the Rmetrics packages.