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Bayesian Stability Filtrations: Indicators, Signal Strengths, and Position Thresholds

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Indicators, Signal Strengths, and Position Thresholds

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Abstract

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

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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.

1) BCP on a rolling PERIOD
- FIXED
- ADAPTIVE

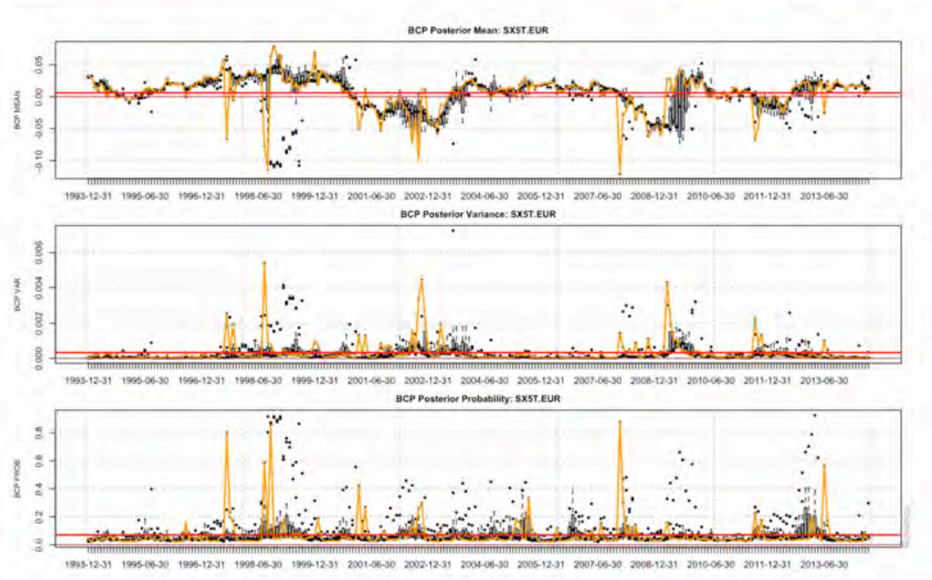


Figure 1: Posterior mean, posterior standard deviation and posterior probability for the logarithmic returns of the Euro Stoxx 50 Index.

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.

Rolling method
PERIOD = 12m

31.8.X1 12 months 31.07.X2

31.07.X2 AVERAGE

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:

ROLLING PERIOD

LAST VALUE

VS.

TIME STEP

RATIO • W PROBS

THRESHOLD QUANTILE

Standard Investment Strategy:

INDICATOR vs. THRESHOLD LEVEL ?!

⇓

SIGNAL

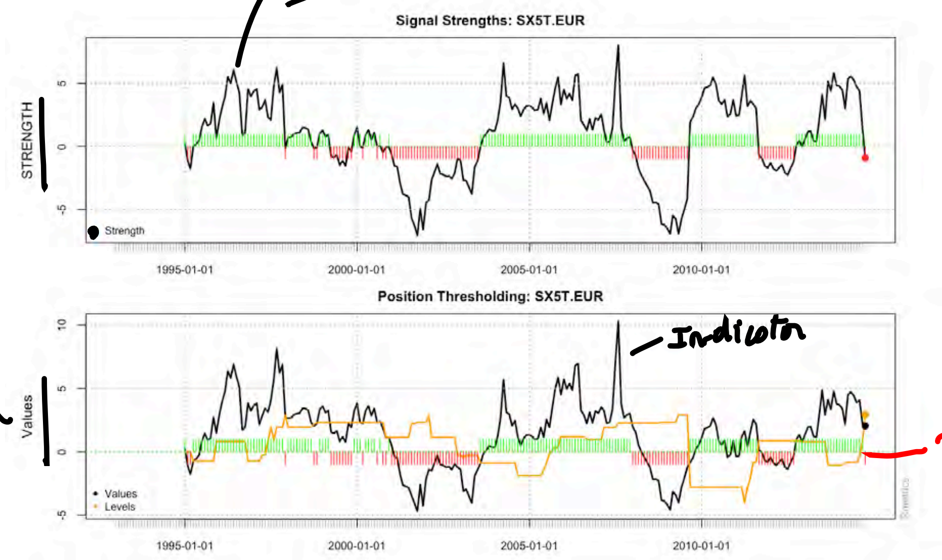
We compute a Bayesian Sharpe Ratio over a rolling window of a given fixed size. The input numbers are the posterior mean, the posterior variances, and the one step ahead forecasted posterior probabilities as shown in Figure 1 by the orange lines. At each time step of a rolling window we calculate the 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*.

INDICATOR

SHARPE RATIO

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.

strenght



Indicator

THRESHOLD

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.

KEY ADVANTAGE !

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.

Strenght can be used for Partial rebalances!

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.

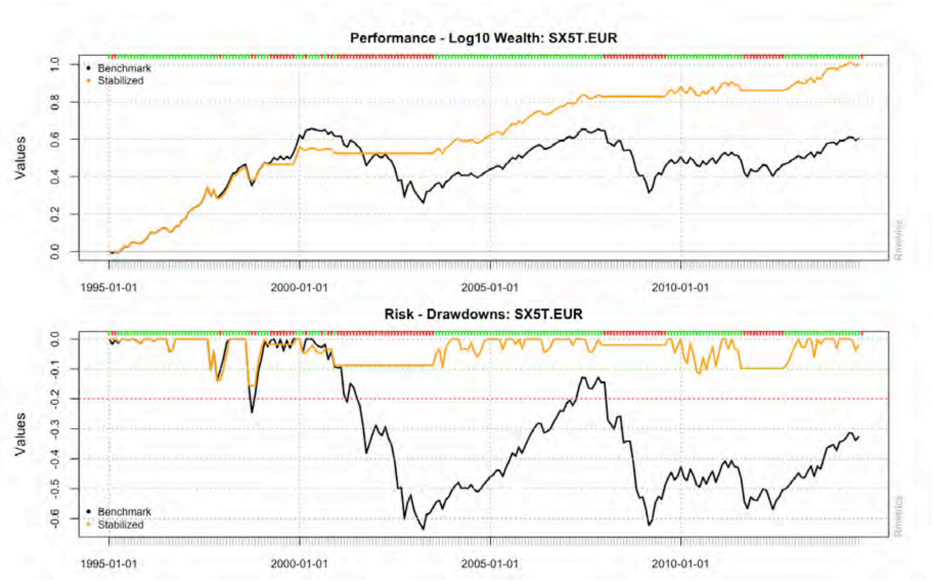


Figure 3: Wealth (upper chart) and Drawdowns (lower chart) for the Euro Stoxx 50 Index (black) and its stabilized counterpart (orange). Green and red rugs correspond to long and short positions.

Risk measures

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.

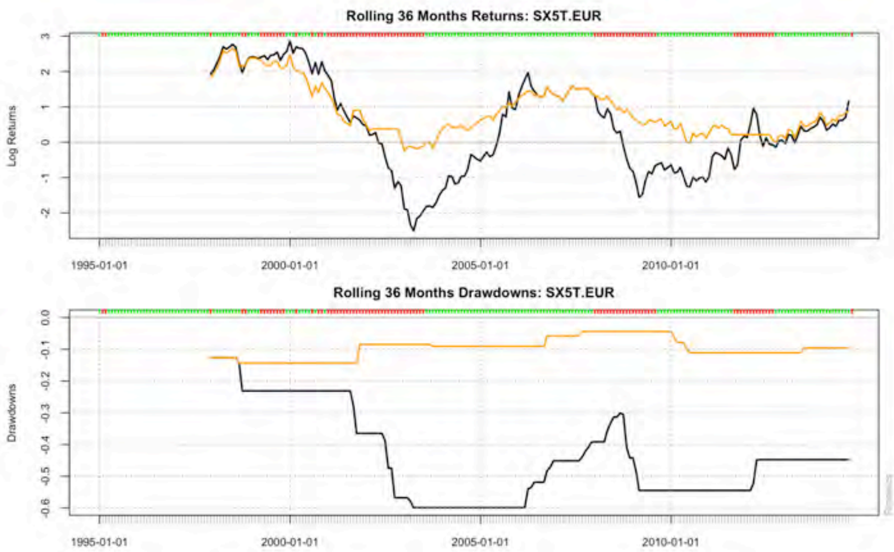


Figure 4: 36 Months rolling returns and drawdowns for the Euro Stoxx 50 Index (black) and its stabilized counterpart. Green and red rugs correspond to long and short positions.

Independent of the starting point, the stabilized index is almost always better regarding performance and always better regarding drawdown?

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.

IMPROVEMENTS
- E(shortfall risk)
- C(drawdown @risk)

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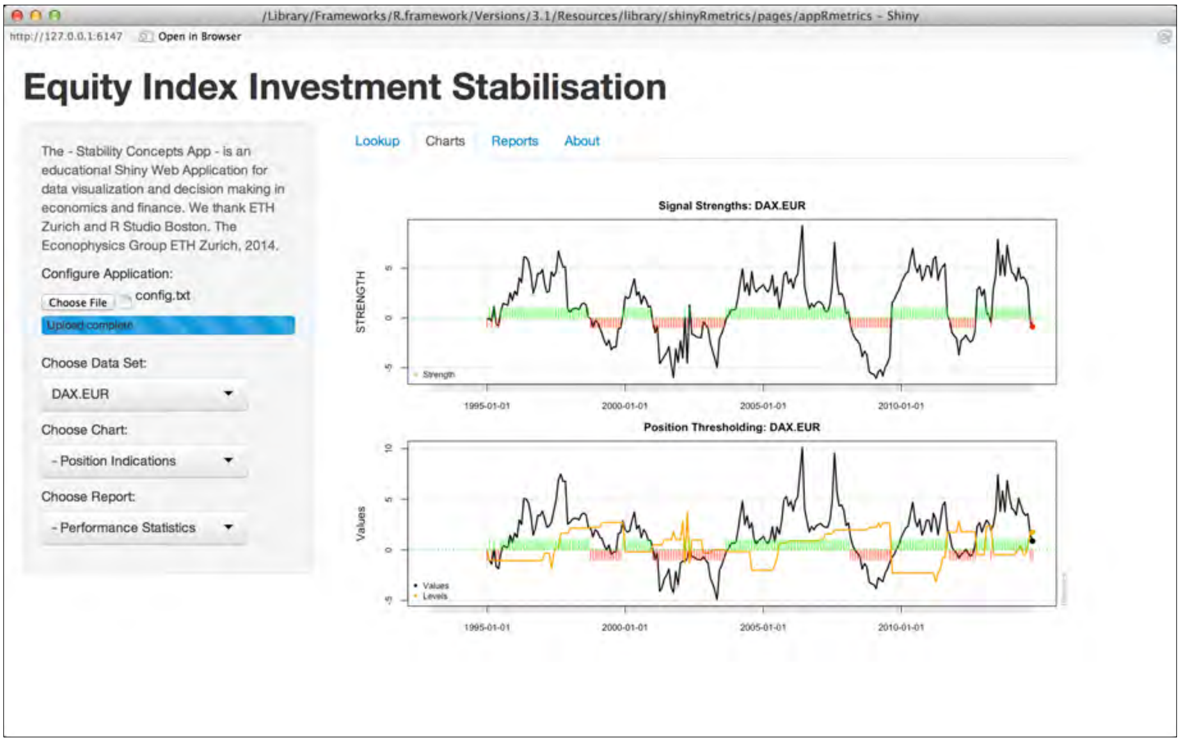
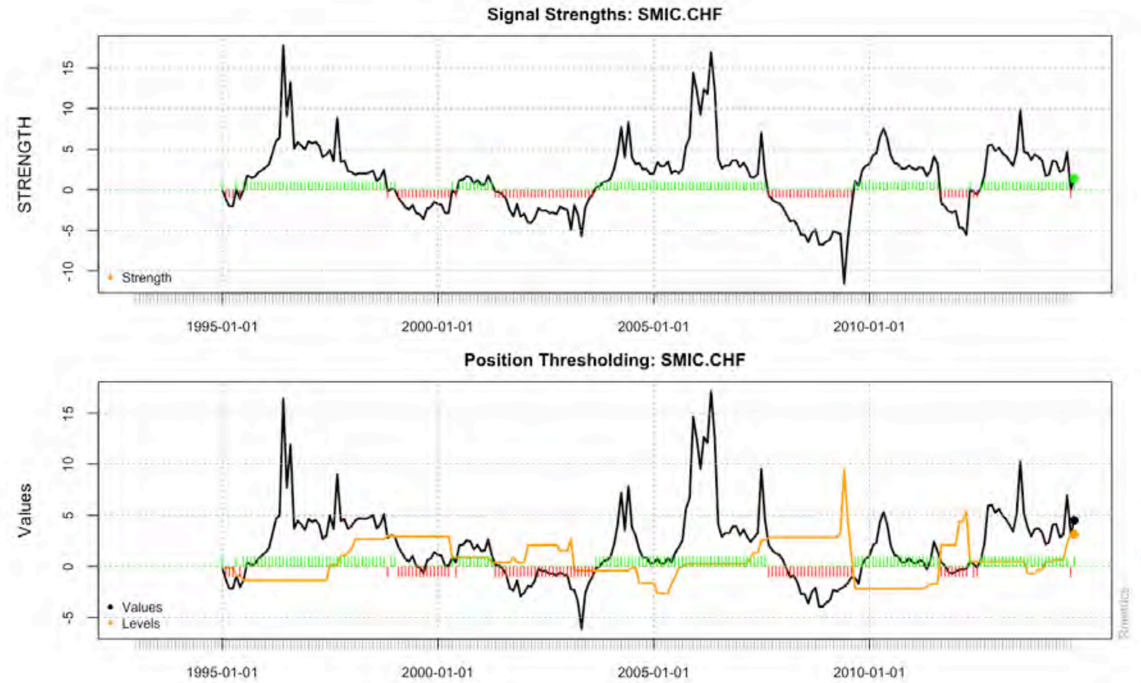
Appendix I

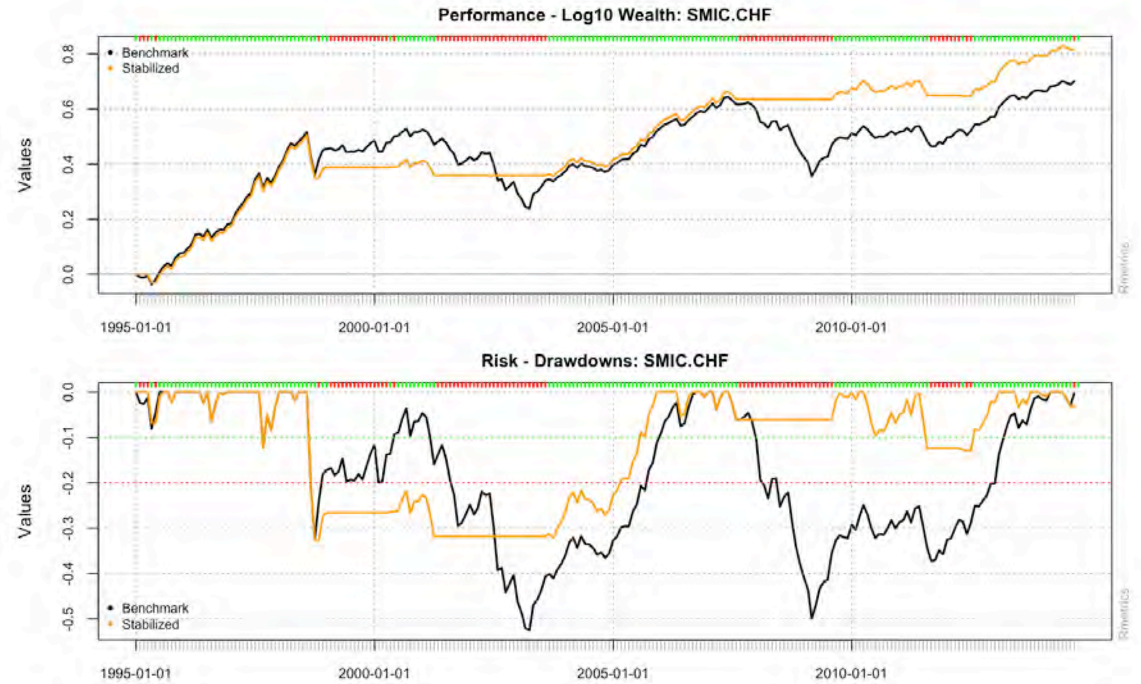
The figure shows a screenshot of the educational R Shiny application named *Equity Index Investment Stabilization.* The application can load data from a predefined set of stock market indices as listed in the "Lookup" Panel. A selected index can then be analyzed and monitored by "Charts" and "Reports".



Source: Econophysics Group 2014

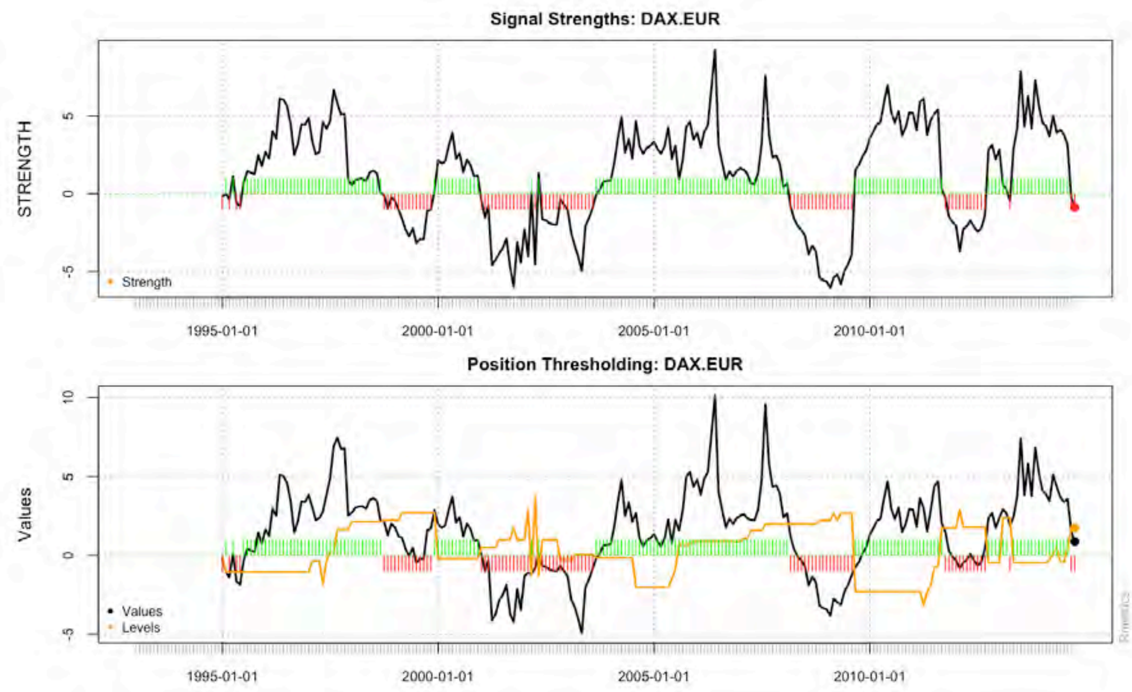
Appendix II Switzerland – Total Return Swiss Market Index as of August/September 2014

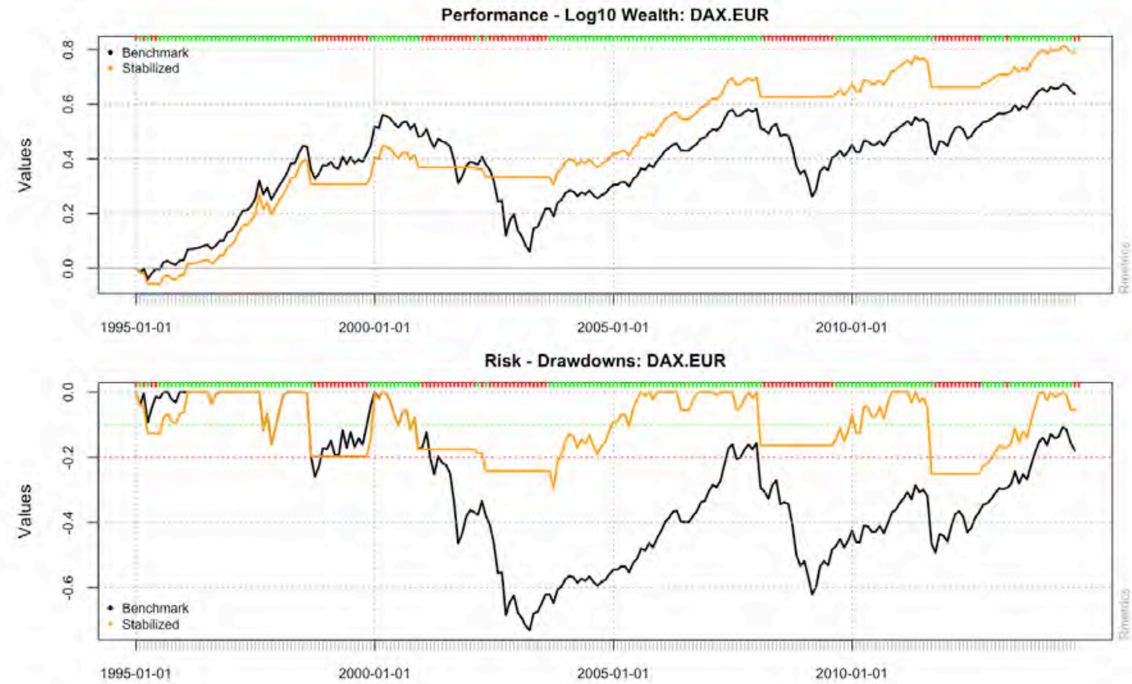




For the description of the charts we refer to the text.

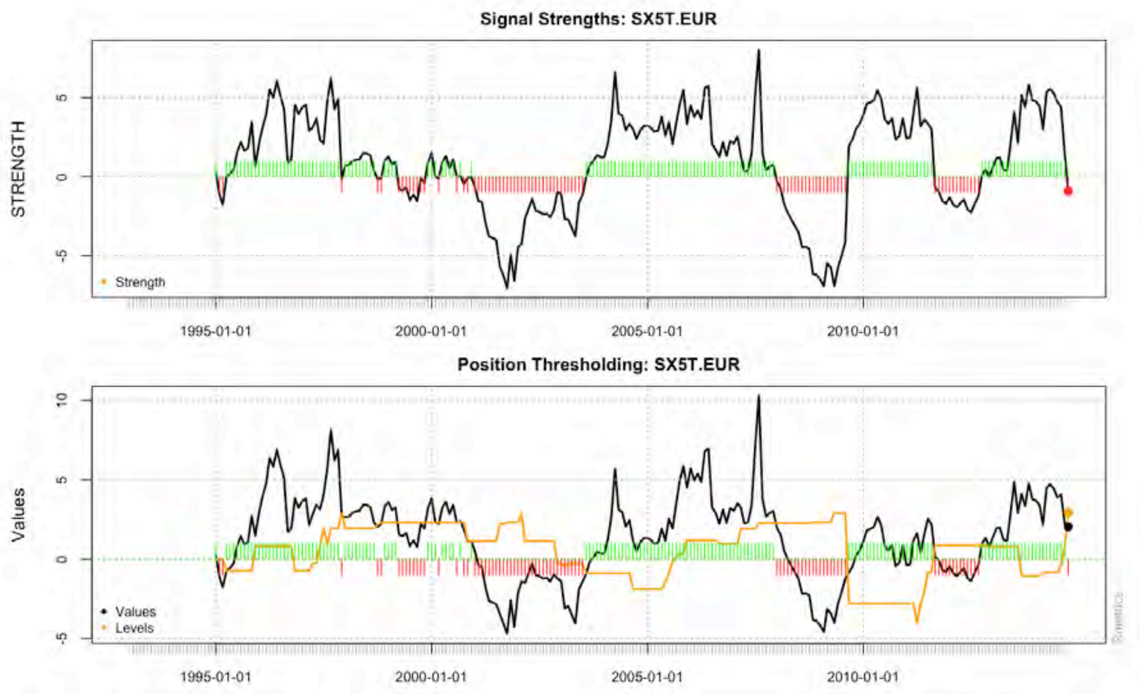
Appendix III Germany – Total Return DAX Index as of August/September 2014

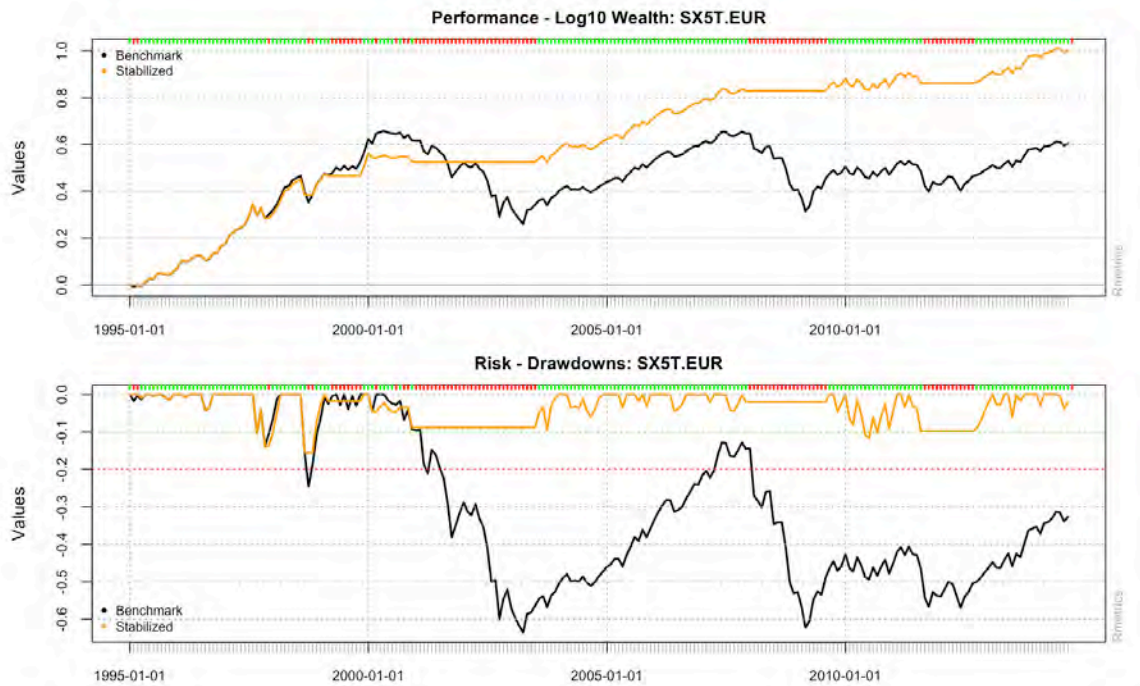




For the description of the charts we refer to the text.

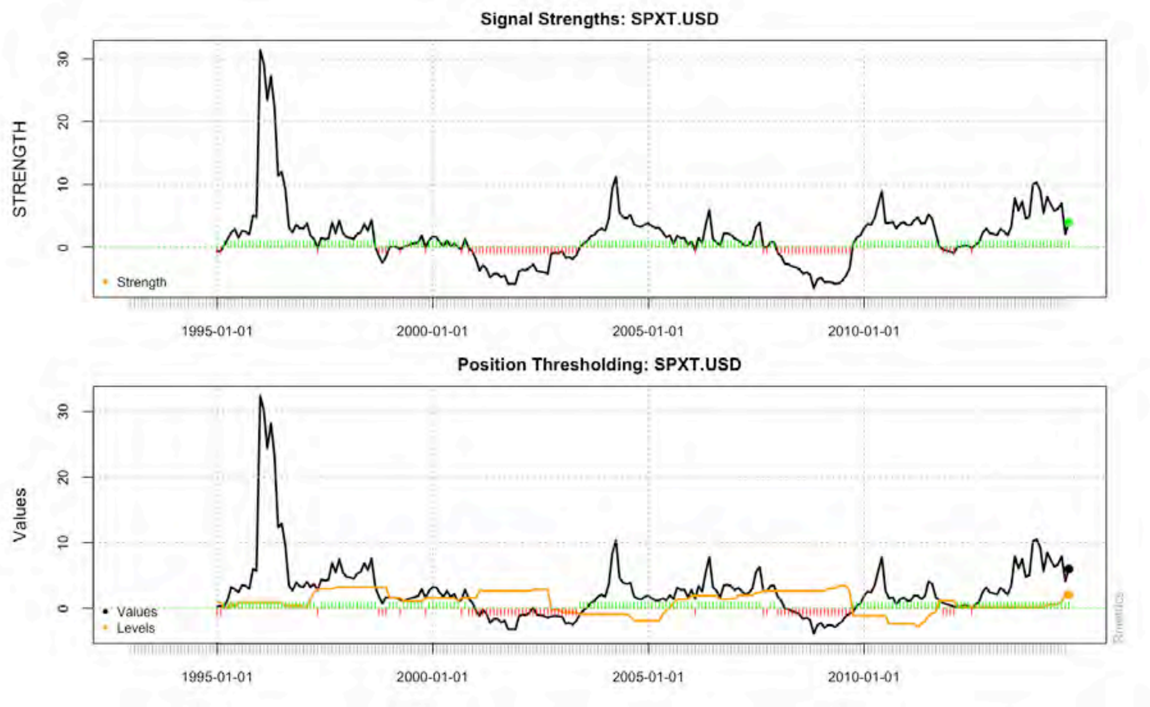
Appendix IV Eurozone – Total Return Euro Stoxx 50 Index as of August/September 2014

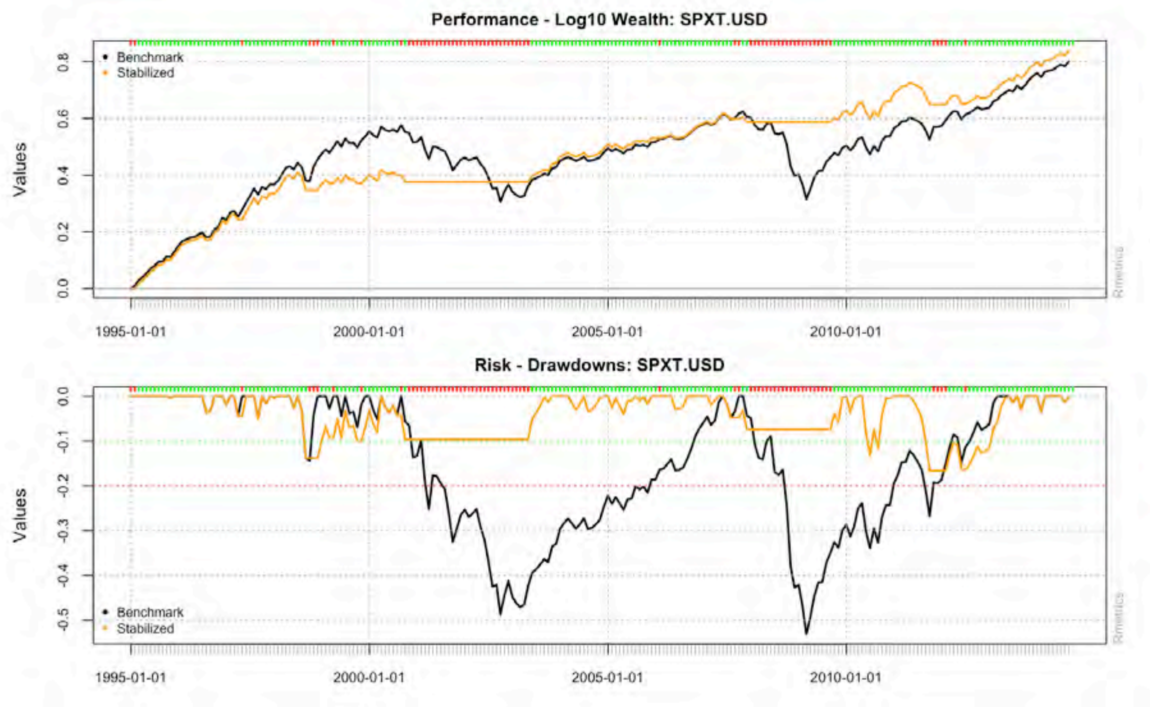




For the description of the charts we refer to the text.

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.

About the Authors

Diethelm Würtz is Professor at the "Institute for Theeoretical Physics" at the Swiss Federal Institute of Technology (ETH) in Zurich. His research interests are in the field of risk management and stability analysis of financial markets. He teaches computational science and financial engineering. He is senior partner of the ETH spin-off company "Finance Online" and president of the "Rmetrics Association in Zurich".

Tobias Setz has a Bachelor and Master degree in Computational Science from ETH Zurich. Currently he is doing his PhD Thesis in the Econophysics Group of Professor Diethelm Würtz. His major research interests are in Bayesian statistics and Wavelet analytics. He is an experienced R programmer and maintainer of the Open Sourse Rmetrics software environment.

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