BCP Stability Analytics

New Directions in Tactical Asset Management

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Stability Analytics

Financial markets and economies are shocked by **crashes** such as the:

- Great Depression
- Oil Crisis
- Black Monday
- Dot-Com Bubble
- Sub Prime Crisis
- ...

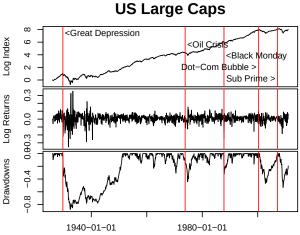

Figure 1: Historical Crises.

Stability Analytics:

- Stability can be expressed through various **views** on a time series.
- We only demand that the result is a value between **0** (stable) and **1** (unstable) for every point of a time series.
- There are different methods which deliver such a measure and all have a different view on a time series; e.g. *wavelets*, *principal components* or *Bayesian change points*.

BCP Stability Analytics

BCP Stability:

- The Bayesian change point (BCP) method is a realization of the structural breaks view: a time series is considered to be a random process with possibliy **changing dynamics**.

BCP Features:

- Early warning signal for changing environments.
- Real time description of transition.

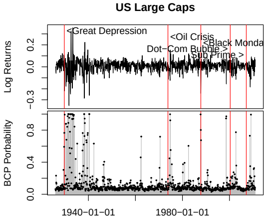

Figure 2: BCP Probabilites.

BCP Relevance:

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

Assumptions

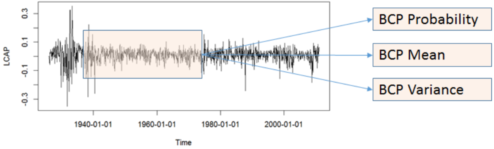

Figure 3: Set of Returns.

- Within the current implementation (bcp package from Chandra Erdman and John W. Emerson) it is assumed that our set of returns ($\vec{r}$) is normally distributed where the parameter μ describes the performance of the returns.
- Also it is assumed that the set is partitioned where for every partition we have a different μ.

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

- The Bayesian nature of the calculations takes care of parameters by replacing them with probability distributions.

Find more about the BCP method within the appendix.

Results

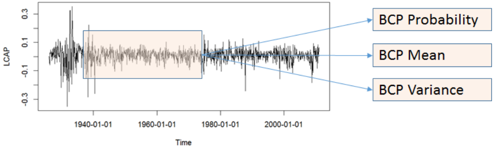

Figure 4: Set of Returns.

If we perform the BCP analysis on our set of returns ($\vec{r}$) we get for very point in time (t_n):

- The posterior probability ($\vec{p}$) which describes the probability that the dynamics (μ) have changed.
- The posterior mean ($\vec{m}$) which is a bayesian estimation for the parameter (μ) that respects the change points.
- The posterior variance ($\vec{s}$) which desicribes the variance within the parameter estimation of μ.

Find more about the BCP method within the appendix.

Change Points: Switch or Transition?

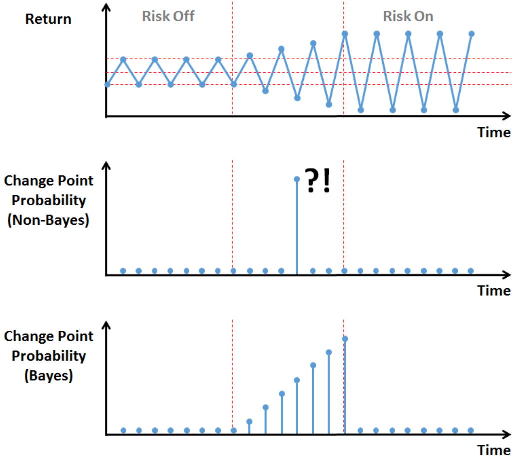

Figure 5: The Bayesian approach.

- Classical approach doesn't respect transition phase.

Large Caps United States (S&P 500)

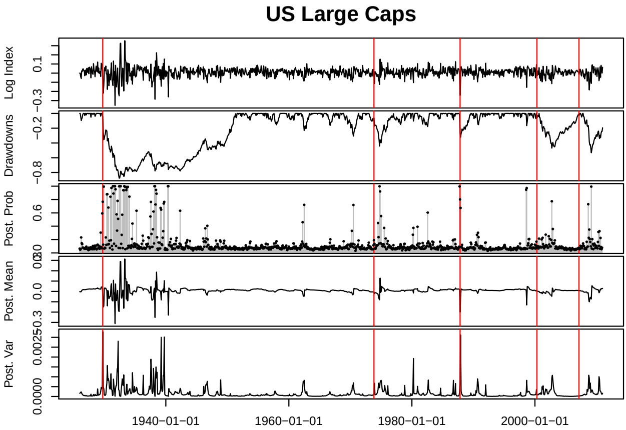

Figure 6: Posterior Results.

S&P 500 vs Random Walk

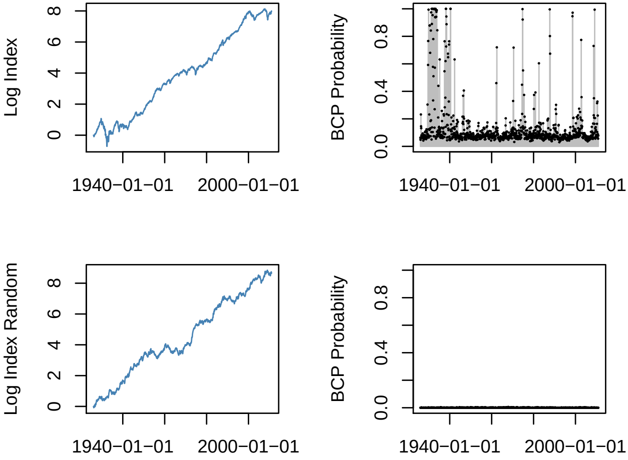

Figure 7: Random Returns.

Bayesian Change Point (BCP) Analysis

The first step towards trading is to make the BCP Analysis on a sliding window.

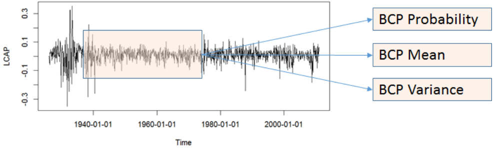

Figure 8: Sliding Window.

- The results can be directly used as an indicator or combined to an indicator.
- The indicator can then be used to directly calculate a signal on whether to leave the market or not or to enhance existing methods like Markowitz portfolio optimization.
- We use an approach to calculate the signals from the indicator that doesn't need any parameters by using the historically best threshold.

Binary Switching

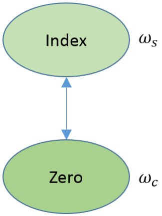

Figure 9: Concept.

- The graph on the left shows 26 equity indices (CHF, USD, EUR, GBP, JPY). As risk-free assets bonds are used.

- The BCP results are combined to an indicator which is used to calculate a signal on wheter to leave the index for a risk-free asset or not.

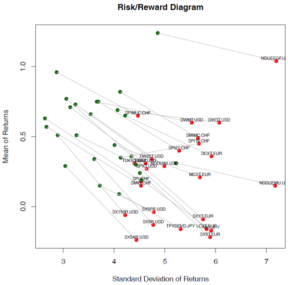

Figure 10: Binary Switching.

Other Approaches

As already indicated the BCP results can be used in various ways:

- Within the appendix you can find an extended example of the binary switching model; the quadriga switching.
- In portfolio optimization there are multiple possibilities to modify the objective function or the constraints.
- Rating and Ranking.

Forex Returns

To stay close to the actual implementation of the Record products (FRB10 and EM) we used the following series and methodology:

- **For the G10 currency pairs:** Monthly carry trade returns starting on 1988-01-01. In total 45 pairs.
- **For the EM currency pairs:** Monthly currency surprise returns starting on 1998-01-01, short USD. In total 18 pairs.

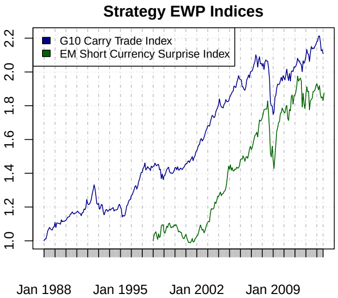

Figure 11: G10 and EM EWP indices.

- **Methodology:** The BCP binary switching methodology was applied on all the underlying currency pairs to create an on and off signal. As risk-free asset cash with zero interest rates was used.

Histogram: All Returns (Untouched)

- The G10 carry trade returns have a mean of 25 basis points.
- The EM currency surprise returns have a mean of 36 basis points.

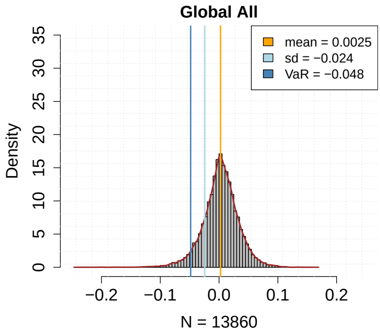

Figure 12: G10 carry trade returns.

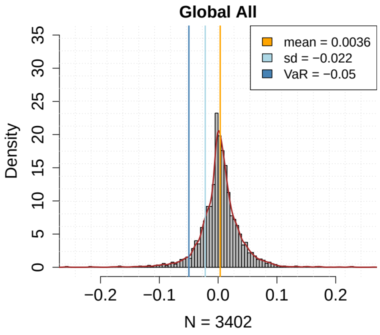

Figure 13: EM short currency surprise returns.

Histogram: Returns kept by BCP

- The G10 carry trade returns have a mean of 31 basis points.
- The EM currency surprise returns have a mean of 50 basis points.

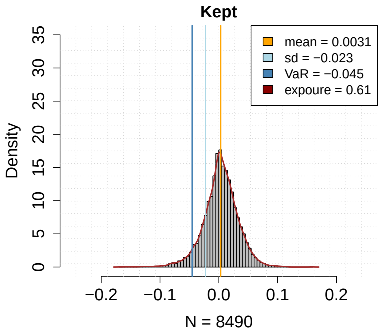

Figure 14: G10 carry trade returns.

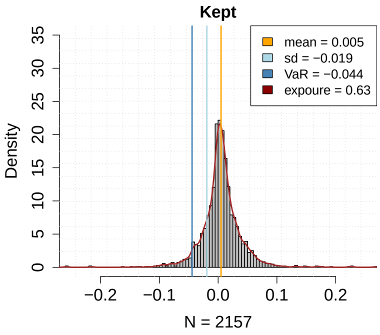

Figure 15: EM currency surprise returns.

Exposure by Return

The pictures show 10'000 randomly selected data sets. For every dataset a selection of random currency pairs (20 for G10 and 10 for EM) and a random window of 5 years was chosen. Then the exposure was plotted against the full market performance.

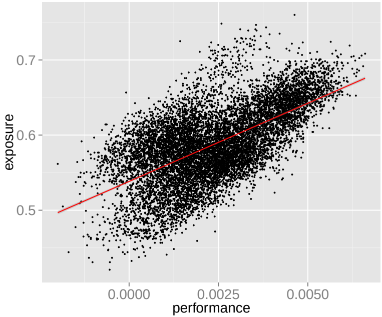

Figure 16: G10 sample means against exposures.

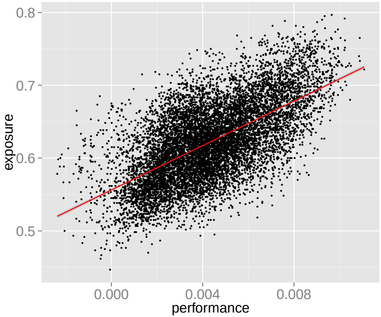

Figure 17: EM sample means against exposures.

About Shiny

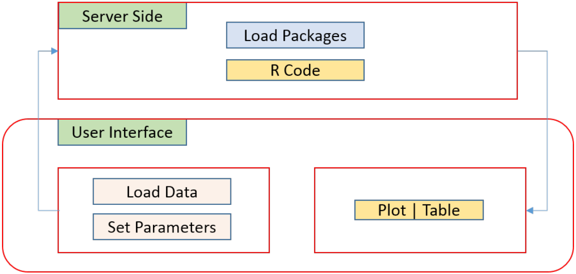

Figure 18: Switching Portfolios.

- Implementation can be done fully in R (No HTML, CSS or JavaScript needed; but possible to use it).
- Very efficient way to examine code by changing data and parameters.
- Results can be made available to colleagues or customers in an appealing way. No R installation or coding knowledge necessary.

Currency Stability Monitor

Choose Data Universe

Figure 19: Choose the data for analysis, strategies and/or portfolios.

Currency Stability Monitor
Apply Strategy

Figure 20: Choose a strategy to apply on the data universe.

Currency Stability Monitor

Apply Strategy

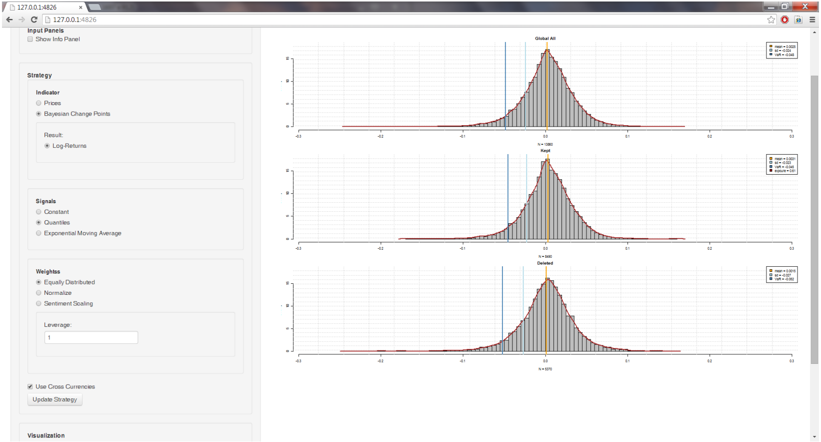

Figure 21: Extend data universe and apply strategy.

Currency Stability Monitor
Analyze Time Series (Univariate)

Figure 22: Analyse single time series from the data universe.

Currency Stability Monitor

Analyze Time Series (Multivariate)

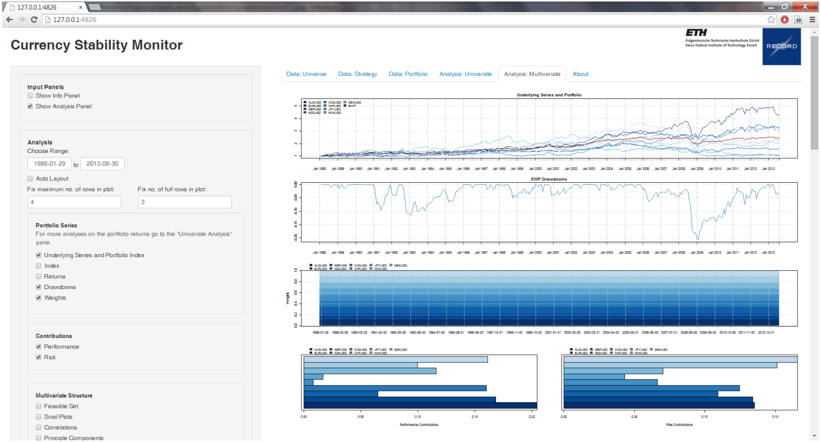

Figure 23: Analyse the dataset as a whole.

Conclusions

- Returns kept by the BCP method are increased and at the same time reduce the exposure to the market.
- Results non-specific to FX. Similiar potential in equities and bonds.
- Easy signal usage possible (e.g. exposure scaling).
- Distributing the results within a company or to cusomers can be done in an appealing and quick way by using shiny.

Thank you!

References

This presentation is based on the following sources:

- 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

R Session Info

This presentation si an example of literate programming. All calculations were done in the R, R Shiny and Rmerics Software Environments.

- R version 3.1.0 (2014-04-10), `x86_64-w64-mingw32`
- Locale: `LC_COLLATE=German_Switzerland. ...`
- Base packages: base, datasets, graphics, grDevices, grid, methods, stats, utils
- Other packages: bcp 3.0.1, fAssets 3010.81, fBasics 3010.86, fMultivar 3010.77, foreach 1.4.2, fPortfolio 3010.80, ggplot2 0.9.3.1, iterators 1.0.7, knitr 1.5, PerformanceAnalytics 1.1.0, RColorBrewer 1.0-5, Rcpp 0.11.1, timeDate 3010.98, timeSeries 3010.97, xts 0.9-7, zoo 1.7-11
- Loaded via a namespace (and not attached): codetools 0.2-8, colorspace 1.2-4, compiler 3.1.0, dichromat 2.0-0, digest 0.6.4, evaluate 0.5.3, formatR 0.10, gtable 0.1.2, highr 0.3, kernlab 0.9-19, labeling 0.2, lattice 0.20-29, MASS 7.3-31, munsell 0.4.2, plyr 1.8.1, proto 0.3-10, reshape2 1.2.2, scales 0.2.3, stringr 0.6.2, tools 3.1.0

The BCP Method

Overview

Assumptions

- A time series is a sequence of obervations which undergoes sudden changes at unknown times (change points).
- The sequence can be partitioned into different blocks separated by the change points (partition).
- Every observation can be described by a parameter value (e.g. the mean) of a probability distribution (e.g. the normal distribution) which does not change within one block.

Note that:

- We are not looking for a certain partition; instead we are taking all possible partitions into consideration.
- This allows for every single point to have its own dynamics.

The BCP Method

Product Partition Models: Prior Design

- Let's assume that very observation X_k has a density (e.g. normally distributed) depending on a parameter θ_k (e.g. the mean). Further, a partition (ρ) is a set of change points i_j that describe where those parameters change. Assuming a Product Partition Model (PPM) we can calculate the density of our model:

$$\left.\begin{aligned} \vec{X} &= (X_1, X_2, \ldots, X_n) \\ \vec{\theta} &= (\theta_1, \theta_2, \ldots, \theta_n) \\ \rho &= (i_0, i_1, \ldots, i_b) \end{aligned}\right\} f(\vec{X}|\vec{\theta}, \rho) = \prod_{k=0}^{b} f_{i_{k-1} i_k}(X_{i_{k-1} i_k}|\theta_{i_k})$$

- If we define a density for the parameters $(f_{i_{k-1} i_k}(\theta_{i_k}))$ we can calculate the so called data factor:

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

- At this point we also define a density for the partition:

$$f(\rho) = K \prod_{k=0}^{b} c_{i_{k-1} i_k}$$

The BCP Method

Product Partition Models: Posterior Design

- The posterior probability density $f(\rho|\vec{X})$ can be calculated by using the posterior cohesions $c_{ij}(\vec{X}) = c_{ij} f_{ij}(X_{ij})$ instead of the prior cohesions c_{ij}.
- By using Bayes' law we can now calculate the conditional density of partition and parameters given the observations as

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

Intuition

If all our assumptions are valid 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. We assume that if the observations can be described by the density parameteres then also the density parameteres can be described by the observations.

The BCP Method

Product Partition Models: Exact Calculation

- By taking into consideration all possible partitions we can now calculate the density (and expectation values) of the parameters independent of whether we know the true partition or not:

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

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

where $k = 1, 2, \ldots, n$ and $i < k \leq j$.

Intuition

By taking the observations ($\vec{X}$) and assuming that our partitions (ρ) and parameters (θ_k) have a certain distribution and by applying Bayes' law we are now able to calculate at every point in time the expectation value of the parameter of the density ($E(\theta_k|\vec{X})$) that describes the dynamics of the observation at that point.

The BCP Method

Implementation: Standard Approach

- Let's define the prior densities of the observations ($\vec{X}$), the parameters ($\vec{\mu}$) and the partiton (ρ):

$$\left.\begin{aligned} f_{ij}(X_{ij}|\mu_j) &\sim N(\mu_j, \sigma^2) \\ f_{ij}(\mu_j) &\sim N(\mu_0, \sigma_0^2/(j-i)) \\ f(\rho) &= g(c_{ij}) \end{aligned}\right\} E(\mu_k|\vec{X}) = \sum_{\rho} E(\mu_k|\vec{X}, \rho) f(\rho|\vec{X})$$

- The cohesions c_{ij} 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 $0 \leq p \leq 1$.

- **Problem:** We have to estimate the parameters σ, p, μ_0 and σ_0 by e.g. using the maximum likelihood method.

The BCP Method

Implementation: Bayesian Approach

- First we have to define independent prior densities for the unknown parameters p, μ_0, σ^2 and $w = \sigma^2/(\sigma_0^2 + \sigma^2)$:

$$\left.\begin{aligned} f(\mu_0) = 1, &\quad -\infty \leq \mu_0 \leq \infty \\ f(\sigma^2) = 1/\sigma^2, &\quad 0 \leq \sigma^2 \leq \infty \\ f(p) = 1/p_0, &\quad 0 \leq p \leq p_0 \\ f(w) = 1/w_0, &\quad 0 \leq w \leq w_0 \end{aligned}\right\} E(\mu_k|\vec{X}) = \sum_{\rho} E(\mu_k|\vec{X},\rho) f(\rho|\vec{X})$$

  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.
- 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).
- **Problem:** The calculation is computationally very intensive ($O(n!)$).

The BCP Method
Implementation: Markov Chain Monte Carlo

- If we generate partitions ρ which are distributed according to $f(\rho|\vec{X})$ we can approximate the solution as:

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

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

- After generating M partitions we can calculate the posterior means m_k, the "naive" posterior variances s_k and the posterior probabilities p_i as:

$$m_k = \frac{1}{M}\sum_{\rho}\hat{\mu_k} = \langle\hat{\mu_k}\rangle_M$$

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

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

Quadriga Switching
Concept

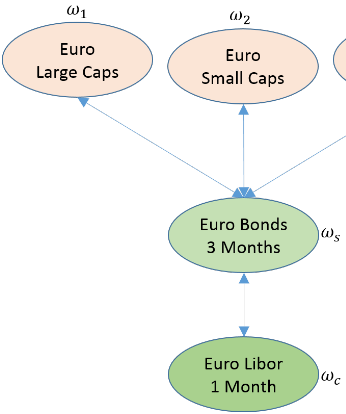

Figure 24: Concept.

- We set $v = 0.25$ where v is the maximum investment into a risky asset.
- In a risky asset we can have either 0 or 25 % of the investment.
- Either in bonds or cash we have 25, 50, 75 or 100 % of the investment.

Quadriga Switching

BCP Wealth

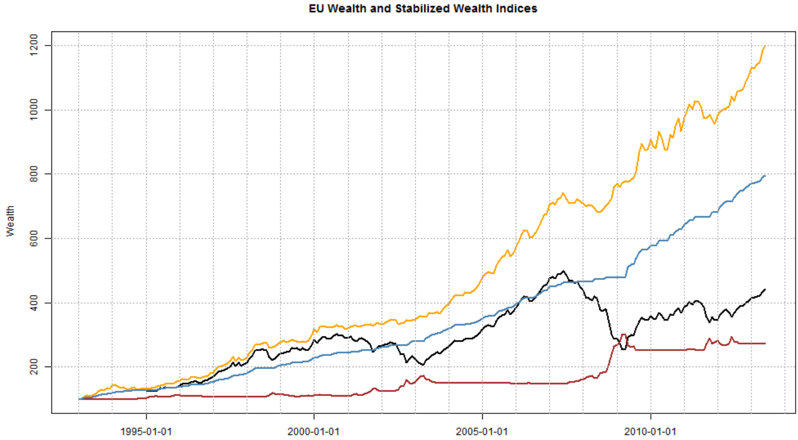

Figure 25: Switching Portfolios.

Quadriga Switching

EMA Wealth

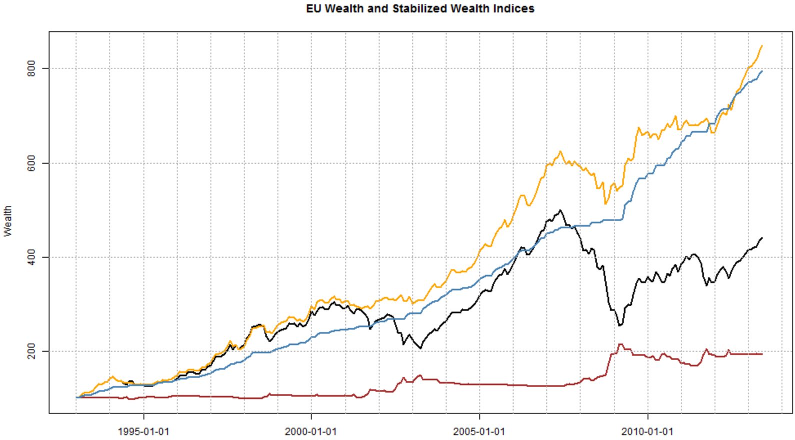

Figure 26: Switching Portfolios.

Quadriga Switching

BCP Drawdowns

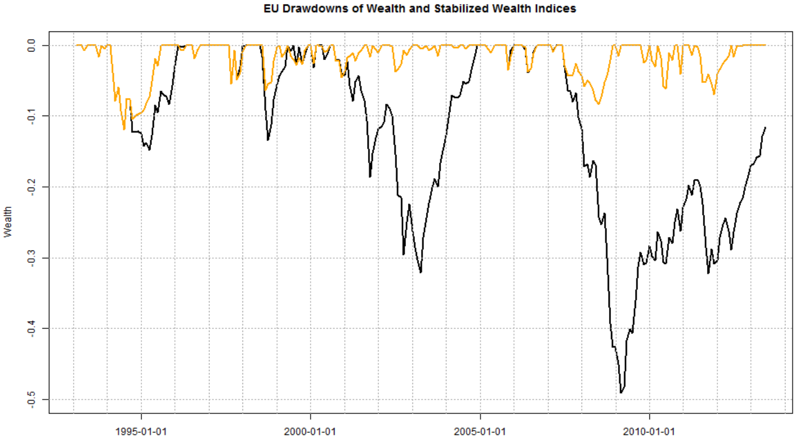

Figure 27: Switching Portfolios.

Quadriga Switching

EMA Drawdowns

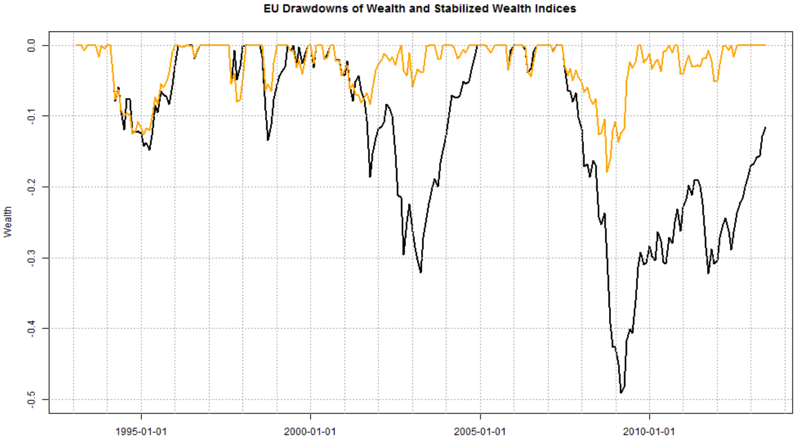

Figure 28: Switching Portfolios.

Quadriga Switching

BCP Betas

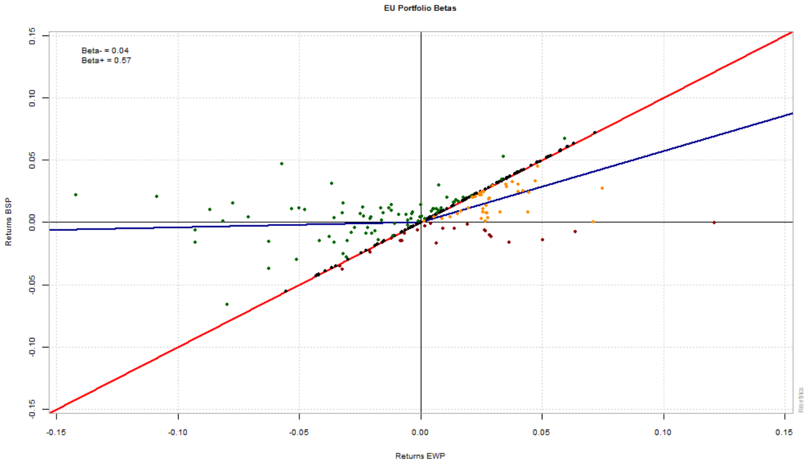

Figure 29: Switching Portfolios.

Quadriga Switching

BCP Positions

Figure 30: Switching Portfolios.

Quadriga Switching

EMA Positions

Figure 31: Switching Portfolios.

Quadriga Switching
BCP Stability

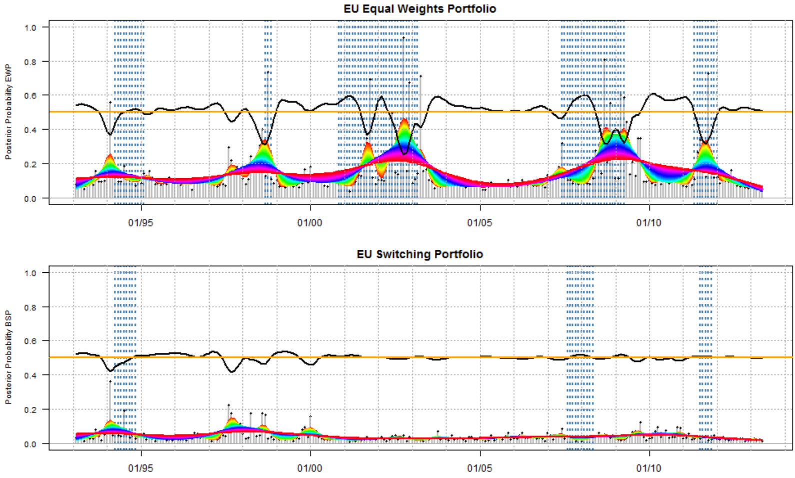

Figure 32: Switching Portfolios.

Quadriga Switching
EMA Stability

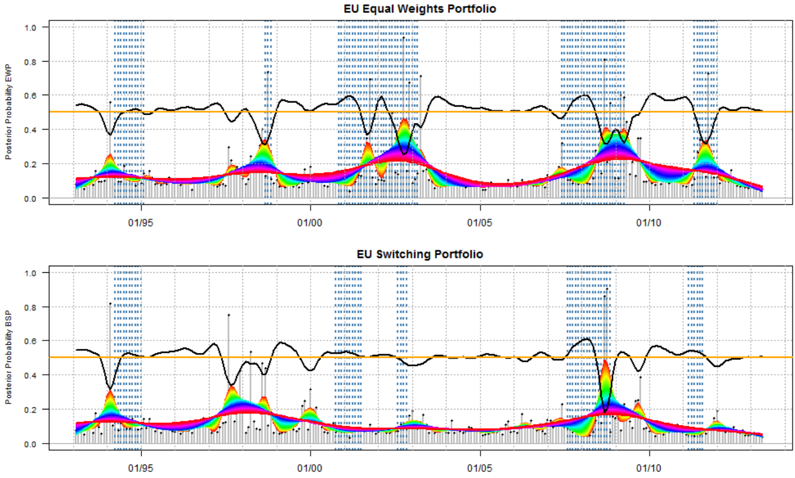

Figure 33: Switching Portfolios.

Upcoming Rmetrics Events

Don't miss the following Rmetrics events:

- **8th R/Rmetrics Workshop & Summer School**
  Taking place in Paris from 26th to 28th of June 2014.
  https://sites.google.com/site/rmetricsparis2014/
- **Advanced R Training**
  Taking place in Zurich on Friday, June 20 and Saturday, June 21.
  https://www.rmetrics.org/Zurich-IV/