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Abstract

In this article we analyse two dynamically allocated U.S. equity/bond indices. These are Barclays Dynamically Balanced Index (USBITR) and NYSE's Dynamically Allocated Index (NYUSDA). The two indices are compared with the results from a downdraft hedging strategy based on Byesian statistics. The approach analyses the location of structural changes and breaks in the dynamics of the underlying stock/bond assets that form the rules for rebalancing the investment. This process of wealth protection may be of general interest for insurane companies and pension funds during times of volatile stock markets and low or even negative interest rates. Downdraft hedging is thus an ideal tool for separately managed accounts, mutual funds and exchange traded funds.

Introduction

Living in times when investments in equities become more and more dangerous and risky, and the earnings from interest rates and the investment in bonds becomes more and more less performant, then insurance companies and pension funds are looking for new investment opportunities. In this context the New York Stock Exchange announced in January 2015 the launch of the *NYSE U.S. Dynamic Allocation Index*, short NYUSDA. The index dynamically allocates the NYSE U.S. Large Cap Equal Weight Index in combination with the NYSE Current 10 Year U.S. Treasury Index and is backcalculated until 1999. The strategy was introduced by Myra Capital [2015b]. The exposure focuses on a mix of the 500 largest equal-weighted (1/n) U.S. Equities and U.S. Treasuries. The dynamic allocation is rule-based shifting between the risky asset (U.S. equities) and the riskless asset (U.S. Treasuries) to significantly reduce drawdowns and to shorten recovery times. The NYSE index belongs to the so called family of *best-of-two indices* and may be managed by exchange options. A strategy that protects an equity/bond from risky drawdowns is often called *downdraft hedging*.

The NYUSDA Index is not the only U.S. best-of-two index. Barclays [2015a] manages an index combining dynamically the S&P500 Index together with their aggregated AGG Bond Index. The ticker of the index is USBITR. For this index the underlying concept is completely different from the NYSE/MYRA strategy: Barclays index uses the historical realized volatility based on 20-days and 40 days to determine the weights between the two assets. Rebalancing is done daily. The index is active since 2013 and backcalculated until 1986. Setz and Würtz [2014] have introduced an alternative strategy for downdraft hedging based on Bayesian statistics. The calculations for the wealth protected benchmark portfolios using this strategy are performed by Rmetrics [2014] at the end of every month.

The benchmarks are composed from three risky assets (two stock and one real estate index) and one bond index, called Quadriga [2014]. A branch of these benchmarks is a best-of-two strategy applied to

the MSCI U.S. Equally Weighted Stock Index and Barclays 7 Years U.S. Bond Index. The index is called in the following ARS, which is short for *An Rmetrics Strategy*.

In this article we analyze and compare in Chapter 1 the performances of Barclays' and NYSE's Indices. We use an approach that was introduced by Würtz et al. [2010] based on a (i) turning point and a (ii) Bayesian change point analytics. In addition we analyse the index in the time-frequency domain to detect non-stationarities by calculating the (iii) spectrum of the Morlet Wavelet. All three methods provide measures for the quality of the steadiness of the underlying dynamical process that generated the indices.

In Chapter 2 we describe our [2014] alternative downdraft hedging strategy. This strategy can be applied to design funds and portfolios that deliver a steady increase in wealth with low drawdowns and short recovery times. We describe how the ARS strategy compares to those used by the Barclays' and NYSE's indices.

In the third chapter we recalculate and explore the dynamical allocated weights over time for all three strategies.

1 Stability Monitoring

For monitoring the quality and stability of indices, funds, and portfolios we have developed a *Stability Monitoring Concept* that consists of three pillars, see Setz und Würtz [2014]: (i) in a first step we inspect the wealth of the investment and calculate traditional performance and risk measures, (ii) in a second step we perform a Bayesian Change Point (BCP) analysis of the dynamics underlying the price process of the assets, (iii) and in a third step we overall visualize the time-frequnecy behaviour by calculating the Morlet wavelet spectrum.

The *Wealth Chart* displays the performance of the considered asset over the last decade, i.e. from the beginning of January 2005 to the end of December 2014. It displays

- the logarithm of the wealth curve,
- the spline smoothed log of the wealth curve,
- the turning points,
- the logarithmic returns.

The BCP analytics performs an analysis of structural changes and break points according to Barry and Hartigan [1993] in the framework of a Markov Chain Monte Carlo Simulation implemented by Emerson and Erdman [2008]; as described by Setz and Wuertz [2014]. As a result we get the probability that the next obersvation in time will be a structural change point. A *BCP Chart* displays several indicators derived from the change point probabilities. This includes

- the *change point probabilities*,
- the *downturn periods* obtained from a spline based turning point analytics,
- the *drawdowns* of the original wealth curve,
- the colored *rainbow band* that provides a measure for the overall strength of the probabilities,
- the *twiggling indicator* for falling and rising index values deviating from a baseline of 0.5.

From the BCP analysis we can derive further stability measures. The (posterior) mean and variance, the worst value of the change point probability, the average spread of the rainbow band, and the regression error for the twiggling indicator.

Further information can be obtained from a spectral analysis using a *Morlet Wavelet Transformation*, see Torrence and Compo [1997], that is an extension to the well known Fourier transformation. Both are time-frequency analysis tools, but wavelets can be used for non-stationary time series. Besides stationary signals the wavelet power spectrum allows to filter out transient signals as well. Thus instabilities caused by any kind of market turbulences can be visualized. This makes the value of the wavelet approach.

Barclays U.S. Dynamic Balance Index: Barclays' index [2015a] reflects the performance of an allocation strategy between the S&P 500 Index and Barclays' U.S. Aggregate Bond Index in accordance with a rules-based model. On a daily basis, the index attempts to allocate weights to the two underlyings based on the historical realized volatilities of both indices. In general, relatively higher realized volatility will mean a relatively smaller weight allocation. For weight determination 20-days and 40-days realized volatility levels are used.

MYRA NYSE Dynamic Allocation Index: The dynamic strategy behind Myra's index [2015b] is completely different from that of Barclays. The index invests at the beginning of each year 50% in equities and 50% in bonds. In the course of the year, successive rebalances are made in the higher-performing asset. Note that this may result in a full investment in the same category by the end of the year. The strategy can for example be realized by using exchange options. The same strategy is applied to Walsers' German Select Fund [2015c].

2 Bayesian Downdraft Hedging

Recently Setz and Würtz [2014] have developed a new Bayesian filtration algorithm which can be used for wealth protection of investments leading to a more steady performance and less risk with higher returns and lower drawdowns with shorter recovery times. This measure is calculated from the above mentioned BCP/MCMC algorithm. We use this approach together with a *Thresholding Decision Rule* (TDR) added by Setz and Würtz [2014].

In a first step we compute on an end-of-month rolling window of a predetermined length the most recent values for the BCP posterior mean (return), the posterior variance (risk), and the posterior probability that the next observation will be a structural change point (stability). From these three values we compute a MCMC averaged *Instantenous Sharpe Ratio* at the most recent point in time T over the period τ of the rolling window. This defines our indicator ς used as a prediction for the next time step, where $\mathbb{E}$ denotes the stability weighted expectation value:

$$\hat{\varsigma}_{T+1} = \mathbb{E}\left[\frac{\hat{\mu}_{T|T-\tau\ldots T}}{\hat{\sigma}_{T|T-\tau\ldots T}}\right]_{(1-\hat{P}_{T-1|T-\tau\ldots T-1})} \tag{1}$$

When the indicator $\hat{\varsigma}_{T+1}$ increases with median $\hat{\mu}$ and decreases with mean absolute deviaton $\hat{\sigma}$ with almost constant high probability in stability $1-\hat{P}$, then we expect a stable and steady trend in the performance with low risk. But when does this behaviour change, and when does the trend revert?

At this point, in a second step, the TDR threshold becomes active: If the most recent indicator value $\hat{\varsigma}_T$ crosses a given quantile level $\hat{\rho}_T$ of the distribution of historical $\hat{\varsigma}$ values $\hat{\varsigma}_{T|T-\tau\ldots T-1}$ from above or below then the distance between the indicator and the level can be used to measure the *signal strength*.

$$\hat{\varsigma}_{T+1} - \hat{\rho}_{T+1} \bowtie 0 \tag{2}$$

When the sign of the signal strength $\hat{\varsigma}-\hat{\rho}$ changes (indicated by the bowtie $\bowtie$ sign) then the next position will be determined, either "one" which recommends to be invested in the equity index or "zero" which recommends to protect the wealth of the investment by hedging with the bond index. The threshold level $\hat{\rho}$ is predicted as the best quantile level from the most recent time step T. A full hedge is not compelling, we can also compute a partial hedge given by the signal strength instead of their signs.

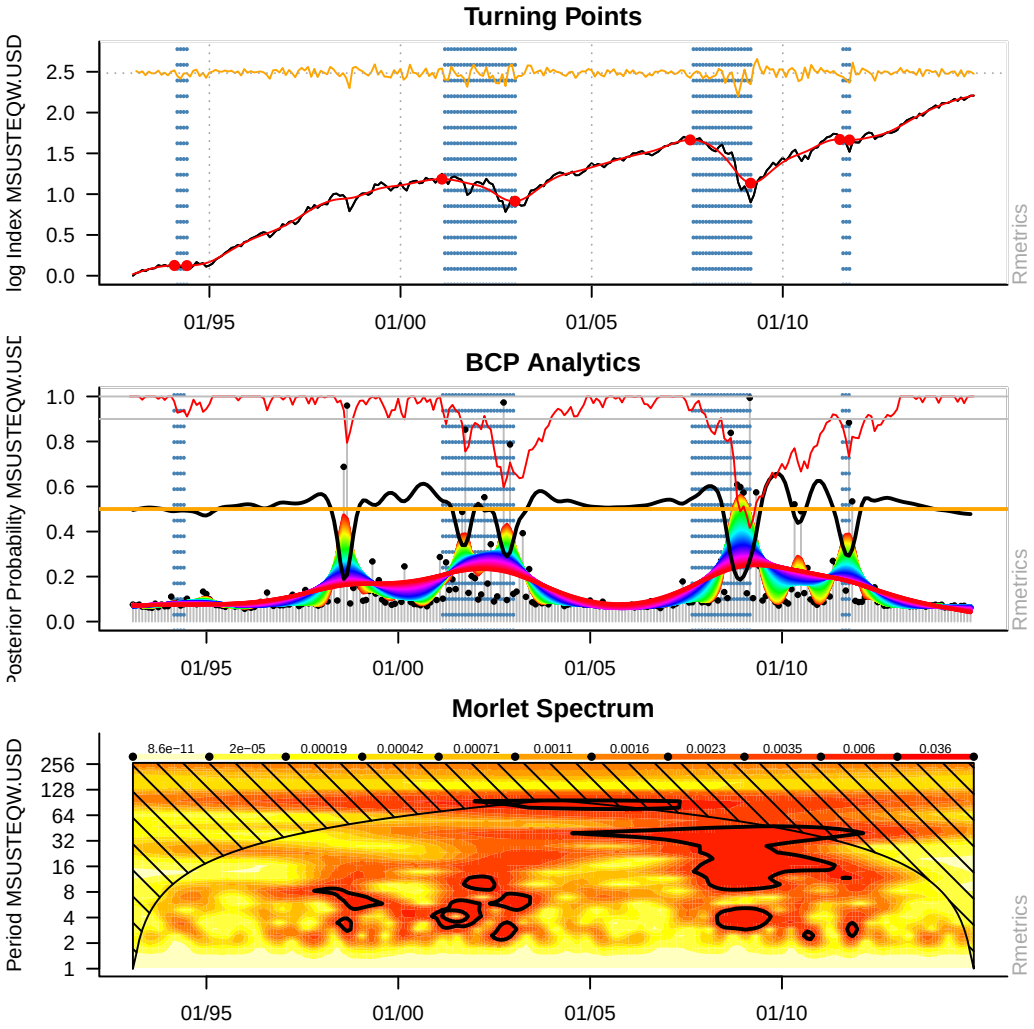

Figure 1: Barclays U.S. Dynamic Balance Index. The underlying downdraft hedging strategy makes use from historical realized volatilities for rebalancing.

How to read this stability chart?
The upper chart shows the turning point analysis. When the straight line (steelblue) is close the the logarithmic wealth curve (black) then the steadiness in the performance will be high. The chart in the middle displays the Bayesian change point analysis. The rainbow band expresses the variability of the probabilities that a point will be a change point. For a stable index the rainbow band is narrow and close to zero. The twiggling indicator (black) about the 1/2 center line (orange) measures the spread of the rainbow band. Thus the twiggling indicator gets for stable indices very close to the center line. The lower chart plots the power spectrum. It should be as homogeneous as possible. A stable index has many small isolated islands and a low variability level expressed by the most right value of the ruler. ■

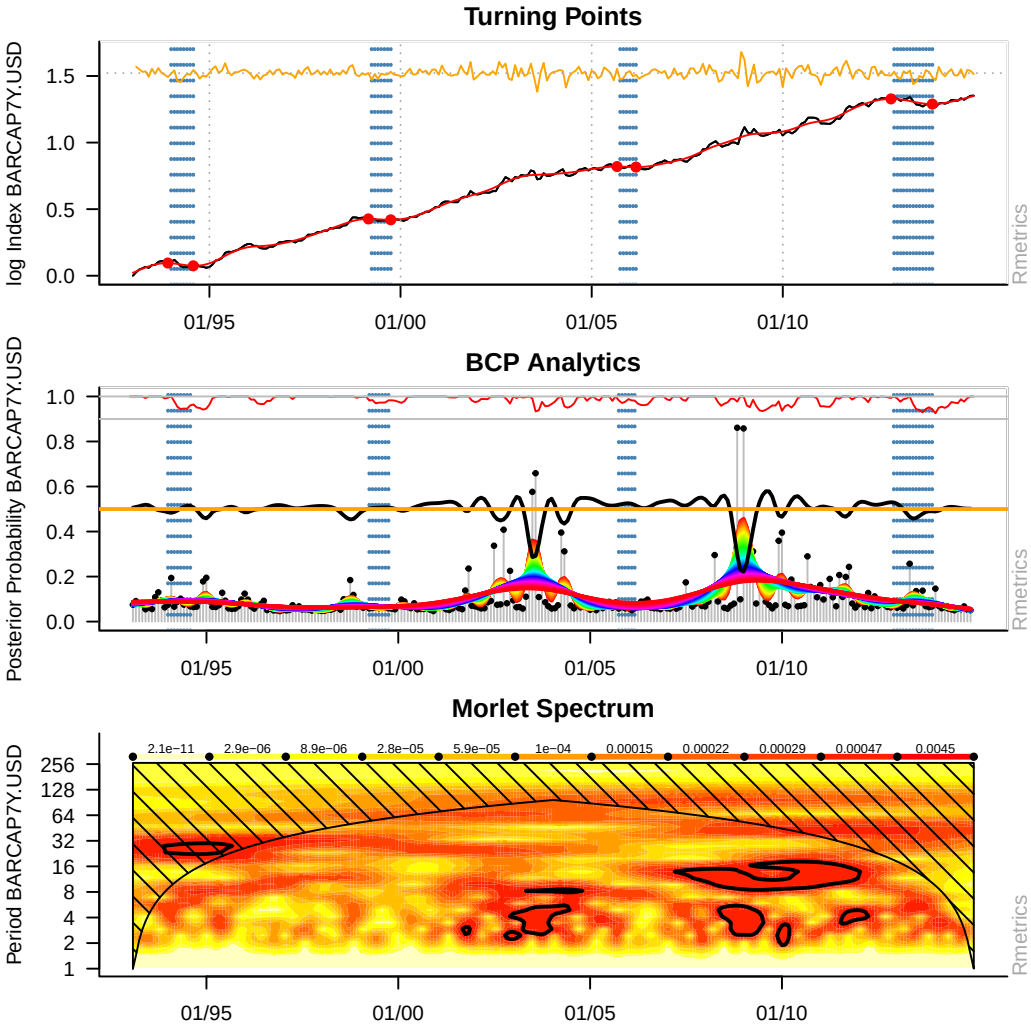

Figure 2: NYSE's U.S. Dynamic Allocation Index. The underlying downdraft hedging strategy makes use of exchange options for rebalancing. ■

Rmetrics Binary Downdraft Hedging Strategy: Rmetrics' downdraft hedging strategy rebalances the Index between the MSCI Equal Weights TR Index and Barclays 7 Year TR Treasury Index. The most straightforward implementation relies on a binary switching of the two assets. In this sense it is a "true" best-of-two index. Both underlying indices are available as exchange traded funds. Therefore a simple implementation of the hedging strategy can be realized by ETFs. Although our strategy does just a simple binary switching of the two assets, one can modify the strategy and think of rules for partial switching as well.

The overall performance for all three downdraft hedged indices are quite similar. They result in a more stable wealth growth with lower drowdowns. This makes the indices interesting for insurance companies and pension funds. Separately managed accounts, mutual funds and exchange traded funds may profit from drawdraft hedging.

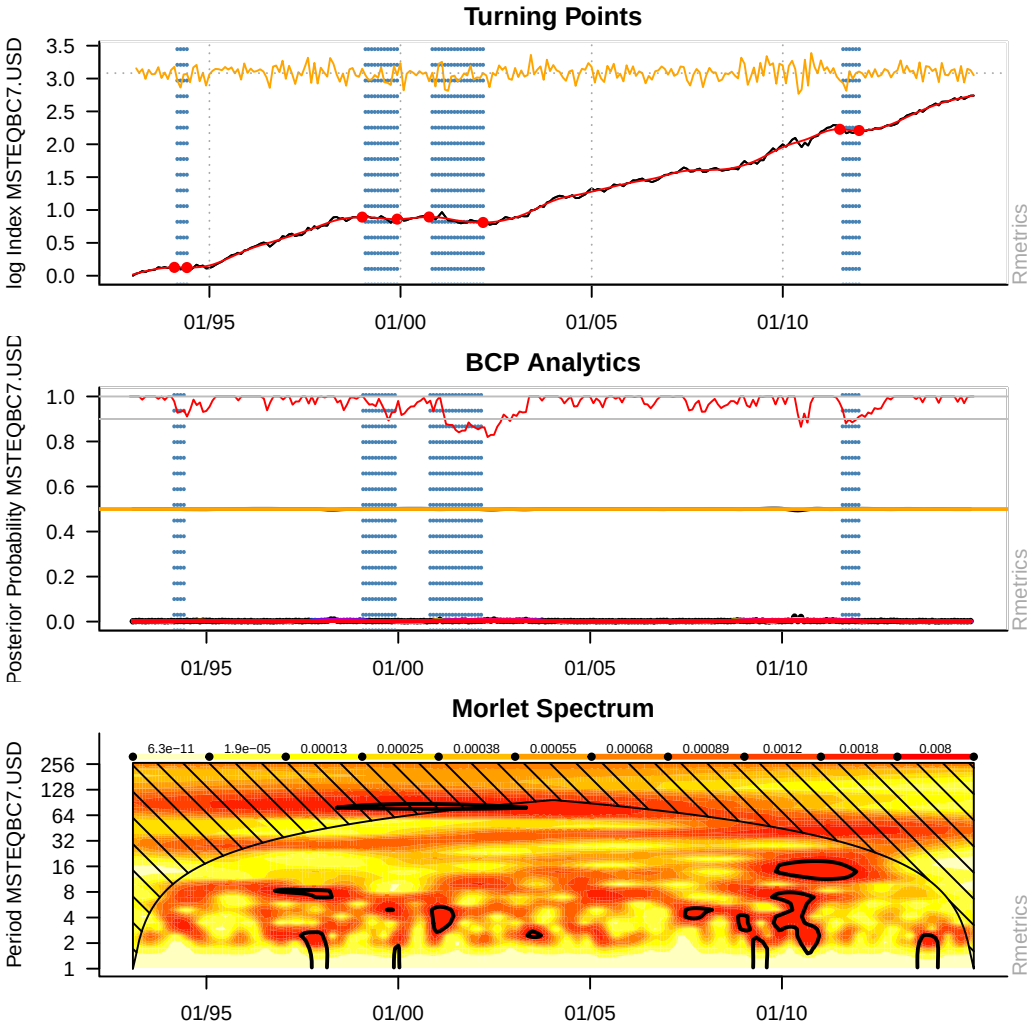

Figure 3: ARS Bayesian Dynamic Allocation Strategy. The underlying downdraft hedging strategy makes use of structural changes and breaks in the assets' price series for rebalancing. ■

3 Dynamic Weights Allocation

We used the end-of-month index values to calculate the log-returns. From these values we derived the weights through the following formula:

$$W_{S,t} = \frac{r_{H,t} - \hat{\rho} - r_{S,t}}{r_{S,t} - r_{B,t}} \tag{3}$$

Here $r_{H,t}$ are the downdraft hedged end-of-month log-returns at time t, $r_{S,t}$ are the end-of-month log-returns of the equities, and $r_{B,t}$ are the end-of-month log-returns of the bonds. $\hat{\rho}$ is a tiny correction return (0.00020 per month) that takes care about the daily (and not monthly) rebalancing of Barclays index. The value for $\hat{\rho}$ is zero for Myra's and Rmetrics' indices since they are rebalanced on a monhtly base. $W_{S,t}$ are the weights for the equity index and $W_{B,t} = 1 - W_{S,t}$ are the weights for the bond index. The equity/bond expectation value for the time averaged weights ratio is equivalent to 41%/59%

for Barclays' Index, to 56%/44% for Myra's Index, and to 79%/21% for Rmetrics' Index. (Note that all returns are log-returns and not discrete returns, this may lead to minor differences when comparing performance numbers.)

The end of year indices are listed in Figure 4. First of all we observe large performance differences. After 10 years Barclays index grows from an investment of 100 USD to a value of 177 USD (a value lower than the SP500 Index), the NYSEs Index to 294 USD, and the Rmetrics strategy to 411 USD. One should also notice the differences in the underlying equity indices when comparing these numbers: The lowest index value can be seen for the S&P index with 209 USD at the end of the period, then the MSCI Index with 229 USD, and the highest index, the NYSE with 250 USD. The reason for this is the fact that equal weighted indices usually show higher returns in comparison to capital weighted indices. There are also minor differences in the bond index performance.

GMT

	SP500	AGG	BARCAP	NYLC	AXTEN	MYRA	MSEQ	BC7Y	ARS
2004-12-31	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
2005-12-31	104.91	102.43	101.11	110.90	101.88	105.88	108.67	102.41	108.67
2006-12-31	121.37	106.90	112.22	128.17	103.24	117.01	123.98	105.23	123.22
2007-12-31	128.16	114.31	116.86	140.55	113.25	124.11	127.78	115.89	128.67
2008-12-31	80.74	120.30	114.98	84.88	136.18	134.45	75.43	136.72	151.80
2009-12-31	102.11	127.44	126.48	113.89	122.72	161.04	107.00	128.47	195.45
2010-12-31	117.49	135.77	138.01	138.89	132.51	179.58	129.82	140.51	237.12
2011-12-31	119.87	146.37	143.68	138.76	155.15	192.23	128.83	162.35	239.32
2012-12-31	139.17	152.59	152.55	162.75	161.45	212.89	150.38	169.18	269.28
2013-12-31	184.25	149.50	169.00	220.00	148.75	263.35	203.40	158.96	364.23
2014-12-31	209.47	158.42	177.02	249.75	165.01	293.73	229.27	173.26	410.55

Figure 4: Listing of the wealth indices. The column names abbreviate the assets (from left to right) SP500 TR Index (col 1), Barclyas U.S. Aggregated Bond Index (col 2), Barclays Dynamic Balanced Index (col 3), NYSE LCap Equal Weights TR Index (col 4), NYSE Current 10 Year Bond Index AXTEN (col 5), Myra NYSE U.S. Dynamic Allocated Index (col 6), MSCI U.S. Equal Weights Index (col 7), Barclays U.S. 7 Years Government Bond Index (col 8), Rmetrics downdraft hedging strategy ARS (col 9). Note all indices have been indexed to 100 at 2004-12-31. ■

Let us trace the time evolution of the weights. The monthly averaged weights from the daily rebalanced Barclays index are highly volatile. The structure in NYSEs weights show clearly the reset at the beginning of every year to a 50%/50% ratio of equities and bonds. The binary Rmetrics downdraft hedging strategy shows only a few rebalances over the whole decade. Note that a binary strategy offers the full range of performance since we are always invested on the high performance side. This observation is confirmed when we are replacing the continuous weights from Barclays' und NYSE's indices.

4 Summary

In this article we have presented and compared three different downdraft hedging approaches consisting of U.S. indices and based on (i) realized volatility, (ii) on exchange options, and (iii) on Bayesian change point analytics. All three approaches fullfill the request to stabilize the index by donwdraft hedging. Quite different is the performance ranging from a moderate (Barclays), via an indermediate (Myria), to a strong (Rmetrics) growth style. The performance over the last ten year is more than a factor of two larger comparing Barcleys' index with Rmetrics' index. Conditional monthly drawdown levels on the 95% confidence interval are for all three hedged indices below 10%.

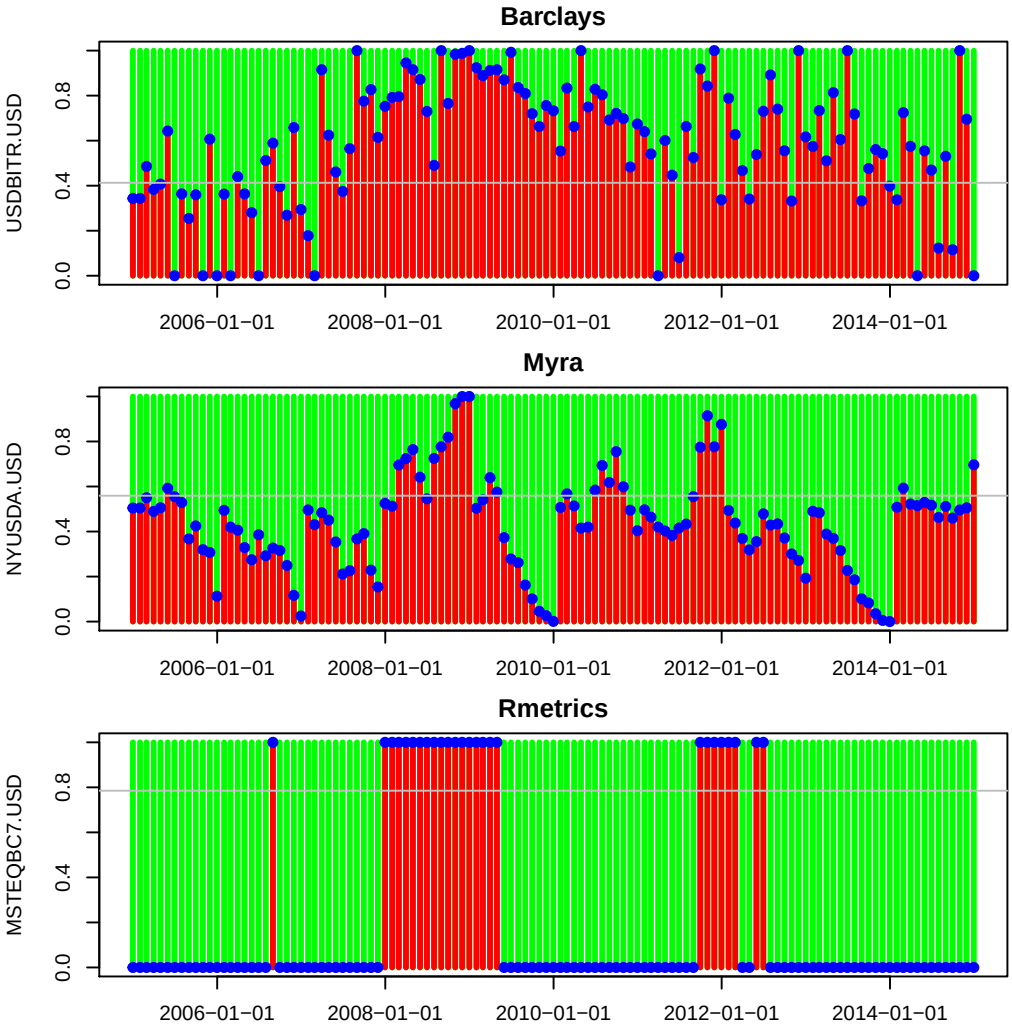

Figure 5: From top to bottom the dynamical Weights for Barclays' Balanced Index, for NYSE's Dynamical Allocated Index, and for Rmetrics' Binary Downdraft Hedging Strategy. The length of the green bars show the weights for the equities, the reds for the bond, the blue dots are the end-of-month weights. The thin horizontal lines express the average weights ratio of equities and bonds. ■

The downdraft hedging approaches are transparent although the details of the implementations are not available. Unfortunately we cannot compare the indices exactly on the same level since they are composed from different equity and bond indices and they are rebalanced on different time horizons. Barclays Dynamic Balanced Index is daily rebalanced, NYSE's Dynamic Allocated Index and the Rmetrics Strategy are monthly rebalanced. Also it is very difficult to judge to which amount transaction costs and other costs may influence and reduce the performance.

In summary we are confident that wealth protection and risk reduction by downdraft hedging using Bayesian statistical approaches will fullfill the expectations from an increasing demand for advanced dynamically managed investment strategies.

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