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No. 2015-03

Rmetrics

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

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First Version 9 January 2015 - This Version 16 February 2015

Introduction

In finance stability indicators are designed to measure and predict the dynamical behaviour of financial time series. This allows a better description and understanding of vulnerabilities, of instabilities and stress resistivity of financial investments and trading decisions. 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.

To demonstrate the usefulness of our approach we calculate for five major developed countries, United States, Japan, Germany, Great Britain, and Switzerland our new structure and stability measure. The dynamic evolution of the economic growth is monitored by MSCI stock market indices [2015]. Beside the broad stock market indices we also investigate the components expressed by capitalization size and investment style, MSCI [1997]. Finally structure and stability of the individual countries are compared with regional aggregated market indices. These include the MSCI European Monetary Unit (EMU) index, the developed MSCI (WORLD) world index, the MSCI emerging market (EM) World index, and the MSCI all countries world index (ACWI) stock market index. All indices are total return indices including dividend payments.

The investigation discusses how to calculate and how to use the BCP filtrations over time to achieve investment goals with higher performance and lower risk. In Chapter 1 we define Bayesian filtrations and show how compute them and how to extract signals. In Chapter 2 we calculate for the selected markets the stabilized wealth index, its drawdowns and recovery times, and the signal strengths ans size and style confidence. Chapter 3 discusses the results. A brief summary chapter put the results together.

1 BCP Filtrations

To characterize the strength of the stability and steadiness of the growth of a stock market index we present the recently by Setz and Würtz [2014] introduced *Bayesian Filtration Measure*. This measure is calculated from the *Bayesian Change Point* (BCP) algorithm of Barry and Hartigan [1992, 1993]. Their approach was extended by Loschi and coworkers [1999, 2001]. We use the *Markov Chain Monte Carlo*

(MCMC) approach as implemented by Emerson and Erdman [2007, 2008], together with the *Thresholding Decision Rule* 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 time point T over the period τ of the rolling window. This defines our indicator ς used as a prediction for the next time step.

$$\hat{\varsigma}_{T+1} = \frac{\hat{\mu}_{T|T-\tau \ldots T}}{\hat{\sigma}_{T|T-\tau \ldots T}}(1 - \hat{P}_{T-1|T-\tau \ldots T-1}) \tag{1}$$

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?

Then 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*.

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

The sign of the signal strength $\hat{\varsigma} - \hat{\rho}$ changes and determines the next position, either one (recommended to be invested) or zero (recommended to protect the wealth of the investment). The threshold level $\hat{\rho}$ is predicted as the best quantile level from the most recent time step T.

2 Wealth Protection of Stock Markets

As broad market measures we use the MSCI *Investable Market Index*, short IMI [2011]. The MSCI IMI indices include large cap, mid cap and small cap segments and provide exhaustive coverage of these size segments by targeting a coverage range of close to 99% of the free float-adjusted market capitalization in each market. The large cap indices target a coverage range of about 70%; the mid cap indices target a coverage range of about 15%; and the small cap indices target a coverage range of about 14%.

First we compute after the closing of the market on the last trading day in each month the filtrated signal strength as the difference of the indicator $\hat{\varsigma}$ and the threshold level $\hat{\rho}$. If the sign is positive we invest in the index, if the sign is negative we protect our investment. In a most simple approximation this means, that we do not invest at all and stay away from the market.

Figures 1 to 5 show this investment process for the MSCI IMI indices for Swizerland (CHF), Germany (EUR), Great Britain (GBP), the United States (USD), and Japan (JPY). The calculations have been done on the last trading day in December 2014 after the market has been closed. This was done together with a forecast for the investment decision for January 2015. The black curve in the upper chart shows the MSCI IMI benchmark index. For all five countries we clearly observe the market drawdowns during the Internet bubble bursting (2002), the sub prime crisis (2008), and the European sovereign debt crisis (2011). The orange curve shows cumulated returns for the filtrated investment.

For all five countries the one month ahead predictive power for the position taking over the last 13 years was extremely high. If we compare the index values of the MSCI benchmark index (black) with the wealth protected stabilized index (orange) we observe a significant outperformance. The drawdowns of the MSCI IMI indices have been lowered by more than a factor of 2 and the recovery times have been widely shortened. This is demonstrated in the upper and middle charts of figure 1 to 5. The flat performance in the index belongs to unstable periods. Note that on the average only twice a protection per year of the index was required. The Japanese market is quite exceptional, and it shows that the filtration process also works very successfully in a volatile sideways trending market.

Figures 6 to 9 show the results for the regional aggregated MSCI IMI indices: the MSCI EMU European Monetary Unit, MSCI World, MSCI EM Emerging Markets, and MSCI ACWI All Countries World Index. All indices again are total return indices and denominated in USD for a better comparison. All four markets MSCI EMU, MSCI WORLD, MSCI EM, and MSCI ACWI show similar results. The three major crisis in 2002, 2008, and 2008 could be cleary identified in advance, and it was possible to protect an investment early enough from large losses. Although the emerging market is since almost five years moving sideways, the filtration measures has successfully protected the wealth of emerging market investments.

3 Variability by Size and Style Components

But how reliable are our results? Is there a difference in performance and risk for large and small cap investments? Is there a difference concerning the investment style by value and growth stocks? As one aspect to answer these question we have analysed the capitalization size and the investment style of the indices. We have calculated the stability of the nine MSCI indices of the Morningstar style box [2004]. These represent large cap, mid cap, and small cap index sizes. For each capitalization size we then distinguish between its growth, blend (core) and value style contributions.

From the nine size and style components we derive the average size and style box stabilities and their average deviations. These values are obtained from robust *median* and *mad* (mean-absolute-deviation) estimators of the single stability strength indicators. The median and mad allow us to determine how reliable the stability of the market with respect to its capitalization size and investment style can be considered.

The results have been illustrated in the lower chart in figures 1 to 9 for the major country and regional aggregated indices. The black curve follows the *median* of the filtration strengths of all nine size and style subindices and the *confidence* bands are defined by the mean absolute deviation *mad*. Due to the definition in equation (1) the filtration is measured in units of the mean absolute deviation. This makes the intepretation easy, numbers are in units of deviations.

The graphs show the three unstable stock market periods (negative filtration strengths) related to the Internet bubble, the sub prime crises, and the European sovereign debt crisis. Following these low performing periods with large losses we observe three periods of significant growth in the indices. In contrast to traditional trading indicators based on moving averages the transition between the different market regimes is extremely sharp. This is a great advantage of the filtration measure compared to other indicators.

This situation has changed during the second and third quarter 2014 when we observe the slowly sliding down of the markets. The filtration values in 2014 have been continuously lowered. This becomes evident in the case of Switzerland, Germanny, and Great Britain where the filtration is twiggling around zero inside the one standard deviation band of the *mad*. This describes a very indifferent market situation where no bsolute clear decision can be made if the markets go up or down in a predictive manner with a stable behaviour. For the United States and Japan the behavour is different. The slowing down of the filtration is also apparent but the positive values are still intact at the end of 2014.

4 Summary

Bayesian filtration measures are useful and reliable indicators for wealth protection of investments in stock makets. Based on more then a decade of historical data filtrations deliver confident results and reliable predictions for a better wealth protection. Especially the accurate timing of switching regimes of gains and losses makes them a valuable tool for protecting portfolios and funds when it becomes necessary. This is an important point for any investment manager to protect the wealth of his funds.

Evenmore like size and style analysis, country rotation and/or industry sector rotation may be used in the future to stabilize stock market investments. Furthermore filtration strengths are measures which allow to control portfolio bandwidths and risk budgets.

MSCI Swiss Stock Market

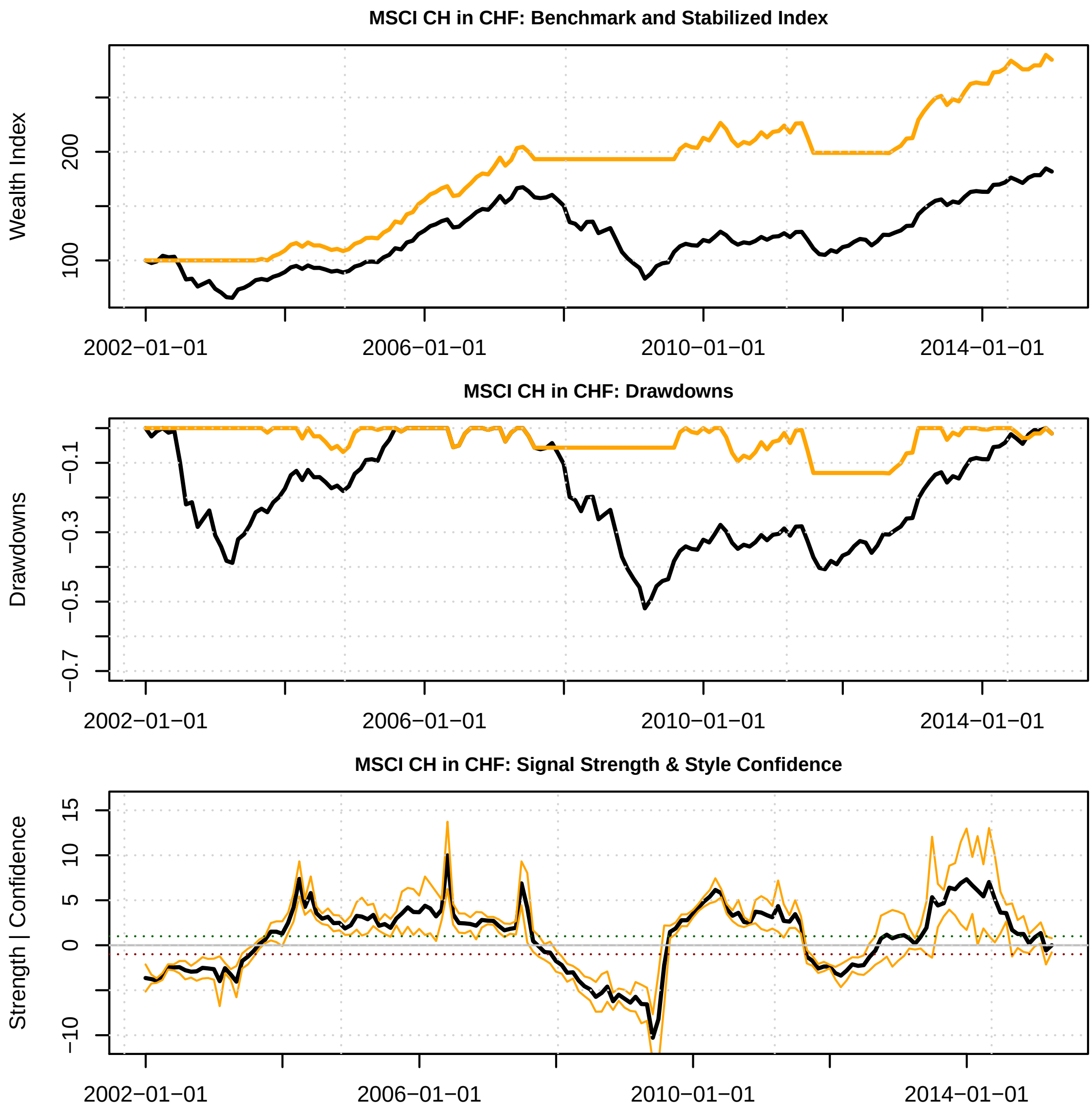

Figure 1: The family of the MSCI Switzerland Indices are free-float-adjusted indices that were designed to measure the performance of the Swiss stock market. For Swiss size and style indices appropriate market sub-indices are available.

MSCI German Stock Market

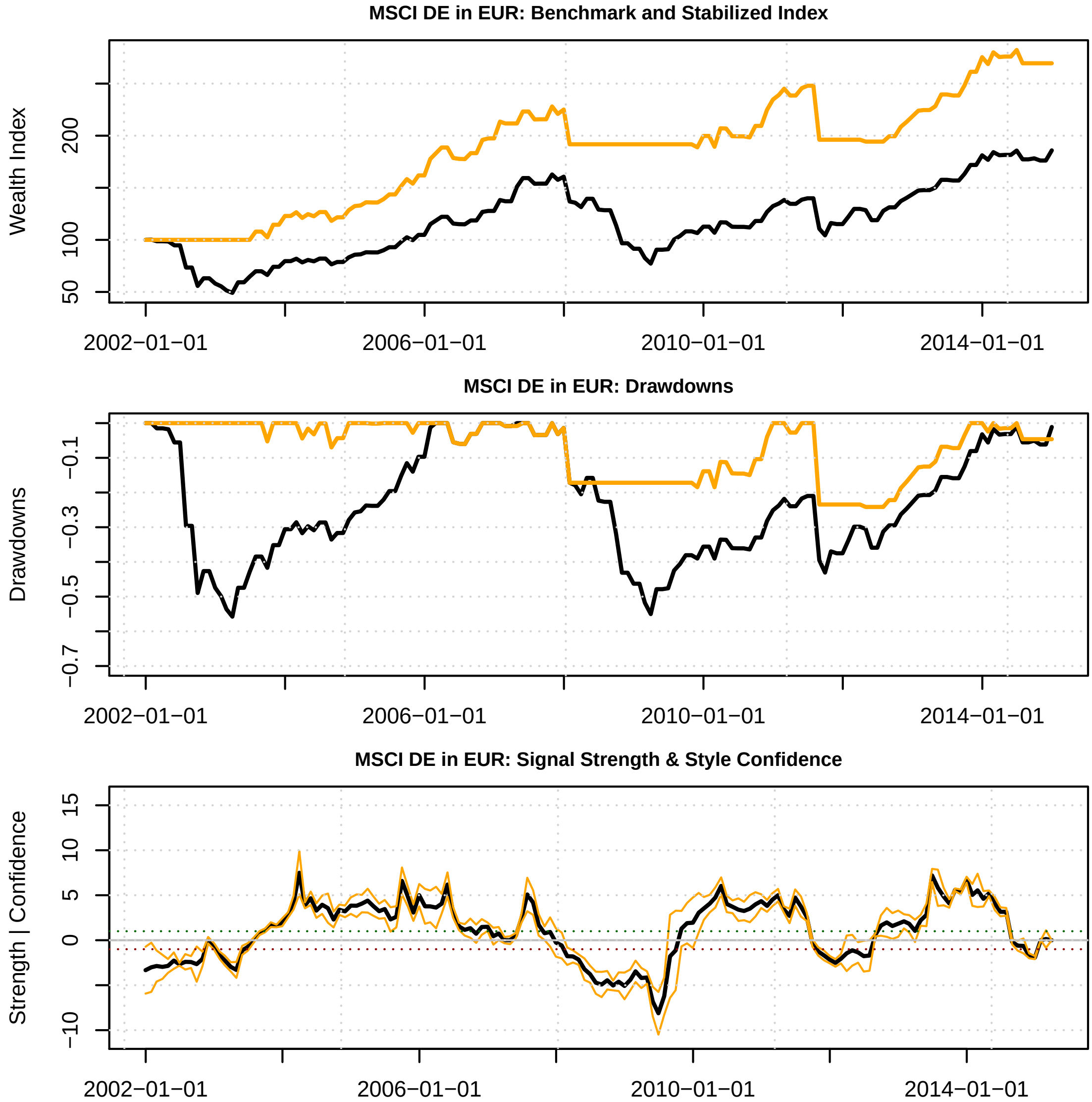

Figure 2: The family of the MSCI Germany Indices are free-float-adjusted indices that were designed to measure the performance of the German stock market. For German size and style indices appropriate market sub-indices are available. MSCI [2014]

Great Britain Stock Market

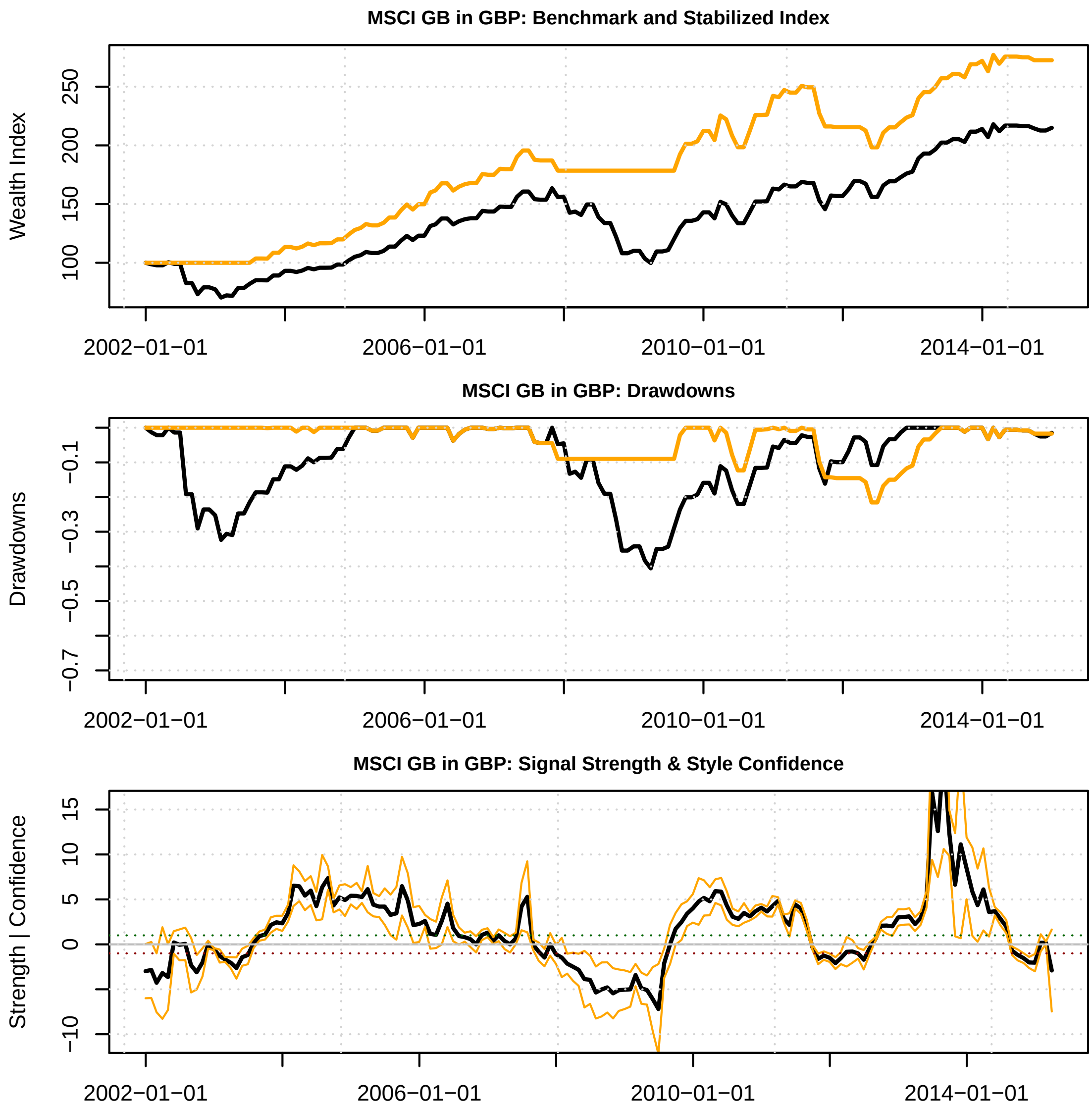

Figure 3: The family of the MSCI Great Britain Indices are free-float-adjusted indices that were designed to measure the performance of the British stock market. For British size and style indices appropriate market sub-indices are available. MSCI [2014]

United States Stock Market

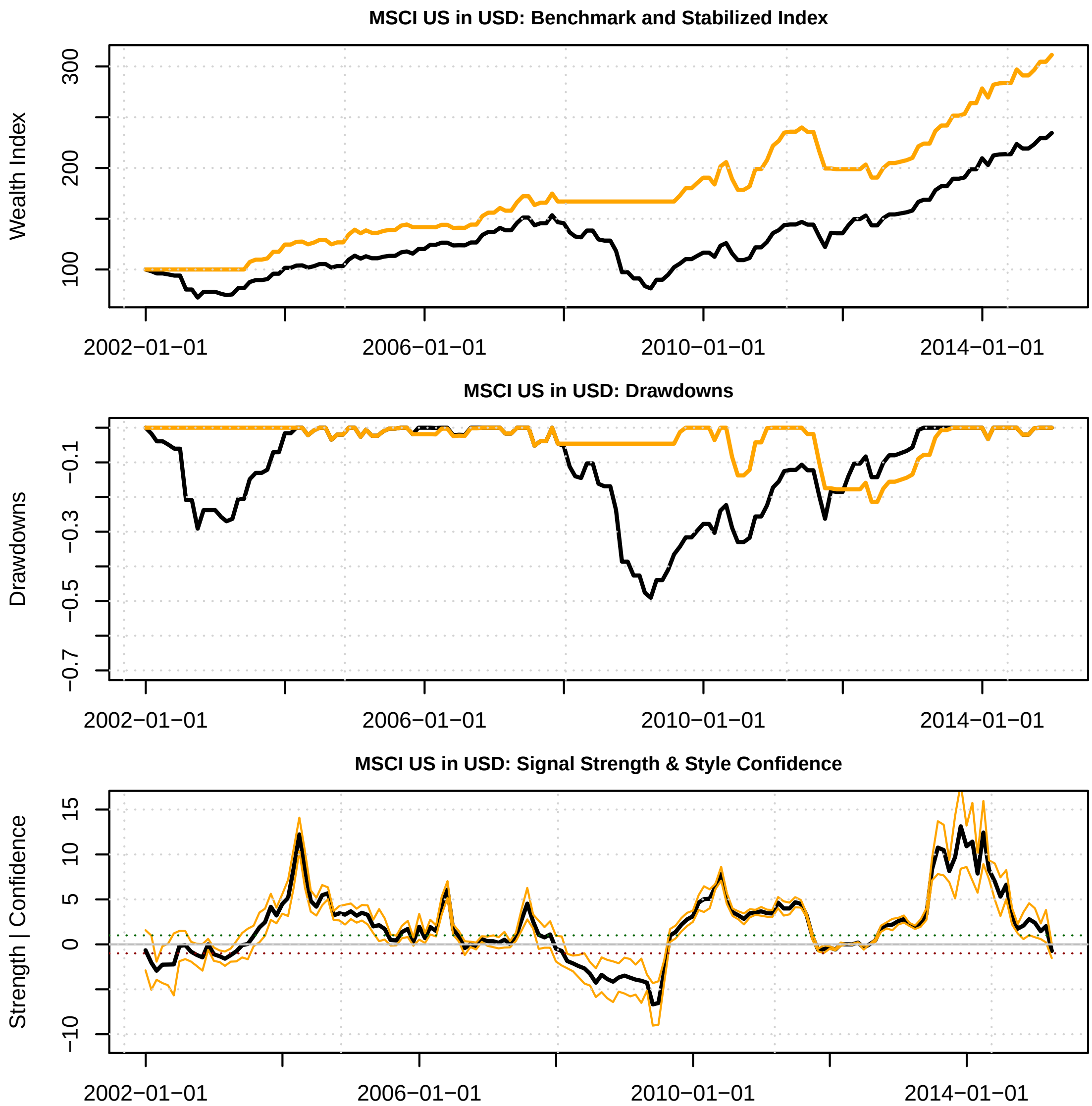

Figure 4: The family of the MSCI Unite States Indices are free-float-adjusted indices that were designed to measure the performance of the U.S. stock market. For U.S. size and style indices appropriate market sub-indices are available. MSCI [2014]

Japanese Stock Market

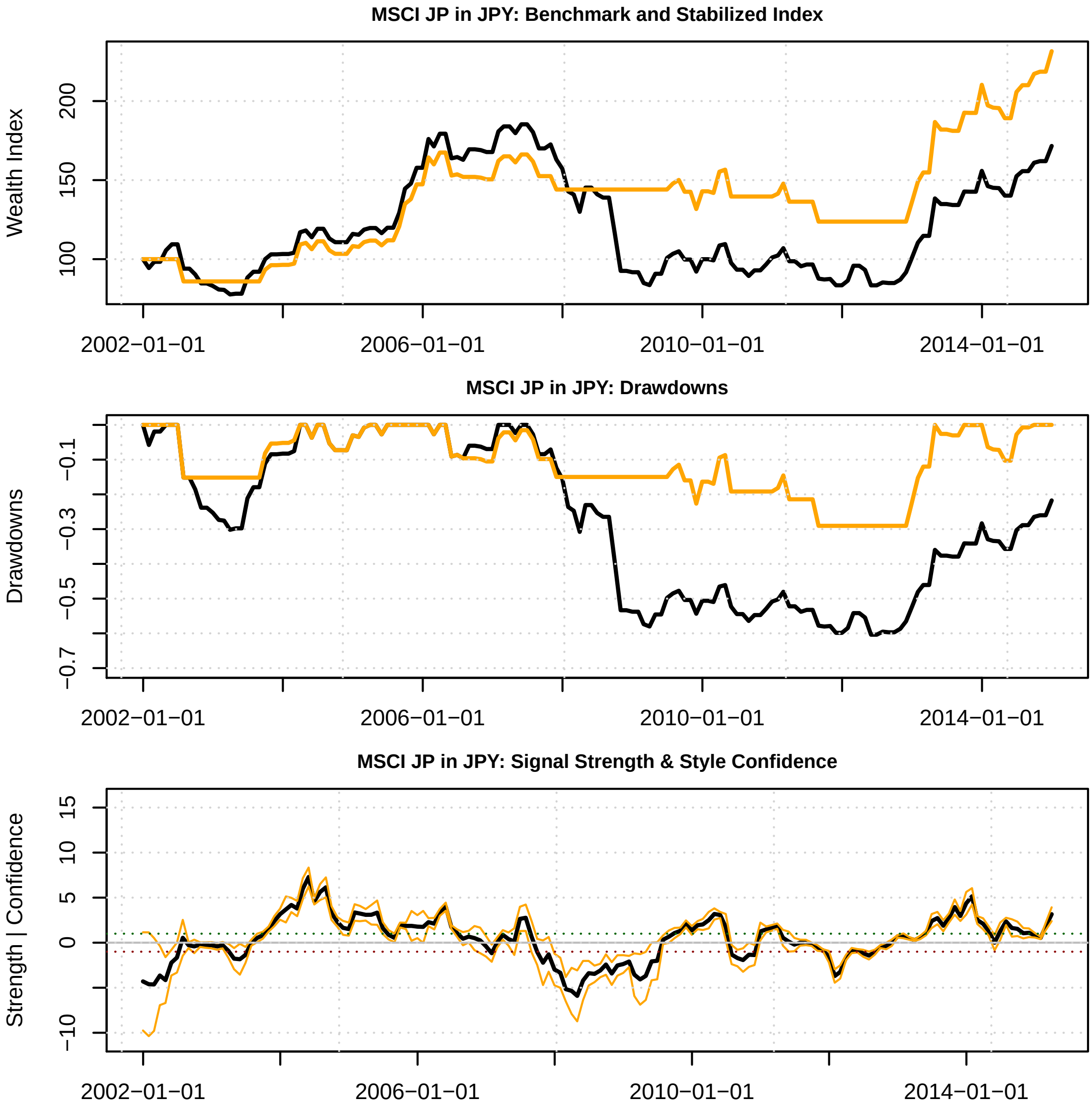

Figure 5: The family of the MSCI Japan Indices are free-float-adjusted indices that were designed to measure the performance of the Japanese stock market. For Japanese size and style indices appropriate market sub-indices are available. MSCI [2014]

MSCI Europe Index

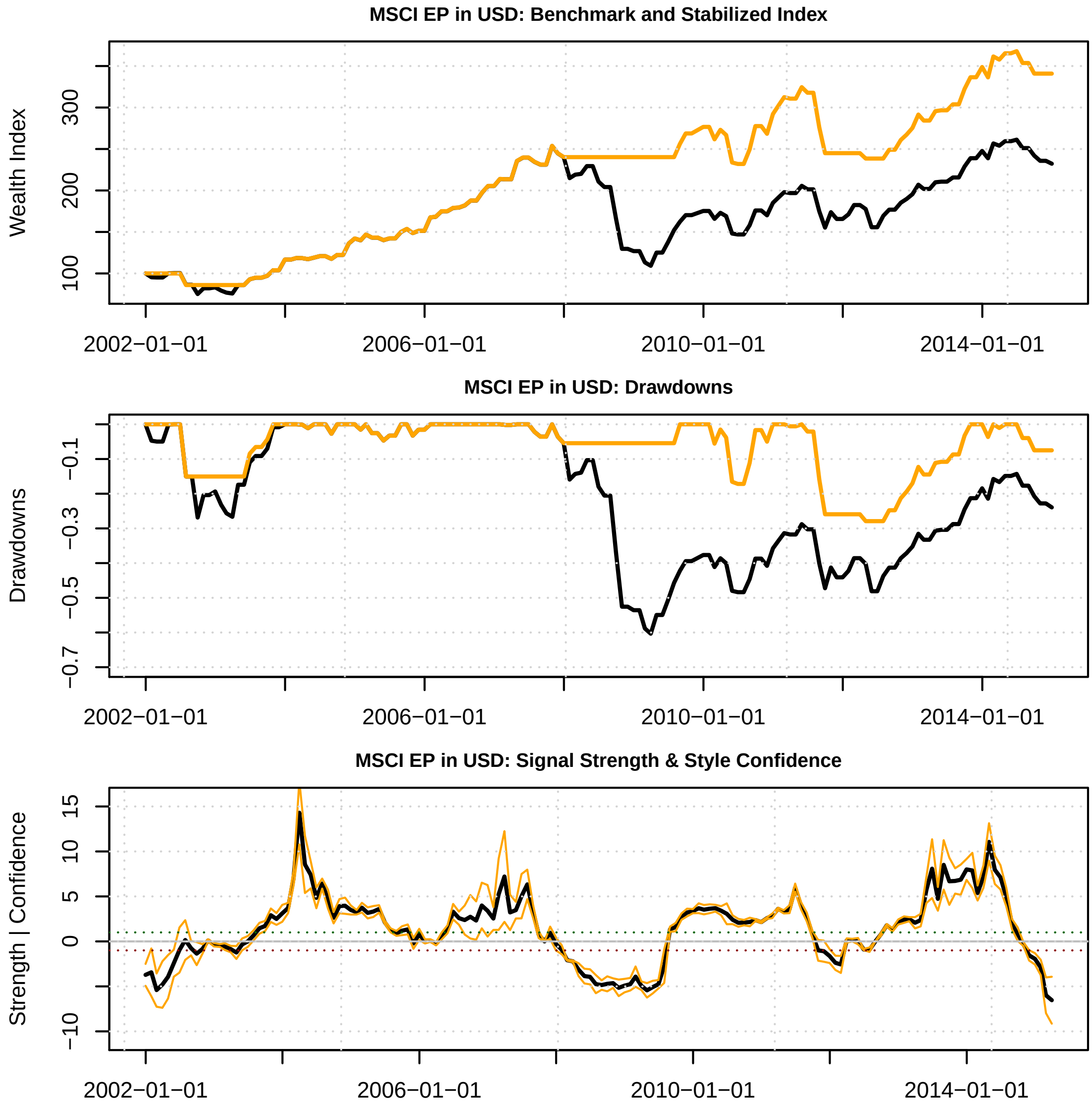

Figure 6: The MSCI Europe Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of the developed markets in Europe. The MSCI Europe Index consists of the following 15 developed market country indexes: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. MSCI [2014]

MSCI World Index

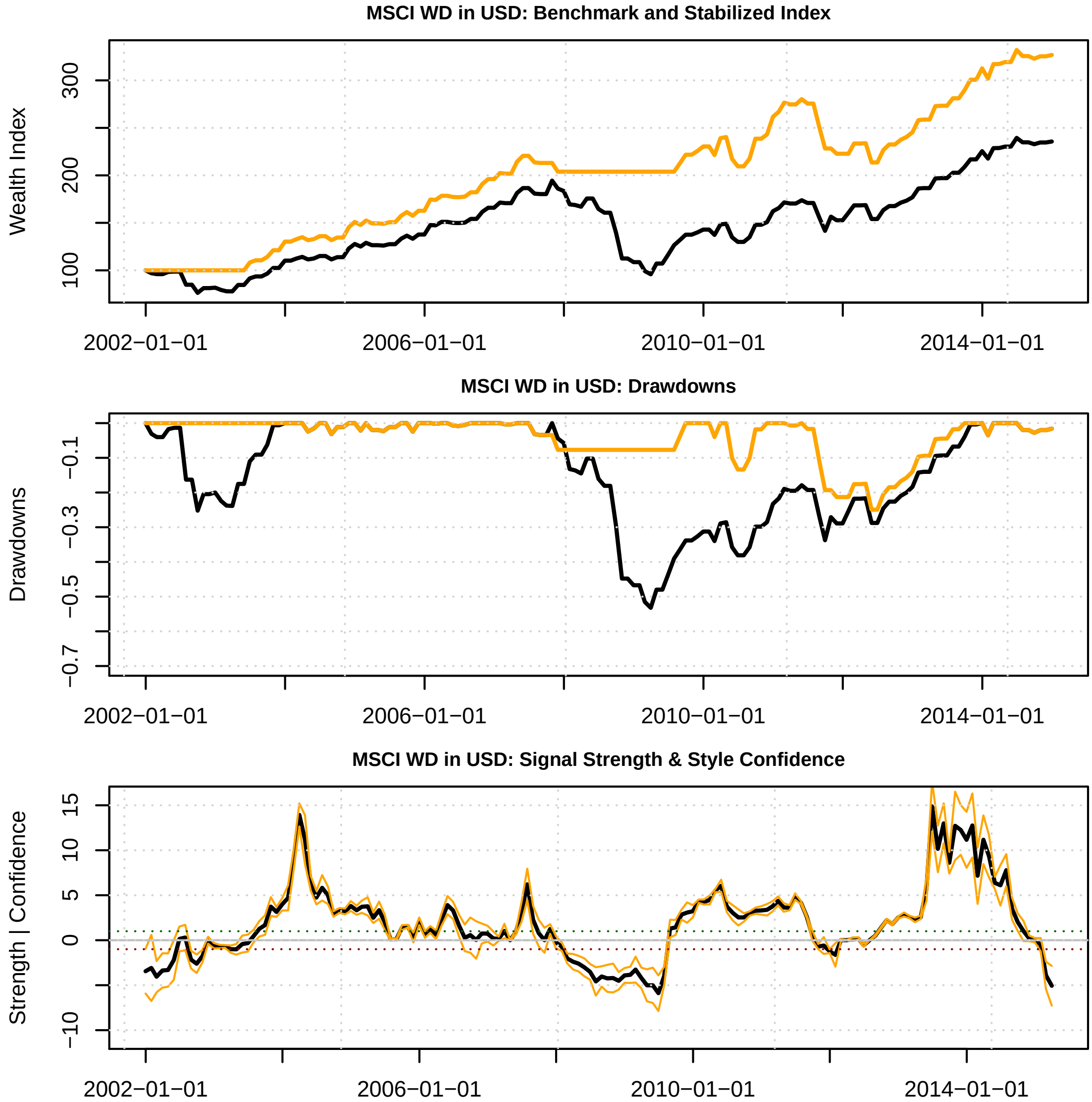

Figure 7: The MSCI World Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of developed markets. The MSCI World Index consists of the following 23 developed market country indexes: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. MSCI [2014]

MSCI Emerging Market Index

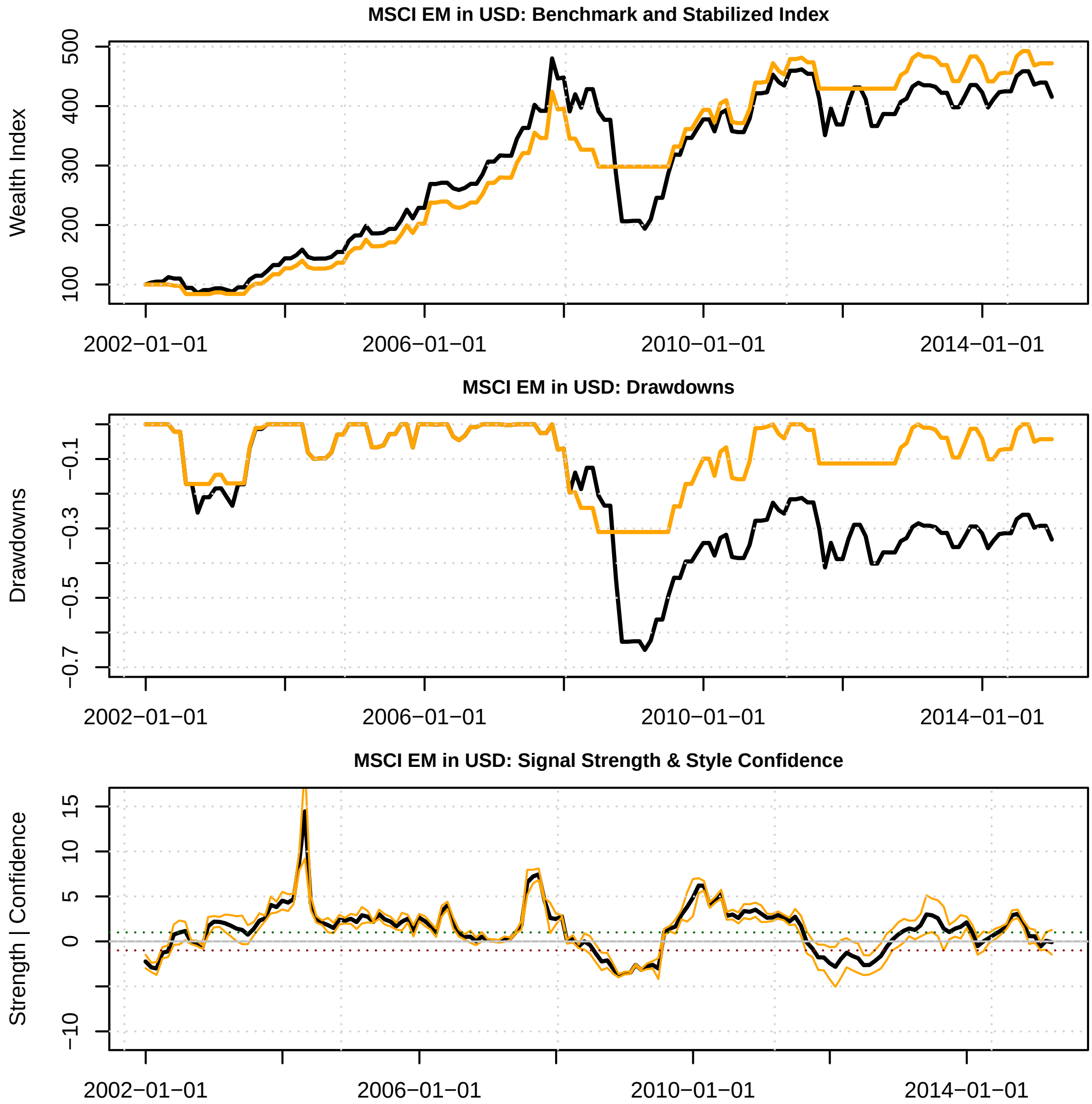

Figure 8: The MSCI Emerging Markets Index is a free float-adjusted market capitalization index that is designed to measure equity market performance of emerging markets. The MSCI Emerging Markets Index consists of the following 23 emerging market country indexes: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirates. MSCI [2014]

MSCI ACWI All Country World Index

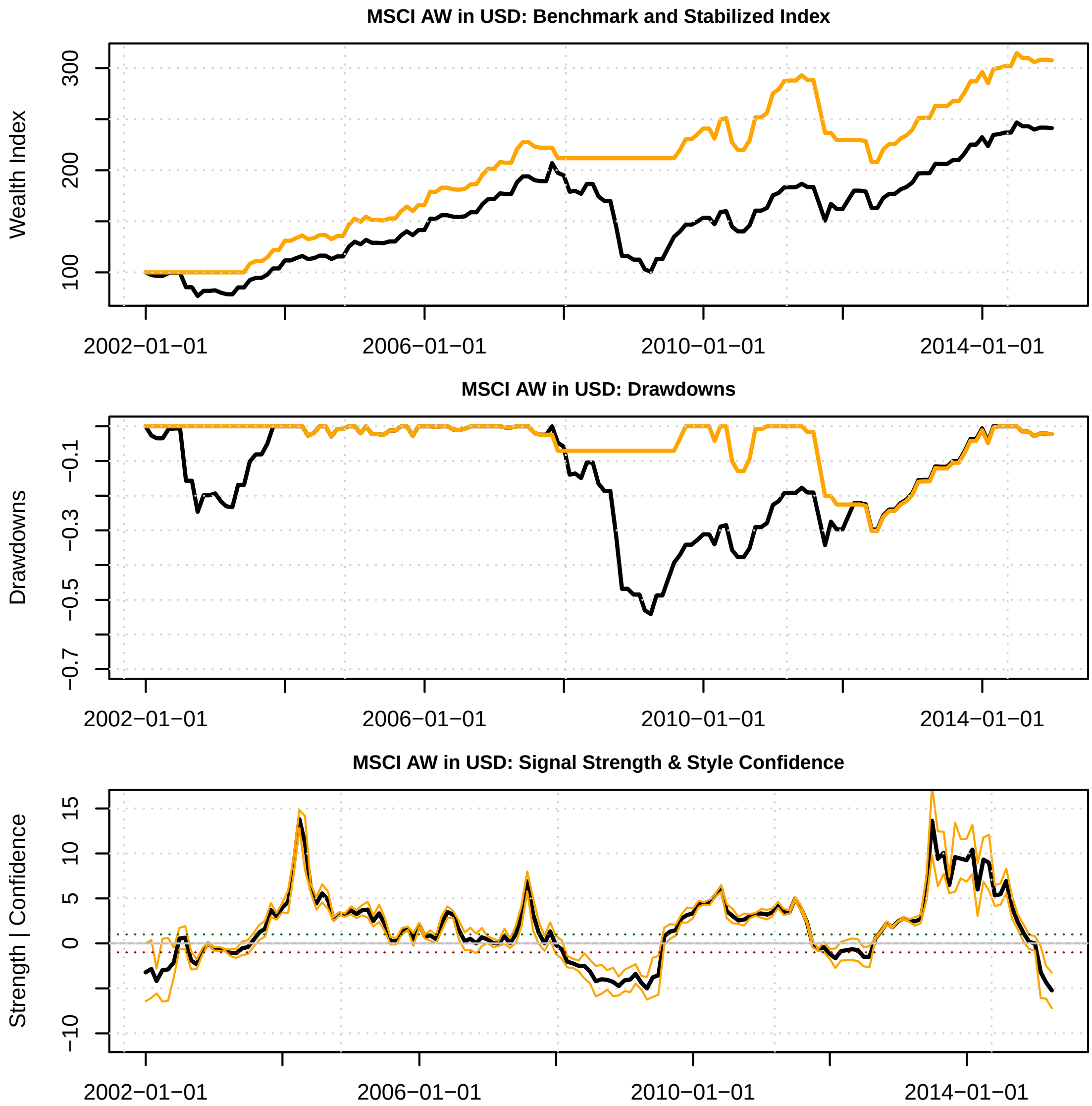

Figure 9: The MSCI ACWI Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of developed and emerging markets. The MSCI ACWI consists of 46 country indexes comprising 23 developed and 23 emerging market country indexes. The developed market country indexes included are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States. The emerging market country indexes included are: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirates. MSCI [2014]

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Acknowledgement

The work presented in this article was partly supported by grants given from ETH Zurich, Rmetrics Association Zurich, and Record Currency Management Windsor, UK.