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Unraveling Liquid Alternatives

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Abstract

We investigate what drives the performance of liquid alternative mutual funds, and if they offer interesting investment opportunities. We define state space models, apply the Kalman filter, and introduce residualized risk factors to perform the best possible return based style analyses. We apply our model also on hedge fund indices to compare the performance of the different type of funds. We find that liquid alternatives do not offer alternative returns in general, as their returns can be explained by common risk factors. Proper implementation of trend rules in several asset classes is the key performance driver of the most successful liquid alternatives. Managed Futures, Market Neutral, and Non-traditional Bond funds offer diversification opportunities for traditional investors. We cannot draw a general conclusion about the relative performance of liquid alternatives to their hedge fund counterparts.

Keywords: Liquid alternatives; state space models; Kalman filter; residualized risk factors

1 Introduction

In this research we consider alternative investment funds. These funds are applying alternative investment strategies and claim to offer different return characterics than traditional mutual funds. Since their introduction alternatives have often received attention from investors. However, current market conditions have intensified their search. Low bond yields, lower expected stock returns and fewer diversification opportunities are drivers for investors to look for alternative investments and diversification opportunities. Hedge funds are known as the main vehicle offering these opportunities, but it is not possible for everyone to invest in them and there are some other issues with hedge funds. Although hedge funds claim to offer alternative returns, this is not always the case. Some hedge funds simply earn risk premia, while the fund managers charge high fees and provide little transparency about the investments. To address these issues fund managers have launched liquid alternative mutual funds.

Liquid alternatives apply liquid variants of hedge fund strategies, while retaining most benefits of mutual funds. They claim to offer high levels of liquidity, charge lower fees, and require lower minimum investments than hedge funds. Besides that, these funds are obliged to report their holdings regularly, since they fall under more strict regulations, similar to that of traditional mutual funds. This results in more transparency and makes them an interesting investment vehicle for investors valuing transparency and liquidity. As a consequence assets under management in the liquid alternative industry have increased more than tenfold over the past decade. With over 700 billion of assets under management the relative size of the industry as part of the complete mutual fund industry has increased significantly as well[1].

In this thesis we investigate whether liquid alternatives really offer alternative returns that result in diversification opportunities for investors with more traditional portfolios. One of the main questions is how liquid alternative mutual funds generate their returns. Do these funds simply have static exposures to well-known risk factors earning the risk premia associated with them in the long run? Or do they allocate their resources to deliver returns that come from other sources? If the latter is the case, investing part of funds' capital in these alternative strategies might be interesting from a diversification point of view.

Ample evidence exist which hedge fund styles offer alternative returns. To distinguish alternative returns from harvesting risk premia Fung and Hsieh (2001) were the first to introduce a factor model specifically for hedge fund returns. This model is still the standard used in return-based style analyses in research on hedge funds. One of the most recent studies is conducted by Cao et al. (2015). They categorize hedge funds based on the investment styles and find different return characteristics per category. Sun et al. (2016) show that hedge funds doing well in difficult periods outperform in subsequent years as well. Academic research on liquid alternatives is much more scarce. The findings of Sun et al. (2016) lead to an extra research question: do liquid alternatives that perform best during bad periods also outperform the other funds in bull

[1] Between 2004 and 2016 the relative size of the liquid alternatives mutual fund industry compared to the broader mutual fund industry increased from 0.75% to 3%. Source: Morningstar mutual fund database

markets? If so, there is persistence in performance of these funds, and it is interesting to figure out what differentiates these funds from the others[2].

The data that we use in this research comes from the Morningstar database. For the funds classified as alternative we downloaded all returns and fund sizes between January 2000 and December 2015 at a monthly frequency. The newly constructed database is unique, since we are the first ones to manually check the categories funds are assigned to. As McCarthy (2014) already pointed out there is quite some misclassification in the Morningstar database. Simply using the Morningstar categories would have reduced the reliability of our results. Where other studies are hampered by this incorrect categorization those checks allow us to perform our analyses on a high quality data set. Besides checks on the investment style we also apply several filters to end up solely with reliable data on funds. We required at least one available fund size, at least two years of return history, and at least 10 million assets under management. To avoid double records in the data set we included one share class per fund. Altogether these filters lead to a reduction of data points from 23,716 to 4,112. Those funds are categorized in one of the following categories: Equity Long/Short, Global Macro, Managed Futures, Market Neutral, Multialternative, Non-traditional Bond, and Volatility. If none of these categories captures the investment profile of the fund, the fund is dropped.

To perform return-based style analyses a factor model is required that contains risk factors in all asset classes liquid alternatives possibly invest in. In the literature the seven-factor model introduced by Fung and Hsieh (2001) has become the standard. Besides equity factors also fixed income, commodities and currency related factors are included in this model. We used this model as a starting point to create the factor model we use in our analyses. We focus on the same asset classes as Fung and Hsieh, but do not include exactly the same factors. We included extra equity related risk factors, as many funds invest (partly) in equities. Besides that we aimed to include tradeable risk factors in our model. For that reason we replaced the term- and default premium in the seven-factor model by tradeable substitutes. As the practical implementation of the option-based trend factors in the model of Fung and Hsieh is difficult, we decided to replace them. We chose for the time series momentum factors in equities, commodities, fixed income, and foreign exchange markets as introduced by Moskowitz et al. (2012).

Since funds can dynamically allocate their investments, we allowed for time-varying exposures to risk factors. Fund managers might for example want to load differently on risk factors during periods of expansion and recessions. We allowed for this specifying the model as a state space model. The data generating process is defined in the observation equation: the factor model. How the parameters (factor exposures) can change over time is defined in the state equation. We assumed the factor loadings to follow a random walk. Due to the random walk specification we did not have to specify when factor exposures might change, and limit the number of parameters to be estimated. Parameters are estimated using Kalman filtering and Kalman smoothing techniques as introduced by Kalman (1960). In Kalman filtering parameter estimates at time t are based on the state (parameter estimates + uncertainties about these

[2] We derive up and down regimes in equity markets using the 200-day moving average of the MSCI World Price Index.

estimates) at time $t-1$ and the newly available data at time t. The Kalman smoother is related to the Kalman filter. Smoothed estimates are based on all available data and the Kalman filter estimates. Using our model with time-varying factor loadings it can be tested if performance is driven by exposure to risk factors or that abnormal results are achieved by superior investment strategies.

Conducting return-based style analyses on the category indices we composed from our dataset we find that only Volatility funds offer alternative returns. They generate positive alpha over the whole sample period, implying their returns are not driven by exposures to the included risk factors. The strong correlation with the equity market index makes them not interesting from a diversification perspective, though. For other categories we find that their results are driven by (time-varying) exposures to risk factors. Managed Futures, Market Neutral, and Non-traditional Bond funds are performing best, and deliver interesting risk-adjusted returns.

Besides analyzing the investment styles we also investigated which alternative strategies add (most) value to traditional portfolios. Adding value can be due to diversification options and/or by providing protection during crises. For diversification purposes Managed Futures, Market Neutral, and Non-traditional Bond funds are interesting to consider. These funds show high Sharpe ratios, and low correlations with the equity market index during good and bad times. The best protection in recessions is given by Managed Futures funds. During down markets those funds show high, positive returns, a negative correlation with the equity market index, and on a yearly basis more than 20% outperformance over the MSCI World Index. Proper implementation of trend rules seems to be the driving factor behind this success.

Lastly we investigated if funds that are doing well in difficult periods show persistence in up markets. We find that all categories that are doing well in down markets, are also doing well in up markets. Market Neutral and Non-traditional Bond funds deliver comparable Sharpe ratios as the market index. For Managed Futures funds the Sharpe ratio is somewhat lower, but still decent. We have to mention that in up markets nearly all categories are doing well, though.

We conclude that liquid alternative mutual funds do not deliver alternative returns in general. However, this does not mean that there are no attractive liquid alternatives. Managed Futures, Market Neutral, and Non-traditional Bond funds offer dynamic strategies that harvest the right risk premia over time. They deliver outstanding risk-adjusted returns during crises and also in up markets their performance is decent. Together with their low or even negative correlations with the equity market this makes them interesting diversification vehicles for more traditional investors.

It is not possible to draw a general conclusion about the relative performance of liquid alternatives to their hedge fund counterparts. For some categories liquid alternatives perform better, while for others the hedge funds outperform. Interesting is that Managed Futures liquid alternatives perform better than their hedge fund counterparts. The liquid alternatives in this category seem not to suffer from the stricter regulations at all. For the Global Macro and Multialternative categories we find the opposite. Hedge funds applying these strategies are highly profitable, while liquid alternatives are not. Paired sample t-tests show that there are no significant differences in returns for liquid alternatives and hedge funds for a single category, though[3]. We observe that succesful implementation of trend rules in multiple asset classes is the key performance driver of well performing funds.

This thesis contributes to the current literature in the following three ways. Firstly, the data set on liquid alternatives used in this research is manually composed from the Morningstar database, and therefore unique and of high quality (complete and without biases). Secondly, a renewed Fung and Hsieh (2001) model is applied on the liquid alternatives asset class in which we allow for time-varying factor loadings. Thirdly, we give a clear risk profile of the funds, and avoid any possible multicollinearity issues by residualization of the risk factors included in the model. Therefore this new approach does not only give a thorough understanding of what drives the performance of funds, but also shows how strongly a fund is leveraging on the market.

The remainder is structured as follows. In Section 2 related literature is discussed to place this research into perspective, and research questions are formulated. In Section 3 the methodology is discussed. Section 4 describes the data. In section 5 the main results are presented as well as some robustness checks. Section 6 concludes.

2 Literature

We place this research into perspective defining alternative investments firstly, and discussing the literature that is currently available on this subject subsequently.

2.1 Alternative Universe

Besides traditional mutual funds investors might want to invest in more alternative strategies. Before going into detail about different strategies we provide a clear picture of what alternative investments are. There are multiple ways to split the universe. One way is to split them by differentiating between alternative investment opportunities and alternative investment strategies. Alternative investment opportunities include investments in non-traditional asset classes as private equity, real estate and commodities. According to Ang (2014) an investor best allocates part of its capital to alternative asset classes for diversification purposes. Alternative investment strategies are strategies that do not invest as traditional equity/bond portfolios. This can be done taking for example short positions in equities or entering in derivative contracts. The strategies investigated in this research are discussed in the next subsection.

Another way to split the alternative investments universe into two groups is by liquidity. Depending on the ability to buy or sell assets (shares) of the fund within a reasonable time period, funds can be defined as liquid or illiquid. Liquidity can be determined by the assets in a fund and/or the investment purposes. The more liquid the assets in a fund are, the easier it is for the manager to liquidate positions allowing investors to withdraw their money at short notice. However, funds applying strategies that use very liquid securities, but making profits when prices or yields converge in the long-run may not allow investors to withdraw money in the meanwhile. As Ang

[3] An overview of the test statistics for all categories in up and down markets can be found in Table 5 in the Appendix.

(2014) describes an illiquidity premium may exist for less liquid investments. Therefore funds can achieve higher long-term returns allocating part of their resources to these investments earning the premium.

Funds offering alternative investment strategies are also known as hedge funds. Hedge funds rely on specific exemptions to the Investment Company Act of 1940 to avoid certain regulations and to have flexibility in the way their fund is structured and operated (Black (2015)). Besides defining hedge funds, Black gives in his paper an extensive introduction on liquid alternatives. He shows similarities with hedge funds, explains regulatory issues for them and discusses their advantages for retail investors. Main findings are that hedge funds require much higher minimum investments and do not provide high levels of liquidity and transparency.

The history of alternative funds is well described by Connor and Woo (2003). The first alternative investment fund was launched in 1948. A strategy that nowadays is seen as a Managed Futures strategy was applied by a commodity trading advisor (CTA). In 1949 the first modern hedge fund was born applying a long/short strategy in the equity market. More funds appeared, but due to a strong upward trend in the stock markets in the end of the 60's, most of the funds hardly took any short positions resulting in highly leveraged long-only equity funds. This led to some big losses for hedge funds in 1969-1970 and many funds that collapsed during the 1973-1974 bear market. After that period it took till the early 90's for hedge funds to become popular under investors again.

New strategies were applied by successful hedge funds and their high returns appeared in newspapers. Investors became attracted again and hedge funds started to implement alternative strategies on a large scale. However, for smaller investors it was not possible to invest in those hedge funds, because of the high minimum required investments. Also illiquidity of hedge funds was seen as a big disadvantage and therefore a new type of funds was launched end of the 90's as well. The first so called liquid alternative mutual funds arose. Claiming to offer alternative, hedge fund-like, strategies for retail investors in the form of open-end mutual funds. However, although the first funds were found in the 90's it is only 10 years ago that liquid alternatives started their rapid rise.

2.2 Alternative Strategies

Nowadays liquid alternatives are widely available for retail investors. Therefore it is interesting for them to know if they add value to their portfolios, but before this question can be answered it is important to understand what the different strategies are. Roughly speaking there are seven main styles: Equity Long/Short, Market Neutral, Non-traditional Bond, Global Macro, Managed Futures, Volatility and Multi-Strategy. Funds applying the first two styles invest in equities taking long and short positions. The difference is that Market Neutral funds attempt to hedge out all market exposure. Non-traditional Bond funds invest in fixed income and debt securities as well as currency related instruments without following a benchmark. Global Macro funds base their holdings in all asset classes primarily on the overall economic and political views of countries, or their macroeconomic principles. Funds applying a Managed Futures strategy seek to profit from trends across many different asset classes. Volatility funds try to benefit from investors willing to pay a premium on securities that give protection. The latter category consists of all funds that invest in all asset classes applying multiple strategies at the same time. It has to be mentioned that these seven categories do not include all hedge fund strategies. There are some other strategies that we do not consider, because they are not applicable in liquid form due to the underlying investments and/or regulatory restrictions.

For investors the added value of liquid alternative mutual funds could lie in extra diversification possibilities. As Lewis (2016) shows in his study on liquid alternatives, and Markwat et al. (2016) in their study on hedge funds, there are certain investment styles that have very low correlations with traditional asset classes, making them good diversifiers to traditional equity/bond portfolios. Next to low correlations with traditional asset classes liquid alternatives may be interesting when they provide an insurance during crisis periods. Investors are in general more concerned about limiting losses in bad times than about maximizing profits in good times. Cao et al. (2015) find that hedge funds applying Global Macro, Managed Futures, and Multialternative strategies provide valuable hedges against bad times. In this research we consider this for liquid alternatives.

2.3 Previous Studies on Liquid Alternatives

Due to the recent emergence of liquid alternatives relatively little research is conducted regarding them yet. The first in-depth study comparing the performance of liquid alternatives with that of hedge funds is of Agarwal et al. (2009). They compare the returns of liquid alternatives and hedge funds over an 11-year time period between 1994 and 2004 using the four-factor model of Carhart (1997) and the seven-factor model of Fung and Hsieh (2004). Agarwal et al. (2009) conclude that, adjusting for common risk factors, and on a net-of-fee basis, hedge funds outperform liquid alternatives by 5-7% per annum. They assign this outperformance (partly) to a better selection skill of the hedge fund managers. However, during these years only a few liquid alternatives are live and limited data is available, not allowing them to divide the funds over different investment strategies. So this might not be a completely reliable conclusion.

McCarthy (2014) was the first to divide liquid alternatives over four well-known categories from the hedge fund industry: Equity Long/Short, Multialternative (or Multi-Strategy), Managed Futures and Market Neutral. McCarthy mainly focusses on the Equity Long/Short strategy in the rest of his study, and compares liquid alternatives holdings and returns with those of hedge funds in this category. He points out that there are differences in equity exposures that might result from regulatory restrictions on liquid alternatives, but that risk adjusted returns do not suffer from these restrictions. Using the Capital Asset Pricing Model (CAPM) and Carhart (1997) four-factor model McCarthy (2014) shows that liquid alternatives in the Equity Long/Short category are reasonable substitutes for Equity Long/Short hedge funds. Another interesting point that McCarthy makes is the misclassification of funds in Morningstar. Nearly 50% of the 83 funds classified as Equity Long/Short at that moment in time do not apply this strategy and are reclassified by the author to categories as Event Driven, Arbitrage, Fund of Funds and Long Equities with Options Overlay.

A similar analysis is performed by McCarthy (2015) for the Multi-Strategy category. For these funds there are substantive differences between the risk adjusted returns on liquid alternatives and hedge funds. Hartley (2016) compares liquid alternatives with hedge funds. He divides the funds in four categories: Equity Long/Short, Market Neutral, Managed Futures and Multi-Strategy to be able to draw conclusions on category level. Hartley (2016) finds that liquid alternatives underperform hedge funds on a net-of-fee basis by 1-2% per annum. This result is mainly driven by a strong underperformance for Multialternative and Managed Futures strategies. For Equity Long/Short and Market Neutral funds no significant differences are observed. Those results for Equity Long/Short and Multialternative funds agree with the results of McCarthy (2014) and McCarthy (2015). The underperformance of Managed Futures is interesting, since Cao et al. (2015) found hedge funds applying this strategy providing valuable hedges in bearish periods. Are liquid alternatives applying Managed Futures strategies still attractive?

In contrast to all these studies in this paper the main focus is not to make a comparison with hedge funds. Instead of solely comparing performances an in-depth analysis on the styles applied by the liquid alternatives is conducted to figure out if these funds provide the claimed alternative returns. All analyses are on category level, so that we can also make a comparison with the results for their hedge fund counterparts. Results for hedge funds found by Sun et al. (2016) are tested in the liquid alternatives universe as well: do liquid alternatives that are doing well in difficult periods also outperform in subsequent years?

2.4 History of Factor Models

Simply comparing returns on investment portfolios is not the way to determine which funds deliver best performance. Over the last decades a lot of research is done to figure out which risk premia exist. To make statements about the risk-adjusted performance of funds it is necessary to figure out how much funds load on proven risk factors. The part of their returns that cannot be explained by exposures to these factors is called Jensen's alpha (Jensen (1968)) and can be seen as the added value of investing in a fund.

Sharpe (1964) and Lintner (1965) were among the first to conclude that assets can be priced using their correlation with the overall stock market. Keeping Markowitz' modern portfolio theory (Markowitz (1952) and Markowitz (1959)) into their mind they introduced the Capital Asset Pricing Model (CAPM). In the CAPM a linear relationship is assumed between the required return on assets and their risk. The market index is the only risk factor included in the CAPM.

While analyzing stock returns using the CAPM, the excess return on a stock (return on a stock minus the risk free rate) is regressed on the excess return on the value weighted market return. Including the market return as explanatory variable helps to filter out overall market movements. The estimate of the constant in the model is called Jensen's alpha (Jensen (1968)) of a stock. The higher the alpha, the more attractive the stock is for investors.

Fama and French (1993) extended the CAPM with two risk factors. One based on size and the other based on value. Fama and French pointed out that stocks of small companies show higher returns than stocks of big companies, and that stocks of companies with high book-to-price ratios do better than stocks of companies with low book-to-price ratios. These small-minus-big and high-minus-low return differentials form together with the excess market return the set of explantory variables in the Fama and French three-factor model.

Jegadeesh and Titman (1993) found empirical evidence that stocks that performed best over the last 6 to 12 months were most likely to continue to do so in the next period. With the return differential between the 'winners' over the last period and the 'losers' over the same period, the so-called momentum factor was born. Carhart (1997) was the first to adopt this factor and introduced the four-factor model for explaining equity returns. He augmented the three-factor model of Fama and French (1993) with the momentum factor of Jegadeesh and Titman (1993).

In the early 2000s interest in alternative investments increased and researchers obtained great interest in explaining their returns. Since these funds also invest in asset classes other than equities, Fung and Hsieh (2001) introduced the seven-factor model. Besides equity factors also fixed income, commodities and currency related factors are in this model to account for risks hedge funds can be exposed to. Later Fung and Hsieh added an emerging market factor to the model to account for differences in returns in emerging and developed markets. This model became the standard in studies on alternative investments.

In this research the seven-factor model is the starting point in the analyses. Some explanatory variables in the model are substituted by comparable factors with a clearer economic interpretation. Others are omitted, while we also add some extra equity factors. We use this model to test if performance is driven by exposure to risk factors or that abnormal results are achieved by superior investment strategies. It has to be mentioned that many more risk factors are discovered over the last decades. Harvey et al. (2016) give an extensive overview of all possibly interesting risk factors. As we want to avoid overfitting, we stick to models with relatively little explanatory variables, though.

In their paper on the estimation of mutual fund styles Swinkels and Van der Sluis (2006) argue that it is not reasonable to assume that investment styles are constant over time. They argue that implicitely accounting for this time-variation using rolling window OLS regressions is inefficient due to its ad hoc chosen window size. Swinkels and Van der Sluis (2006) propose to specify a state space model in which the parameters (factor exposures) can change at any moment in time. Using the Kalman filter to estimate the parameters most information is extracted from the data. As we aim to fully understand what liquid alternatives are doing, we specify our models similar, and apply the Kalman filter for parameter estimation as well.

3 Methodology

3.1 Model Specification and Parameter Estimation

A factor model for explaining fund returns in the most general form is given by the following formula:

$$r_{i,t} = X_t'\beta_{i,t} + \varepsilon_{i,t}, \qquad\qquad \varepsilon_{i,t} \sim N(0, \Omega_i) \tag{1}$$

where $r_{i,t}$ denotes the return on fund i at time t, X_t contains the returns on the risk factors at time t, $\beta_{i,t}$ are the factor exposures of fund i at time t, and $\varepsilon_{i,t}$ is the obsevation noise, or unexplained part of the fund return by the factor model. By assumption this error term is normally distributed with mean 0 and variance Ω_i. For simplicity we let all subscripts i drop out.

In previous literature on alternatives factor exposures are assumed to be constant over time, which implies that β_t equals β for all t. As we assume that funds adjust their exposures to risk factors over time based on signals and/or changing market circumstances, the model specification with time-varying parameters is crucial for the analyses we want to perform. We consult the book of Durbin and Koopman (2001) to find such a model specification and to derive the formulas for parameter estimation.

To allow for time-varying parameters in our model we set up a state space model to define the dynamics. The observation equation represents the assumed data generating process for which we choose a factor model. How the parameters in the model can change over time is defined in the state equation. To be able to pick up sudden changes in factor exposures we assumed a random walk process for this. We used the Kalman filter to estimate the time-varying parameters. The main advantages of the Kalman filter over (exponentially weighted) rolling window OLS regressions are that using this filter it is not necessary to specify beforehand at which moment in time changes in factor exposures occur and which observations are (most) informative. The state space model looks as follows:

$$r_t = X_t\beta_t + \omega_t, \qquad\qquad \omega_t \sim N(0, R) \tag{2}$$

$$\beta_t = \beta_{t-1} + \nu_t, \qquad\qquad \nu_t \sim N(0, Q) \tag{3}$$

Although there are several alternative specifications for the state equation, we choose the random walk process based on economic and econometric arguments. We expect views of managers, and so their loadings on risk factors, to change over time. The random walk specification does allow for this, and so the Kalman filter is able to pick up sudden changes directly. The most usual alternatives, (restricted) AR models, are not able to pick up those sudden changes. AR models imply that fund managers have long term targets to which the factor exposures return after deviations.

Performing some tests in which an AR(1) model is defined as state equation we find AR(1) parameters close to one, and drift parameters around zero. Implying that the random walk model is suitable. More advanced or restricted AR models lead to a sharp increase in the number of parameters to be estimated. This is also unlikely as overfitting becomes a serious issue, because our data set contains only 16 years of monthly data.

3.1.1 Kalman Filter

The Kalman filter gives time-varying, unbiased parameter estimates with the lowest possible uncertainty. But to get a better understanding of the Kalman filter we give the complete derivation of all formulas. For simplicity we derive the Kalman filter equations for the state space model as given by equations (2) and (3).

In the Kalman filter at any moment in time a parameter estimate is made based on all previous observations. This estimate is called the predicted state estimate:

$$\hat{\beta}_{t|t-1} = E[\beta_t|\mathrm{I}_{t-1}]$$

There is uncertainty about this estimate that is captured in the error covariance of the predicted state estimate:

$$P_{t|t-1} = Var[\beta_t|\mathrm{I}_{t-1}]$$

As soon as a new observation is available, the predicted state estimate and its covariance is updated. Those variables are called the updated or filtered state estimate: $\hat{\beta}_{t|t}$ and updated covariance matrix: $P_{t|t}$. The updated estimates are the estimates at time t given all information upto and including time t:

$$\begin{aligned} \hat{\beta}_{t|t} &= E[\beta_t|\mathrm{I}_t] \\ P_{t|t} &= Var[\beta_t|\mathrm{I}_t] \end{aligned}$$

We define the updated state estimate as a linear combination of the predicted state estimate and the new observation:

$$\hat{\beta}_{t|t} = K_t^* \hat{\beta}_{t|t-1} + K_t r_t \tag{4}$$

We want to find the Kalman gain K_t that results in an unbiased estimate with minimum state estimate error covariance. To find this Kalman gain we have to define the expectation of the estimation error:

$$\begin{aligned} E[\tilde{\beta}_{t|t}|\mathrm{I}_t] &= E[\beta_t - \hat{\beta}_{t|t}|\mathrm{I}_t] \\ &= [I - K_t^* - K_t X_t] E[\beta_t|\mathrm{I}_t] \end{aligned} \tag{5}$$

Combining equation (5) with the requirement of an unbiased estimation error we find the following definition for K_t^*:

$$K_t^* = I - K_t X_t \tag{6}$$

Inserting definition (6) into equation (4) leads to the following definition for the updated state estimate:

$$\begin{aligned} \hat{\beta}_{t|t} &= K_t^* \hat{\beta}_{t|t-1} + K_t r_t \\ &= \hat{\beta}_{t|t-1} + K_t(r_t - X_t \hat{\beta}_{t|t-1}) \\ &= \hat{\beta}_{t|t-1} + K_t v_t \end{aligned} \tag{7}$$

We combine those results with the aim to minimize the state estimate error covariance. For this we define the updated covariance matrix as $P_{t|t} = E[\tilde{\beta}_{t|t}\tilde{\beta}_{t|t}^{'}]$ and re-write the definition of $\tilde{\beta}_{t|t}$ so that we get an expression for $P_{t|t}$ in terms of K_t^* and K_t:

$$\begin{aligned}
\tilde{\beta}_{t|t} &= \beta_t - \hat{\beta}_{t|t} \\
&= \beta_t - K_t^* \hat{\beta}_{t|t-1} - K_t r_t \\
&= K_t^* \beta_t - K_t^* \hat{\beta}_{t|t-1} - K_t \omega_t
\end{aligned}$$

Using this expression for $\tilde{\beta}_{t|t}$, the fact that the covariance of a constant (β_t) is zero, and the fact that the correlation between $\hat{\beta}_{t|t-1}$ and ω_t is zero, we find the following expression for $P_{t|t}$:

$$\begin{aligned}
P_{t|t} &= Cov(\tilde{\beta}_{t|t}) \\
&= K_t^* Cov(\hat{\beta}_{t|t-1}) K_t^{*'} + K_t Cov(\omega_t) K_t^{'} \\
&= [I - K_t X_t] P_{t|t-1} [I - K_t X_t]^{'} + K_t R K_t^{'} \qquad (8)
\end{aligned}$$

Finally we want to find K_t that minimizes the state estimate error covariance. To do so we set the first order derivative of the trace of $P_{t|t}$ with respect to K_t equal to zero:

$$\begin{aligned}
\frac{\partial Tr[P_{t|t}]}{\partial K_t} &= 0 \\
K_t &= P_{t|t-1} X_t^{'} (X_t P_{t|t-1} X_t^{'} + R)^{-1} \qquad (9)
\end{aligned}$$

where we used the fact that $P_{t|t-1}$ and $(X_t P_{t|t-1} X_t^{'} + R)$ are symmetric by definition. In our univariate situation $(X_t P_{t|t-1} X_t^{'} + R)$ is a scalar. We get the following recursive Kalman filtering equations:

$$\begin{aligned}
v_t &= r_t - X_t \hat{\beta}_{t|t-1} \qquad (10) \\
F_t &= X_t P_{t|t-1} X_t^{'} + R \qquad (11) \\
K_t &= P_{t|t-1} X_t^{'} F_t^{-1} \qquad (12) \\
\hat{\beta}_{t|t} &= \hat{\beta}_{t|t-1} + P_{t|t-1} X_t^{'} F_t^{-1} v_t \qquad (13) \\
P_{t|t} &= P_{t|t-1} - P_{t|t-1} X_t^{'} F_t^{-1} X_t P_{t|t-1} \qquad (14) \\
\hat{\beta}_{t+1|t} &= \hat{\beta}_{t|t} \qquad (15) \\
P_{t+1|t} &= P_{t|t} + Q \qquad (16)
\end{aligned}$$

In case an AR(1) process would be chosen for the way exposures change over time, the state equation is replaced by an AR(1) model. The state space model looks as follows:

$$\begin{aligned}
r_t &= X_t \beta_t + \omega_t, \qquad \omega_t \sim N(0, R) \qquad (17) \\
\beta_t &= \delta + \Phi \beta_{t-1} + \nu_t, \qquad \nu_t \sim N(0, Q) \qquad (18)
\end{aligned}$$

and the derivation of all formulas is similar as shown before. Only the expressions for K_t, $\hat{\beta}_{t+1|t}$, and $P_{t+1|t}$ change:

$$
\begin{aligned}
K_t &= \Phi P_{t|t-1} X_t' F_t^{-1} && (19)\\
\hat{\beta}_{t+1|t} &= \delta + \Phi \hat{\beta}_{t|t} && (20)\\
P_{t+1|t} &= \Phi P_{t|t} \Phi' + Q && (21)
\end{aligned}
$$

Having these closed form solutions for the parameter estimates the only thing that is left is to get values for R, Q, δ, and Φ. In our situation R is a scalar, and we assume Q to be a diagonal matrix. Imposing this restriction on Q is necessary to limit the degrees of freedom. The relative size of R to the main diagonal elements of Q is very important. It determines which fraction of the unexplained return is seen as signal that the parameter estimates are not optimal and which fraction is observation noise. Therefore we decided not to set these values ex-ante, but to determine the optimal values for R and Q using maximum likelihood estimation. In case of an AR(1) model in this optimization procedure also values for δ and Φ are obtained.

3.1.2 Kalman Smoother

As we perform ex-post return-based style analyses, it might make sense to use all available data to estimate factor exposures over the whole period. In Kalman smoothing the parameter estimates are calculated using all information from the Kalman filter (parameter estimates and uncertainties) and the full data set. So the conditional density of the parameter vector β_t given the entire return series $\mathrm{I}_T = r_1, .., r_T$ is derived for $t = 1, .., T$.

This means we have to calculate the conditional mean $\hat{\beta}_t$ and variances V_t for $t = 1, .., T$:

$$
\begin{aligned}
\hat{\beta}_{t|T} &= E[\beta_t | \mathrm{I}_T]\\
V_{t|T} &= Var[\beta_t | \mathrm{I}_T]
\end{aligned}
$$

From the Kalman filter we obtain the errors $v_1, .., v_T$, so we can define $v_{t:T}$ as $[v_t', .., v_T']'$. Note hereby that I_T is fixed when I_{t-1} and $v_{t:T}$ are fixed. To calculate $E[\beta_t|\mathrm{I}_T]$ and $Var[\beta_t|\mathrm{I}_T]$ we use the definition for the conditional distributions of β_t and $v_{t:T}$ given I_{t-1}. Using the fact that $v_t, .., v_T$ are independent of I_{t-1}, and of each other with zero means we can re-write $\hat{\beta}_t$:

$$
\begin{aligned}
\hat{\beta}_{t|T} &= E[\beta_t | \mathrm{I}_T]\\
&= E[\beta_t | \mathrm{I}_{t-1}, v_{t:T}]\\
&= E[\beta_t | \mathrm{I}_{t-1}] + \sum_{j=t}^{T} Cov(\beta_t, v_j | \mathrm{I}_{t-1}) Var(v_j | \mathrm{I}_{t-1})^{-1} v_j\\
&= b_t + \sum_{j=t}^{T} Cov(\beta_t, v_j) F_j^{-1} v_j && (22)
\end{aligned}
$$

Note that b_t is used here to denote the parameter estimates of the Kalman filter. To find an expression for $Cov(\beta_t, v_j)$ we use the innovation analogue of the state space model:

$$
\begin{aligned}
v_t &= X_t e_t + \omega_t && (23)\\
e_{t+1} &= L_t e_t + \nu_t - K_t \omega_t && (24)
\end{aligned}
$$

where e_t is the state estimation error: $e_t = \beta_t - b_t$, with $Var(e_t) = P_t$[4]. Returning to the definition of $\hat{\beta}_t$ in equation (22) we see that we need an expression for $Cov(\beta_t, v_j)$. Using definitions (23) and (24) we can re-write $Cov(\beta_t, v_j)$ for $j = t, .., T$ as:

$$
\begin{aligned}
Cov(\beta_t, v_j) &= E[\beta_t v_j' | \mathrm{I}_{t-1}]\\
&= E[\beta_t e_j' | \mathrm{I}_{t-1}] X_j' && (25)
\end{aligned}
$$

What is left is to find a (recursive) formula for $E[\beta_t e_j' | \mathrm{I}_{t-1}]$:

$$
\begin{aligned}
E[\beta_t e_t' | \mathrm{I}_{t-1}] &= E[\beta_t (\beta_t - b_t)' | \mathrm{I}_{t-1}]\\
&= P_t\\
E[\beta_t e_{t+1}' | \mathrm{I}_{t-1}] &= E[\beta_t e_{t+1}' | \mathrm{I}_{t-1}]\\
&= E[\beta_t e_t' | \mathrm{I}_{t-1}] L_t'\\
&= P_t L_t'\\
E[\beta_t e_{t+2}' | \mathrm{I}_{t-1}] &= E[\beta_t e_{t+2}' | \mathrm{I}_{t-1}]\\
&= P_t L_t' L_{t+1}'\\
&\vdots\\
E[\beta_t e_T' | \mathrm{I}_{t-1}] &= P_t L_t' L_{t+1}' ... L_{T-2}' L_{T-1}' && (26)
\end{aligned}
$$

Note that for $t = T$ holds that:

$$L_t' L_{t+1}' ... L_{T-2}' L_{T-1}' = I$$

and for $t = T - 1$:

$$L_t' L_{t+1}' ... L_{T-2}' L_{T-1}' = L_{T-1}'$$

[4] We find those expressions re-writing the innovations v_t as:

$$
\begin{aligned}
v_t &= y_t - X_t b_t\\
&= X_t \beta_t + \omega_t - X_t b_t\\
&= X_t e_t + \omega_t
\end{aligned}
$$

and the predicted state estimation error as:

$$
\begin{aligned}
e_{t+1} &= \beta_{t+1} - b_{t+1}\\
&= \beta_t + \nu_t - b_t - K_t v_t\\
&= \beta_t + \nu_t - b_t - K_t X_t e_t - K_t \omega_t\\
&= e_t + \nu_t - K_t X_t e_t - K_t \omega_t\\
&= [I - K_t X_t] e_t + \nu_t - K_t \omega_t\\
&= L_t e_t + \nu_t - K_t \omega_t
\end{aligned}
$$

Plugging in expression (25) in equation (22) results in:

$$\hat{\beta}_t = b_t + \sum_{j=t}^{T} E[\beta_t e_j' | \mathrm{I}_{t-1}] X_j' F_j^{-1} v_j \tag{27}$$

in which we can use definition (26) to get the parameter estimates:

$$\begin{aligned}
\hat{\beta}_T &= b_T + E[\beta_T e_T' | \mathrm{I}_{T-1}] X_T' F_T^{-1} v_T \\
&= b_T + P_T X_T' F_T^{-1} v_T \\
\hat{\beta}_{T-1} &= b_{T-1} + E[\beta_{T-1} e_{T-1}' | \mathrm{I}_{T-2}] X_{T-1}' F_{T-1}^{-1} v_{T-1} + E[\beta_{T-1} e_T' | \mathrm{I}_{T-2}] X_T' F_T^{-1} v_T \\
&= b_{T-1} + P_{T-1} X_{T-1}' F_{T-1}^{-1} v_{T-1} + P_{T-1} L_{T-1}' X_T' F_T^{-1} v_T \\
&: \\
\hat{\beta}_t &= b_t + P_t X_t' F_t^{-1} v_t + P_t L_t' X_{t+1}' F_{t+1}^{-1} v_{t+1} + .. + P_t L_t' .. L_{T-1}' X_T' F_T^{-1} v_T \\
&= b_t + P_t q_{t-1} \qquad (28)
\end{aligned}$$

where q_{t-1} can be calculated recursively using:

$$\begin{aligned}
q_T &= 0 \\
q_{T-1} &= X_T' F_T^{-1} v_T \\
q_{T-2} &= X_{T-1}' F_{T-1}^{-1} v_{T-1} + L_{T-1}' X_T' F_T^{-1} v_T \\
&: \\
q_{t-1} &= X_t' F_t^{-1} v_t + L_t' q_t \qquad (29)
\end{aligned}$$

Besides the parameter estimates we are also interested in the uncertainty in these estimates. Similar to the way we found recursive formulas for the smoothed parameter estimates we can find expressions for the corresponding covariance matrices. We apply the formula for conditional variance:

$$\begin{aligned}
V_{t|T} &= Var[\beta_t | \mathrm{I}_T] \\
&= P_t - \sum_{j=t}^{T} Cov(\beta_t, v_j | \mathrm{I}_{t-1}) F_j^{-1} Cov(\beta_t, v_j | \mathrm{I}_{t-1})' \\
&= P_t - \sum_{j=t}^{T} E[\beta_t e_j'] X_j' F_j^{-1} X_j E[\beta_t e_j']'
\end{aligned}$$

to end up with the following expression for V_t:

$$V_t = P_t + P_t N_{t-1} P_t \tag{30}$$

Using that $N_T = 0$ by definition N_{t-1} can be calculated recursively via:

$$N_{t-1} = X_t' F_t^{-1} X_t + L_t' N_t L_t \tag{31}$$

Putting equations (28), (29), (30), and (31) together we end up with the Kalman smoothing recursions:

$$q_{t-1} = X_t' F_t^{-1} v_t + L_t' q_t \tag{32}$$
$$\hat{\beta}_t = b_t + P_t q_{t-1} \tag{33}$$
$$N_{t-1} = X_t' F_t^{-1} X_t + L_t' N_t L_t \tag{34}$$
$$V_t = P_t + P_t N_{t-1} P_t \tag{35}$$

In which we use the updated parameter estimates b_t and corresponding covariances P_t from the Kalman filter, and auxiliary matrices F_t, K_t, and L_t as defined below:

$$\begin{aligned} F_t &= X_t' P_t X_t + R \\ K_t &= P_t X_t' F_t^{-1} \\ L_t &= I + K_t X_t \end{aligned}$$

3.1.3 Model Specification

After discussing the estimation techniques we continue with the model specification. Although the Fung and Hsieh (2001) seven-factor model is the standard in studies on alternative investments and the risk factors capture most of the return sources, we decided to use the model just as a starting point.

Considering the equity related part of the model Fung and Hsieh (2001) initially only include an equity market index and trend factor. One of the factors that we add to the model is the emerging market factor (Fung and Hsieh (2011)). There are differences in excess returns on emerging and developed market indices. Since funds can invest in different countries and markets, differences in returns can be driven by the overall performance in the market they invest in. In the seven-factor model the global market index is included. Since this index is value weighted it is highly influenced by developed market stocks. Therefore we include both the developed, and emerging market index.

Besides these market indices we also include other equity related factors in the model. Most important reasons for this are the fact that many liquid alternative funds invest in equities, and that for equities a lot of research is done in which stylized facts are found. For mutual funds it is known that they base their holdings on the anomalies associated with these stylized facts, so we expect (some) liquid alternatives to do so as well. Those factors are the size and value factors introduced by Fama and French (1993), the cross-sectional momentum factor introduced by Jegadeesh and Titman (1993), and the more recently by Frazzini and Pedersen (2014) introduced Betting-against-Beta factor. Frazzini and Pedersen (2014) have found evidence that low-beta stocks show higher risk-adjusted returns than high-beta stocks. They explain their finding arguing that many investors are restricted in the sense that they cannot apply leverage to get higher expected returns. Instead of using leverage and buying the 'optimal asset mix' they overweigh assets with high expected returns, or high-beta stocks. As a result these stocks become overpriced and the real expected returns go down. The Betting-against-Beta factor Frazzini and Pederson propose arbitrages out this phenomenon by short-selling the high-beta stocks and going long in the low-beta stocks.

Considering the option-based trend factors the first thing that stands out is that the returns on these factors are highly volatile and show very extreme values. Together with their difficult practical implementation this is the reason we decided to exclude these variables from the model. Since trend in asset classes is generally seen as a good explanatory variable for fund returns, simply omitting these three factors is not a good idea. We substitute them by four trend factors introduced by Moskowitz et al. (2012). These trend factors are based on persistence in returns for one to twelve months across all assets in the four asset classes they consider. Moskowitz et al. (2012) finally based a trading strategy on these findings in commodities, equities, fixed income, and foreign exchange markets to obtain the trend factor returns.

For bonds less stylized facts are known. Bond funds mainly base their positions on macro circumstances. Therefore we include two macro variables in the model: the global term and default premium. Fung and Hsieh (2001) have comparable factors in their model, but these factors are not tradeable. This is an important difference with the factors that we include. When factors are non-tradeable it is not possible to replicate fund returns taking the same exposures to the risk factors.

3.1.4 Residualization of Risk Factors

Considering the full-sample correlations between the risk factors we selected, we do not find very strong correlations (see Table 3 in the Appendix). However, if we investigate how the correlations between factors behave over time, we conclude that some factors are strongly correlated to the market index from time to time (see Figure 1 for 36-month rolling window correlations). As we allow for time-varying factor exposures this may lead to multicollinearity issues in periods where correlations are high. To overcome this problem we decided to residualize the risk factors, and make them orthogonal to the market index. In this residualization we regress the risk factor on the market index, and save the unexplained part, or residual, as residualized risk factor. Pagan (1984) proofs in his paper on the analysis of regressions with generated regressors that both the parameter estimates, and the standard errors for the residualized risk factors are consistent.

As most risk factors are only strongly correlated with the market index from time tot time, we conclude that residualizing the risk factors using a full sample regression in which parameters are constant, is not optimal. A rolling window OLS approach is more efficient, as it still results in consistent parameter estimates and standard errors, but does not imply that the market beta of risk factors is constant over time.

In this situation issues associated with (exponentially weighted) rolling window OLS regressions rise again. The estimates are highly dependent on the ad hoc chosen window length and weighing scheme, and outliers generally have a strong impact. For those reasons we decided to specify a state space model as in equations (2) and (3) for residualization of the risk factors, and apply the Kalman filter for the parameter estimation.

Applying the Kalman filter to estimate the market dependence of the risk factors we

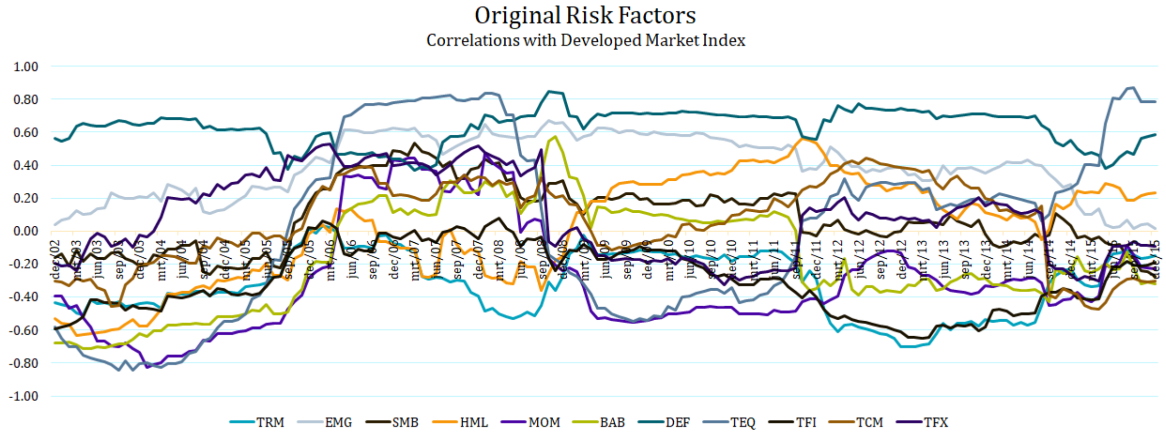

Figure 1: Correlations between the developed market index and the other risk factors over time
This figure illustrates how strong the equity market dependence of risk factors is, and how it changes over time.

find that returns on many risk factors can be replicated taking time-varying exposures to the market index. Since we allow for time-varying parameters in the factor model this would cause multicollinearity problems. In other words: it would not be possible to identify if returns are driven by exposure to the market index or exposure to the risk factor. Figure 11 in Appendix .. shows the correlations of the included risk factors with the market index over time. Those correlations are substantially lower than the ones we found in figure 1)

Those technical issues are not the only reason for residualization of the risk factors. Also from an economic point of view it is an interesting technique. We aim to give a clear risk profile of investment strategies. Exposures to the equity and bond markets are generally seen as good measures for this. If there is market exposure hidden in other factor exposures, it is desirable to make this visible in one plot that displays the aggregated market exposure. For all equity-related risk factors and the default premium, we use the developed equity market index. For the fixed income trend factor we use the term premium. As it makes no sense from an economic point of view we do not residualize the commodities and currencies trend factors.

3.1.5 Our Factor Model

The model that is used to get risk-adjusted performances is based on the Fung and Hsieh (2001) seven-factor model. Most risk factors from the original model are substituted by tradable and/or better interpretable factors. Some other factors are added, and we make use of residualized risk factors to get a better understanding of the risk profile of the funds. The model is given in equation (1), where $r_{i,t}$ denotes the return of fund (index) i at time t. The sub-indices i and t of the parameters allow for both differences in exposures over time, and differences in exposures between funds (indices). We have included the following risk factors as explanatory variables[5]:

[5]We applied residualization techniques to make the risk factors market neutral, and avoid multicollinearity in our models. A detailed description of the factor construction can be found in the data section.

- DEV: the excess return on the value weighted developed market index;
- EMG: the residualized excess returns on the emerging market index;
- SMB: residualized return on the global size factor. The return differential between small market capitalization stocks and big market capitalization stocks;
- HML: residualized return on the global value factor. The return differential between stocks with high book-to-price ratios and stocks with low book-to-price ratios;
- MOM: residualized return on the global momentum factor. The return differential between stocks that performed best during the past 12 months and stocks that performed worst in these months, with a delay of 1 month;
- BAB: residualized return on the global betting-against-beta factor. The excess return on a self-financing, beta-neutral portfolio that is long low beta stocks, and short high beta stocks;
- TRM: the term premium. The excess return on the Barclays Global Treasury index over the US 3-month LIBOR;
- DEF: the residualized default premium. The excess return on the Barclays Global Corporate Investment Grade index over the Barclays Global Treasury index;
- TEQ: the residualized return on the trend factor in equity markets;
- TFI: the residualized return on the trend factor in fixed income related products. Note that this factor is residualized using the term premium;
- TCM: the return on the trend factor in commodity markets;
- TFX: the return on the trend factor in foreign exchange markets;

3.1.6 Smaller Models

For Equity Long/Short and Non-traditional Bond funds we do not include all risk factors. To avoid overfitting we define two different models for these categories. For Equity Long/Short funds we only include the equity-related factors: DEV, EMG, SMB, HML, MOM, BAB, and TEQ. As in the complete model all risk factors are residualized on the developed market index. For Non-traditional Bond funds only bond-related factors are included: TRM, DEF, and TFI. As the developed market index is not included we do not residualize the default premium in this model.

4 Data

Due to the increased interest of investors in liquid alternatives and reporting obligations for those funds, more reliable data has become available over the last years. The major data provider that has liquid alternatives data available is Morningstar. Therefore we decided to download the data for this research from the Morningstar mutual fund database.

4.1 Data Description

For funds that are listed in the Morningstar alternative category, data is collected on all possibly useful fields: share classes, more specific investment style classifications, investment area, inception dates, benchmarks, fees, and more. For the time period January 2000 - October 2016 monthly returns in the base currency as well as fund sizes in euros are available. Returns are net-of-fees. Within the alternative category 23,716 records are found. Each record contains information on all variables for a particular fund or share class.

Inspecting the data we found evidence that not all data points correspond with unique funds. We found that all share classes of funds were included in the database and that some funds appeared more than once, but under a slightly different name. To create a database containing unique funds for which sufficient information is available we performed manual checks and applied some general filters.

The first filter that we applied is a filter on the minimum number of available fund sizes. At least one fund size is needed to know anything about the assets under management in a fund. As can be seen in Figure 2 this led to a reduction in records of 1,652. Secondly, the assets under management for every record is considered. If the average fund size over the live-period is below 10 million euro, the fund is omitted. We have several motivations for this requirement. For smaller funds it is difficult to find information making it more complicated to assign them to the right category. Besides that we analyze data on category level, and the influence of these funds on value weighted category indices is negligible. Applying this filter another 4,962 records drop out. The third requirement is that at least two years (24 months) of return data is available. There are two main reasons for this requirement. The first is that it is much more difficult to find information about strategies for funds that have not been live for a longer period. The second that sufficient return data is necessary to analyze funds properly over time. After applying these three filters more than half of the data points was filtered out.

Next, we performed some more advanced actions to clean up the database further. To figure out which records are unique funds, and which are different share classes of the same fund, we did two checks. The first is based on the average fund size. For most of the funds in the database fund sizes of all share classes were equal to the sum of assets under management in all share classes together. Based on the average fund sizes we could distinguish which records were different share classes of the same fund and which were not. As the returns on all share classes are practically the same we included the record with most available return data in case multiple share classes were available. We decided not to pick the institutional share class per se, as Hartley (2016) does, as we figured out that the share class field is not always reliable in Morningstar. The second check is based on returns. Returns of all records were compared with each other and if records show spurious similarities in returns manual checks are performed to figure out if these records are indeed different share classes of the same fund. With this check we also detected funds for which the assets under management per share class are available in Morningstar. For those funds we merged the fund sizes and the share class with the longest return history is included. Doing this we end up with 3,940

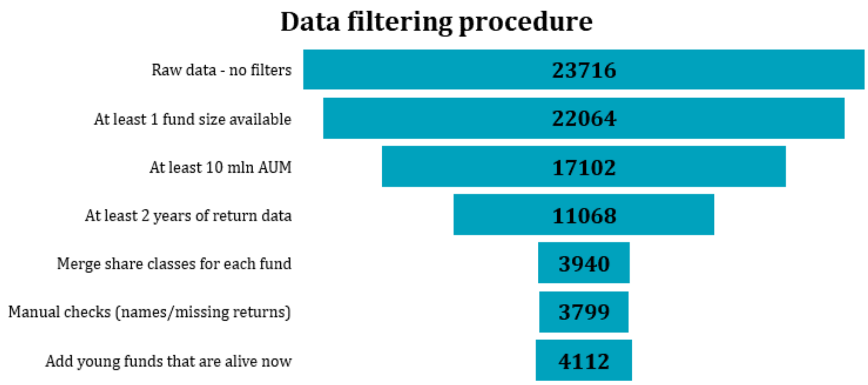

Figure 2: Data filtering procedure

unique funds. Finally, exceptional cases in which fund returns are missing during the live-period are checked. If randomly distributed over the whole live period returns are missing, funds are removed from the database. If only a very small fraction of the returns is missing, funds may be included.

Since there are quite some funds that are currently live, but do not have a return history of 24 months, we take this group of funds under consideration. This is done to reduce a possible bias towards older funds in the end of the sample. All funds with at least 12 returns that are currently live and do satisfy the other filtering constraints are included in the final sample of 4,112 funds. The evolution of the funds excluded from/included in the database is shown in figure 2.

4.1.1 Hedge Fund Indices

For hedge funds we solely downloaded returns on hedge fund indices as defined by Credit Suisse. For the category indices Equity Long/Short, Global Macro, Managed Futures, Market Neutral, Multistrategy, and Fixed Income Arbitrage we downloaded monthly returns in USD between January 2000 and December 2015.

4.1.2 Creating Excess Returns

To create excess returns we deducted the monthly risk free rate in the base currency of the fund from the fund or index return. For this we used the 3-month LIBOR that we downloaded from Bloomberg.

4.2 Categorization of Funds

After filtering out all uninformative data points the next step was to categorize the funds. The seven categories are defined in section 2.2. Funds that did not belong to any of those categories are placed in the category ‘Other’. As McCarthy (2014) pointed out there is quite some category misclassification within the Morningstar database. Therefore we used the Morningstar categories only to make a global division. All funds are checked afterwards and if necessary re-categorized. This way we obtain a

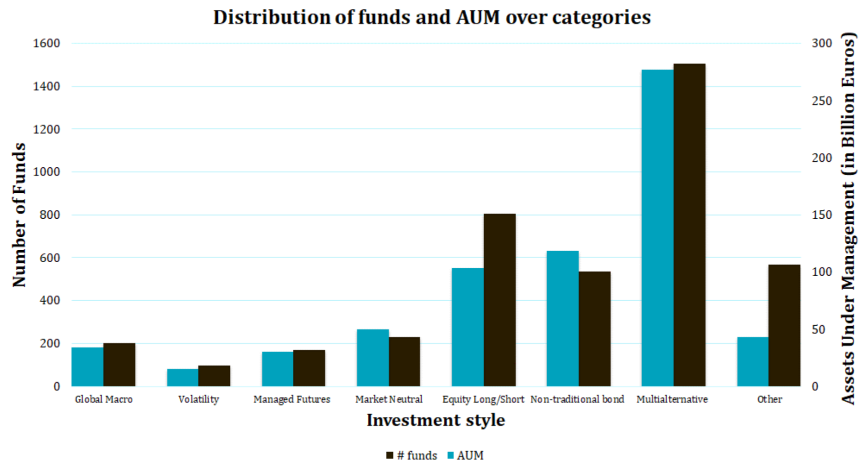

Figure 3: Distribution of funds over categories

high quality database with very adequate classification. The distribution of funds, based on both the number of funds and the total assets under management, over these categories is presented in Figure 3. Most funds belong to the Multialternative category. There are substantial amounts of funds in all categories.

Having categorized all funds based on their investment styles we get an overview of the number of active funds within each category at every moment in time. As displayed in Figure 4 there are funds alive in each category at every moment in time. This allows us to create portfolios of funds for all investment styles over the complete history. The distribution of funds over the categories is quite constant over time (see Appendix A, Figure 10). The relative size of the Global Macro, Managed Futures, and Multialternative categories seems to increase slightly, while the category 'Other' decreases.

It has to be mentioned that the last year of data is omitted in Figure 4. As we require at least 12 available returns for funds to be included in the database, funds launched in last year of the database are filtered out. However, funds that quit their operations during this year are included, which would result in a misleading figure in which the number of active funds seems to decline over this period. The figure with relative sizes of categories over time does not change including the last 12 months. This implies no abnormal mortality pattern in these months.

Figure 5 presents the number of live and death funds over time. Considering the graph and the underlying data no strange mortality patterns are found. During and after the financial crises of 2008 and 2011 we see an increase in the number of funds that collapse, but even more new funds are launched.

4.2.1 Creating Category Indices

Having categorized all funds enables us to create indices. For robustness checks we made both value and equally weighted indices. To weigh the funds in the value weighted indices we used the assets under management in Euros.

4.3 Data Biases

A well-known phenomenon in all kind of databases is that the data contains biases. There are plenty of biases, and before we start using our data we have to be aware of the possible biases included in it. Since there is little research done on liquid alternatives, we consult the literature on hedge funds of Ackermann et al. (1999), Brown et al. (1999), Fung and Hsieh (2000), and Agarwal et al. (2010) to figure out which biases may be present.

Since hedge funds do not have a reporting obligation there are biases in hedge fund databases as survivorship bias, backfilling bias, smoothing bias, and self-reporting bias. Those biases can strongly influence results, and complicate analyses, so we have to check for their presence in our database as well. An extensive study on the so-called self-reporting bias in hedge fund databases is published by Agarwal et al. (2010). Hedge funds are not obliged to report returns, holdings, and strategies to authorities or databases. As a result some hedge funds only report when it suits them best or do not report at all, and it is also not transparent which styles they apply. This makes it extra difficult to group and analyze them properly.

About survivorship, backfilling, and smoothing biases several papers are published by for example Ackermann et al. (1999), Brown et al. (1999), Fung and Hsieh (2000). They try to quantify the impact of biases on average hedge fund performances, and find evidence that positive and negative biases offset each other. A brief explanation of the different biases follows.

Survivorship bias is present in databases if funds that are not live, are not in the database (anymore). When funds are not in a database since their inception, a backfill bias arises if these funds only report part of their past returns. These are in general the good returns that show their attractiveness. Smoothing biases may be present since funds want to pretend to deliver stable, not so volatile returns over time. Funds do not report the true monthly returns, but report returns over longer horizons.

The data used in this research comes from the Morningstar mutual fund database. Despite the fact that the Morningstar database is a self-reporting database, which means that funds are not obliged to report to Morningstar, we assume it to contain complete, high-quality data. We expect less biases than in hedge fund databases for several reasons. Firstly, Morningstar is a data provider whose data is widely used among (institutional) investors to select the funds they invest. Since there are no limits on the maximum number of investors in a LAMF, it is very interesting for fund managers to be present in the database with their funds to raise extra capital. LAMF do have a reporting obligation to authorities as well. As a result returns on the funds are already publicly available, which makes it a smaller step for fund managers to report them also to Morningstar.

As Black (2015) describes in his study hedge funds fall under a specific exemption of the 40's act. Therefore hedge funds do not have a reporting obligation, but do have a limit on the maximum number of investors in the fund. Successful hedge funds that are 'full' feel no incentive to be in databases. This would only give away information about their strategies and would not lead to capital inflow. These two facts are main differences between liquid alternatives and hedge funds, and support our assumption

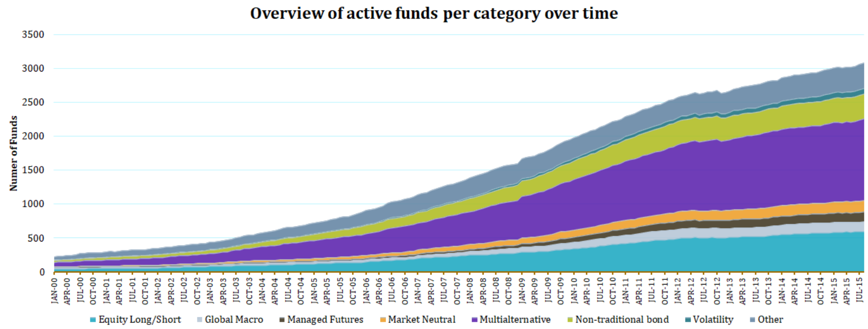

Figure 4: Evolution of number of funds per category over time

that a self-reporting bias is less likely to be present in the Morningstar database.

Considering our database backfill and smoothing biases are highly unlikely to be present, since returns of all funds are included as of inception date till the date they stop operating. A survivorship bias may be in the database as Morningstar started to clasify funds as liquid alternatives in 2006. However, it has to be mentioned that the total number of active funds was very small beforehand, which makes it less likely that there is a huge bias. Also in the rest of the database no evidence is found for a survivorship bias.

Investigating the database we found that there is a lag of about a month in the reporting of fund returns. By excluding data of the last two months from the database problems associated with this delay in reporting were solved easily. Besides that we found that all funds launched in recent years were available in the database directly afterwards. The latter confirms our statement about the absence of backfill and smoothing biases. So to conclude, we find evidence that our data is of high quality and does not contain severe biases.

4.4 Factor Data

To apply the factor model introduced in sections 3.1.5 and 3.1.6 we need data on the explanatory variables, or risk factors. We download this data from different sources. Data on global market, size, value, and momentum factors as in the Carhart (1997) four-factor model is collected from the library on the website of Kenneth French. Data on bond yields needed to construct the term- and default premium are downloaded from the website of the Federal Reserve. The return differential between developed and emerging markets is downloaded from the website of David Hsieh.

Monthly data on global time-series momentum, or trend factors in commodities, equities, fixed income, and foreign exchange markets, as described by Moskowitz et al. (2012), are downloaded from the website of AQR. From the same library data is collected on the Betting-against-Beta factor Frazzini and Pedersen (2014) introduced.

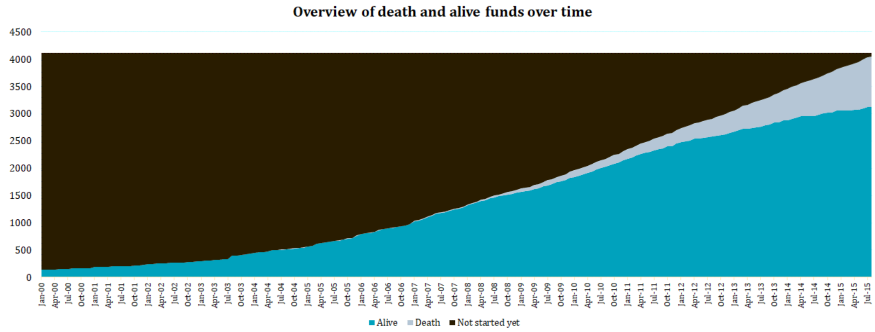

Figure 5: Overview of death and alive funds over time

4.4.1 Residualization of Risk Factors

In the ideal situation all factors in a model are orthogonal to each other, so that only pure factor exposures are measured. A principal components analysis creates such a situation, but the lack of economic interpretations for the factors makes this technique less desirable for style analyses. To get as close as possible to the theoretically optimal situation, we introduce the residualized risk factor. We construct those factors filtering out exposure to the common risk factor. For all equity-related risk factors and the default premium, this is the developed equity market index. For the fixed income trend factor we use the term premium. As it makes no sense from an economic point of view the commodities and currencies trend factors are not residualized.

For the residualization of risk factors we set up a restricted version of the state space model as in equations (2) and (3). Alpha is restricted to be constant over time. We replace the fund return by the return on the risk factor, and as explanatory variable we include the developed market index (or term premium). For our analyses we are interested in the unexplained, or idiosyncratic, part of the factor returns. We save the residuals of the regression as residualized risk factor.

Figure 6 shows the results of the residualization regression for the equities trend factor. The fit of the regression is 0.89 and learns us that it is possible to replicate the return on this factor nearly perfect taking time-varying exposures to the equity market index. However, extreme positions to the market index have to be taken to achieve this. Over time the leverage varies between -3 and +5. This implies that a constant trend exposure of 0.5 in a portfolio corresponds with a market beta ranging between -1.5 and +2.5. From the perspective of an investor it is desirable to be aware of this. The residualized risk factor offers the solution: it makes the (strong) market exposure hidden in the risk factor visible, while at the same time a consistent estimate is presented for the factor exposure.

4.4.2 Simulation Experiment with Residualized Risk Factors

Both from a theoretical and economical point of view it makes sense to residualize risk factors. In this section we show the practical advantages of residualization using a simulation experiment.

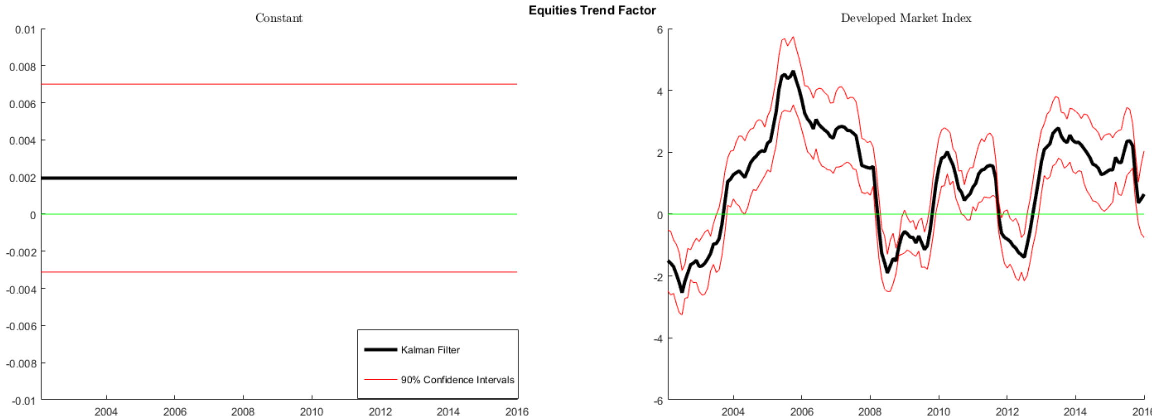

Figure 6: Residualization of equities trend factor

Our main goals are to define risk-adjusted returns, and to figure out on which risk factors funds are loading. Besides that it is interesting to say something about the risk profile of a fund, based on another criterion than volatility. Comparable to the market beta for stocks (Sharpe (1964)), the criterion that we use is the fund's exposure to the developed equity market index. Using residualized risk factors in a factor model the exposure to the market index displays the aggregated market exposure resulting from all positions. By means of a simulation experiment we show the difference in 'observed riskiness' found in a normal factor model, and in a model with residualized risk factors.

For the experiment we simulated returns for a fund that is loading on two risk factors: the developed equity market index and the equities trend factor. We used real return data on the two risk factors and an arbitrarily chosen weighing scheme. For completeness we also added some noise. The returns are simulated as follows:

$$R_t^{sim} = \beta_t^{DEV} DEV_t + \beta_t^{TEQ} TEQ_t + \varepsilon_t \qquad\qquad \varepsilon_t \sim N(0, \sigma)$$

We define a state space model as in equations (2) and (3), and estimate the parameters using the Kalman filter. Firstly, we estimate the parameters in the model with the normal risk factors. As we know the data generating process we can compare the estimated exposures (blue line) with the true exposures (green line) in Figure 7. It can be seen that the estimated exposures are very close to the real exposures.

Secondly, we estimate the parameters including the residualized equities trend factor in the model (red line). This way the equity market exposure implicitely captured in the equities trend factor is made visible. The estimated exposure to the residualized equities trend factor coincides with the true exposure to the equities trend factor. However, the estimated exposure to the developed equity market index differs substantially from the 'true exposure'. The aggregated market exposure resulting from positions in both the market index, and the equities trend factor is made visible. From a risk management perspective this is interesting. Relying on the results of the model with normal risk factors we would conclude that the fund was playing a conservative strategy with low to moderate equity market and equities trend exposure. However,

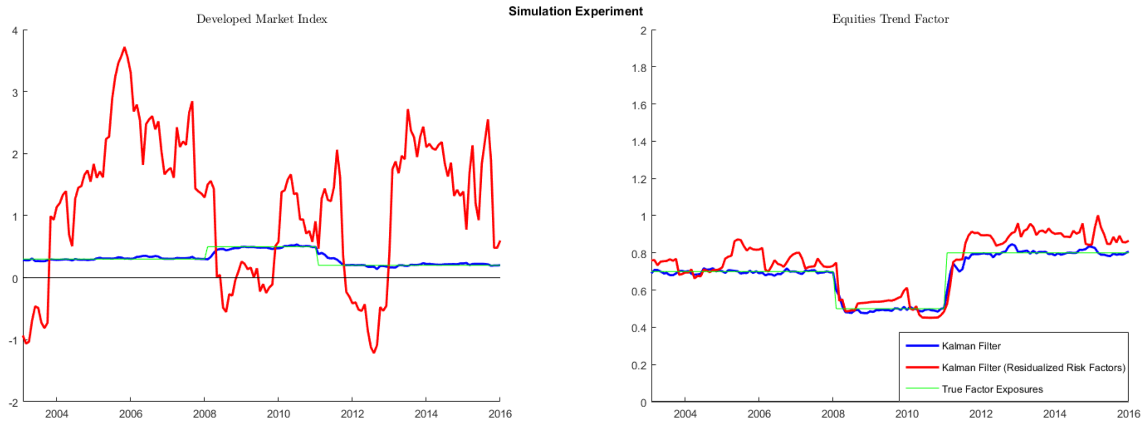

Figure 7: Simulation experiment 2-factor model

Figures 6 and 7 learn us that playing this trend rule results in extreme exposures to the market index. The fund is much more risky than we would conclude at first sight.

4.4.3 Real World Example: MSCI USA Min Vol Index

To show the power of residualization and the efficiency of the Kalman filter we perform multiple return-based style analyses on the MSCI USA Min Vol Index. We specify two factor models: one with 'normal' risk factors, and the other with residualized risk factors. We estimate the parameters in both models using both the Kalman filter, and a 36-month rolling window OLS approach.

We downloaded monthly returns on the MSCI USA Min Vol Index between 1990 and 2017 from Bloomberg. As the index is based on the US universe we also downloaded risk factors based on the US universe from the data library of Kenneth French. We include the US market index, and the size, value, momentum, and low volatility factor. All risk factors are residualized using the US market index. To be able to estimate the parameters with the Kalman filter we defined a state space model as in equations (2) and (3).

Before we compare the outcomes of both methods with each other, we summarize the expectations we had about the index. As we analyze a market index we expect a constant market beta close to one. We know that the MSCI USA Min Vol Index solely contains large and mid caps, so based on that we assume to find a slightly negative size exposure in our analyses. Lastly, we expect the index to load (strongly) positive on the low volatility factor. Going one step further, we expect to find a market beta significantly below 1 in the model with residualized risk factor. This is due to the negative market exposure captured in the low volatility factor, and the power of residualization to make the aggregated market exposure visible.

The results presented in Figure 8 confirm most of our expectations. Considering the factor exposures given by the Kalman filter (blue lines) we conclude that the index has a strong market dependence, a large cap bias, and a positive loading on the low volatility factor. We also find evidence that the aggregated market exposures resulting

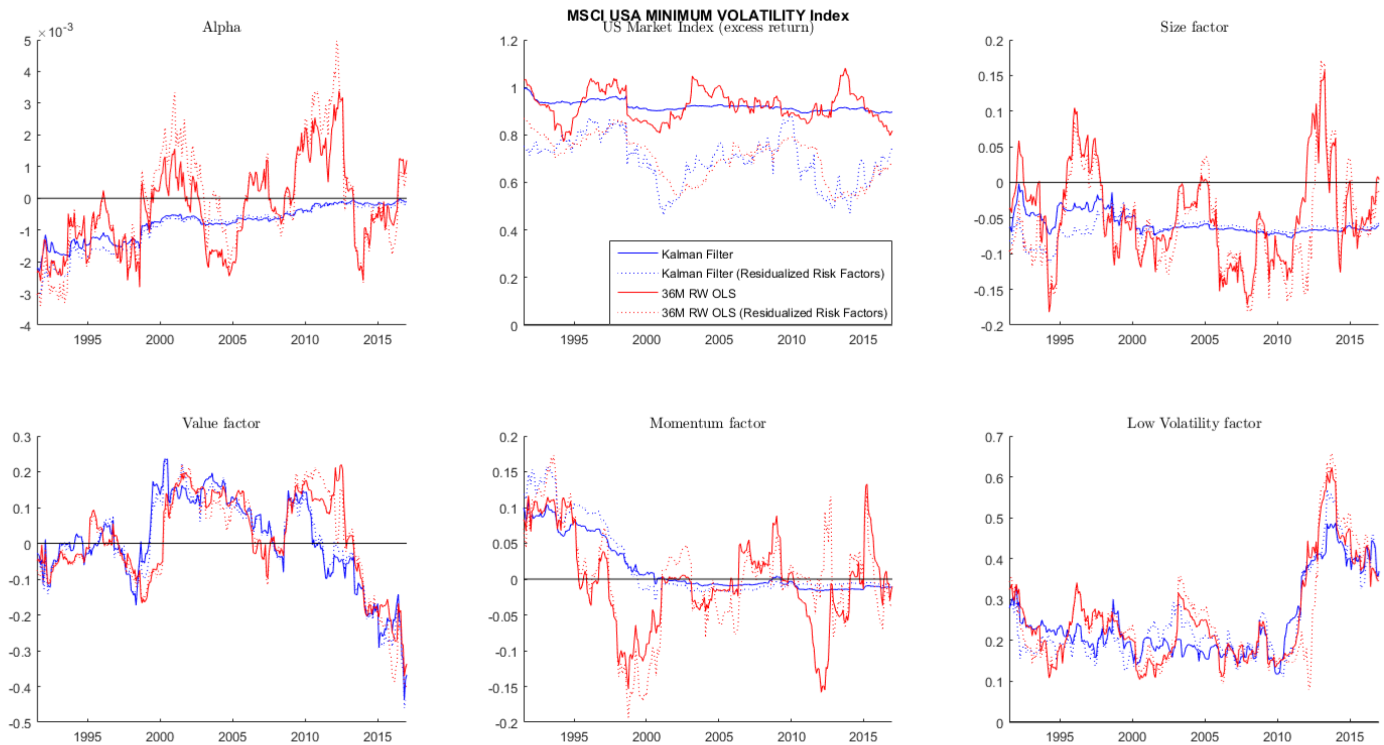

Figure 8: MSCI USA Min Vol Index analyzed

from loadings to all risk factors lies substantially lower than we would conclude based on the model with normal risk factors. Interesting to see is the (undesired) value exposure that is given by the index. Between 2000 and 2010 there was a bias towards value stocks, while growth stocks are overweighted in the index in more recent years. For an investor buying the index assuming to get pure low volatility exposure this is undesirable.

If we compare the parameter estimates from both estimation techniques we observe substantial differences. There is much more variation in the parameter estimates from the rolling window OLS approach (red lines) than in the estimates of the Kalman filter (blue lines). Relating the variation in the rolling window OLS estimates to our knowledge about the index, we have to conclude that the estimates are not reliable. This can best be seen in the plots with market and size exposure. The constituents in the index are solely large and mid caps, and are pretty constant over time. Observing absolute differences in market exposure over time from 0.3 (ranging from 0.8 and 1.1) in the model with normal risk factors is therefore highly unlikely. The same holds for the implied small cap bias in the index. The rolling window OLS approach is highly sensitive to outliers and seems to suffer from the 'ghost effect' (Dunis et al., 2004), while the Kalman filter shows to be very robust.

5 Results

In this section the main results are presented, but before summing up all results a short introduction to the analyses is given. All analyses are performed on the value weighted category indices as introduced in section 4.2.1. We performed two analyses: a simple return analysis and a return-based style analysis. Besides that we test the diversification opportunities of liquid alternatives.

In the return-based style analysis we explain the results that we find applying factor models on the category indices. We compare the situation in which we assume constant factor exposures over time with the situation in which we allow for time-varying ones. We also specifically focus on the exposures in down markets, and consider if managers take significantly different positions during down market. The last thing we are interested in is how alpha changes when we allow for time-varying exposures.

To test the diversification opportunities we create a 50-50 equity-bond benchmark portfolio. From this benchmark we allocate 10%, 30%, or 50% to a liquid alternative category index. To quantify the diversification opportunities we compare the returns, volatilities, and Sharpe ratios of the 90/10, 70/30, and 50/50 portfolios[6] over all market regimes (see Table 2). We test for both the volatility, and Sharpe ratios if they have changed significantly. For the volatility we apply an F-test. F-test statistics can be found in Table 6 in the Appendix. To test for differences in Sharpe ratios we apply the methodology as introduced by Bailey and Lopez de Prado (2012). They use the fact that Sharpe Ratios are asymptotically normal distributed, even if the returns are not, to derive the probablistic Sharpe Ratio. Results for all tests on Sharpe ratios can be

[6]The 90/10 portfolio invests 90% of its capital in the 50-50 equity-bond portfolio, and 10% of its capital in a liquid alternative category index.

		MSCI World	Liquid Alternatives Indices EQ_LS	GM	MF	MN	MA	NTB
UP	Average Return	10.2%	4.8%	0.0%	3.8%	1.7%	2.4%	1.4%
	Volatility	11.4%	4.8%	2.7%	8.5%	1.7%	3.0%	1.7%
	Sharpe Ratio	0.89	1.00	0.02	0.45	1.02	0.80	0.86
DOWN	Average Return	−12.2%	−3.6%	−4.4%	10.6%	1.6%	−6.6%	2.0%
	Volatility	21.9%	6.0%	6.0%	13.5%	5.7%	7.6%	3.5%
	Sharpe Ratio	−0.56	−0.60	−0.74	0.79	0.28	−0.87	0.58
ALL	Average Return	2.4%	2.0%	−1.4%	6.0%	1.7%	−0.6%	1.6%
	Volatility	15.8%	5.4%	4.1%	10.4%	3.5%	5.1%	2.4%
	Sharpe Ratio	0.15	0.38	−0.35	0.58	0.48	−0.12	0.68

(a) Return analysis liquid alternatives

		MSCI World	Credit Suisse Hedge Fund Indices EQ_LS	GM	MF	MN	MA	NTB
UP	Average Return	10.2%	7.4%	6.8%	1.6%	1.5%	8.0%	4.6%
	Volatility	11.4%	7.6%	4.9%	11.1%	3.3%	3.5%	2.9%
	Sharpe Ratio	0.89	0.97	1.38	0.15	0.46	2.29	1.62
DOWN	Average Return	−12.2%	−3.3%	7.5%	8.4%	−7.3%	−1.0%	−1.8%
	Volatility	21.9%	8.9%	6.5%	12.7%	18.1%	6.8%	8.9%
	Sharpe Ratio	−0.56	−0.37	1.15	0.66	−0.40	−0.15	−0.20
ALL	Average Return	2.4%	3.8%	7.0%	3.8%	−1.4%	5.0%	2.5%
	Volatility	15.8%	8.2%	5.5%	11.6%	10.6%	4.9%	5.6%
	Sharpe Ratio	0.15	0.47	1.28	0.32	−0.13	1.01	0.45

(b) Return analysis hedge funds

Table 1: Return analyses

found in Tables 8 and 9 in the Appendix.

Combining the results of the analyses we draw a general conclusion about each category. We answer the research questions: do they offer interesting return characteristics and/or diversification opportunities. Afterwards we compare the performance of the liquid alternatives with that of hedge funds with similar investment strategies. For this we use the same two analyses as before. We compare the return characteristics over different market regimes (Table 1), and compare the exposures to risk factors that we find in the factor models. We conduct a paired-sample t-test to test if there are significant differences in returns of liquid alternatives and hedge funds. Test statistics can be found in Table 5 in the Appendix. Lastly we investigate what differentiates the top performing funds from the worst performing funds within each category. Note that all returns, volatilities, and Sharpe ratios displayed and discussed in this section are annualized. We start the section with the most promising categories.

5.1 Managed Futures

Examining the return characteristics of the Managed Futures index (Table 1a) the first thing that we notice is the excellent performance in down markets. While most indices show negative or low returns, Managed Futures are delivering high returns (+10.6% annualized) and a high Sharpe ratio (0.79). During down markets the correlation with the equity market index is strongly negative: -0.52. Together with the decent performance in up markets those return characteristics are promising.

The results of analyzing the Managed Futures index returns using our factor model can be found in Figure 9. Assuming constant factor exposures (light green lines), we conclude that they do not deliver alpha. Positive loadings on the four trend factors, and the term and default premium seem to explain the returns.

If we allow for time-varying factor exposures (blue line) the fit of the regression improves significantly. At the same time alpha becomes slightly negative, though. Exposures to the four trend factors are relatively constant, and significantly positive. Exposures to most of the other risk factors are not significantly different from zero. There are significant loadings and obvious fluctuations in the equity market and value exposures, though. The time-varying exposure to the equity market index is a direct result of the residualization technique that we applied on most risk factors. We make the hidden market exposure in the equities trend factor visible. The significantly positive loading on the value factor early 2000s is probably due to the high returns (positive trend) in those stocks after the dot-com bubble.

If we focus on the exposures during down markets (shaded red areas in Figure 9) we find that Managed Futures start to bet against beta, and lower their exposure to the developed equity market index during crises. Both results are likely consequences of playing on trend in equity markets (or: good market timing).

Combining the results of both analyses we conclude that Managed Futures apply dynamic investment strategies by focussing on the trend rules. We also conclude that negative alpha while allowing for time-varying factor exposures does not necessarily imply that funds cannot offer great returns and/or diversification opportunities. Alpha is per definition lowered by performance fees and other costs, and good factor timing (or even implementation) can definitely be seen as skill (or alpha). The latter is an interesting question for further research: is there a way to quantify the 'alpha' that results from good factor timing?

The diversification opportunities for Managed Futures are presented in Tables 2, 6, and 9. We study the change in performance when fractions of the 50-50 equity-bond portfolio are invested in the Managed Futures liquid alternative index. Allocating resources to the Managed Futures index results in much better returns and a significantly lower volatility during down markets. As a direct result Sharpe ratios increase significantly when at least 30% of the resources are allocated to the Managed Futures index (p-values of 0.00). The full sample Sharpe ratio can even be increased from 0.15 to 0.60 by allocating 50% of the portfolio to the Managed Futures index.

The return characteristics for Managed Futures hedge funds are the same as for the liquid alternatives. We find low, but positive returns in up markets (Sharpe ratio of 0.15) and excellent performance in down markets (Sharpe ratio of 0.66). Somewhat surprising is the outperformance of liquid alternatives, though. Annually their returns are 2.2% higher than for their hedge fund counterparts, while we examine similar volatility and factor loadings (see Figure 12 in the Appendix). This leads to a significantly higher full sample Sharpe ratio for liquid alternatives (0.58 versus 0.32).

5.2 Market Neutral

Market Neutral funds show very stable returns under all circumstances. In both up and down markets there is little volatility in the returns (1.7% and 5.7% respectively) and on average the returns are positive: 1.6-1.7% per year. Together with the weak correlation of Market Neutral funds with the equity market (≈ 0.4) over both regimes these return characteristics are interesting.

Results for the return-based style analyses can be found in Figures 13 and 14. Assuming constant factor exposures Market Neutral funds seem to offer positive alpha over the whole sample period. They have little market exposure and a small cap bias. If we allow for time-varying factor exposures the model fit increases drastically and results change. Alpha disappears and although loadings on most risk factors do not change a lot and are low in absolute sense, there are remarkable differences with the constant factor loadings. The constant estimates seem to be highly influenced by the 2008 financial crisis. During the crisis most estimates coincide with the time-varying ones. We notice that there are significant exposures to the default premium, betting-against-beta, and currencies trend factor over time. We cannot find clear patterns in this time-variation, though.

To conclude: Market Neutral funds seem to get their solid performance under all circumstances from picking the right assets with little market dependence over time. As a result Market Neutral funds generate decent Sharpe ratios and show low correlations with the equity market index. Regarding the extremely low levels of volatility and correlations with the equity market in both up and down markets, Market Neutral funds offer interesting diversification opportunities for conservative investors. Tables 2, 6, and 9 show us the change in performance when fractions of the 50-50 equity-bond portfolio are invested in the Market Neutral liquid alternative index. Returns become

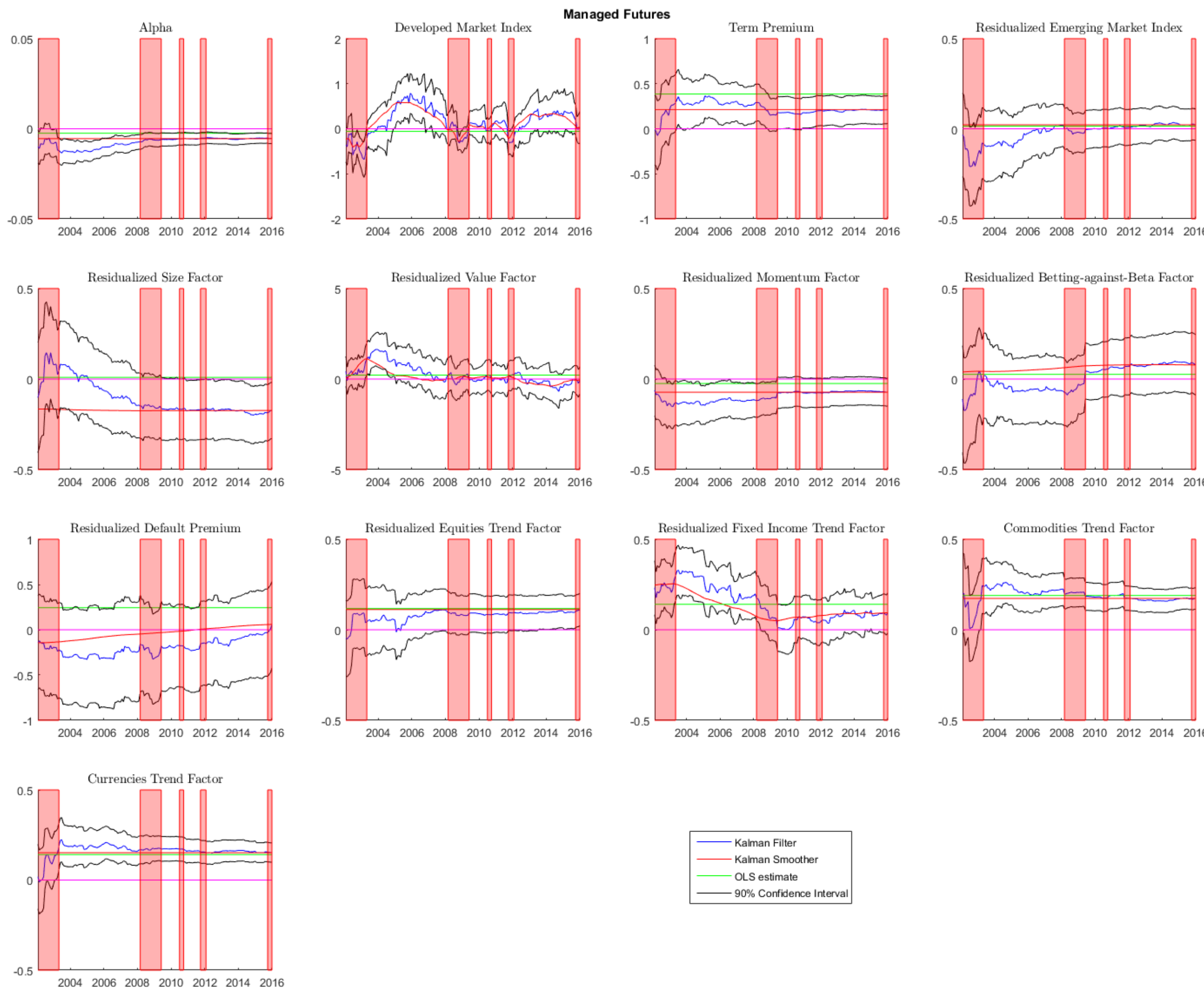

Figure 9: Managed Futures Index analyzed

less extreme when a larger part of the portfolio is invested in the Market Neutral index. The returns are a bit lower during up markets and less negative during down markets. However, the significantly lower volatilities in both regimes result in increased Sharpe ratios in both regimes. Over the whole sample the Sharpe ratio can be increased from 0.15 to 0.29 by allocating 50% of the portfolio to the Market Neutral index. According to the p-value of 0.08 in Table 9 the Sharpe ratio can be significantly improved on a 10% significance level.

The return characteristics of hedge fund and liquid alternative Market Neutral funds are similar to some extent. They show low correlations with the equity market in both up and down markets (0.25-0.5). In down markets we find a strong underperformance for the hedge fund index that leads to a significantly lower Sharpe ratio for them, though. It has to be mentioned that this is a direct result of the Madoff scandal during the 2008 financial crisis. Based on factor loadings it is not possible to draw a general conclusion about the differences between liquid alternatives and hedge funds. The factor loadings are completely different for both types of funds, but no clear patterns are visible.

5.3 Non-traditional Bond

For Non-traditional Bond funds we find the best full sample Sharpe ratio of all categories: 0.68. In both up and down markets the funds show positive returns on average (1.4% and 2.0% respectively) and low levels of volatility (1.7% and 3.5% respectively). Somewhat surprising is the moderate positive correlation of 0.56 with the equity market in down markets.

Results for the return-based style analyses can be found in Figures 15 and 16. Assuming constant factor loadings over time we observe strong positive exposures to the term and default premium, and a bit of alpha. If we allow for time-varying exposures we also find positive alpha, but only till 2008. During and shortly after the crisis alpha becomes negative, after which alpha disappeared. For the exposures to the risk factors the patterns are completely different. Till 2004 the exposure to the term premium increases gradually over time. Afterwards the exposure remains at the same level. The exposure to the default premium seems to be related to the state of the equity market. Several months before recessions in equity market fund managers start to increase their exposure to the default premium. In the first half of the sample Non-traditional Bond funds load significantly positive on the fixed income trend factor. After a sharp decrease in this exposure during the 2008 financial crisis the funds did not load on this factor anymore.

Combining the results of both analyses we conclude that Non-traditional Bond funds apply dynamic strategies that result in excellent performance in down markets. Analyzing the return characteristics of the risk factors we conclude that during the dot-com bubble Non-traditional Bond funds got their strong performance harvesting the term premium and playing on trend in fixed income markets. While during the 2008 financial crisis the strong loading on the term premium is the main driver of the decent performance.

From a diversification perspective Non-traditional Bond funds are interesting as well. As can be seen in Tables 2, 6, and 9 combining the Non-traditional Bond index with the benchmark portfolio leads to a significant[7] increase in full sample Sharpe ratio from 0.15 up to 0.3. Returns become less extreme when a larger part of the portfolio is invested in the Non-traditional Bond index. During up markets returns are a bit lower, while returns are less negative during down markets. The significantly lower volatilities in both regimes are the key driver behind the better Sharpe ratios.

Based on the return characteristics liquid alternatives are more attractive from a diversification perspective than their hedge fund counterparts. They show lower levels of volatility[8], and positive returns in both up and down markets, resulting in a significantly better full sample Sharpe ratio (0.68 versus 0.45, with a p-value of 0.04). Exposure to the term premium seems to be the key performance driver for both types of funds. Hedge funds are timing the default premium and fixed income trend factor, but this does not lead to better performance. Especially in down markets the stronger exposure to the default premium costs performance.

5.4 Equity Long/Short

Considering the returns of the Equity Long/Short category we find similar results as for the MSCI World Index. High positive Sharpe ratios in up markets (1.00), but strongly negative ones in down markets (-0.60). There is also a strong correlation with the equity market index of 0.87 during down markets.

Results for the return-based style analyses can be found in Figures 17 and 18. Under the assumption of constant factor exposures Equity Long/Short funds seem to offer alpha. Besides that we find that they load positively on the developed market index, and the size and momentum factors. If we allow for time-varying exposures, results change drastically. Alpha becomes negative over the whole period and exposures to most factors change substantially over time. Shortly before and during down markets exposures to the equity market index, the value factor, and equities trend factor are lowered significantly. The trend exposure becomes even negative during the crises. This is undesirable as it implies that during the dot-com bubble and 2008 financial crisis Equity Long/Short funds played against trend in equities. During the Chinese banking liquidity crisis in 2013 we notice a sharp decrease in the exposure to emerging equity markets.

Putting the results of both analyses together learns us that the factor timing of Equity Long/Short funds is not good. They show bad returns and high correlations with the equity market during crises, implying that they do not pick the right stocks, just follow the market, and implicitely play against trend. From a diversification perspective this is not ideal. Allocating resources from the benchmark portfolio to the Equity Long/Short index only results in slightly better Sharpe ratios in up markets (See Table 2).

Equity Long/Short hedge funds and liquid alternatives show similar return characteristics and correlations with the equity market index. Hedge funds deliver better

[7]When 50% of the portfolio is allocated to the Non-traditional Bond index, and on a 10% significance level

[8]1.7% and 3.5% for liquid alternatives versus 2.9% and 8.9% for hedge funds in respectively up and down markets

returns in up markets (7.4% versus 4.8%), but this comes together with a higher volatility (7.6% versus 4.8%), resulting in a slighly lower Sharpe ratio (0.97 versus 1.00). Also the factor exposures are quite similar. Only the exposures to the betting-against-beta and equities trend factors are different. Hedge funds show more time-variation in betting-against-beta exposure, but load constant, and positively on trend. Liquid alternatives seem to fail playing the trend rule, resulting in negative trend exposures during recessions.

5.5 Global Macro

Global Macro funds show the worst returns of all indices. In up markets the average return is 0%, while they lose 4.4% per year in down markets. Results for the return-based style analyses can be found in Figures 19 and 20. If we analyze the returns assuming constant exposures, we find negative alpha, and no strong factor loadings. Allowing for time-variation leads to different observations. Global Macro funds seem to offer positive alpha till the 2008 financial crisis. Afterwards alpha turns negative. We find little variation in most exposures so that they coincide with the constant parameter estimates. From the 2008 financial crisis onwards they start to load on the fixed income trend factor. At the same time they change from a positive to a negative loading on the momentum factor, and increase their loading on the default premium.

Although we find positive alpha during the first half of the sample, this does not lead to good performance. After the 2008 financial crisis there is no alpha anymore, and the performance is still bad. Where successful funds stop loading on the fixed income trend factor, Global Macro funds start to load positively on it during the crisis.

As expected Global Macro funds do not offer diversification opportunities. Allocating resources from the 50-50 equity-bond portfolio to the Global Macro index results in worse Sharpe ratios.

Where Global Macro liquid alternatives show the worst performance of the universe, Global Macro hedge funds are outstanding. They deliver extremely good (risk adjusted) returns in both up and down markets (6.8% and 7.5% respectively), and show very low correlations with the equity market index (≈ 0.3). If we consider the factor exposures in Figure 20 we see that Global Macro hedge funds load strongly on the four trend factors. Besides that they take time-varying exposures to the betting-against-beta factor. Picking high beta stocks in up markets, and low beta stocks in down markets. Even after deducting all factor premia Global Macro hedge funds offer strong, positive alpha over the whole sample.

5.6 Multialternative

For Multialternative funds we find comparable return characteristics as for the MSCI World Index: strongly positive Sharpe ratios in up markets (0.80), and strongly negative ones in down markets (-0.87). From the return-based style analyses (Figures 21 and 22) we learn that Multialternative funds offer negative alpha assuming constant factor loadings over time. They load positively on both equity market indices, and the fixed income trend factor. A negative exposure to the term premium is found. Allowing for time-varying exposures we still find negative alpha, and similar factor loadings as before. Besides that we find that Multialternative funds start to get more exposure to momentum and low beta stocks over time. Shortly before and during crisis periods they take stronger exposures to the default premium. They keep on increasing this position from 2011 onwards.

Combining all results we conclude that Multialternative funds do not generate alpha, and offer no interesting investment or diversification opportunities at all. This is proven by the numbers in Tables 2, 6, and 9. Investing in the Multialternative index instead of the benchmark portfolio results in worse returns and Sharpe ratios during both market regimes.

The return characteristics for liquid alternatives and hedge funds are similar. Both types of funds perform well in up markets, badly in down markets, and show strong correlations with the equity market index. The hedge fund variants give higher returns and a significantly higher full sample Sharpe ratio (1.01 versus -0.12), though. Analyzing the returns with a factor model learns us that the main difference is in the exposures to the trend factors. The hedge funds have positive exposures to the commodities and currencies trend factors, while liquid alternatives have not. Besides this we see a strongly positive alpha for hedge funds in this category.

5.7 Volatility

Analyzing the return characteristics of Volatility funds we conclude that they are not interesting. They show low returns in up markets (1.6%), negative returns and high volatility in down markets (-1.9% and 7.1% respectively), and also a very strong correlation with the equity market index (≈ 0.8).

Results for the return-based style analysis can be found in Figure 23. Assuming constant factor exposures we find positive alpha, and exposures to a few risk factors. They load negatively on the default premium and betting-against-beta factor, and positively on the developed market index and fixed income trend factor. When we allow for time-variation in the exposures, we still find positive alpha. Over time Volatility funds seem to load differently on size, momentum, and trend in fixed income markets. Remarkably the exposure to the developed equity market index increases during crises.

The promising results (in terms of alpha) of the return-based style analysis are not confirmed by the return analysis. The returns of Volatility funds are alternative in the sense that we cannot explain them by exposures to well-known risk factors. The strong correlation with the equity market index and the negative Sharpe ratio in crisis periods make them not interesting from a diversification perspective, though. Allocating a fraction of the benchmark portfolio to the Volatility index does not positively influence the returns, volatilities or Sharpe ratios under any market condition. A comparison with hedge funds cannot be made, as there does not exist a Volatility category in the Credit Suisse database.

Table 2: Diversification opportunities

		Benchmark portfolio 50% equities - 50% bonds	Benchmark + Equity Long/Short 50/50	70/30	90/10	Benchmark + Global Macro 50/50	70/30	90/10	Benchmark + Managed Futures 50/50	70/30	90/10	Benchmark + Market Neutral 50/50	70/30	90/10
UP	Average Return	**5.0%**	−0.1%	0.0%	0.0%	−2.5%	−1.5%	−0.5%	−0.6%	−0.4%	−0.1%	−1.7%	−1.0%	−0.3%
	Volatility	**5.7%**	−0.9%	−0.6%	−0.2%	−1.9%	−1.2%	−0.4%	0.1%	−0.3%	−0.2%	−2.4%	−1.5%	−0.5%
	Sharpe Ratio	**0.87**	0.14	0.10	0.03	−0.23	−0.11	−0.03	−0.12	−0.01	0.02	0.14	0.07	0.02
DOWN	Average Return	**-6.3%**	1.3%	0.8%	0.3%	0.9%	0.6%	0.2%	8.1%	4.8%	1.6%	3.9%	2.3%	0.8%
	Volatility	**10.9%**	−6.1%	−5.8%	−5.5%	−7.1%	−6.4%	−5.6%	−5.1%	−5.5%	−5.5%	−7.7%	−6.7%	−5.7%
	Sharpe Ratio	**-0.58**	−0.03	−0.02	−0.01	−0.10	−0.06	−0.02	0.88	0.35	0.06	0.24	0.11	0.03
ALL	Average Return	**1.2%**	0.4%	0.2%	0.1%	−1.3%	−0.8%	−0.3%	2.4%	1.4%	0.5%	0.2%	0.1%	0.0%
	Volatility	**7.9%**	−1.7%	−1.1%	−0.4%	−2.3%	−1.4%	−0.5%	−2.0%	−2.1%	−0.9%	−3.0%	−1.9%	−0.6%
	Sharpe Ratio	**0.15**	0.11	0.06	0.02	−0.17	−0.09	−0.03	0.45	0.29	0.09	0.14	0.07	0.02

		Benchmark portfolio 50% equities - 50% bonds	Benchmark + Multialternative 50/50	70/30	90/10	Benchmark + Non-tradional Bond 50/50	70/30	90/10	Benchmark + Volatility 50/50	70/30	90/10
UP	Average Return	**5.0%**	−1.3%	−0.8%	−0.3%	−1.8%	−1.1%	−0.4%	−1.7%	−1.0%	−0.3%
	Volatility	**5.7%**	−1.6%	−1.0%	−0.3%	−2.3%	−1.4%	−0.5%	−2.1%	−1.3%	−0.4%
	Sharpe Ratio	**0.87**	0.02	0.02	0.01	0.06	0.03	0.01	0.02	0.02	0.01
DOWN	Average Return	**-6.3%**	−0.2%	−0.1%	0.0%	4.1%	2.4%	0.8%	2.2%	1.3%	0.4%
	Volatility	**10.9%**	−6.8%	−6.2%	−5.6%	−7.5%	−6.6%	−5.7%	−7.3%	−6.5%	−5.7%
	Sharpe Ratio	**-0.58**	−0.16	−0.09	−0.03	0.24	0.11	0.03	0.10	0.05	0.02
ALL	Average Return	**1.2%**	−0.9%	−0.6%	−0.2%	0.2%	0.1%	0.0%	−0.4%	−0.2%	−0.1%
	Volatility	**7.9%**	−1.7%	−1.1%	−0.4%	−3.2%	−1.9%	−0.7%	−2.0%	−1.3%	−0.4%
	Sharpe Ratio	**0.15**	−0.11	−0.06	−0.02	0.15	0.07	0.02	−0.01	−0.01	0.00

The first column contains return data on the benchmark portfolio. The other columns contain relative values of the hybrid portfolios to the benchmark. A positive value denotes a higher return, volatility, or Sharpe ratio for the hybrid portfolio than for the benchmark.

5.8 Top-Bottom Quintile Analyses - What Do Top Funds Do Differently?

Within categories there are top performing and worst performing funds. We have split the universe to compare the factor exposures of the top and bottom quintile funds[9]. We determine the cumulative performance for all funds over a calendar year, and group them based on this. The 20% funds with the highest return come in the top bucket. The 20% funds with the lowest return come in the bottom bucket. Using the fund returns we create equally weighted portfolio returns for each year. Note that it is impossible to create investment portfolios this way, since future returns are used in the composition. The purpose of this analysis is solely to figure out what drives the differences in returns of top and bottom funds.

5.8.1 Managed Futures

The first observation we make analyzing Figures 24 and 25 is that the top funds offer positive alpha over the whole sample period, while the bottom funds do not. This is not the only difference, though. Top funds have strong, positive exposures to the equities trend factor, while the bottom funds have not. Where top funds seem to properly implement the four trend rules (resulting in constant exposures to these factors), bottom funds do not succeed in it. As a result they do not have constant, positive exposures, but time-varying ones. For top funds we find significant time-variation in the exposure to the betting-against-beta factor. During crises they select the low-beta stocks, while during expansions the focus is on high-beta stocks.

All things considered we conclude that the top performing managed futures funds differentiate themselves from the worst performing ones implementing the four trend rules properly.

5.8.2 Market Neutral

For the top performing funds (Figure 26) we find significantly positive alpha over the whole sample, while the bottom funds (Figure 27) deliver negative alpha. Market neutral funds do not have very strong factor loadings, so there are little obvious differences between the factor exposures of top and bottom funds. Most remarkable difference is in the developed equity market exposure. Top funds seem to be really 'market neutral', while bottom funds show strong exposures to the equity market during recessions.

5.8.3 Non-traditional Bond

The difference in alpha between top and bottom funds is also very clear for non-traditional bond funds. Top funds deliver strongly positive alpha (Figure 28); bottom funds strongly negative alpha (Figure 29). Considering the factor exposures we find that the top funds are in general loading much stronger on the term premium and fixed income trend factor. The most obvious difference is in the loading on the default premium. Where top funds limit their exposure to this factor during crises, the bottom funds are not able to do this in time.

[9]Note that all figures can be found in the Appendix

We can conclude that the top performing non-traditional bond funds are able to load constantly on the fixed income trend factor, and that they are timing the default premium much better than the bottom funds.

5.8.4 Equity Long/Short

As expected we find positive alpha for the top performing funds (Figure 30), and negative alpha for the bottom ones (Figure 31). Interesting to see is the inverse pattern of equity market exposure of both groups. Where top funds take high exposures to the equity market during expansions and low exposures during recessions, bottom funds show the opposite pattern. Besides that we observe that the top performing funds load significantly stronger on the equities trend factor. Once again indicating that loading on trend is key for strong performance.

5.8.5 Global Macro

For Global Macro funds we find even for the bottom funds positive alpha till 2006. For top funds alpha is significantly positive over the whole sample. Considering the factor exposures in Figures 32 and 33 there are no clear patterns visible for the top and bottom funds, so it is not possible to conclude what is the driving force for the performance difference.

5.8.6 Multialternative

Besides a significant difference in alpha there are no obvious differences in factor exposures between the best (Figure 34) and worst performing funds (Figure 35). The top funds offer positive alpha over the whole sample, the bottom funds negative alpha. The main differences in factor exposures are in the developed and emerging equity market factors. Top funds load slightly stronger on emerging markets. Bottom funds show higher developed market exposure during recessions.

5.8.7 Volatility

For volatility funds we find that the returns are alternative for both top and bottom funds (Figures 36 and 37). However, top funds generate significantly positive alpha, while bottom funds do not. For top funds we only find exposure to the betting-against-beta factor. For bottom funds it is the strong equity market exposure during recessions that influences their performance negatively.

6 Conclusion

Wrapping up the results we conclude that liquid alternative mutual funds do not deliver alternative returns in general. Only Volatility funds offer alternative returns. They generate positive alpha over the whole sample period, implying their returns are not driven by exposures to the included risk factors. A strong correlation with the equity market index makes them not interesting from a diversification perspective, though.

This does not mean that there are no attractive liquid alternatives. Managed Futures, Market Neutral, and Non-traditional Bond funds are performing good, and deliver interesting risk-adjusted returns. These funds offer dynamic strategies that harvest the right risk premia over time. They deliver outstanding risk-adjusted returns during crises, and also in up markets their performance is decent. Together with their low or even negative correlations with the equity market this makes them interesting diversification vehicles for more traditional investors.

Returning to the research question if liquid alternatives can be a valuable addition to traditional portfolios, we conclude that although returns on most liquid alternatives can be explained by exposures to common risk factors, the funds can still be interesting for investors with more traditional portfolios. Managed Futures, Market Neutral, and Non-traditional Bond funds are interesting to consider from a diversification perspective. These funds show high Sharpe ratios, and low correlations with the equity market index during good and bad times. The best protection in recessions is given by Managed Futures funds. During down markets those funds show high, positive returns, a negative correlation with the equity market index, and on a yearly basis more than 20% outperformance over the MSCI World Index. Proper implementation of trend rules seems to be the driving factor behind this success.

We also investigated if funds that are doing well in difficult periods show persistence in up markets. We find that all categories that are doing well in down markets are also doing well in up markets. Market Neutral and Non-traditional Bond funds deliver comparable Sharpe ratios as the market index in up markets. For Managed Futures funds the Sharpe ratio is somewhat lower, but still decent. In up markets nearly all categories are doing well, though.

It is not possible to draw a general conclusion about the relative performance of liquid alternatives to their hedge fund counterparts. For some categories liquid alternatives perform better, while for others the hedge funds outperform. Interesting is that Managed Futures liquid alternatives perform better than their hedge fund counterparts. The liquid alternatives in this category seem not to suffer from the stricter regulations at all. For the Global Macro and Multialternative categories we find the opposite. Hedge funds applying these strategies are highly profitable, while liquid alternatives are not. We observe that succesful implementation of trend rules in multiple asset classes is the key performance driver of well performing funds.

7 Recommendations for Further Research

As good factor timing can be seen as skill of an investment manager it would be interesting to see if there is a way to quantify the 'alpha' of a fund that results from good factor timing. Further research must be conducted to find a model or technique to achieve this.

References

Carl Ackermann, Richard McEnally, and David Ravenscraft. The performance of hedge funds: Risk, return, and incentives. *The Journal of Finance*, 54(3):833–874, 1999.

Vikas Agarwal, Nicole M., and Narayan Y. Naik. Hedge funds for retail investors? an examination of hedged mutual funds. *Journal of Financial and Quantitative Analysis*, 44(2):273–305, 2009.

Vikas Agarwal, Vyacheslav Fos, and Wei Jiang. Inferring reporting biases in hedge fund databases from hedge fund equity holdings. *Management Science*, 2010.

Andrew Ang. *Asset Management: A Systematic Approach to Factor Investing*. Oxford University Press, 2014.

David H. Bailey and Marcos M. Lopez de Prado. The sharpe ratio efficient frontier. *Journal of Risk*, 2012.

Keith Black. Defining liquid alternative investments. *The Journal of Alternative Investments*, 17(3):6–25, 2015.

Stephen J. Brown, William N. Goetzmann, and Roger G. Ibbotson. Offshore hedge funds: Survival and performance 1989-1995. *The Journal of Business*, 72(1):91–117, 1999.

Charles Cao, David Rapach, and Guofu Zhou. Which hedge fund styles hedge against bad times? 2015.

Mark M. Carhart. On persistence in mutual fund performance. *The Journal of Finance*, 52:57–82, 1997.

Gregory Connor and Mason Woo. *An Introduction to Hedge Funds*. The London School of Economics and Political Science, 2003.

Christian L. Dunis, Jason Laws, and Patrick Naïm. *Applied Quantitative Methods for Trading and Investment*. Wiley Finance, 2004.

James Durbin and Siem J. Koopman. *Time Series Analysis by State Space Methods*. Oxford University Press, 2001.

Eugene Fama and Kenneth French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(3), 1993.

Andrea Frazzini and Lasse Heje Pedersen. Betting against beta. *Journal of Financial Economics*, 111(1):1–25, 2014.

William Fung and David A. Hsieh. Performance characteristics of hedge funds and commodity funds: Natural versus spurious biases. *Journal of Financial and Quantitative Analysis*, 35(3):291–307, 2000.

William Fung and David A. Hsieh. The risk in hedge fund strategies: Theory and evidence from trend followers. *The Review of Financial Studies*, 14(2):313–341, 2001.

William Fung and David A. Hsieh. Extracting portable alphas from equity long-short hedge funds. *Journal of Investment Management*, 2(4):1–19, 2004.

William Fung and David A. Hsieh. The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds. *Journal of Empirical Finance Elsevier*, 18(4):547–569, 2011.

Jonathan Hartley. Liquid alternative mutual funds versus hedge funds. *Working Paper*, 2016.

Campbell Harvey, Yan Liu, and Heqing Zhu. Editor's choice ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68, 2016.

Narasimhan Jegadeesh and Sheridan Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91, 1993.

Michael C. Jensen. The performance of mutual funds in the period 1945-1964. *The Journal of Finance*, 23:389–416, 1968.

Rudolph Emil Kalman. A new approach to linear filtering and prediction problems. *Transactions of the ASME -Journal of Basic Engineering*, 82:35–45, 1960.

Craig Lewis. Liquid alternative mutual funds: An asset class the expands opportunities for diversification. 2016.

John Virgil Lintner. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47:13–37, 1965.

Harry M. Markowitz. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Journal of Finance*, 7(1):77–91, 1952.

Harry M. Markowitz. Portfolio selection: Efficient diversification of investment. cowles-foundation monograph. *New York: Wiley*, 16, 1959.

Thijs Markwat, Roderick Molenaar, and Rolf Hermans. The added value of hedge funds in pension portfolios. 2016.

David McCarthy. Hedge funds versus hedged mutual funds: An examination of equity long/short funds. *The Journal of Alternative Investments*, 16(3):6–24, 2014.

David McCarthy. Hedge funds versus mutual funds 2: An examination of multialternative mutual funds. *The Journal of Alternative Investments*, 17(3):5–25, 2015.

Tobias J. Moskowitz, Yao Hua Ooi, and Lasse Heje Pedersen. Time series momentum. *Journal of Financial Economics*, 104:228–250, 2012.

Adrian Pagan. Econometric issues in the analysis of regressions with generated regressors. *International Economic Review*, 25(1):221–247, 1984.

William F. Sharpe. Capital asset prices - a theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442, 1964.

Zheng Sun, Ashley W. Wang, and Lu Zheng. Only winners in tough times repeat: Hedge fund performance persistence over different market conditions. *Finance and Economics Discussion Series 2016-030. Washington: Board of Governors of the Federal Reserve System*, 2016.

Laurens A. P. Swinkels and Pieter J. Van der Sluis. Return-based style analysis with time-varying exposures. *The European Journal of Finance*, 12(6-7):529–552, 2006.

8 Appendix

Derivation Kalman smoothing recursions:

$$\begin{aligned}
V_T &= P_t - E[\beta_T e_T']X_T' F_T^{-1} X_T E[\beta_T e_T']' \\
&= P_T - P_T X_T' F_T^{-1} X_T P_T \\
V_{T-1} &= P_{T-1} - P_{T-1} X_{T-1}' F_{T-1}^{-1} X_{T-1} P_{T-1} - P_{T-1} L_{T-1}' X_T' F_T^{-1} X_T L_{T-1} P_{T-1} \\
&\vdots \\
V_t &= P_t + P_t N_{t-1} P_t \qquad (36)
\end{aligned}$$

where N_{t-1} can be calculated recursively using:

$$\begin{aligned}
N_T &= 0 \\
N_{T-1} &= X_T' F_T^{-1} X_T \\
N_{T-2} &= X_{T-1}' F_{T-1}^{-1} X_{T-1} + L_{T-1}' X_T' F_T^{-1} X_T L_{T-1} \\
&\vdots \\
N_{t-1} &= X_t' F_t^{-1} X_t + L_t' N_t L_t \qquad (37)
\end{aligned}$$

Putting equations (28), (29), (36), and (37) together we end up with the Kalman smoothing recursions:

$$\begin{aligned}
q_{t-1} &= X_t' F_t^{-1} v_t + L_t' q_t \qquad (38) \\
\hat{\beta}_t &= b_t + P_t q_{t-1} \qquad (39) \\
N_{t-1} &= X_t' F_t^{-1} X_t + L_t' N_t L_t \qquad (40) \\
V_t &= P_t + P_t N_{t-1} P_t \qquad (41)
\end{aligned}$$

In which we use the updated parameter estimates b_t and corresponding covariances P_t from the Kalman filter and help-matrices F_t, K_t, and L_t as defined below:

$$\begin{aligned}
F_t &= X_t' P_t X_t + R \\
K_t &= P_t X_t' F_t^{-1} \\
L_t &= I + K_t X_t
\end{aligned}$$

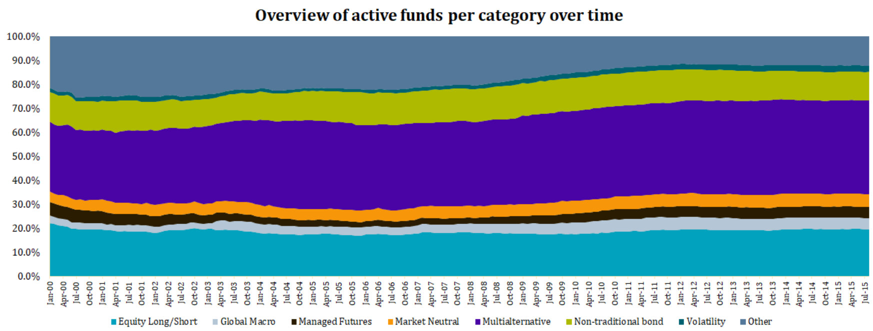

Figure 10: Evolution of number of funds per category over time

Table 3: Full-sample correlations between risk factors

	DEV	TRM	EMG	SMB	HML	MOM	BAB	DEF	TEQ	TFI	TCM	TFX
DEV	1	−0.28	0.33	0.00	−0.14	−0.37	−0.27	0.63	−0.08	−0.32	0.01	−0.03
TRM		1	−0.03	0.01	0.02	0.18	0.16	−0.25	0.00	0.64	0.06	0.08
EMG			1	0.34	−0.03	−0.16	0.09	0.39	−0.04	0.01	0.01	0.02
SMB				1	−0.04	0.19	0.20	0.16	0.05	0.04	0.13	−0.03
HML					1	−0.04	0.41	−0.04	0.06	0.01	−0.05	−0.05
MOM						1	0.39	−0.35	0.44	0.16	0.32	0.13
BAB							1	0.01	0.16	0.17	0.18	0.01
DEF								1	−0.22	−0.18	0.02	0.04
TEQ									1	0.11	0.21	0.26
TFI										1	0.14	0.25
TCM											1	0.36
TFX												1

Table 4: Full-sample correlations between risk factors in our factor models

	DEV	TRM	EMG	SMB	HML	MOM	BAB	DEF	TEQ	TFI	TCM	TFX
DEV	1	0.21	0.06	−0.01	−0.01	−0.06	−0.02	0.00	0.01	−0.44	0.01	−0.03
TRM		1	0.11	0.11	0.03	0.04	0.26	−0.55	−0.13	−0.01	0.06	0.05
EMG			1	0.29	−0.12	−0.13	−0.05	0.06	−0.08	0.03	−0.08	0.03
SMB				1	−0.08	0.20	0.17	0.01	−0.03	−0.03	0.12	−0.01
HML					1	−0.12	0.28	−0.11	−0.03	−0.14	−0.12	−0.12
MOM						1	0.28	−0.13	0.25	0.04	0.24	0.02
BAB							1	−0.11	−0.07	−0.10	0.12	−0.01
DEF								1	0.11	0.05	0.00	0.10
TEQ									1	0.09	0.07	0.15
TFI										1	0.10	0.19
TCM											1	0.36
TFX												1

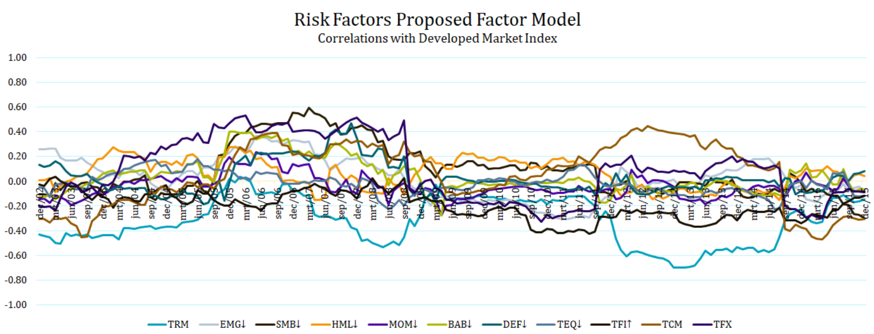

Figure 11: Time-varying correlations between the developed market index and the other risk factors in our factor models

	Paired sample t-test statistics					
	EQ_LS	GM	MF	MN	MA	NTB
UP	−0.18	−0.39	0.12	0.01	−0.57	−0.33
DOWN	−0.02	−0.44	0.09	0.15	−0.23	0.16

Table 5: T-test statistics for paired sample t-tests

The test statistics in this table are the result from paired sample t-tests between liquid alternatives and hedge funds. On a 5% significance level test statistics between -1.96 and 1.96 imply no significant differences in returns. Positive values denote higher average returns for liquid alternatives.

Table 6: F-test statistics for F-tests on differences in volatilities

F-test	Benchmark + Equity Long/Short			Benchmark + Global Macro			Benchmark + Managed Futures			Benchmark + Market Neutral		
50/50 Equity/Bond	50/50	70/30	90/10	50/50	70/30	90/10	50/50	70/30	90/10	50/50	70/30	90/10
F-statistic (UP)	0.713	0.793	0.919	0.454	0.635	0.866	1.049	0.894	0.920	0.330	0.547	0.832
F-statistic (DOWN)	0.565	0.718	0.899	0.527	0.687	0.886	0.312	0.360	0.711	0.425	0.605	0.852
F-statistic (ALL)	0.624	0.749	0.908	0.500	0.668	0.879	0.561	0.545	0.785	0.385	0.580	0.843

F-test	Benchmark + Multialternative			Benchmark + Non-tradional Bond			Benchmark + Volatility		
50/50 Equity/Bond	50/50	70/30	90/10	50/50	70/30	90/10	50/50	70/30	90/10
F-statistic (UP)	0.515	0.680	0.884	0.361	0.573	0.843	0.409	0.606	0.855
F-statistic (DOWN)	0.649	0.767	0.915	0.364	0.574	0.843	0.641	0.768	0.917
F-statistic (ALL)	0.608	0.741	0.906	0.358	0.570	0.841	0.551	0.705	0.893

The test statistics in this table are the result from F-tests on differences in volatilities between a benchmark portfolio and multiple hybrid portfolios. We compare volatilities during up markets, down markets and over the full sample period. Test statistics are below 1 as we want to test whether the volatility is significantly lower for the hybrid portfolio, or not. Critical values are different for the test statistics in up markets, down markets, and full sample and can be found in Table 7

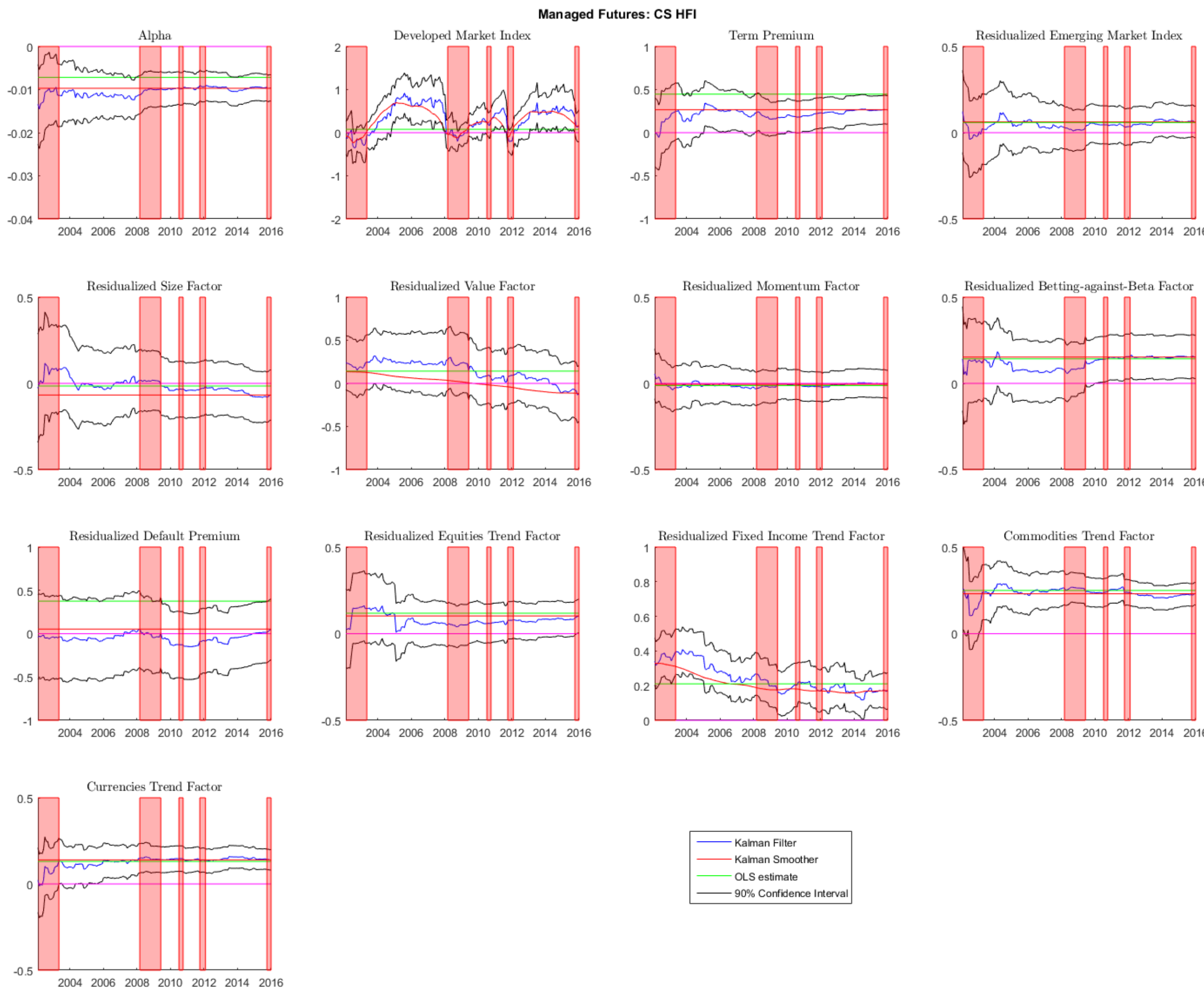

Figure 12: Managed Futures Hedge Fund Index analyzed

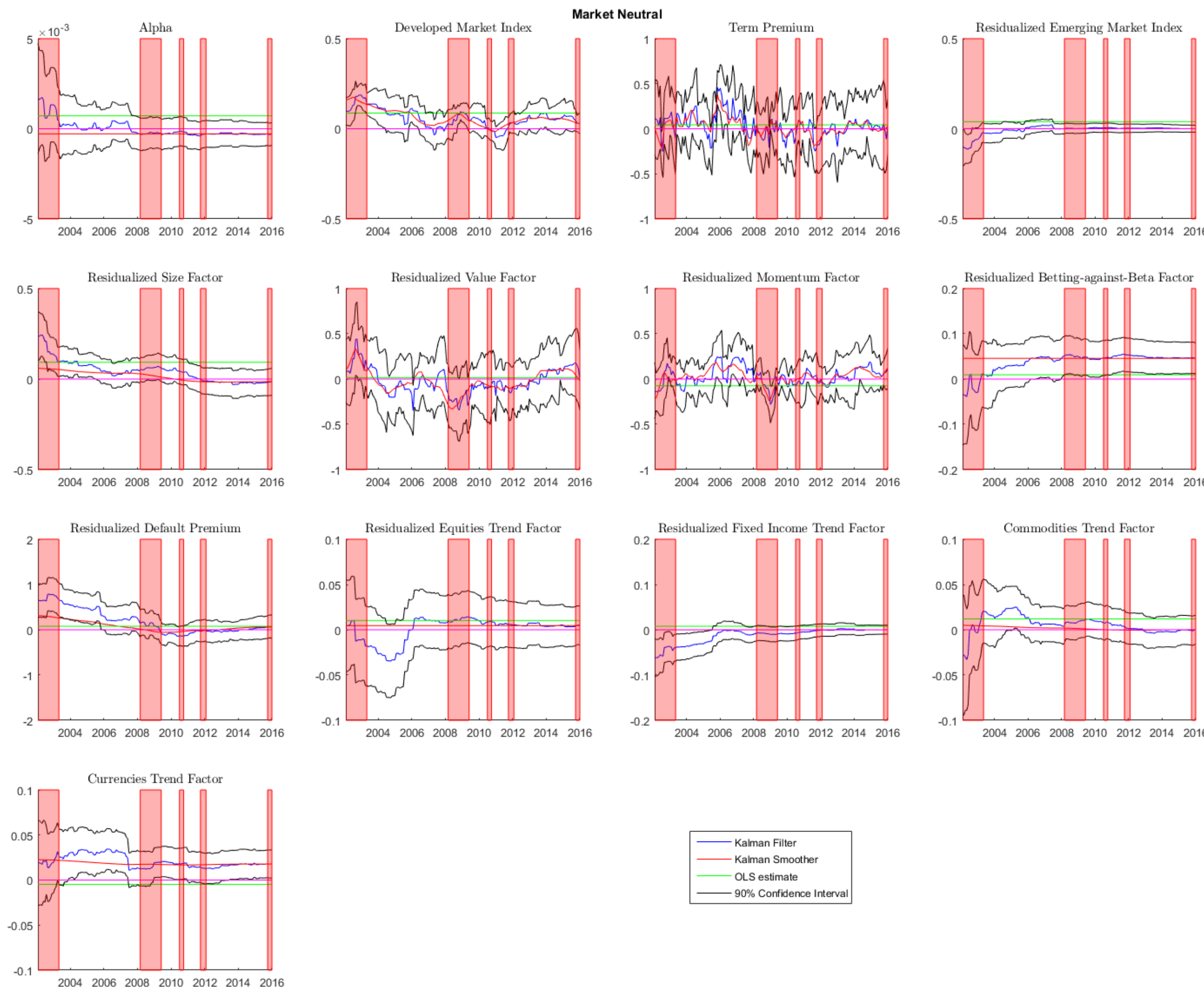

Figure 13: Market Neutral Index analyzed

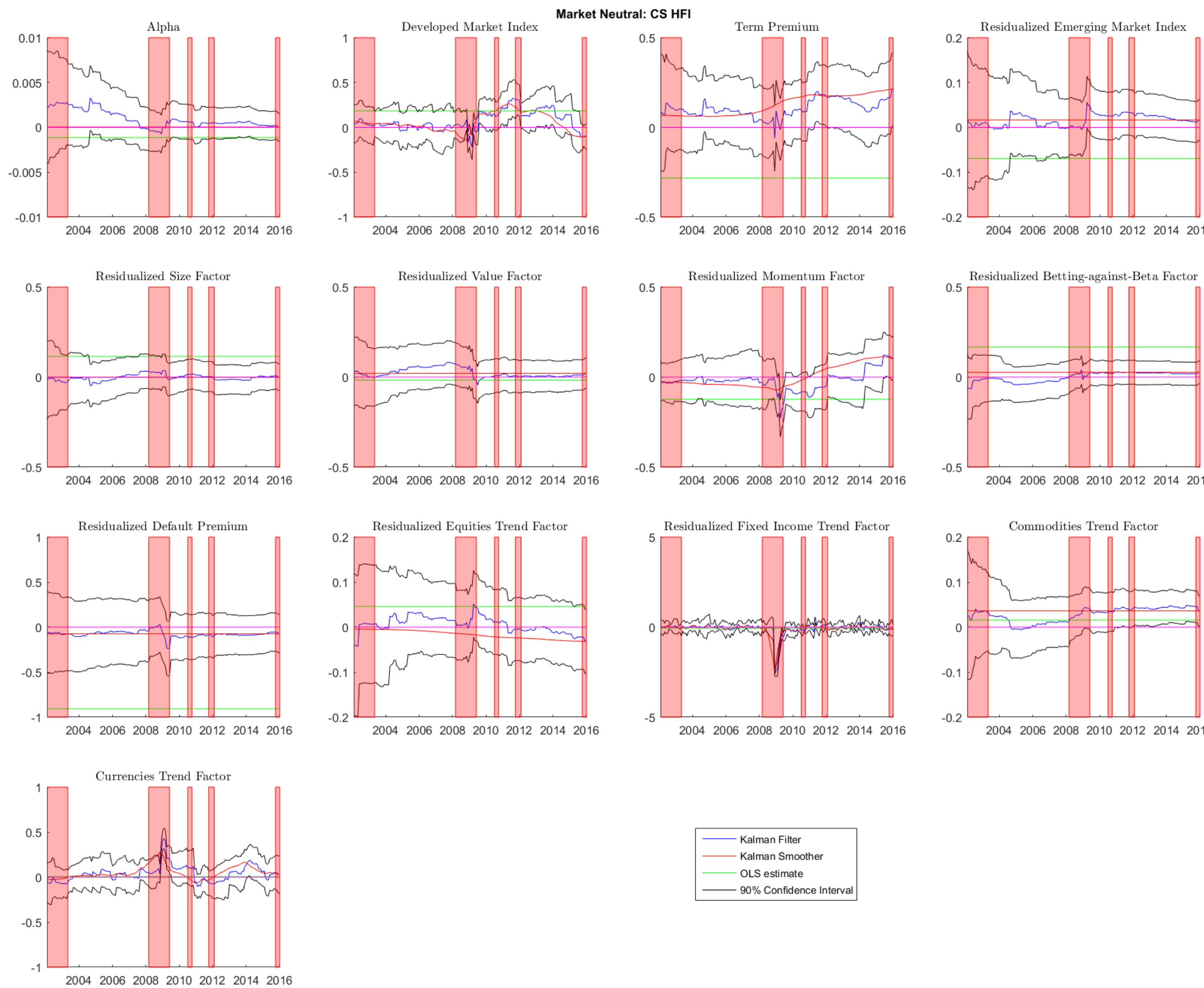

Figure 14: Market Neutral Hedge Fund Index analyzed

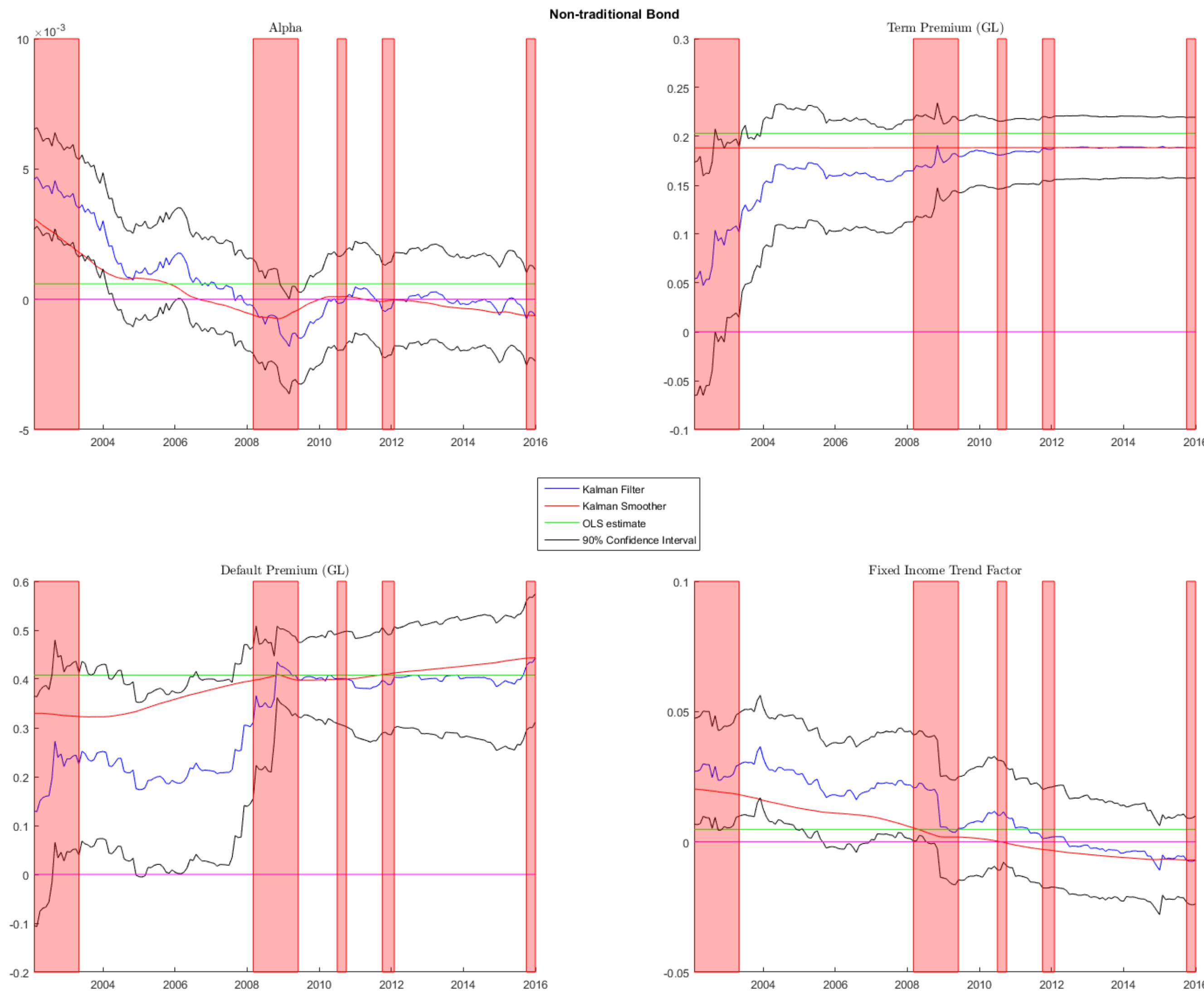

Figure 15: Non-traditional Bond Index analyzed

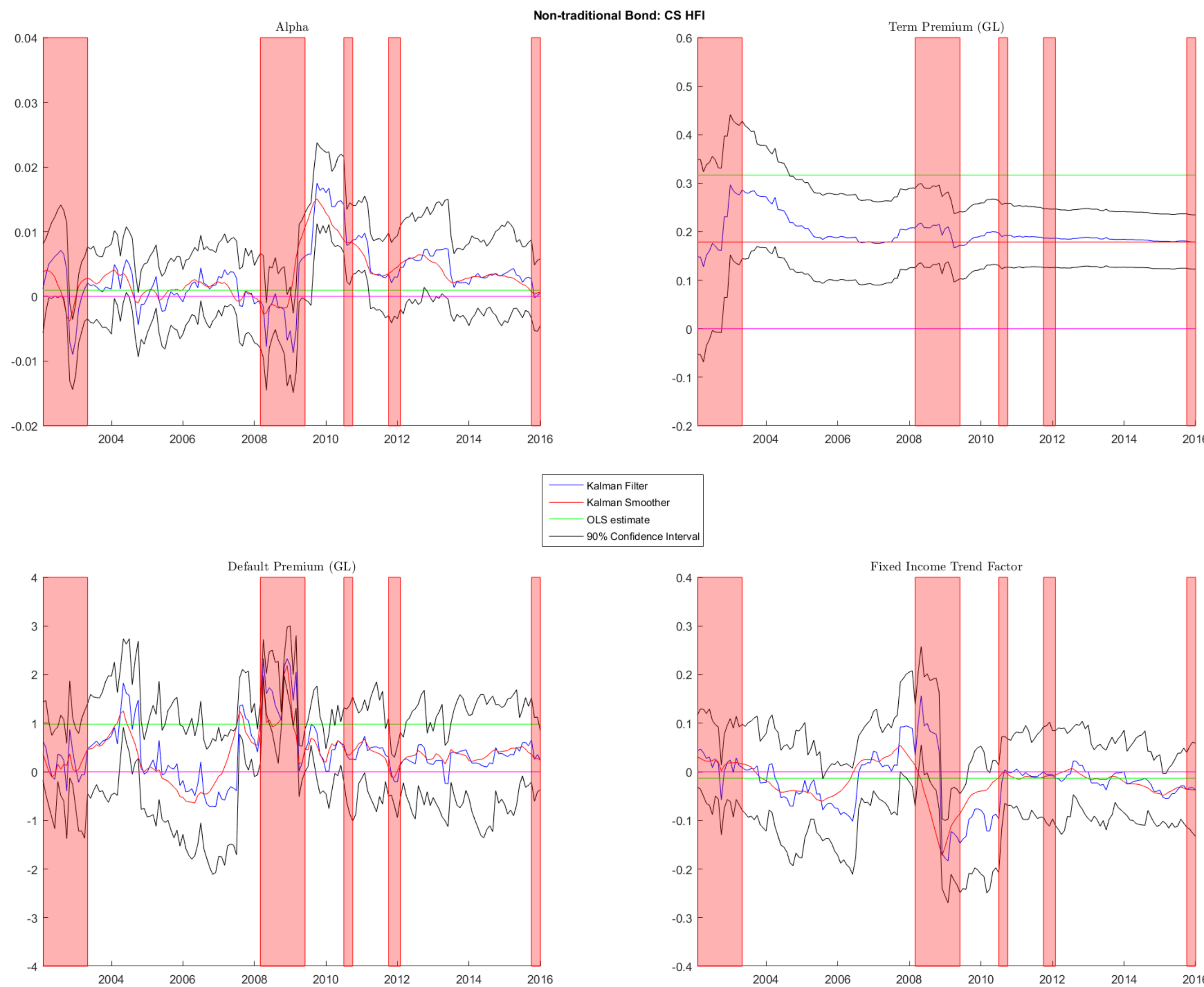

Figure 16: Non-traditional Bond Hedge Fund Index analyzed

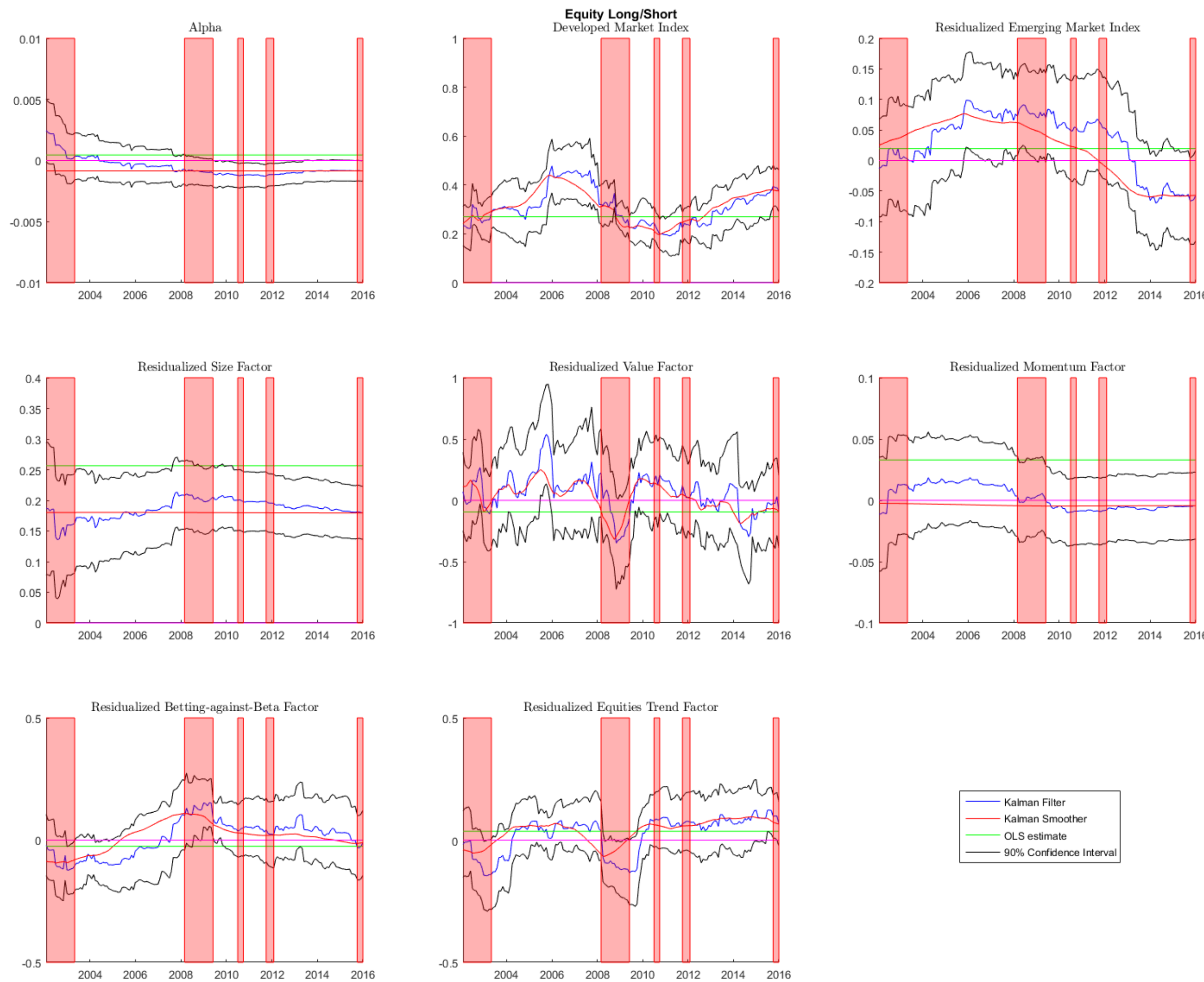

Figure 17: Equity Long/Short Index analyzed

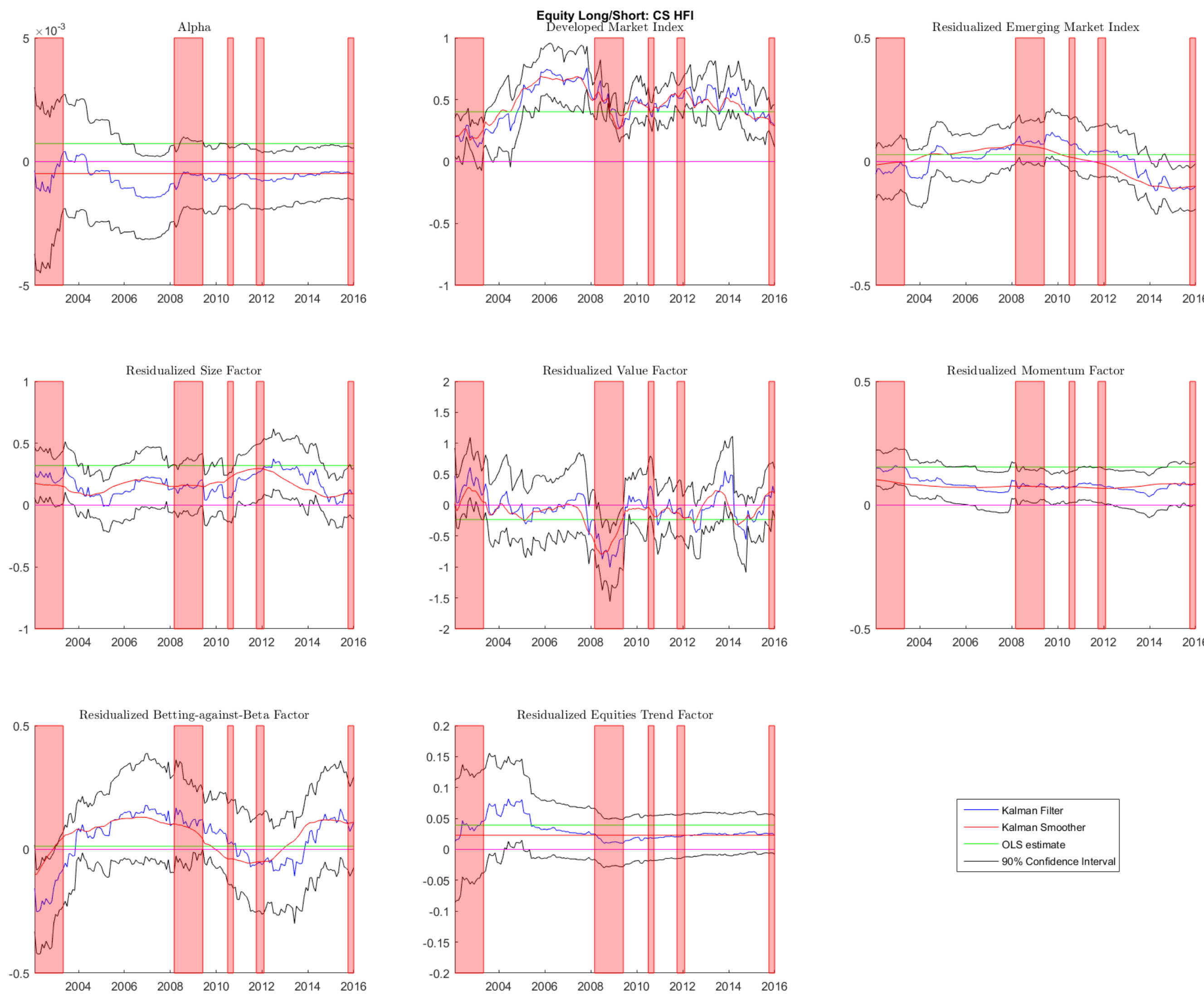

Figure 18: Equity Long/Short Hedge Fund Index analyzed

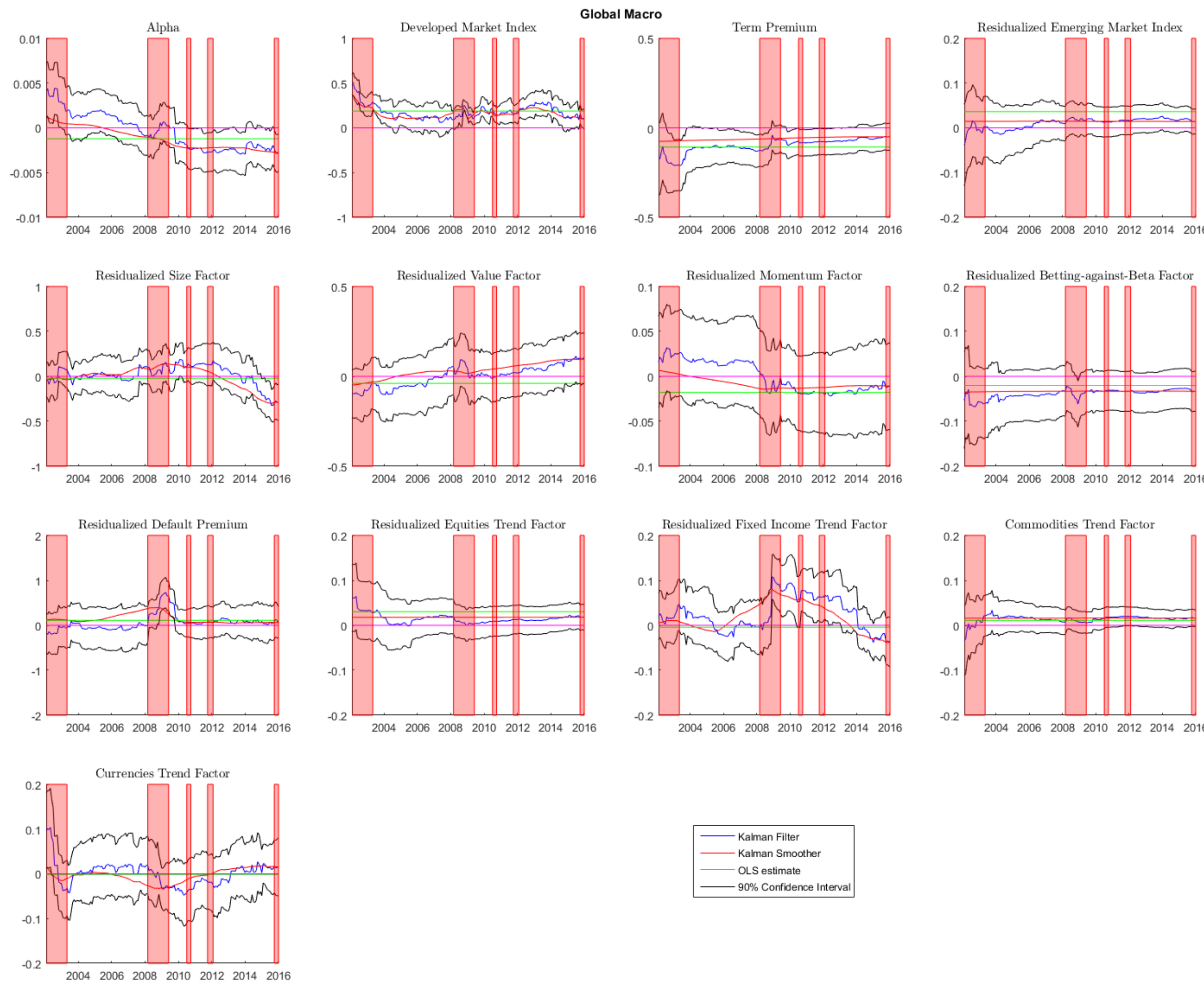

Figure 19: Global Macro Index analyzed

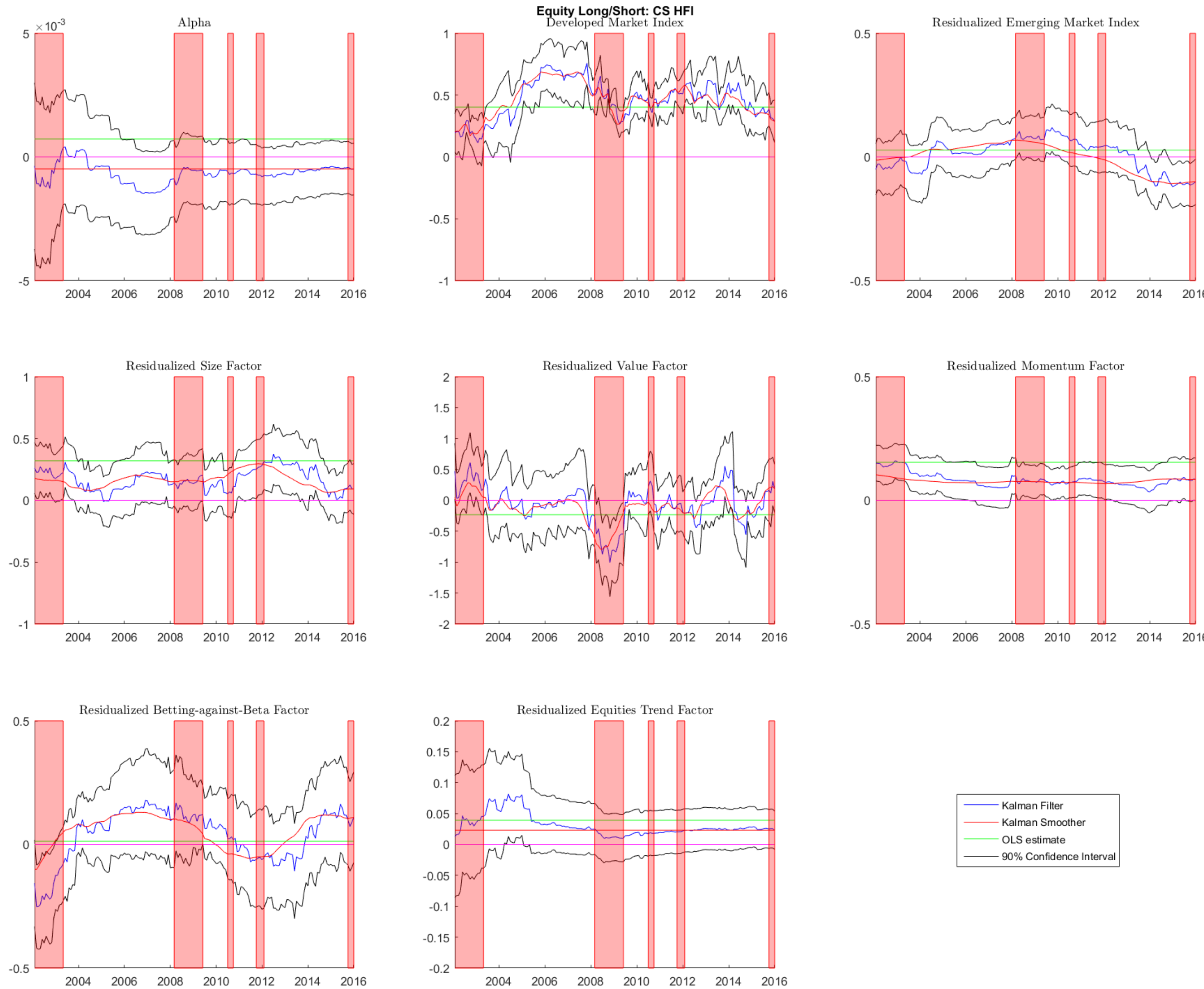

Figure 20: Global Macro Hedge Fund Index analyzed

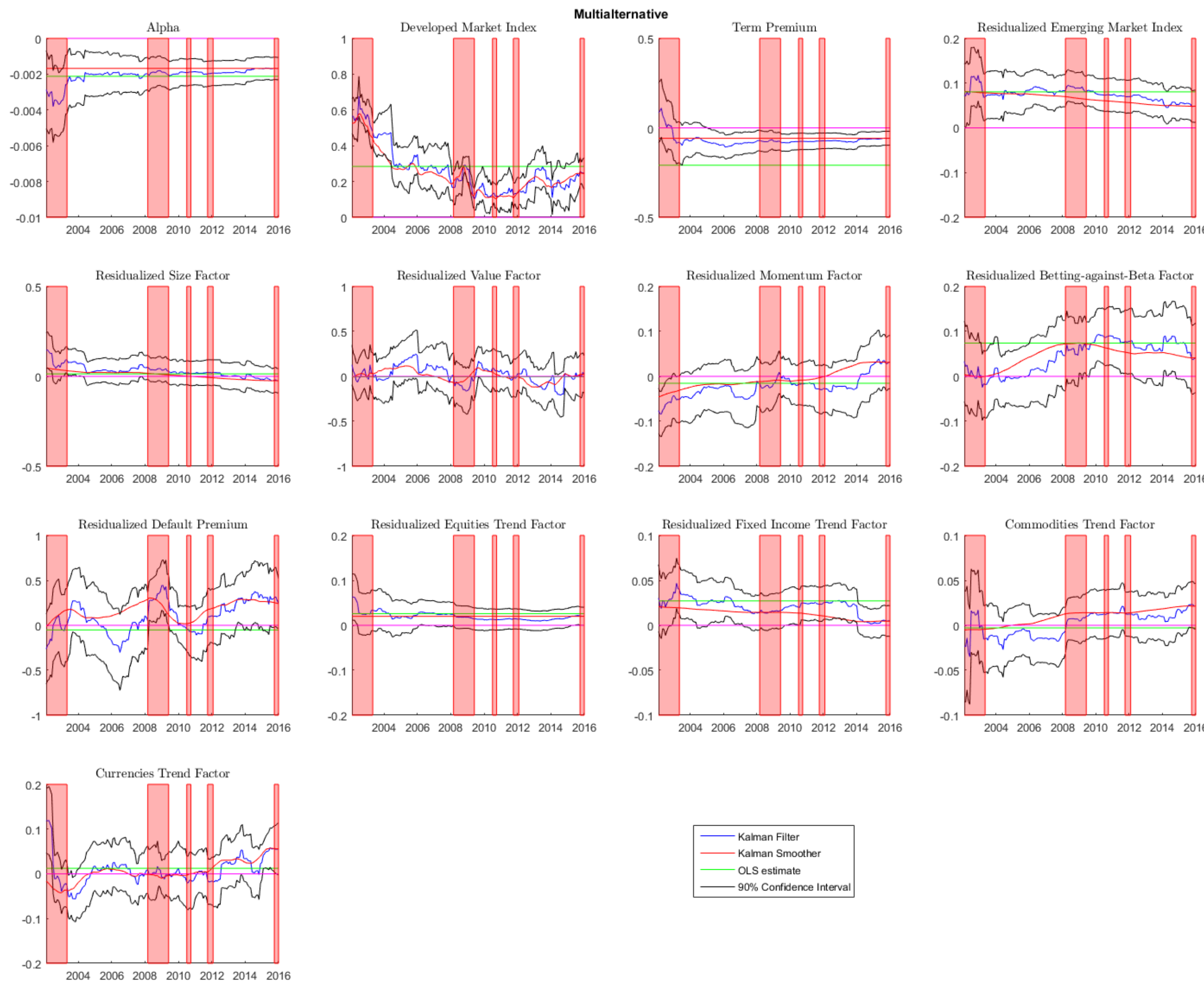

Figure 21: Multialternative Index analyzed

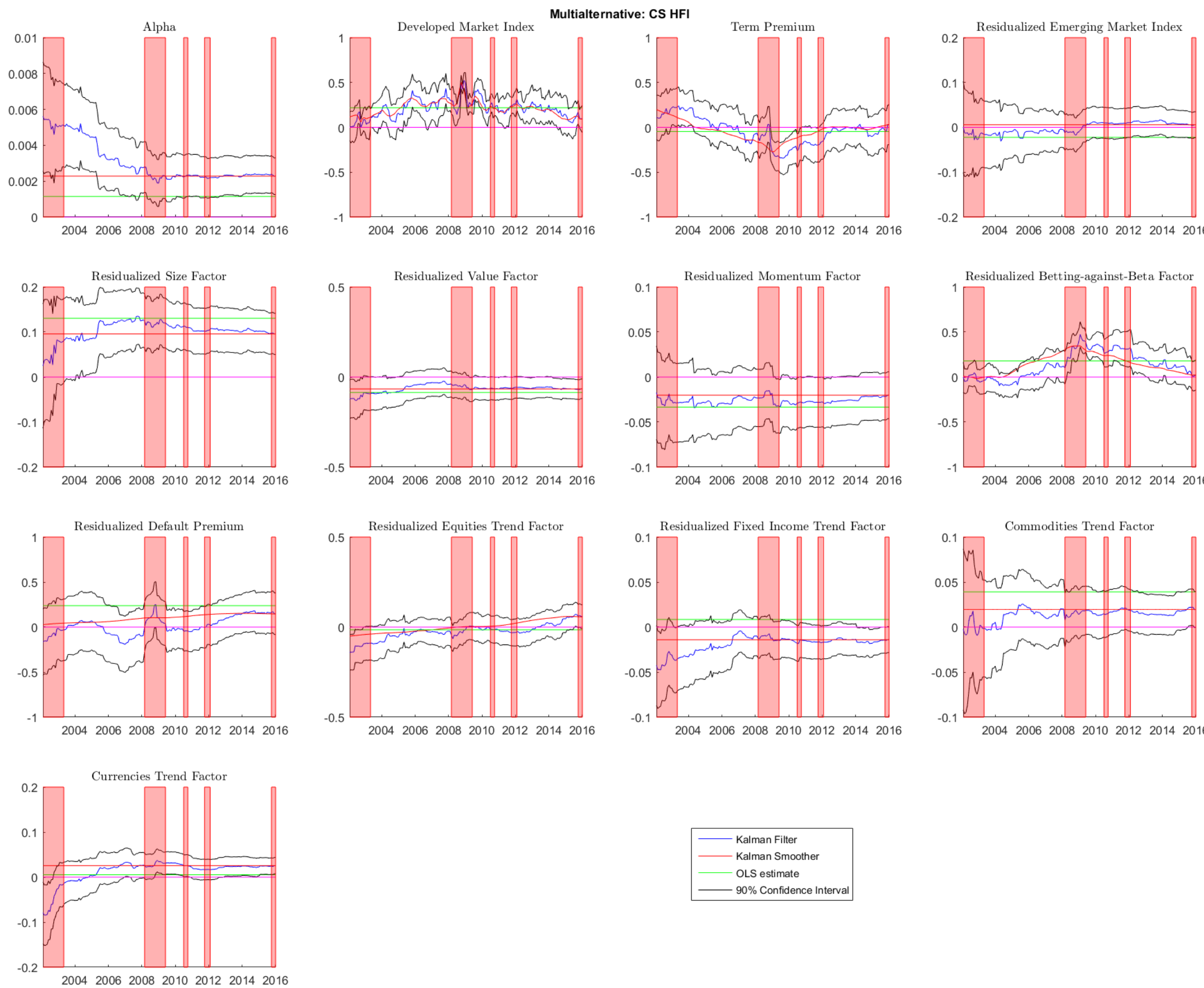

Figure 22: Multialternative Hedge Fund Index analyzed

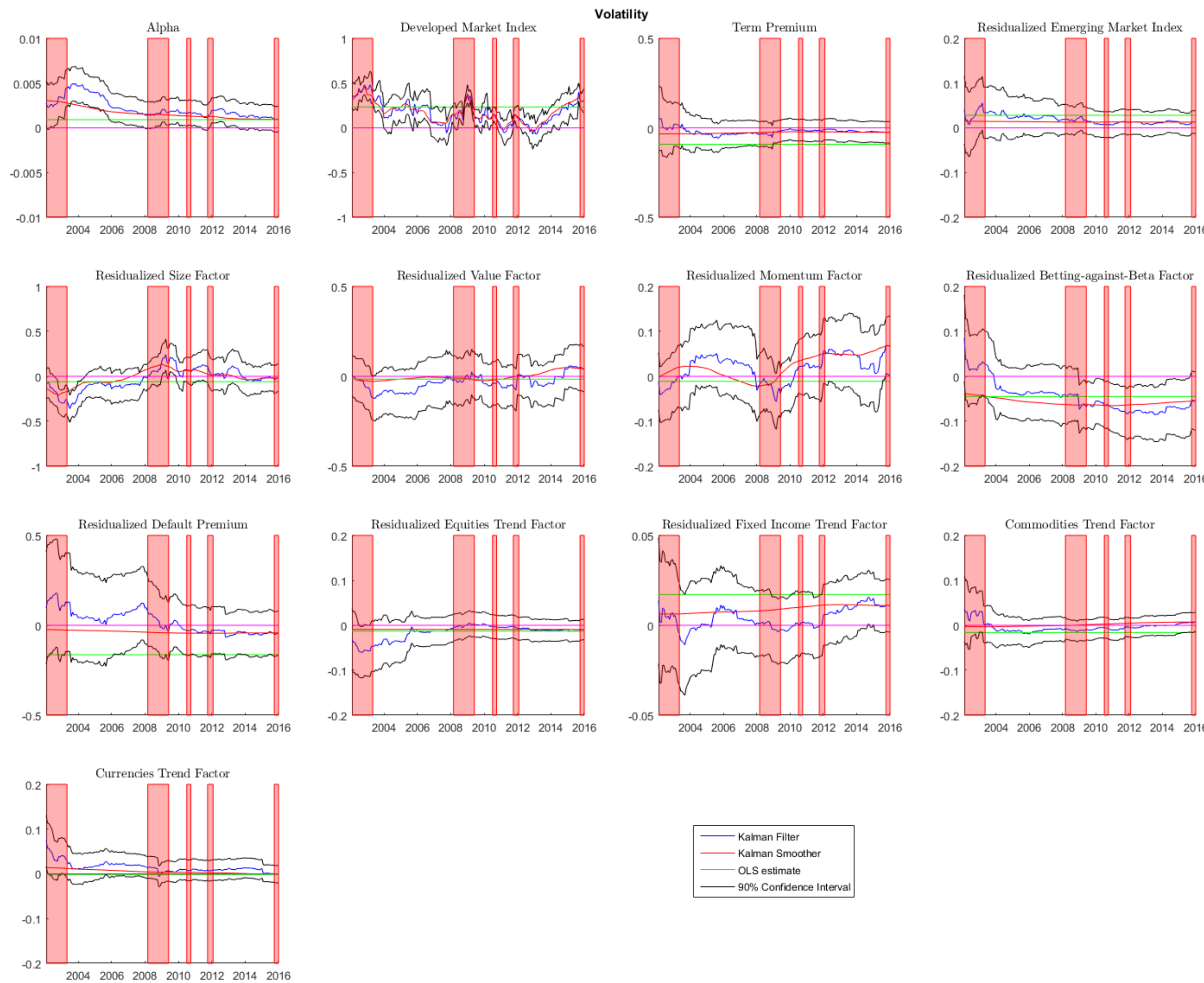

Figure 23: Volatility Index analyzed

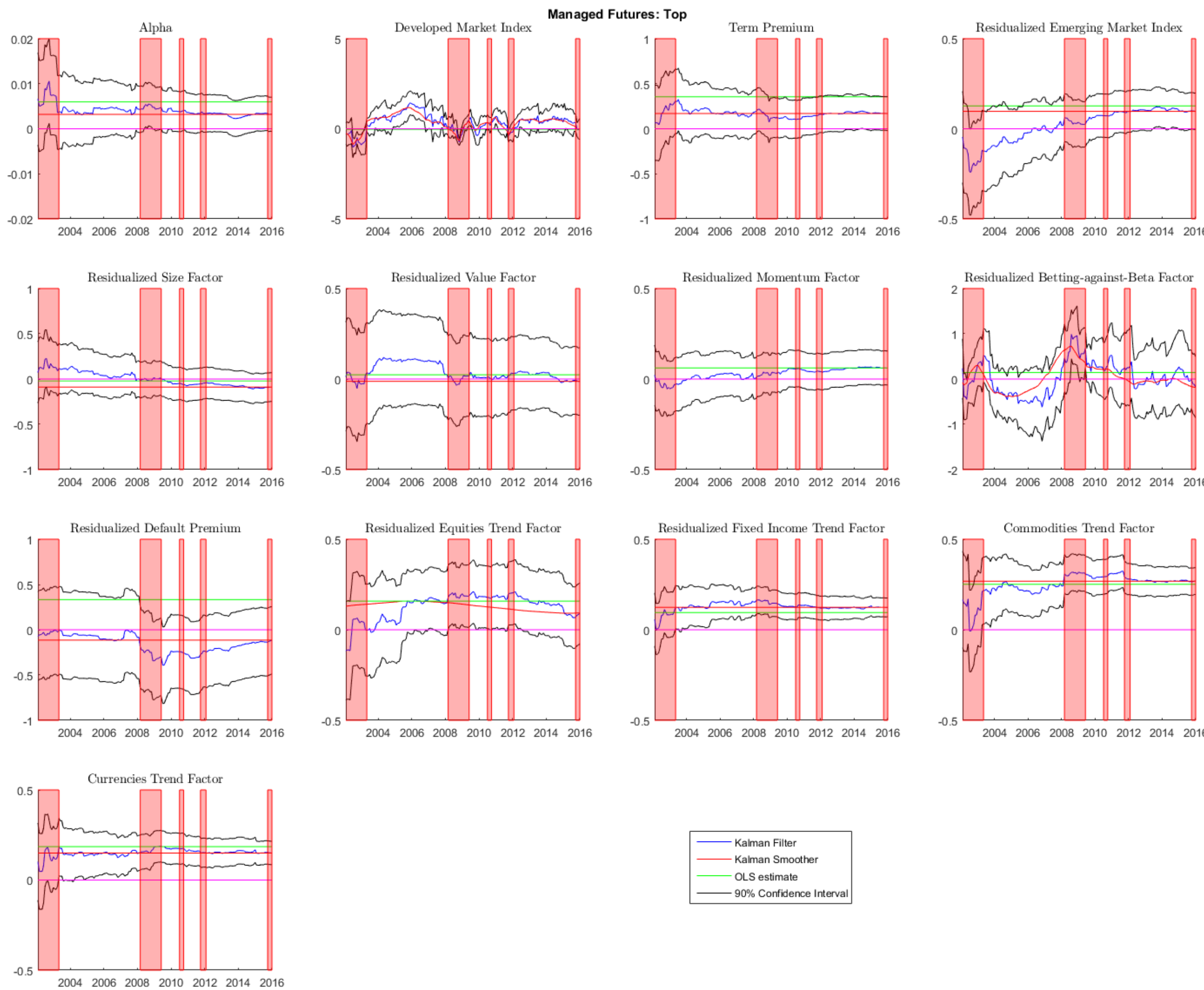

Figure 24: Top Managed Futures funds analyzed

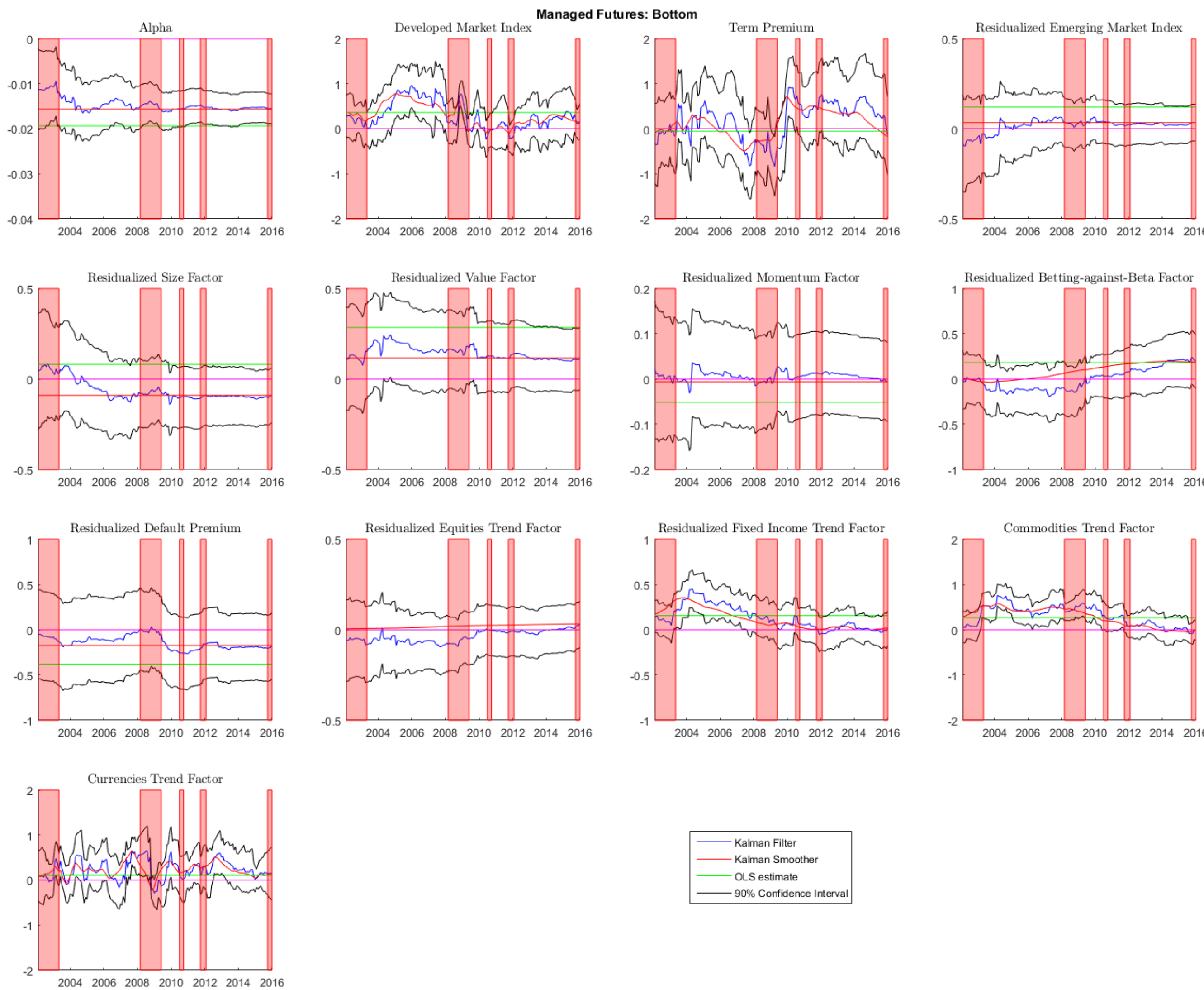

Figure 25: Bottom Managed Futures funds analyzed

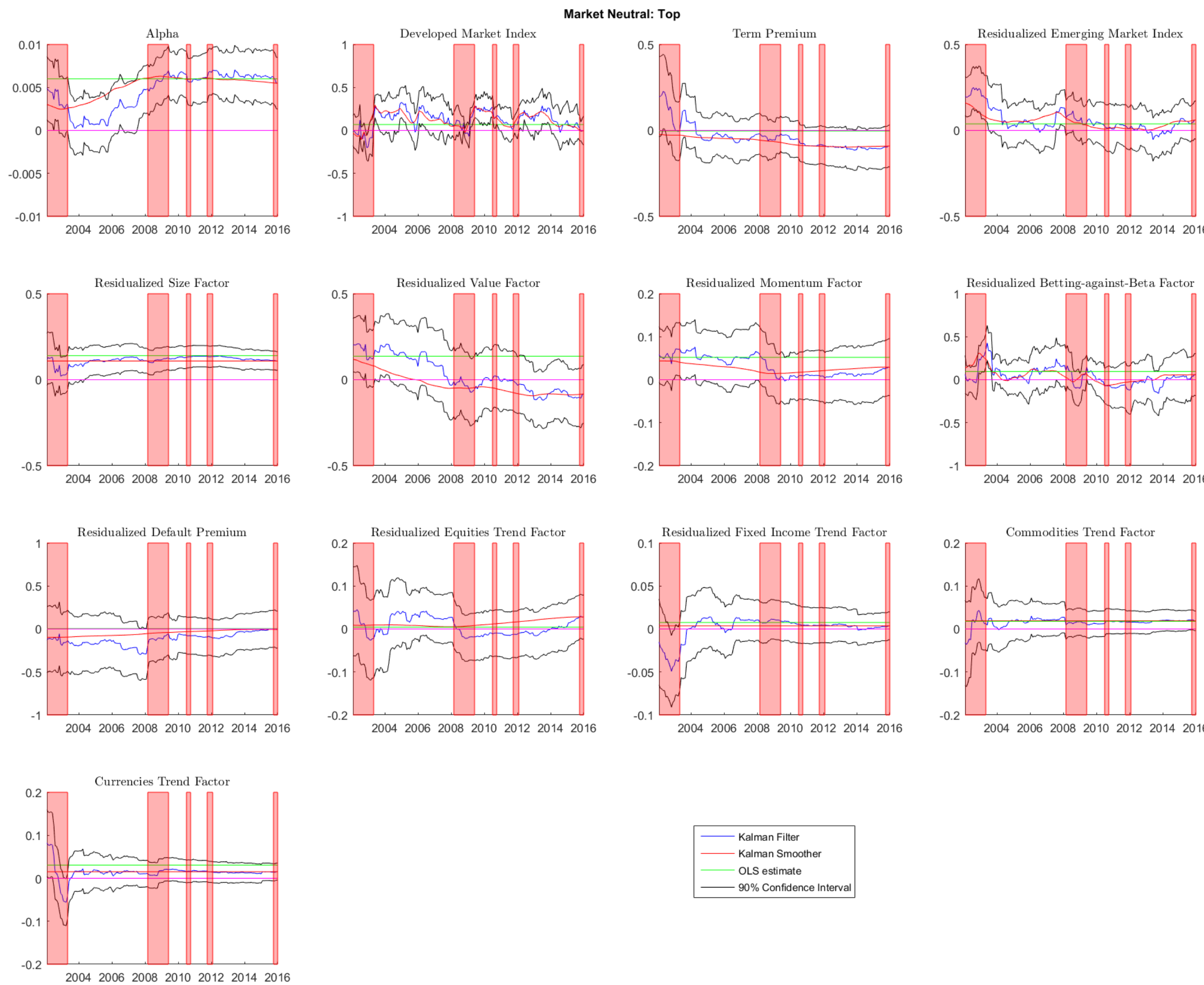

Figure 26: Top Market Neutral funds analyzed

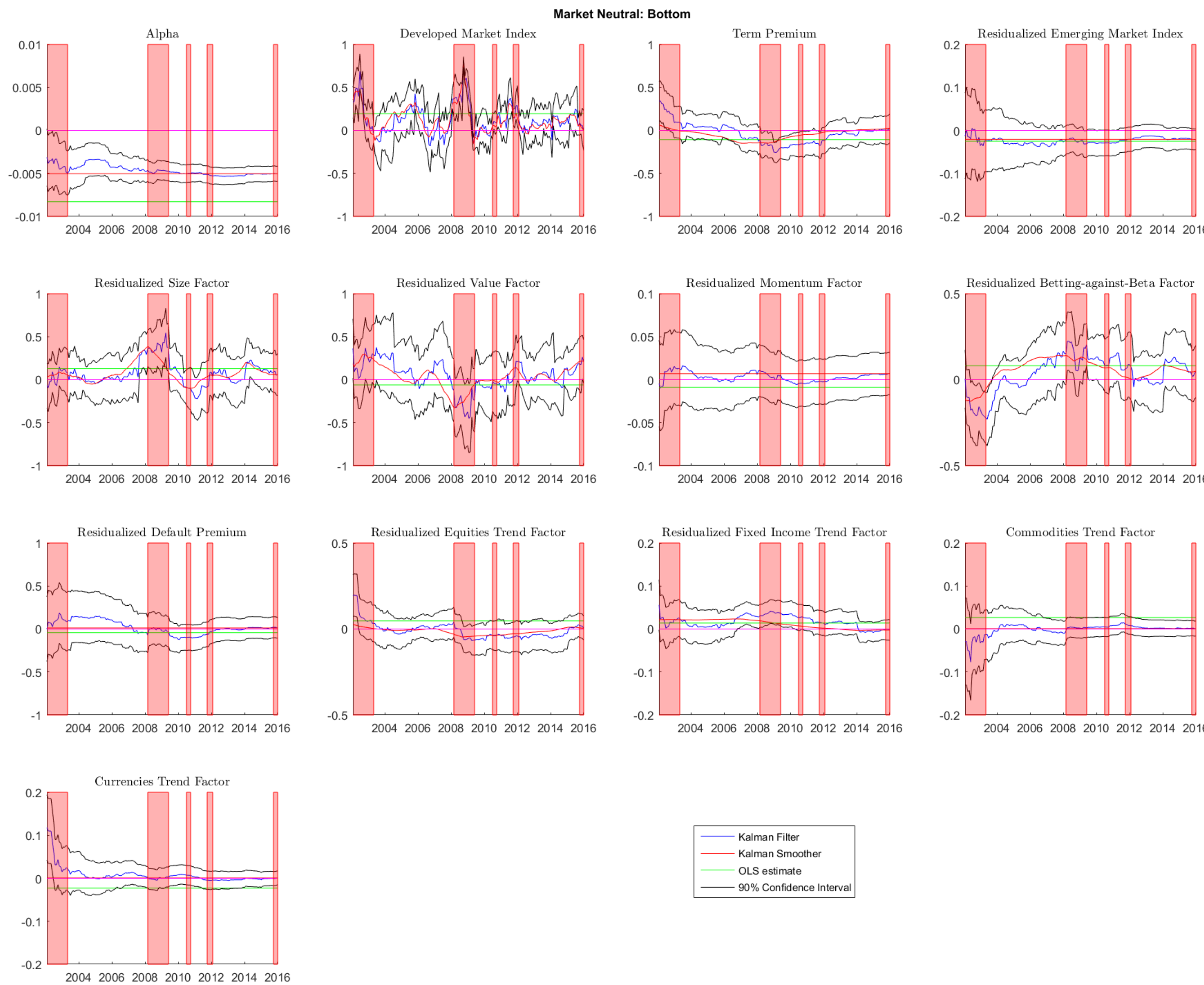

Figure 27: Bottom Market Neutral funds analyzed

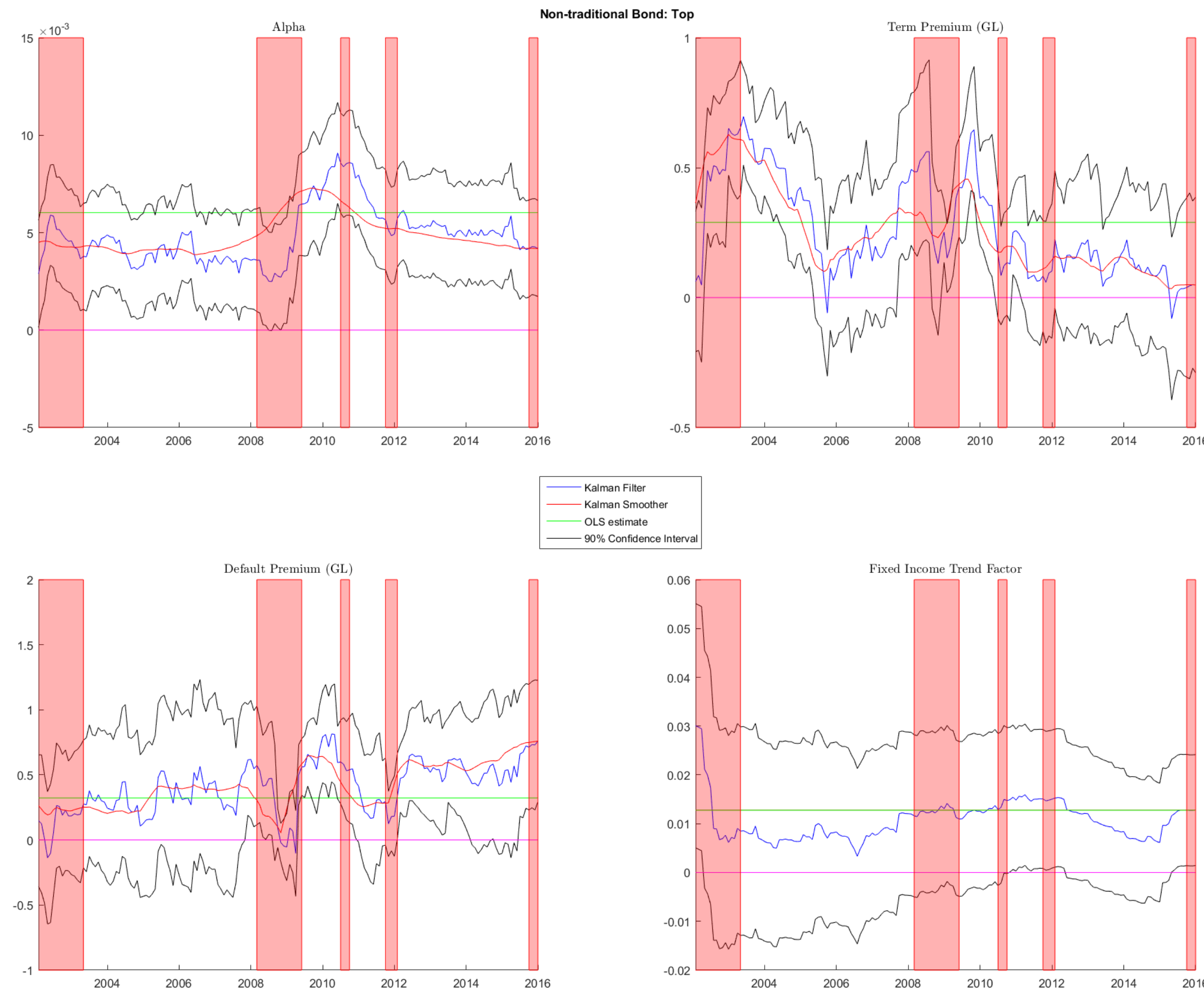

Figure 28: Top Non-traditional Bond funds analyzed

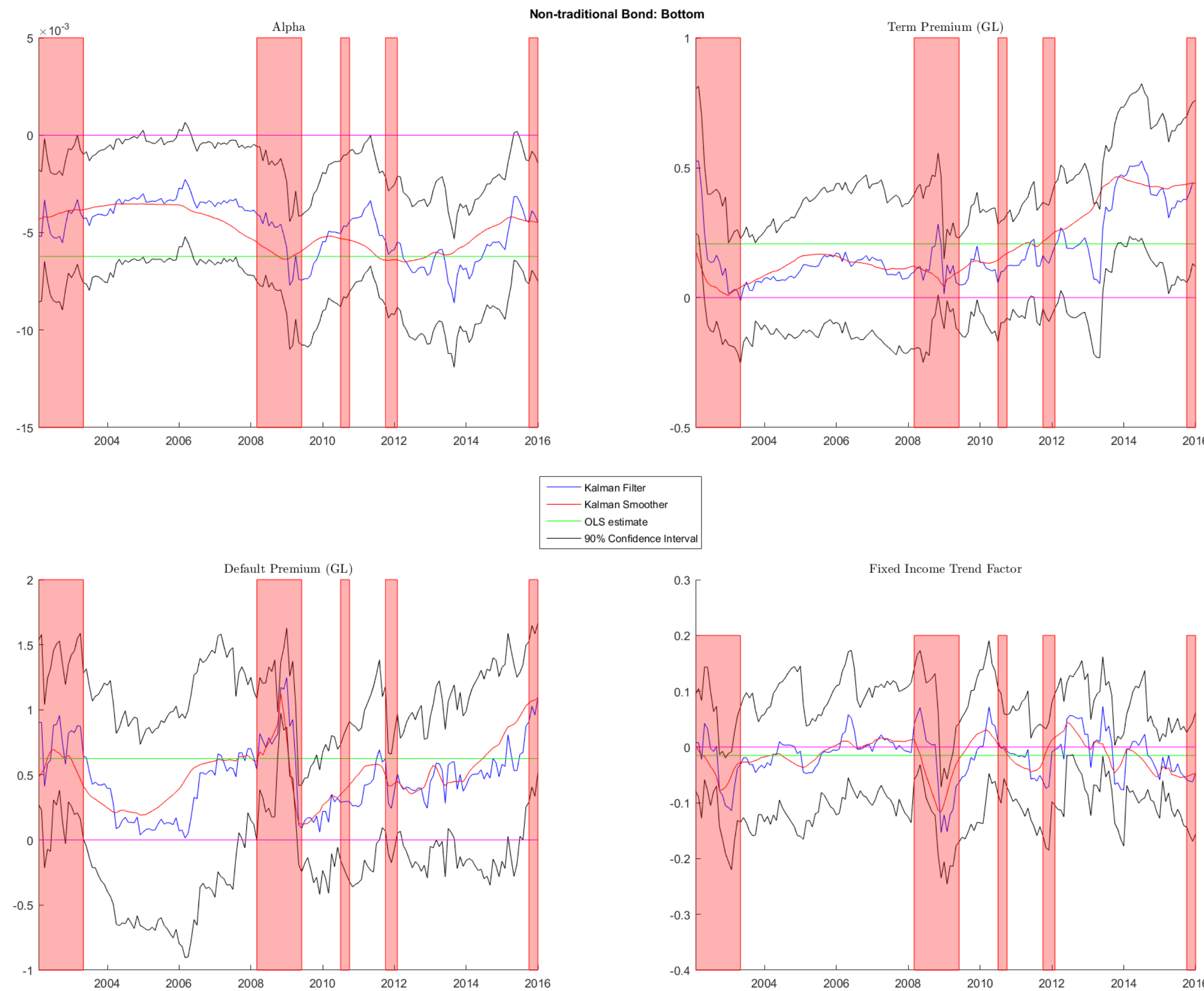

Figure 29: Bottom Non-traditional Bond funds analyzed

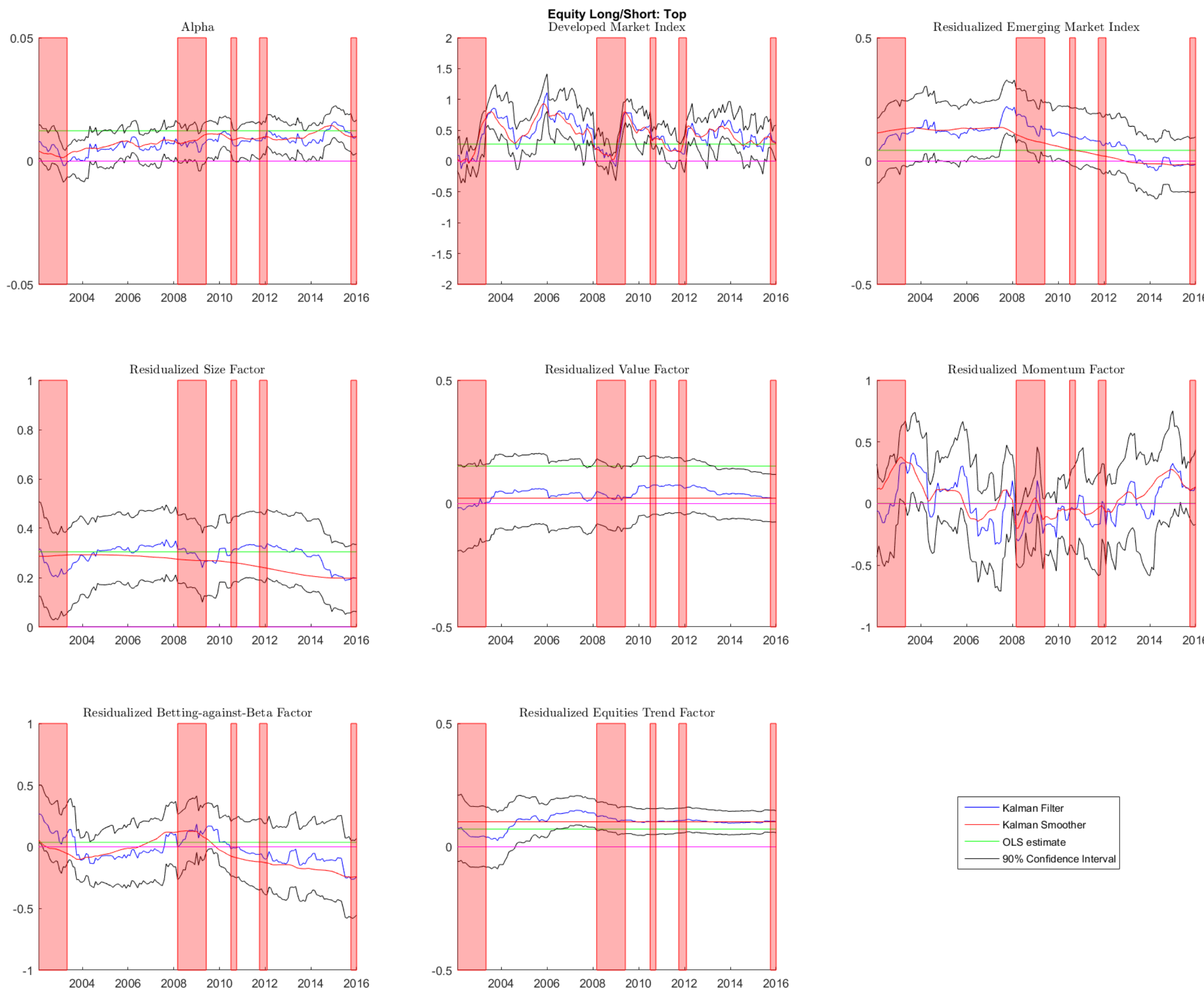

Figure 30: Top Equity Long/Short funds analyzed

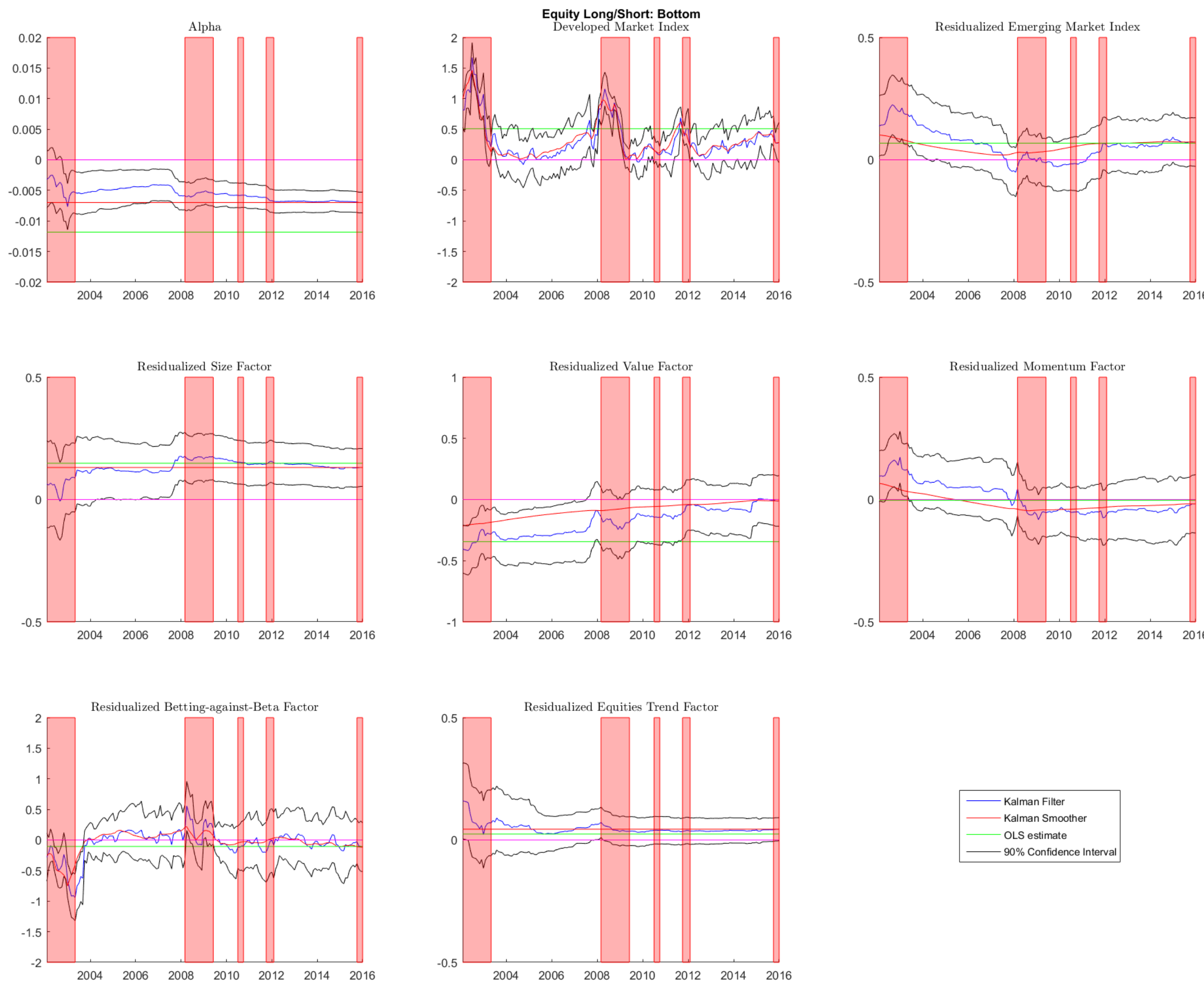

Figure 31: Bottom Equity Long/Short funds analyzed

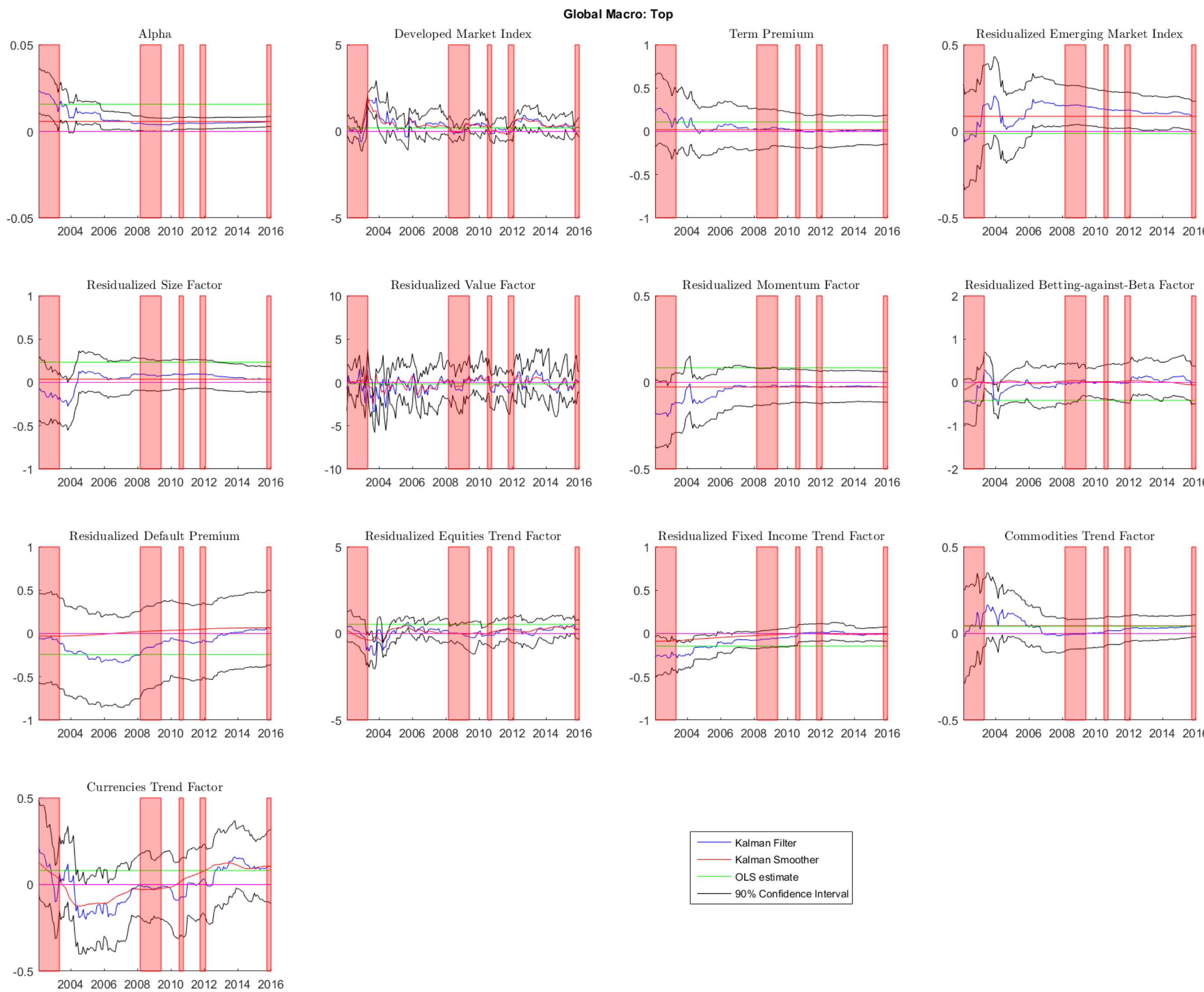

Figure 32: Top Global Macro funds analyzed

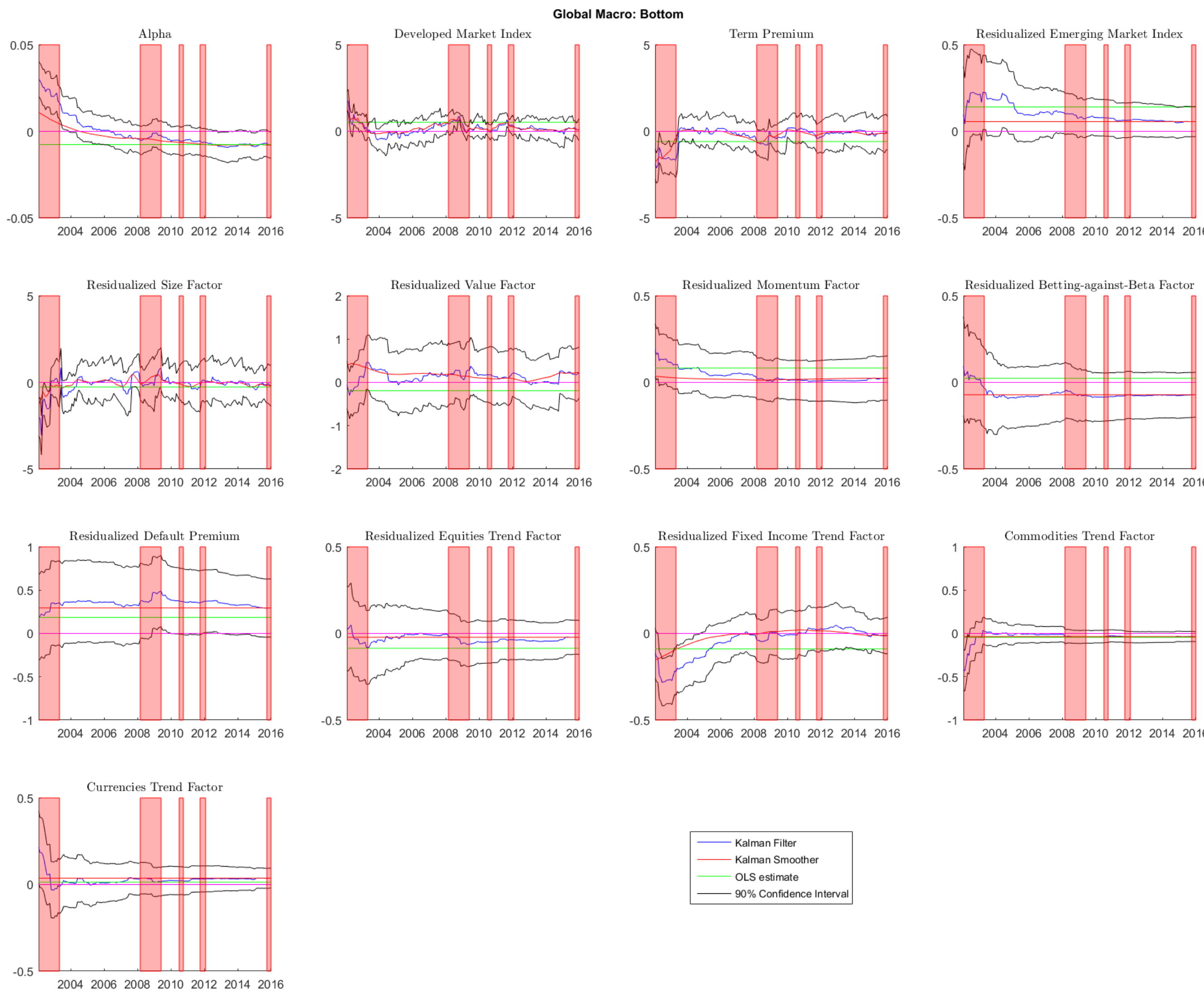

Figure 33: Bottom Global Macro funds analyzed

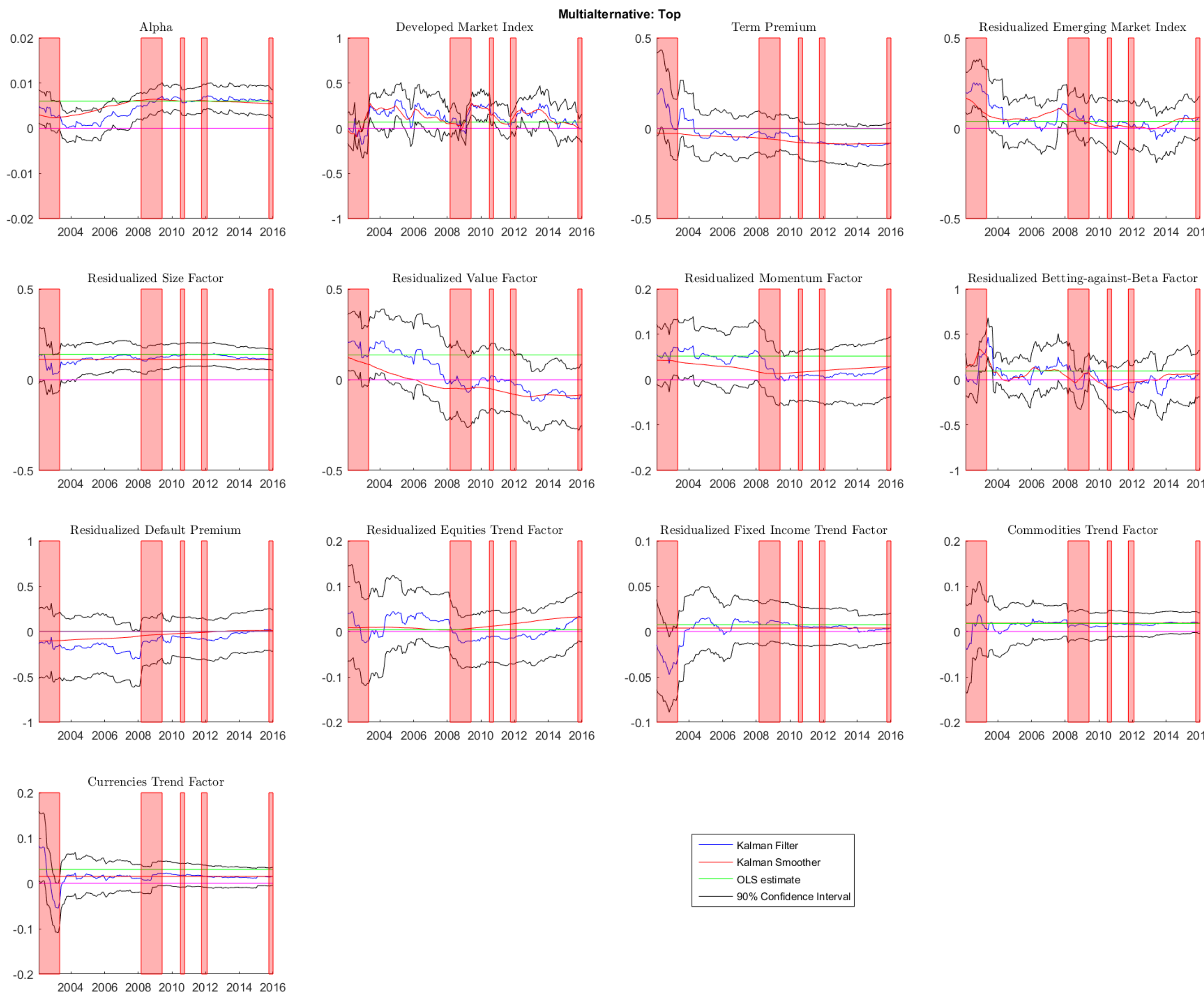

Figure 34: Top Multialternative funds analyzed

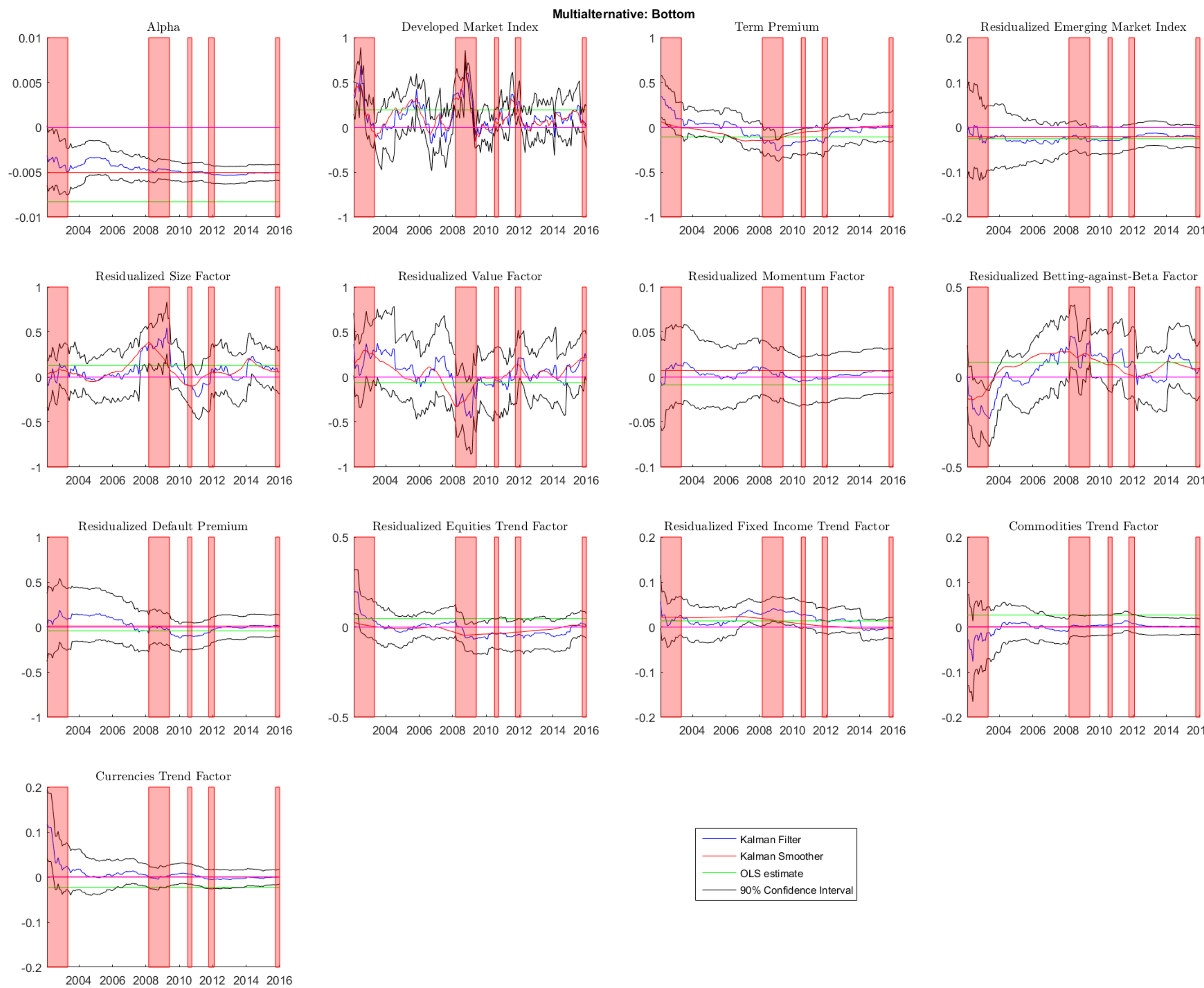

Figure 35: Bottom Multialternative funds analyzed

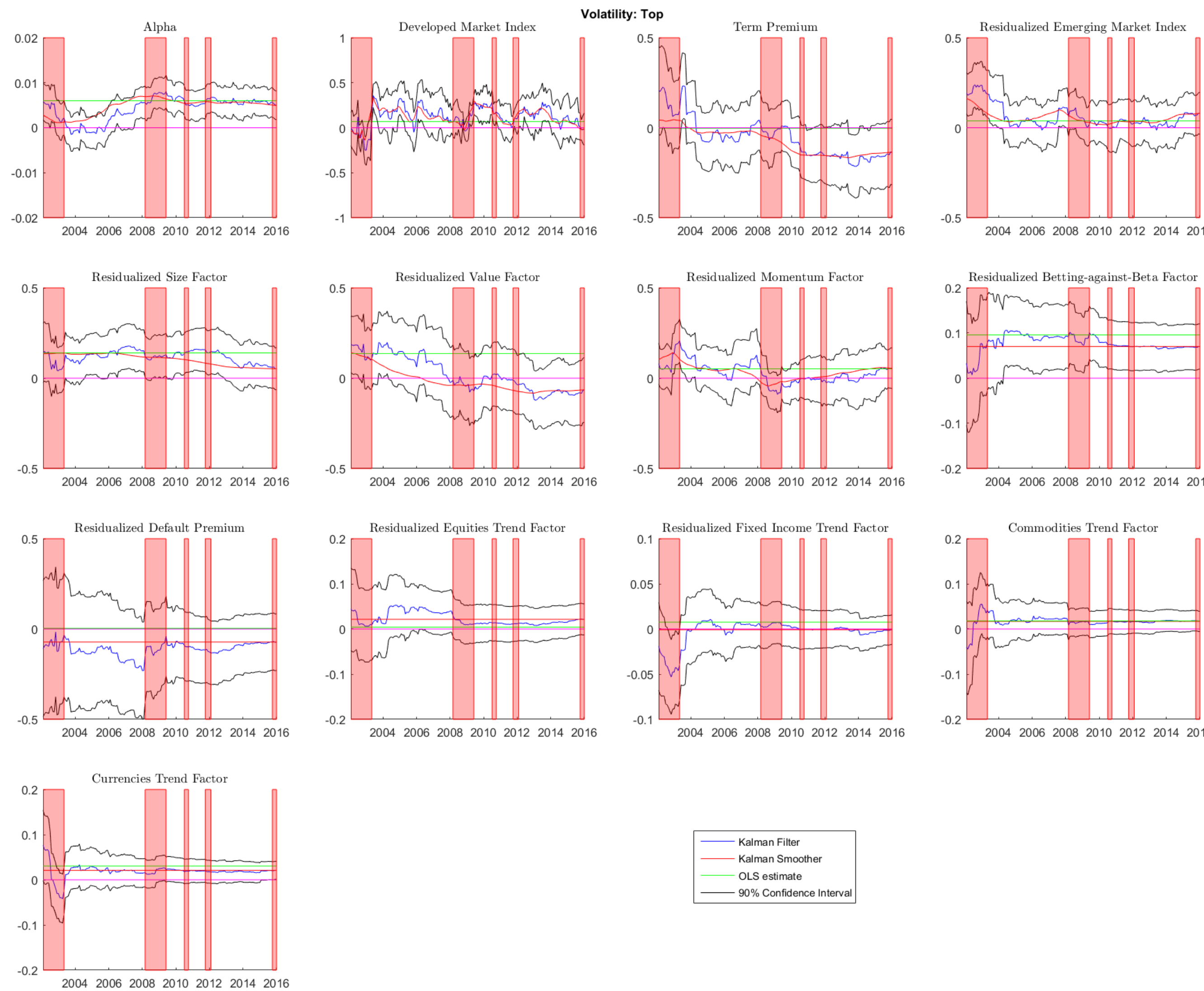

Figure 36: Top Volatility funds analyzed

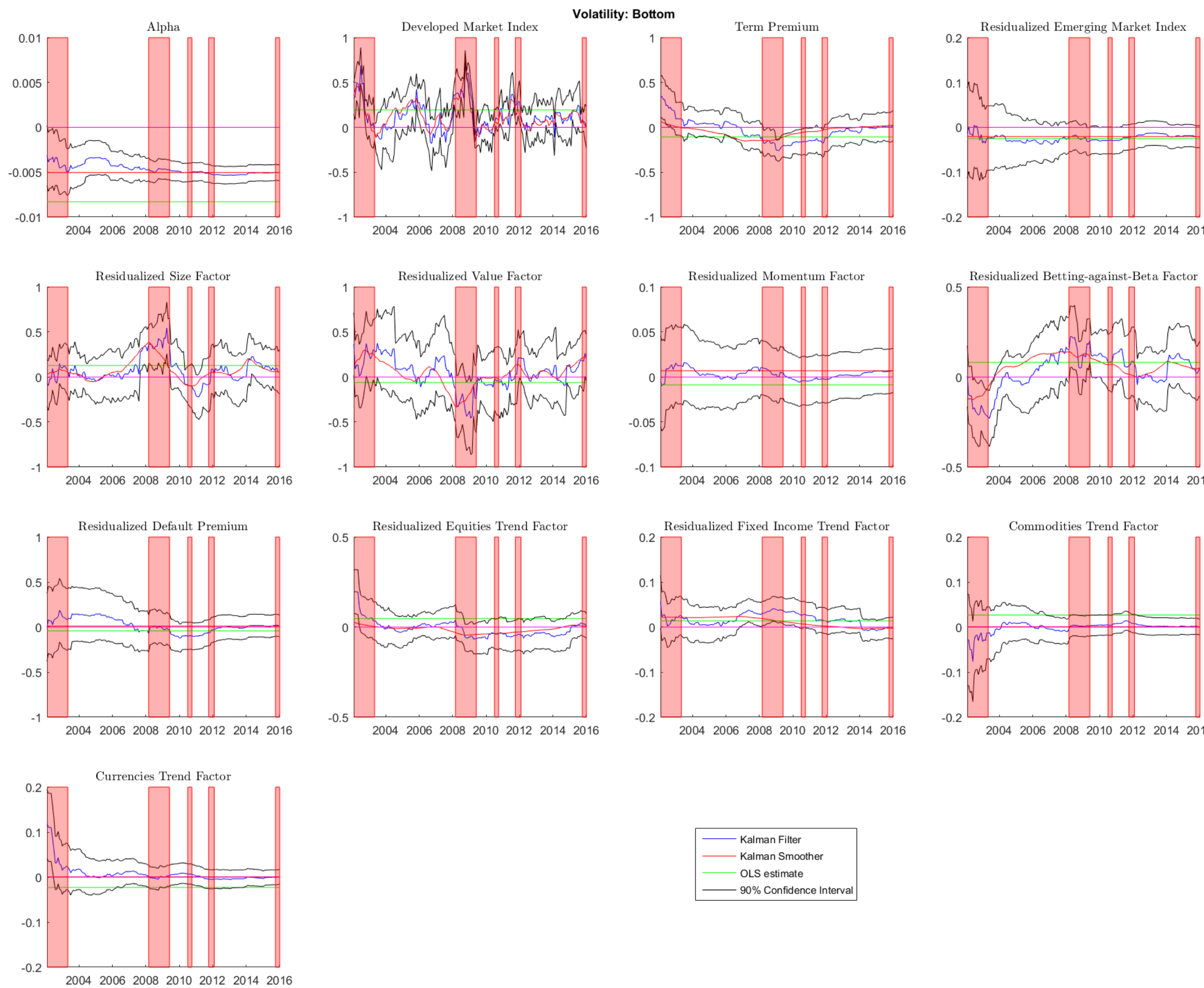

Figure 37: Bottom Volatility funds analyzed

Table 7: Critical values F-tests over different regimes

critical values F-distribution		$\alpha = 0.1$	$\alpha = 0.05$	$\alpha = 0.01$
UP	$F_{129,129}$	0.797	0.748	0.662
DOWN	$F_{61,61}$	0.719	0.654	0.547
ALL	$F_{191,191}$	0.830	0.788	0.713

Table 8: Test on significant changes in Share ratios between liquid alternatives and hedge funds

	EQ_LS	GM	MF	MN	MA	NTB
Sharpe Ratio liquid alternatives	0.38	−0.35	0.58	0.48	−0.12	0.68
Sharpe Ratio hedge funds	0.47	1.28	0.32	−0.13	1.01	0.45
Test statistic	−1.15	−25.58	4.01	6.01	−17.12	2.03
Probablistic Sharpe Ratio	0.25	0.00	0.00	0.00	0.00	0.04

A positive test statistic in this table learns us that the liquid alternative mutual funds have a higher full sample Sharpe ratio than their hedge fund counterparts. The probablistic Sharpe ratios denote the probability that the Sharpe ratio of the liquid alternative index is significantly different from the Sharpe ratio of the hedge fund index.

Table 9: Test on significant changes in Sharpe ratios for hybrid portfolios

	Benchmark + Equity Long/Short			Benchmark + Global Macro			Benchmark + Managed Futures			Benchmark + Market Neutral		
	50/50	70/30	90/10	50/50	70/30	90/10	50/50	70/30	90/10	50/50	70/30	90/10
Sharpe Ratio	0.26	0.21	0.17	−0.02	0.06	0.13	0.60	0.45	0.24	0.29	0.22	0.17
Test statistic	1.34	0.76	0.24	−2.41	−1.20	−0.34	6.83	4.11	1.13	1.74	0.90	0.26
Probablistic Sharpe Ratio	0.18	0.44	0.81	0.02	0.23	0.73	0.00	0.00	0.26	0.08	0.37	0.80

	Benchmark + Multialternative			Benchmark + Non-tradional Bond			Benchmark + Volatility		
	50/50	70/30	90/10	50/50	70/30	90/10	50/50	70/30	90/10
Sharpe Ratio	0.05	0.10	0.14	0.30	0.22	0.17	0.14	0.15	0.15
Test statistic	−1.43	−0.75	−0.22	1.77	0.90	0.26	−0.18	−0.08	−0.02
Probablistic Sharpe Ratio	0.15	0.45	0.83	0.08	0.37	0.80	0.86	0.93	0.98

A positive test statistic in this table learns us that the hybrid portfolio has a higher full sample Sharpe ratio than the benchmark portfolio. The probablistic Sharpe ratios denote the probability that the Sharpe ratio of the hybrid portfolio is significantly different from the Sharpe ratio of the benchmark portfolio.