Return-based style analysis with time-varying exposures*

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Abstract

This paper focuses on the estimation of mutual fund styles by return-based style analysis. Often the investment style is assumed to be constant through time. Alternatively, time variation is sometimes implicitly accounted for by using rolling regressions when estimating the style exposures. The former assumption is often contradicted empirically, and the latter is inefficient due to its ad hoc chosen window size. We propose to use the Kalman filter to model time-varying exposures of mutual funds explicitly. This leads to a testable model and more efficient use of the data, which reduces the influence of spurious correlation between mutual fund returns and style indices. Several examples indicate that a more reliable style estimate can be obtained by modeling the style exposure as a random walk, and estimating the coefficients with the Kalman filter. In certain cases, the differences with traditional techniques can be substantial. This may impact the conclusions presented in the literature on e.g. mutual fund misclassification or performance measurement.

Keywords: Kalman filter; Mutual funds; Style analysis

JEL classification: C22; C61; C63; G11; G20; G23

1 Introduction

The investment style of a mutual fund is not always clear for investors not acquainted with its manager or the philosophy of the fund family it belongs to. Due to the large number of mutual funds these days, it is almost impossible for an investor to grasp all information regarding their investment styles. For a potential investor in mutual funds, a tool introduced by Sharpe (1992) might be appropriate to get a first impression of the historical exposures of the fund. Sharpe's method for analyzing mutual funds is known as *return-based style analysis* (RBSA). Basically, RBSA is constrained regression of the returns of the mutual funds on relevant style indices.

A major drawback of RBSA in its original form is the basic assumption that the investment style of a fund remains fixed over the sample period. The use of so called *rolling regressions* alleviates this drawback to a certain extent. In a rolling regression the investment style is not fixed over the entire sample period but over a given estimation window. In empirical work, the length of this window is often chosen to lie somewhere between 24 and 60 months. This window is shifted month by month over the sample period. There is no theoretical argument that defends the use of rolling estimation windows when styles vary over time. In practice the use of rolling windows causes a sub-optimal use of the data by picking an ad hoc window size.

In this paper, we contribute to the discussion by *explicitly modeling time variation* in the investment style of a mutual fund manager. In order to do this, we use the *Kalman filter* approach, which has several advantages over standard regression techniques. The main advantage for this application is the more efficient use of the information, while allowing for time variation in exposures. Throughout this paper, the more familiar term Kalman *filter* is used, while we actually use the Kalman *smoother*. The difference between the two is the conditioning information set. The filter is conditional on information up to time t and thus more appropriate for prediction, while the smoother is conditional on the entire sample, and hence more suited for descriptive reasons. Since our main goal is to describe the investment styles of mutual funds over a certain period, the use of the Kalman smoother instead of the Kalman filter is warranted.

In our setup, the entire sample period is used to estimate exposures in each period. Consequently, no choice of window length has to be made. The Kalman filter optimally determines the weights of each of the observations in determining the exposure. Furthermore, the model specification can be tested and confidence bounds on the exposures are readily obtained by applying the Kalman filter.

The structure of the remainder of this paper is as follows. Section 2 motivates the use of style analysis. In section 3, the model is described and the similarities between the traditional models and the Kalman filter approach are indicated. In Section 4, two stylized examples are presented in order to compare our approach with traditional rolling window regressions. Section 5 contains the empirical application in which we estimate the investment style of two mutual funds. Finally, Section 6 concludes.

2 Mutual fund misclassification

The number of mutual funds has increased rapidly over the last decade. Despite the generally poor performance of mutual fund managers, individual investors have increased their demand for investment management; see e.g. Gruber (1996), and Chan, Chen & Lakonishok (1999). The specific needs of investors are reflected by a variety of funds with different investment objectives. For a large part of the funds the fund's name describes its style rather adequately. However, a substantial part of the funds have misleading names, vague investment objectives, or pursue a different style than advertized.

It is not obvious why mutual funds are unclear about their investment policy, since potential investors need detailed fund information to construct an optimal portfolio of mutual funds. Uncertainty about the style of the mutual fund obscures their informed decision and may be a hindrance for investors. A possible reason for vagueness in the stated objective of the mutual fund is lawsuit avoidance. While temporary deviations from the style are often observed, the official investment objective is rarely changed. Consequently, the stated objectives of the funds should not be too stringent and possess a certain degree of vagueness. To illustrate this we quote from the 2001 prospectus of the Templeton World Fund. Its main investment objective is stated: *Under normal market conditions, the Fund invests mainly in the equity securities of companies listed anywhere in the world, including emerging markets. At least 65% of its total assets will be invested in issuers located in at least three different countries (including the U.S.).*

Another possible reason for misleading fund names or objectives is to blur the investor's notion of the riskiness of the strategy. Taking on more (undiversifiable) risk usually leads to higher expected returns. Sirri & Tufano (1998) indicate that mutual funds with a high rank in the performance lists of magazines attract more money from the investing public. This might be an incentive for a mutual fund manager to indulge in more risky asset categories. As DiBartolomeo & Witowski (1997) phrase it: *The easiest way to win a contest for the largest tomato is to paint a cantaloupe red and hope the judges do not notice.* It is our task to be the judge in this contest and identify the large tomatoes from the painted cantaloupes. In other words, identification of exposures to relevant risk factors is of primary importance.

There is ample evidence of the misclassification of mutual funds. For example, both DiBartolomeo & Witowski (1997) and Brown & Goetzmann (1997) use the realized fund returns as inputs for their analysis. Their results suggest that up to 40% of mutual funds are in one way or another misclassified. Kim, Shukla & Tomas (2000) report misclassification up to 50% when also taking into account other fund attributes than risk and return measures. These studies do not take into account style changes, or use only a limited amount of data to estimate the investment style of a mutual fund. For instance, DiBartolomeo & Witowski (1997) and Brown & Goetzmann (1997) take 60 and 24 months, respectively.

3 Determination of the investment style

The RBSA introduced by Sharpe (1992) concentrates on estimating a portfolio that could have been tracked by an investor at relatively low cost. This tracking portfolio is constrained in two ways. First, short sales are prohibited. Second, in order to interpret the exposures as portfolio holdings, their sum should equal one. We follow DeRoon, Nijman & TerHorst (2000) in their terminology in which they name RBSA subject to both constraints *strong* RBSA. RBSA where both sets of restrictions are relaxed is named *weak* RBSA.[1] An intermediate form with the portfolio restriction but without the short-sales restrictions is labeled *semi-strong* RBSA. We argue later that the short-sale restrictions are in general irrelevant, and should be imposed in certain special cases only.

The interest from our style analysis is not the actual *holdings* of a mutual fund, but the *exposures* to certain style categories. This means that a portfolio of US stocks which are sensitive to European markets results in an exposure towards these markets. This is relevant information for an investor, since she is now also exposed to risks associated with European market conditions. So, Sharpe's famous "Duck theorem" applies here: *If it walks like a duck and talks like a duck, for all important purposes, it* is *a duck.*

In weak RBSA, the exposures of the mutual fund are obtained by minimizing the squared errors of the equation

$$R_t^{fund} = \alpha + \beta_1 \cdot R_t^{index1} + \ldots + \beta_K \cdot R_t^{indexK} + \varepsilon_t^{fund}, \quad t = 1, \ldots, T, \tag{1}$$

where R_t^{fund} denotes the total return of the fund, and R_t^{indexi} the return on style index i, and ε_t^{fund} the fund specific error terms. The standard assumption that the error terms are uncorrelated with the style indices is made. Usually however, two restrictions

[1] Alternatively, Agarwal & Naik (2000) label RBSA without restrictions *generalized* RBSA.

are imposed. The first restriction is the *portfolio restriction* which requires that the estimations for the parameters β_i can be interpreted as portfolio holdings in style i. This (equality) restriction is

$$\sum_{i=1}^{K} \beta_i = 1. \tag{2}$$

The equations (1) and (2) together are called semi-strong RBSA. A second restriction is the *short sale restriction*, which imposes that all estimated portfolio holdings should be long positions. These (inequality) restrictions are

$$\beta_i \geq 0, \qquad i = 1, \ldots, K. \tag{3}$$

This does not mean that short sales *in general* are prohibited. It states that short sales *in style categories* are not allowed. Strong RBSA is obtained by equation (1) together with restrictions (2) and (3). This is the Sharpe (1992) method of determining a funds investment style.

Because of the inequality constraints, the coefficients cannot be obtained by applying ordinary least squares (OLS). Quadratic programming (QP) algorithms solve for the exposures $\beta_1, \ldots, \beta_K$. However, as opposed to OLS, confidence regions are not readily obtained when using QP. Attempts to resolve this problem have been made by Lobosco & DiBartolomeo (1997), and Otten & Bams (2000), amongst others.

One of the implicit assumptions of the original RBSA is that the exposures stay constant over the sample period. This is highly unlikely in practice. Therefore, rolling regressions are often reported. In this way, the exposures $\beta_1, \ldots, \beta_K$ are not estimated over the entire sample period but over windows (sub-samples). For instance, when a 36-month window is used, the coefficients are estimated over the first three years of the sample. The window moves forward one month, deleting the first observation and adding the observation of the next period. In this way, time-varying exposures are obtained.

However, the use of sub-samples instead of the entire sample means the implicit introduction of time-varying exposures in an ad hoc manner. This approach still assumes that style exposures stay constant over the 36 months estimation period. Implicitly, this creates a contradiction unless the exposure is constant over the entire sample period. Especially in case of a change in fund management the assumption of constant exposures within the 36 months window is restrictive. Another shortcoming of a rolling window approach is that estimates rely on historical returns only at each point in time. Our approach takes into account all information both before and after that period. Modeling the time-varying exposures explicitly leads to (a) a testable model, and (b) efficient use of the data because of the structure that is imposed by the model. The possibility to test the validity of our model assumptions against alternatives makes this technique attractive. Such test can be important, since misspecification may lead to erroneous inferences. When our model is appropriately chosen, the optimal use of the available data is guaranteed by applying the estimation technique we propose.

We propose an approach different from the traditional rolling window regressions to model time variation in fund exposures, using the *Kalman filter*. First, we explain this method in the weak RBSA form, so without the short sale and portfolio constraint. Time variation is introduced to the model in equation (1) by the following set of equations

$$R_t^{fund} = \alpha_t + \beta_{1,t} \cdot R_t^{index1} + \ldots + \beta_{K,t} \cdot R_t^{indexK} + \varepsilon_t, \quad (4)$$

$$\alpha_{t+1} = \alpha_t + \xi_{0,t+1,} \quad (5)$$

$$\beta_{i,t+1} = \beta_{i,t} + \xi_{i,t+1}, \quad (6)$$

for $i = 1, \ldots, K$, and $t = 1, \ldots, T$. Furthermore, the error terms are

$$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2), \qquad \xi_{j,t} \sim NID(0, \sigma_{j,\xi}^2), \quad j = 0, ..., K$$

where NID indicates an independent sequence of normally distributed random numbers. The initial conditions for the exposures is a (proper) diffuse prior. More specifically, $(\alpha, \beta')' \sim N(0, \kappa \cdot I_{K+1})$, with κ a large but finite number, and I_{K+1}, the identity matrix of dimension $K+1$. We decide to model the time variation in exposures as in equation (6), which states that the exposure in this period is the exposure in the previous period plus a style shock. The exposures $\beta_{i,t}$ are non-stationary in this model. This means that the model allows the exposures to evolve in such a way that fundamental changes in the investment style can be accommodated. The same applies for the manager ability, which is modeled in equation (5).

The model presented above is in *state space* form, with equation (4) being the *measurement* equation, and (5) and (6) being the *transition* equations. This enables us to directly apply the Kalman filter, which returns the parameters of the model, including the β_t-s. The variance of the disturbances can be estimated efficiently by using maximum likelihood, while the β_t-s are calculated recursively.[2] Model (4)–(6) is

[2] We use the Ox-based computer package Ssfpack to evaluate the system. For a detailed description of Ox see Doornik (1998). Ssfpack is described by Koopman, Shephard & Doornik (1999).

known as the *random walk model*; see Rosenberg (1973) and Harvey (1993) p. 408.

Models in state space form have been used extensively in engineering. More recently, these models have found their way into econometrics and finance. Extensive treatments of the theory and applications of the Kalman filter in the field of econometrics are Harvey (1993), and Durbin & Koopman (2001), amongst others. Finance related applications include the modeling of stochastic volatility and term structure models for interest rates. Applications modeling time-varying market exposures by the Kalman filter include Wells (1994) (Swedish stocks), McKenzie, Brooks & Faff (2000) (Australian industry indices), and Black, Fraser & Power (1992) (UK unit trusts), amongst others.

The specification in (6) assumes a random walk for the style exposures, since we a priori do not know whether the manager is increasing or decreasing her exposure over time. However, in certain cases, the style estimation can be improved upon by generalizing the model further. The random walk model can be extended in order to account for slowly moving deviations of the exposure from its long term mean $\overline{\beta}$. In other words, a manager may deviate for a number of periods from the normal exposure to a style category, but eventually the exposure will revert back to this normal level. The transition equation (6) for the exposures is replaced by

$$\beta_{i,t+1} = \overline{\beta} + \rho_i \left(\beta_{i,t} - \overline{\beta}\right) + \xi_{i,t+1} \tag{7}$$

with ρ_i a free parameter that indicates the dependency between the exposure of this month and the exposure of last month. The model in (4) and (7) is the *return to normality* model, see Harvey (1993) p. 410 for a detailed description. To prevent an explosive system, the parameters ρ are required to be smaller or equal to one in absolute value. If ρ is positive, this implies persistent deviations from the overall mean. Negative values of ρ can be interpreted as overshooting the movement to the average style in each period. We expect ρ to be close to unity in which the exposure in a particular period is highly dependent on the exposure of the previous period, and is only marginally affected by the overall mean. If ρ equals one the random walk equation presented in (6) is obtained, because $\overline{\beta}$ disappears.

The time-invariant weak RBSA regression model can be obtained as a special case of the models presented above which allow for time-variation. The estimates for α and β_i are then constant over time, which requires the transition equations to be of the form,

$$\begin{aligned} \alpha_{t+1} &= \alpha_t \\ \beta_{i,t+1} &= \beta_{i,t}. \end{aligned} \tag{8}$$

The disturbance term ξ has disappeared (or has zero variance, which is essentially the same). This is a nested model and can be tested for validity.

In order to incorporate the portfolio restriction (i.e. all exposures sum to one), as is used in the (semi-) strong RBSA literature, in the state space model, the betas should be reparameterized. This is a fairly simple operation, and has little impact on the estimation procedure.[3] We decide to model the returns of the mutual funds as well as the returns on the style indices in excess of the risk free rate. This is equivalent

[3]In fact, the K random walks for each β_i are replaced by a series of $K-1$ random walks for the newly defined parameters γ_j, from which the β_i-s are obtained as $\beta_{i,t+1} = \frac{1}{K} + \sum_{j=1}^{K-1} \omega_{i,j}\gamma_{j,t}$, with ω_j representing the weights. For instance, when $K=3$, the weights are (-1,0), (1,-1), and (0,1).

to the inclusion of cash as a style index and incorporating the portfolio restriction. The advantage of this approach is the direct link to asset pricing models like e.g. the arbitrage pricing theory (APT) developed by Ross (1976). The investment styles serve as the risk factors relevant for the potential investor in the mutual fund.

The restriction of non-negativity of the parameters is harder to establish, because this introduces nonlinearities in the state-space model. One possible modification is inspired by the modeling of interest rates, which are typically positive. This involves reducing the variance when the exposure gets close to zero. Another possibility is transforming the model by taking logarithms, implying lognormal disturbances. However, we assert the non-negativity restriction is unnecessary for this application, so we do not pursue along these lines to find a solution. Better ways to cope with this problem are subject of further research.[4] On the other hand, we argue in line with DeRoon et al. (2000) that imposing the non-negativity restrictions is in general not necessary. In fact, using these restrictions may lead to inconsistent parameter estimates in this application, in which we want to determine the investment style of a mutual fund.

An example of an application in which the non-negativity constraints are useful is when the estimated investment style should be replicable for an investor with short-sale constraints. The performance of this constrained investor can be used for comparison with the performance of the mutual fund, given that they have the same (non-negative) style exposures.

[4] Imposing the non-negativity constraints along these lines requires the use of the *extended* Kalman filter which cannot be implemented by using Ssfpack. See Harvey (1989) pp. 160–2 for a discussion on this topic.

In most other applications, the necessity for non-negative exposures is less clear. The use of inappropriate short-sale restrictions may lead to biased or even inconsistent estimates of the exposures. This is clearly at odds with the goal of determining the true underlying investment style of the mutual fund, which is the focus in our paper. When the indices representing the investment styles are inappropriately chosen, e.g. high correlation (or *near-multicollinearity*) or the omission of a relevant asset class, the exposures might become negative even when there is no reason to believe this is the case in reality. We suggest a careful selection of the style indices before applying RBSA. This means that style indices should have low correlation and describe as much as possible from the investment opportunity set of the mutual fund manager.[5]

Furthermore, Agarwal & Naik (2000) suggest omitting the restrictions when applying RBSA to hedge funds. While mutual fund managers are often not allowed to take (large) short positions, this is common practice for hedge fund managers who have almost no limitations in this respect.

4 Stylized examples

The performance of the method described in the previous section can be analyzed by stylized examples in which we a priory fix the exposures of the managed fund. This way, a comparison can be made between the estimated exposures by the Kalman filter approach we advocate or the rolling window regressions that are used in many other

[5] Like Lobosco & DiBartolomeo (1997) we argue that indices that are highly correlated for a longer period of time are essentially capturing the same style and should be treated as one and the same style.

empirical applications. In this section, we present two examples. These examples are stylized and we do not expect any of the existing mutual funds to exactly follow these particular strategies. However, these examples might provide more insight in the pros and cons of the different methods when estimating the style exposures of mutual funds. The two artificial funds we present are a fund that changes its style only once, and a fund with highly volatile exposures. For these two stylized examples, we estimate the random walk model as described by (4)–(6).

The first example consists of a fund that invested all its assets in the MSCI USA index from May 1979 until December 1989, and from January 1990 until April 1999 the fund invested all assets in the MSCI Europe.[6] The estimated USA exposure of this artificial fund is shown in Figure 1. We observe that the Kalman smoother starts with the reduction in the USA exposure a little before the actual turning point January 1990. For some applications, the use of data from the future is not allowed. In such case, the use of the Kalman filter instead of the smoother is more adequate. The estimates based on the filter are displayed in the bottom panel of the figure. The middle panel graphs the 36-month rolling window estimator. The three panels of the figure show the difference between the Kalman approach and the traditional rolling window method. Obviously, it takes about 36 months in order for the rolling window estimator to arrive at the zero level. The use of a shorter window would have resulted

[6] In principle, the fund could have invested in other assets and generated exactly the same return pattern as the time series used in our example. This does not alter our conclusions, since we are interested in the exposures and not the actual holdings of the mutual fund under consideration. See for a description of the style indices Section 5.

in a quicker adaptation to the new situation. The use of the Kalman filter technique does not require an ad hoc chosen window length, but it endogenously determines the optimal window length (weighting scheme) to balance the trade-off between the time-variation in the style exposures and the accuracy with which they are estimated. The confidence bounds in the rolling window regressions suggest falsely that there is an extremely high level of confidence about the investment style of the fund. The Kalman approach accounts for this uncertainty at each point in the sample.

The second example consists of a mutual fund with highly volatile exposures. The style of this fund is to invest in the MSCI Europe in odd years and in the MSCI Pacific in the even years. The estimation results for the Europe exposure of the random walk model are shown in Figure 2. These graphs clearly indicate the drawback of the 36-month rolling window. When a mutual fund changes styles within the window length, the rolling window estimator is using information which it should better disregard because it is too old. Due to this suboptimal use of the data, the style estimates in the middle panel are poor at each point in the sample. By using the Kalman smoother approach, the high volatility of the investment style is recognized and hence the estimation window is adapted to fit the data as good as possible. Clearly, it would be easier to determine the true underlying investment style from this example by looking at the top or bottom panel instead of the middle panel. The use of the Kalman filter technique is most beneficial when managed funds with frequently changing investment styles are considered.

In order to quantify our visual inspection on the performance of the three methods, we also calculated the distance between the estimated exposures and the true exposures. In the first example, the true exposure equals one for the US before 1990, and zero afterwards. The total deviations over the May 1982 to April 1999 period are presented in Table 1. The two distance measures we tabulate are the sum of the absolute deviations and the quadratic deviations. From Table 1 it follows that the 36-month rolling window estimator performs much worse than the Kalman smoother and filter, with absolute deviations of 16.29, 2.28, and 0.27, respectively. This poor performance is due to the slow adaptation of the coefficient estimate because of the relatively long window. The filter performs better than the smoother in this case, which might seem counter-intuitive since the smoother uses more data. However, like the name suggests, the change in investment style is smoothed by using the entire data set, and hence the exposure deviations start before the style shift. The filter is more suitable in the case of a jumpy style shift.

For the second example, the difference between the rolling window estimate and the Kalman approach is even more pronounced. While the relative deviations are less than in the first example, the absolute deviations are large. The sum of squared deviations is 54.2 for the rolling window, 20.3 for the filter, and 8.7 for the smoother. Interestingly, the exposure estimates do benefit from using future data in this case, leading to a substantial better performance for the style estimation of the fund in this example.

The results from this section show that the rolling window approach which is used in many empirical applications is generally not suitable when the coefficients are changing over time. The evidence presented in this section can be used to improve existing results on performance measurement conditional on mutual fund investment style. In the next section, we use two real mutual funds to show how our technique works in practice.

Another application of our method could be to investigate hedge funds, which are commonly believed to exhibit more volatile style exposures than mutual funds; see for a more detailed description of hedge fund styles Fung & Hsieh (1997), Brown & Goetzmann (2001), and Agarwal & Naik (2000), amongst others.

5 Data and empirical analysis

In the previous section, we have shown the advantages of the Kalman filter approach by investigating the exposures of two artificially created mutual funds. In this section, we examine the regional exposures of two real mutual funds by applying the technique described earlier. This section starts by a short description of the data before we turn to the empirical part of our paper.

The data on the mutual funds are from the Morningstar database. Since our primary interest is in the regional style allocation of funds, we searched through this database for mutual funds that are categorized by Morningstar as *world investors*. We decided to use two funds with inception dates before 1980, in order to obtain enough possible time variation. The funds we explore are Templeton World (class A) and Putnam Global Growth (class A).[7] The style indices we decided to use are the regional indices provided by Morgan Stanley Capital International (MSCI). To be more specific, we use the Europe, USA and Pacific total return indices (in US dollars). These comprise the major stock markets in which mutual funds with a world scope tend to

[7] In previous versions of this paper the Oppenheimer Global fund was examined as well. However, no new insights emerged from the analysis of this fund, and hence we do not include it here for reasons of brevity.

invest. Our data set consists of monthly total return data from May 1979 to April 1999. The data on the risk free rate are obtained from the website of Kenneth French.

The set of regional style indices is in principle motivated by the interests of the potential investor, and need not be in line with style definitions of the mutual fund management. Buetow, Johnson & Runkle (2000) argue that style indices should be fund dependent instead. However, they concentrate on performance measurement of a manager with a known benchmark, while our focus is on determining the investment style of a fund we know very little about. In this application, the only information we use about the fund is the Morningstar classification and the return history.

Some descriptive statistics of our data are presented in Table 2. The two mutual funds we investigate are quite similar, with an average return of 1.3 percent per month and standard deviation of 4.2 and 4.3 percent per month. The correlation between both funds is relatively high, roughly 84 percent. The style indices representing stocks differ more than the funds, which can be observed by for example the average returns, which are 1.5 and 0.8 percent per month for the US and the Pacific, respectively. The largest correlation between the stock indices is 61 percent, which reflects the relation between stock returns in the US and Europe.

We start with a case study of the Templeton World fund. Below, we present results for another US based mutual fund which also reports an international investment style, the Putnam Global Growth fund. In Section 3, we motivated the use of semi-strong RBSA in this analysis rather than its widely used strong form counterpart, which prohibits negative exposures, as developed by Sharpe (1992). We analyze the exposures of the mutual fund by the model described in (4)–(6), using 240 months of return history, and three regional indices covering the lion's share of the world market. The returns on the mutual funds and style indices are in excess of the risk free rate. So, we use semi-strong RBSA, with the exposure to cash equal to one minus the sum of the exposures to the other style factors.

In figures 3–5, the exposures of the Templeton World fund are displayed using the 36-month rolling window regressions and our Kalman filter approach. We skip the first 36 months, since parameter estimates for these first months are highly volatile because of the low number of observations. A first observation is that the exposures do seem to vary substantially over time.[8] Both the rolling regressions and the smoothed lines show an increase of exposure for Europe and the Pacific, while the US exposure decreases. A turning point in investment style seems to be in the early 1990s, when these exposure shifts are starting. This seems to violate the assumption of constant exposures over the entire sample period.

The rolling regressions, which allow for variation in exposure over time, are in this respect closer to the smoothed style. However, there are long periods of substantial differences, for example, the period 1990 to 1993 in Figure 3. This difference can be explained rather easily. The rolling regressions use 36 months of historical data at each point in time. Therefore, it takes some time to accommodate a sudden style change. In contrast, the smoothed line is obtained by using the entire sample period. This allows usage of return information *after* the period to estimate its exposure.

[8] This is supported by the CUSUM and CUSUMSQ test for parameter stability displayed in the appendix. A table with results from Chow tests is provided as well, amplifying the conclusions from former tests.

Another disadvantage from the rolling regressions compared to the smoothed line is its jumpy nature. It seems that the estimated changes from month to month are – at least partly – due to sampling error of the estimates. This notion is supported by the 95% confidence bounds, which are rather wide. Using the entire sample period, together with random walk style changes, leads to smoother estimates, which are more robust for spurious correlation between the style indices and mutual fund returns.

At the start of our sample, when there are only few observations, uncertainty about the parameter estimates is relatively high. The most confident estimates are obtained in the middle of the sample. This is easily interpretable, since we have information about the behavior of the fund a long time before and after this point. The somewhat wider confidence bounds towards the end of the sample are due to the lack of knowledge of the behavior of the fund in the future.

When looking at Figure 5, which shows the exposure of the Templeton World fund towards Pacific stocks, we observe that only in the last few years a significant exposure to this market is developed. During a small part of the sample (1985–1987), we see that the estimated exposure is negative. There is no need to be concerned about this, since we immediately see that this is not a significant exposure, and might be due to estimation error. When the true exposure is exactly zero chances are still 50% that an exposure will be negative. Therefore, an investor with short sales constraints should not be concerned about this negative exposure.

The results presented in this paper depend of the assumptions of the model presented in (4)–(6). In the transition equation, we specify that the style exhibits a random walk. This is motivated by the fact that we do not want to use the prior information of a decrease or increase in the exposure of a certain style. However, a more general model would be to replace (6) by (7), since the parameter ρ_i is now not fixed to unity as in the random walk specification. The return to normality model (7) is also estimated for both funds, the results are displayed in Table 3. The results indicate that the choice of a random walk model is fairly accurate, since the mean reversion parameters ρ_i are close to unity for the at least two of exposures. More general specifications, e.g. vector auto regressive models, might be estimated to allow for interaction effects between exposures of different styles and correlations between the disturbance terms. This is a topic for further research.[9]

Thus far, we have presented returns on the Templeton World fund, an arbitrarily chosen world investing fund with inception date before 1980. We also analyze the Putnam Global Growth fund in Figure 6–8. We observe that the fund has remained relatively stable over the last decade of our sample. The most pronounced style shifts seem to have taken place in the late 1980s, when the pacific exposure is reduced and the Europe exposure has increased.

In order to zoom in on the different estimation methods, we display the Pacific exposure estimates of the Putnam fund in Figure 9. The differences are of substantial economic magnitude. For example, the exposure estimate which keeps the exposure

[9] We also assumed normally distributed innovations in the model. Extensions to non-normal errors involve more complicated integration techniques (e.g. Markov Chain Monte Carlo). This cannot be solved in a standard way by Ssfpack. Though monthly returns are usually somewhat fat tailed, we expect this will only have minor influence on the results presented here. Even when disturbances are not normally distributed, many optimality properties of the Kalman filter still remain, see Harvey (1989) p. 111.

constant over the entire sample period seems to be very restricted, since it does not account for the relatively high Pacific exposure in the beginning of the 1980s, and the low exposure in the second half of the 1980s. The Kalman smoother is often earlier in detecting an investment style change than the filter or the rolling window estimator. For example, in 1985 the smoothed estimate is 20 percent, while the filtered estimate is about 40 percent. Only one year later, the filtered estimate reaches the 20 percent level. The earlier detection of style shifts is due to the use of the entire sample for each smoothed style estimate. When the use of future information is undesirable, the Kalman filter can be used instead. These estimates resemble the rolling window estimates more closely, but notice the difference of about 15 percentage points in 1983 and 1995, which is an economically significant magnitude.

An investor considering a fund which claims to be a style timer with regard to regions should exhibit a positive correlation between its exposure and the return on the style index. For example, when a mutual fund manager reduces her exposure to the Pacific, and the corresponding index has low realized returns, we attribute this to timing ability of the fund manager. The resulting correlations of the two mutual funds of this empirical application are presented in Table 4. The results in this table indicate that the regional style exposure of the Templeton World moves in the opposite direction of the returns on the regional indices for our sample period. This holds for all three estimation methods, but the rolling window estimate is less negative about timing skills than the filter and smoother, with only -1.4 percent for the Pacific correlation. The results on the Putnam Global growth fund are less clear cut. According to this simple correlation analysis, the timing in the US market is positive when the Kalman smoother is used (7.6 percent), and negative for the other methods (-1.9 and -3.8 percent for the rolling window and Kalman filter, respectively). The timing on the Pacific market is positive for the rolling window estimates (3.6 percent), while for both the Kalman filter and smoother the timing ability for this market is negative (-3.0 and -6.3 percent, respectively). Note that these results *do not imply that there is no style timing* in these funds, the correlation analysis only suggests this is not the case for regional styles. The fund manager might still be adding value by timing other styles or picking the right stocks within these regions.

The empirical results presented in this section together with the stylized examples of the previous section indicate that the traditional methods to estimate the investment style of mutual funds can be improved. Depending on the particular application the researcher has in mind, the Kalman smoother or filter can be used to improve the estimates of the investment style of mutual funds considerably. The novelty of this paper is the introduction of these types of models into this strand of literature. The substantial difference in style exposures that results from implementation of this technique for our examples may shed new light on the conclusions from the existing literature on e.g. mutual fund misclassification or performance evaluation. These are interesting topics for further research.

6 Conclusions

Return-based style analysis is a useful and quickly applicable tool for investors to get a first impression about the investment philosophy of a mutual fund or the family it belongs to. In addition, the results from style analysis are often used for performance measurement. There is ample evidence that the investment style of managed funds is time-varying, which complicates the style estimation in a standard regression framework. Often, time-varying exposures are incorporated implicitly by using rolling window estimators. The length of this window is generally chosen ad hoc and not motivated by statistical theory. Moreover, the assumption that styles are constant within each of the estimation windows is inconsistent by itself, unless the style is constant over the entire sample period. We introduce an alternative statistical model and estimation technique which alleviates these problems while explicitly incorporating style changes.

In this paper, the Kalman filter approach is used to explicitly model time variation of exposures for return-based style analysis. In contrast with rolling window regressions, the entire sample period can be used to obtain efficient estimates of the exposures at each point in time. In addition, our style estimates change smoothly over time, reducing the influence of spurious correlation between style indices and mutual fund returns in small samples. We present two stylized examples in order to demonstrate the huge differences that may be obtained by rolling window regressions instead of the Kalman filter approach. From these stylized examples it follows that the Kalman filter and smoother are much closer to the true underlying investment style than the rolling window alternative.

The estimation procedure we advocate in this paper is applied on two US based mutual funds which report and international investment style. The substantial differences that can be observed between the traditional rolling window estimates and the Kalman filter approach may impact the conclusions from the existing literature on e.g. mutual fund misclassification or performance evaluation. We leave this topic for further research.

For practical purposes, we note that the use of the Kalman filter techniques in finance has increased lately, which has resulted in the possibility to estimate these state space models by standard econometric software packages. For example, one can use Ox or Matlab.[10]

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[10] For more information on Ox, surf to www.oxmetrics.com or www.ssfpack.com, and for information on Matlab, consult www.mathworks.com.

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		Rolling	Filter	Smoother
Example 1:	Absolute	16.29	0.27	2.28
USA exposure	Squared	10.23	0.02	1.24
Example 2:	Absolute	98.62	31.81	25.67
Europe exposure	Squared	54.22	20.31	8.74

Table 1: Deviations of the style estimates from the 36-month rolling window, Kalman filter, and Kalman smoother. The row "Absolute" contains the total absolute deviation between the true style and the estimated style. The row "Squared" contains the total squared deviation between the true style and the estimated style. The period over which the difference is evaluated is May 1982 to April.1999.

	mean	std	skew	x-kurt	min	max	corr			
Templeton World	1.31	4.2	-1.0	3.7	-20.9	11.1	1.00			
Putnam Global Growth	1.33	4.3	-1.0	3.1	-20.7	10.1	0.83	1.00		
MSCI Europe	1.35	4.7	-0.6	1.6	-19.0	12.4	1.00			
MSCI US	1.47	4.3	-0.7	3.3	-21.2	13.3	0.61	1.00		
MSCI Pacific	0.83	5.2	-0.3	1.4	-18.6	18.2	0.48	0.41	1.00	
Risk free	0.57	0.2	1.0	0.7	0.2	1.4	-0.10	-0.10	0.01	1.00

Table 2: Descriptive statistics for our data set. The first three lines are the mutual funds, and the bottom three lines are the style indices. The sample period is 20 years, May 1979 to April 1999. The columns contain information about the mean and standard deviation in percent per month, the skewness, excess kurtosis, minimum, and maximum return per month. A negative skewness points to a higher probability for large negative values relative to positive values. A positive excess kurtosis indicates fat-tailed returns (relative to the normal distribution). The correlation between the two mutual funds, and between the three regional style indices and the risk free rate is reported in the right side of the table.

Parameter	Style	Templeton	Putnam
ρ_1	Europe	1.000	1.000
ρ_2	USA	0.772	0.813
ρ_3	Pacific	0.996	1.000

Table 3: Estimation results for the return-to-normality model for the Templeton World and Putnam Global Growth fund. The parameter ρ denotes the level of persistence of deviations from the long-term mean $\overline{\beta}$.

Fundname	Region	Rolling	Filter	Smoother
Templeton	Europe	-2.7	-4.8	-2.6
World	USA	-7.1	-10.5	-9.2
	Pacific	-1.4	-7.1	-8.6
Putnam	Europe	2.9	2.1	8.0
Global	USA	-1.9	-3.8	7.6
Growth	Pacific	3.6	-3.0	-6.3

Table 4: Correlations between style exposure and style returns. The US based mutual funds with an international investment perspective are the Templeton World and the Putnam Global Growth fund. The correlation is calculated over the period May 1982 to April 1999.

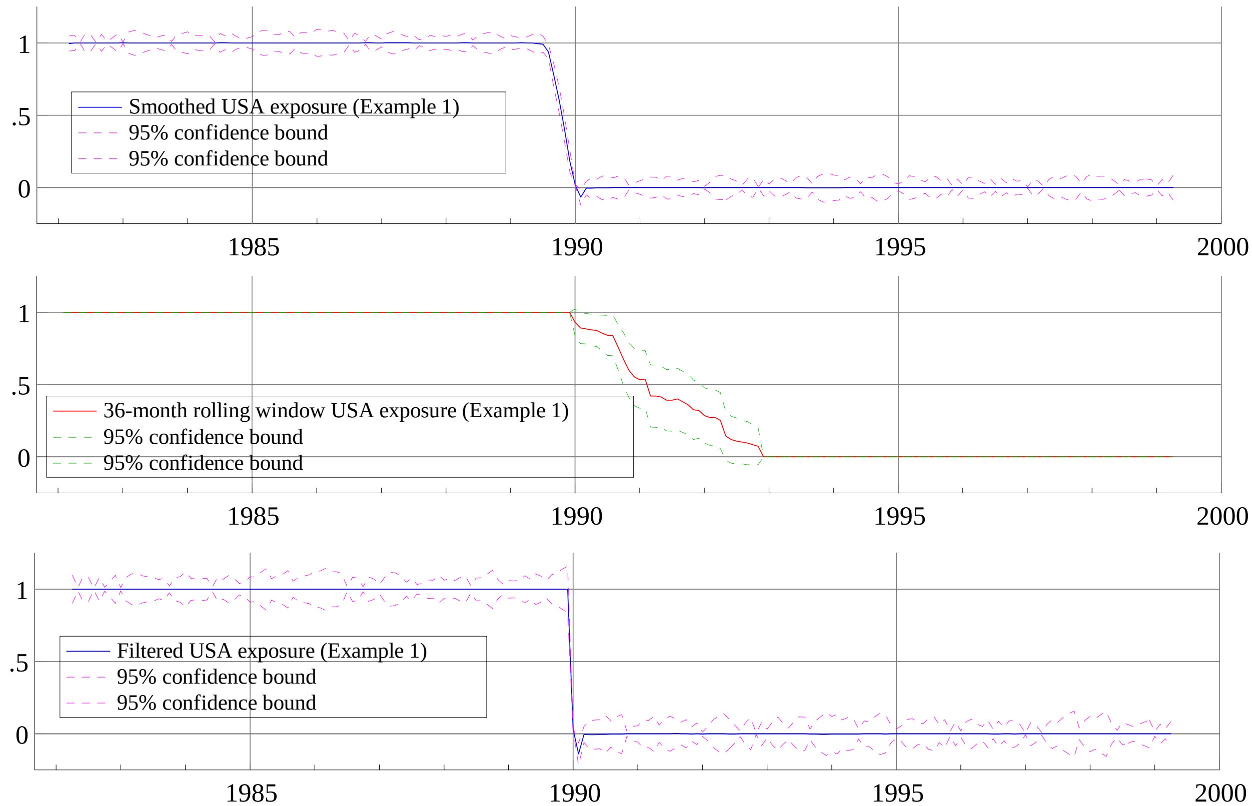


Figure 1: Exposures for the regional style index USA for the artificial fund which invests all its assets in the MSCI USA from May 1979 to December 1989 and in the MSCI Europe from January 1990 to April 1999. The top panel displays the exposure estimates of the random walk model using Kalman smoothing. The middle panel graphs the 36-month rolling regressions. The bottom panel displays the exposure estimates using Kalman filtering. All panels contain 95% confidence levels for the estimated parameters.

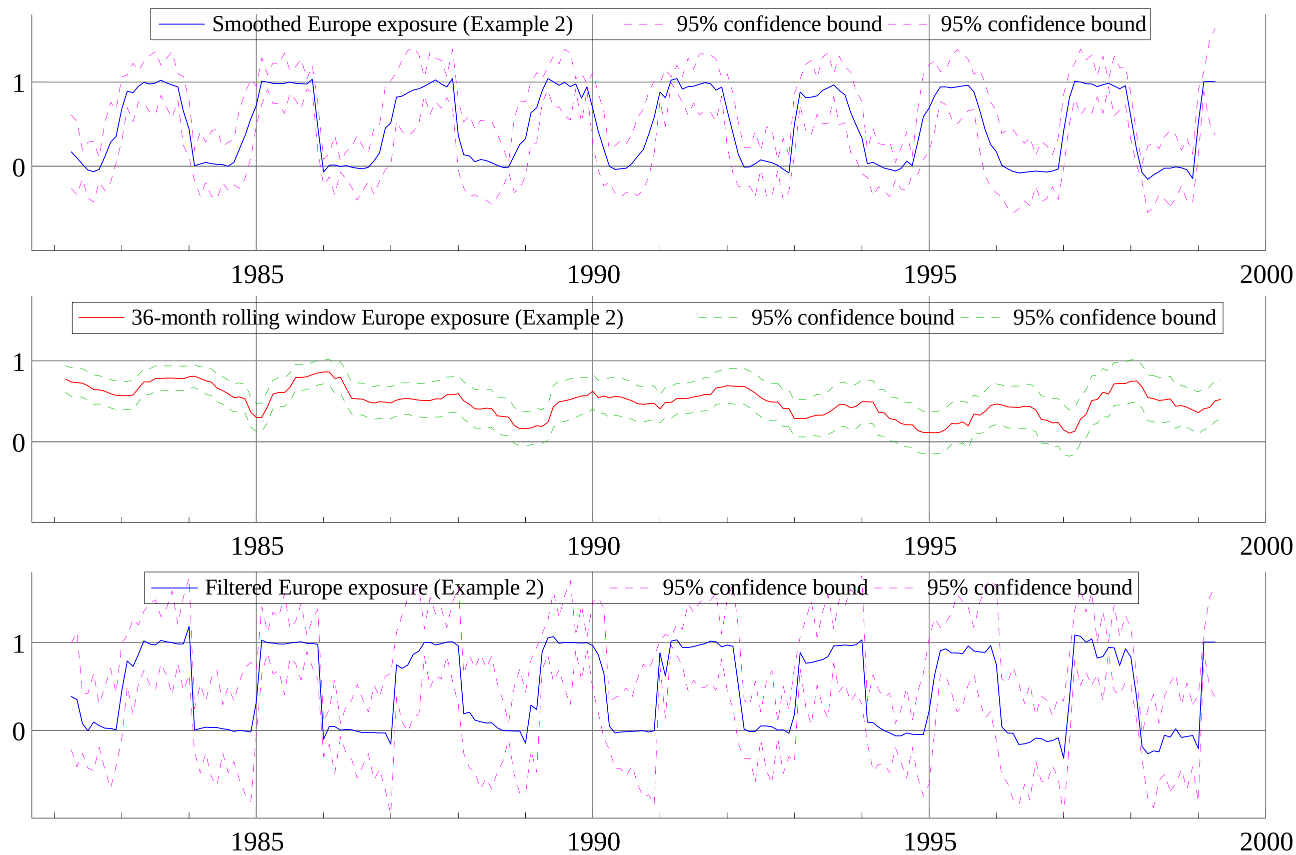


Figure 2: Exposures for the regional style index Europe for the artificial fund which invests all its assets in the MSCI Europe in odd years and all its assets in the MSCI Pacific in even years during the period May 1979 and April 1999. The top panel displays the exposure estimates of the random walk model using Kalman smoothing. The middle panel graphs the 36-month rolling regressions. The lower panel displays the exposure estimates using Kalman filtering. All panels contain 95% confidence levels for the estimated parameters.

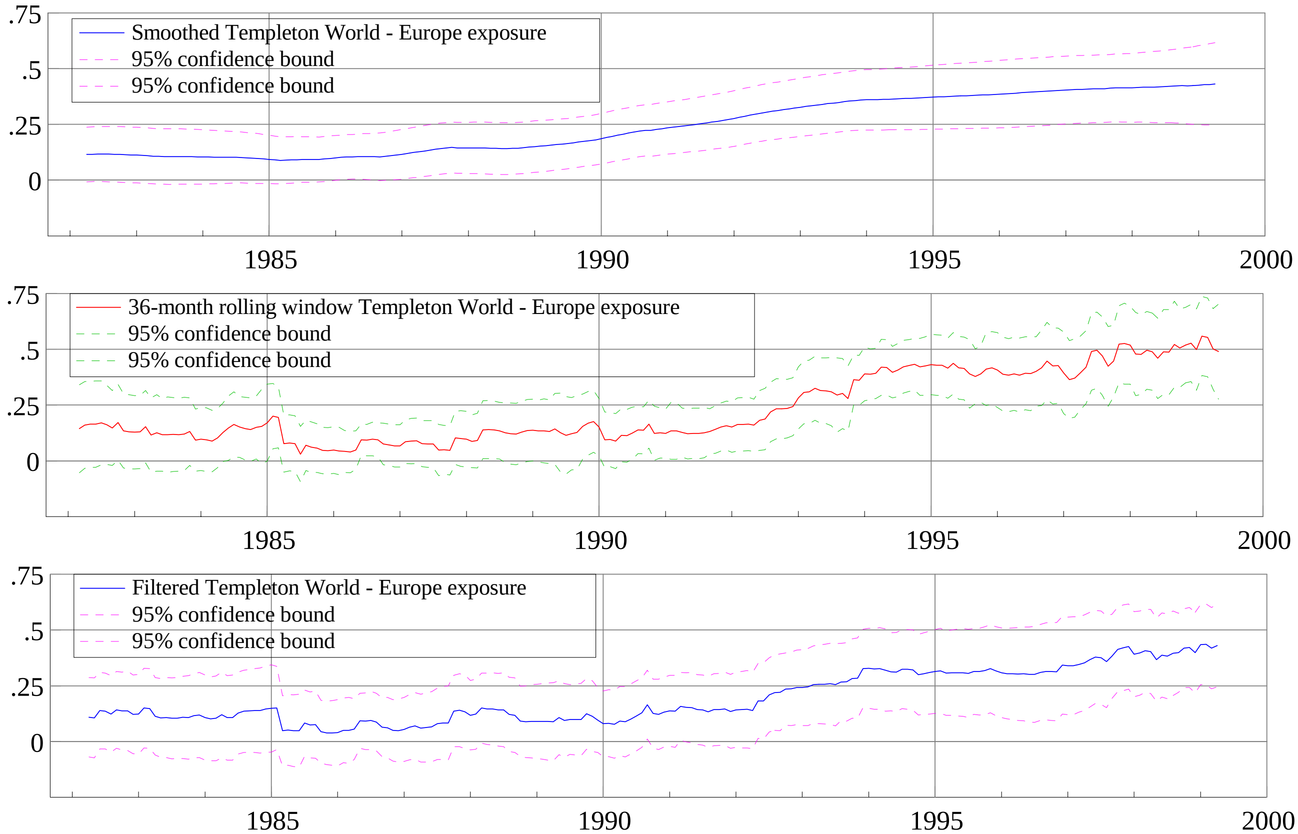


Figure 3: Exposure for the regional style Europe for the Templeton World fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The top panel displays the exposure estimates of the random walk model using Kalman smoothing. The middle panel graphs the 36-month rolling regressions. The bottom panel displays the exposure estimates using Kalman filtering. All panels contain 95% confidence levels for the estimated parameters.

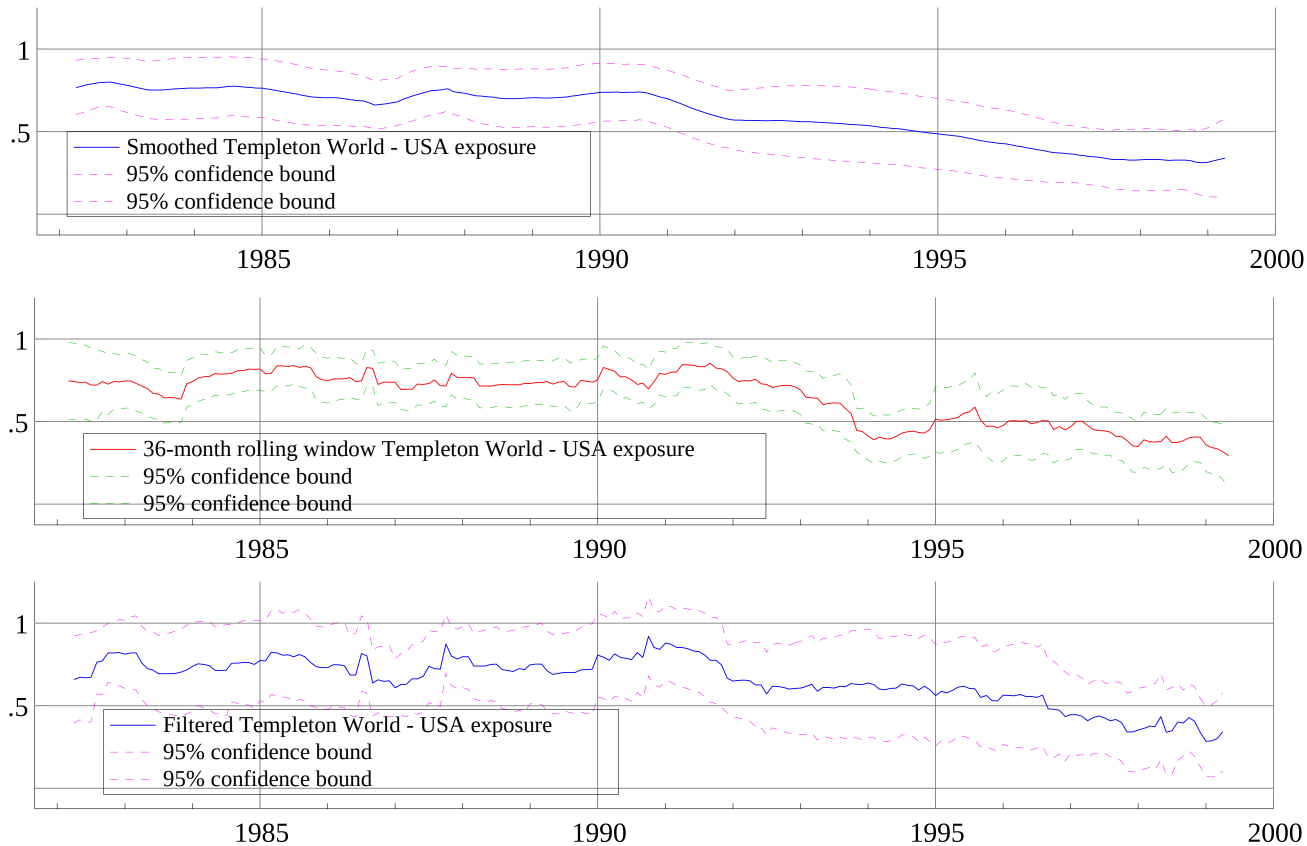


Figure 4: Exposure for the regional style USA for the Templeton World fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The panel above displays the exposure estimates using Kalman smoothing. The panel below graphs the 36-month rolling regressions. Both panels contain 95% confidence levels for the estimated parameters.

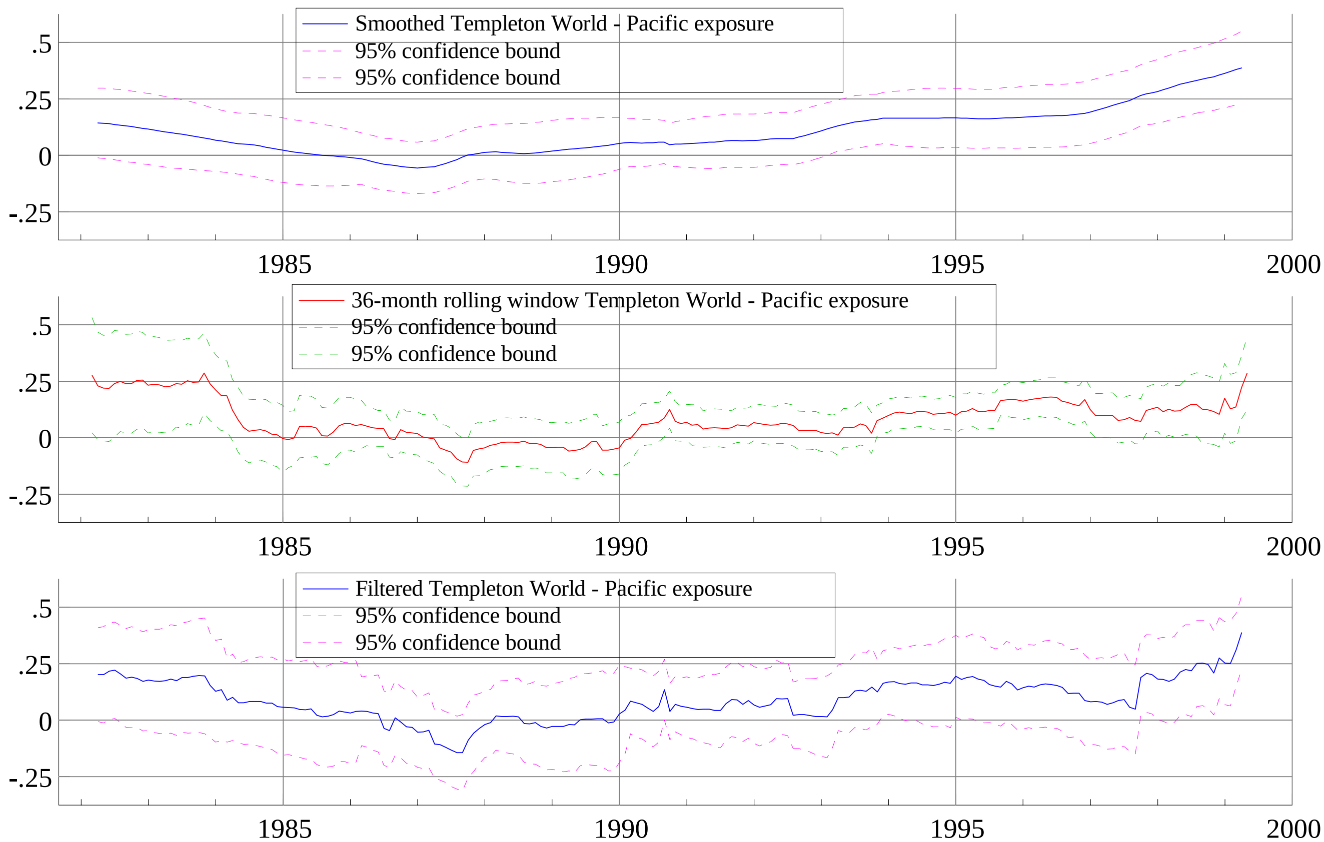


Figure 5: Exposure for the regional style Pacific for the Templeton World fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The top panel displays the exposure estimates of the random walk model using Kalman smoothing. The middle panel graphs the 36-month rolling regressions. The bottom panel displays the exposure estimates using Kalman filtering. All panels contain 95% confidence levels for the estimated parameters.

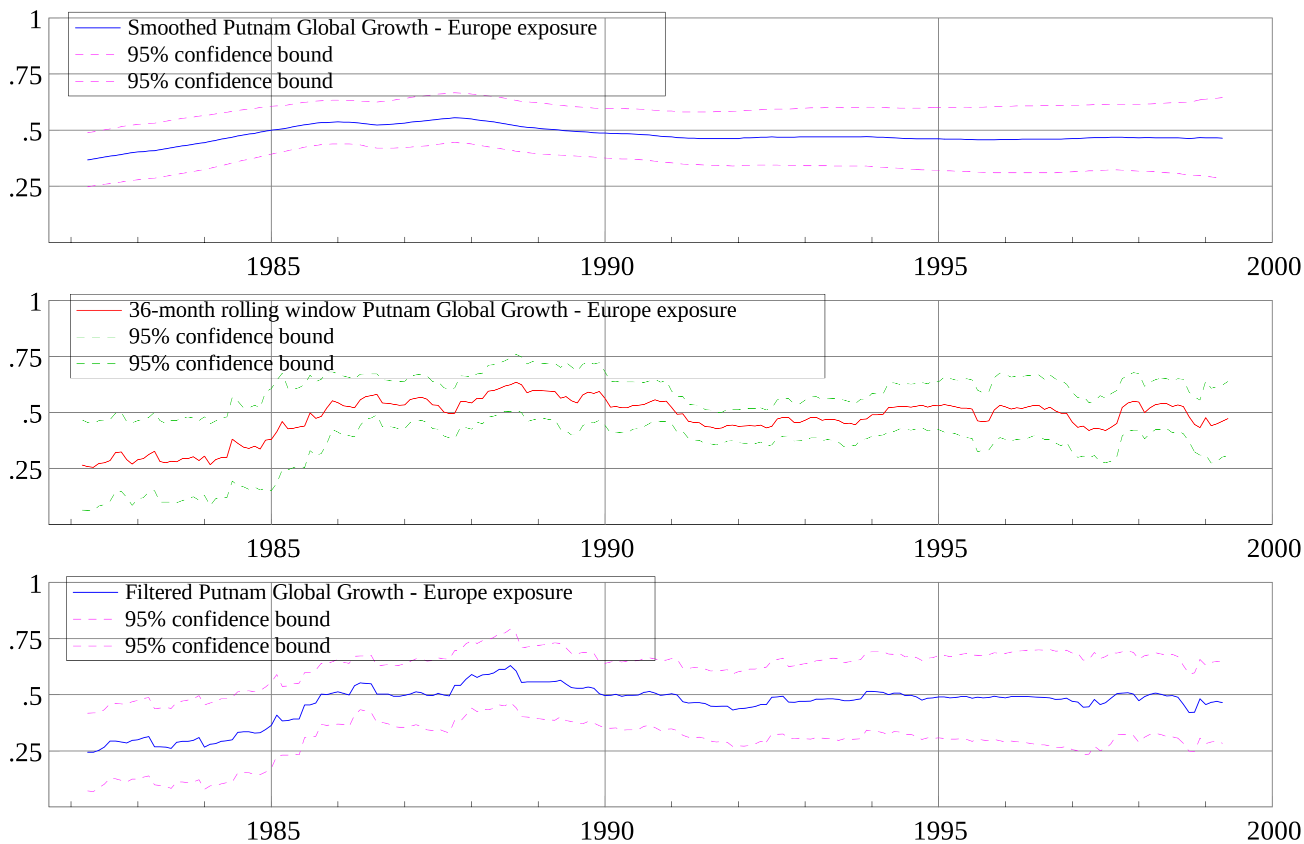


Figure 6: Exposure for the regional style Europe for the Putnam Global Growth fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The top panel displays the exposure estimates of the random walk model using Kalman smoothing. The middle panel graphs the 36-month rolling regressions. The bottom panel displays the exposure estimates using Kalman filtering. All panels contain 95% confidence levels for the estimated parameters.

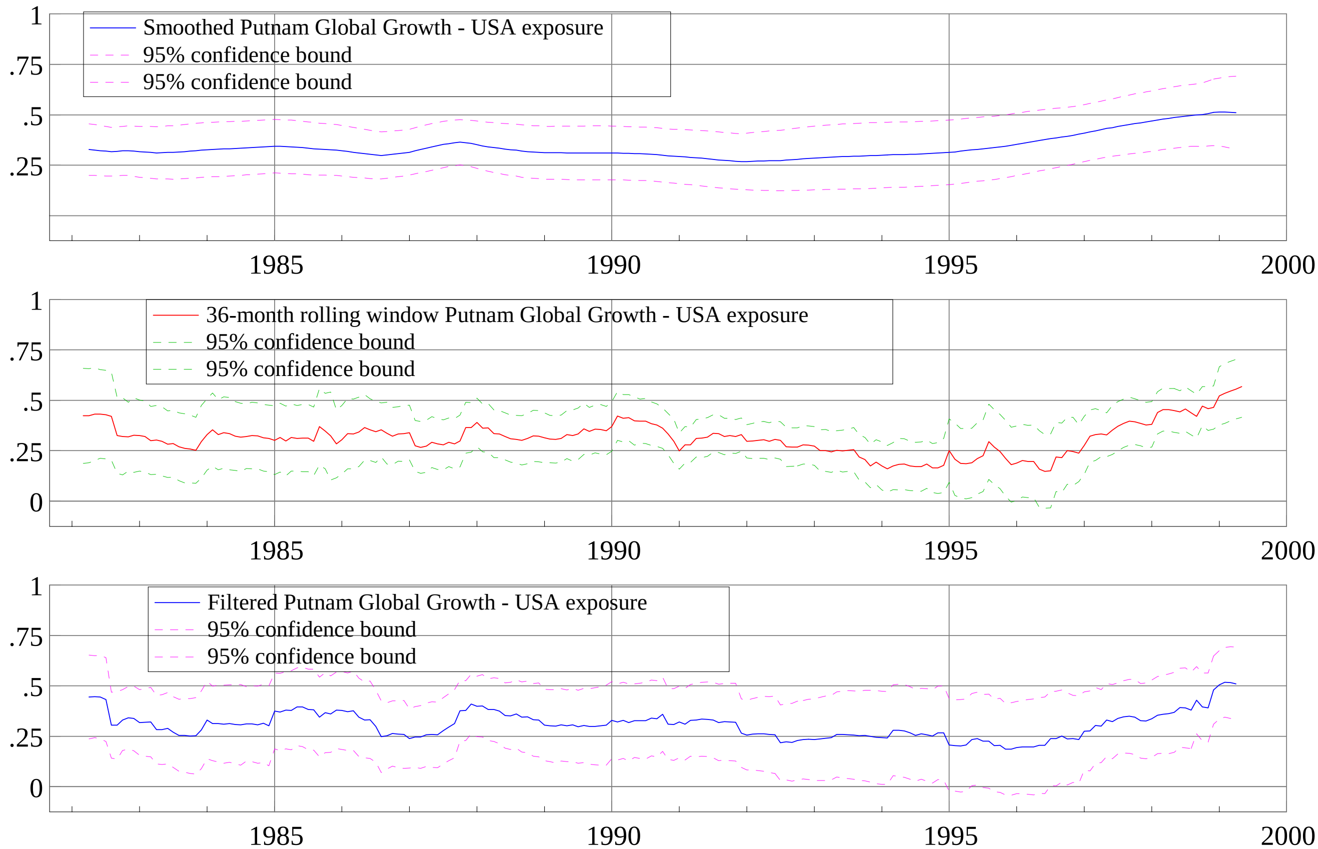


Figure 7: Exposure for the regional style USA for the Putnam Global Growth fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The top panel displays the exposure estimates of the random walk model using Kalman smoothing. The middle panel graphs the 36-month rolling regressions. The bottom panel displays the exposure estimates using Kalman filtering. All panels contain 95% confidence levels for the estimated parameters.

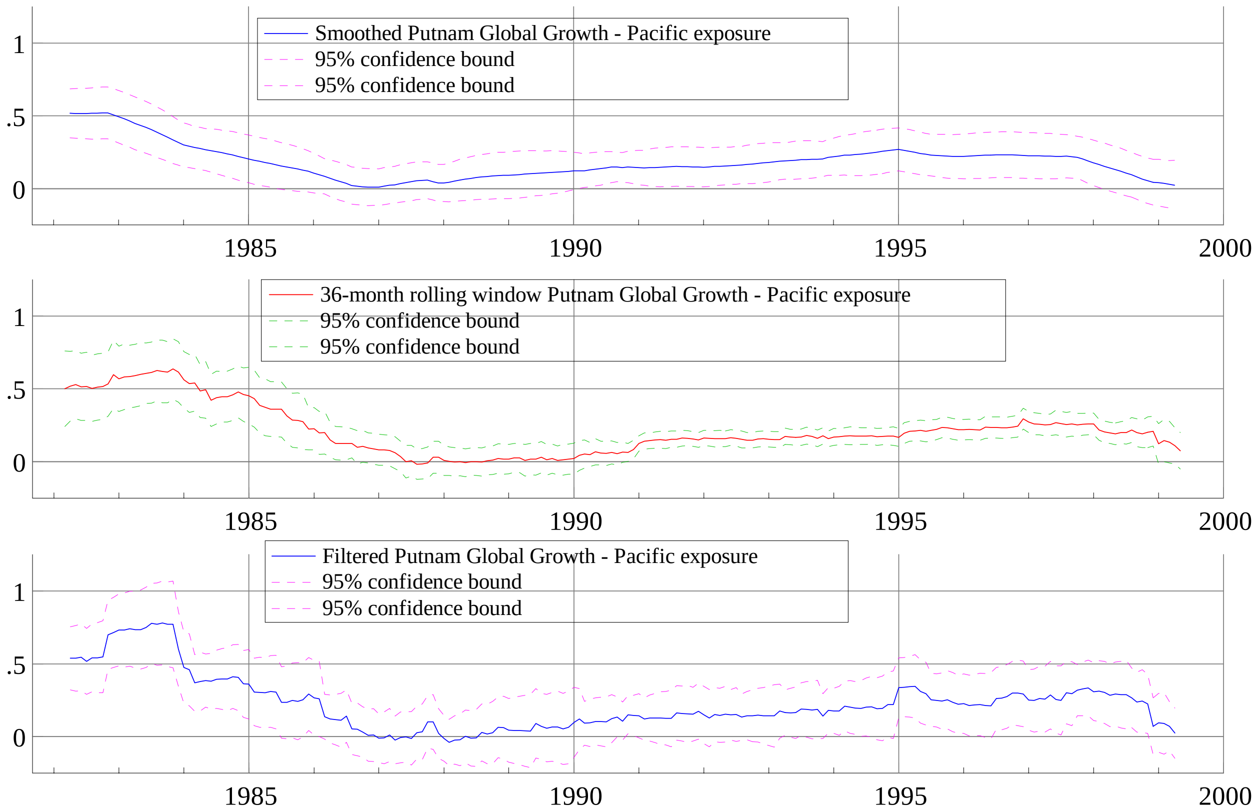


Figure 8: Exposure for the regional style Pacific for the Putnam Global Growth fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The panel above displays the exposure estimates using Kalman smoothing. The panel below graphs the 36-month rolling regressions. Both panels contain 95% confidence levels for the estimated parameters.

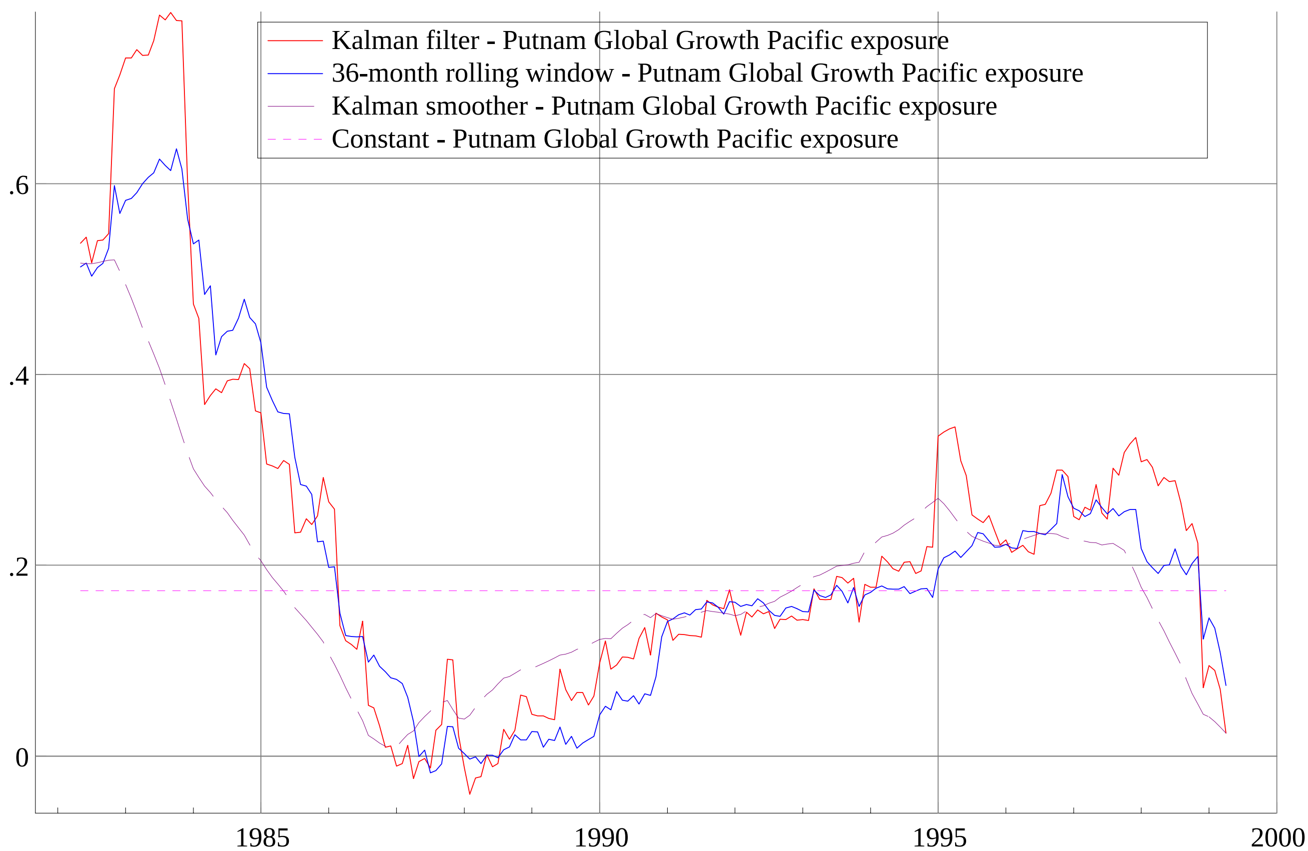
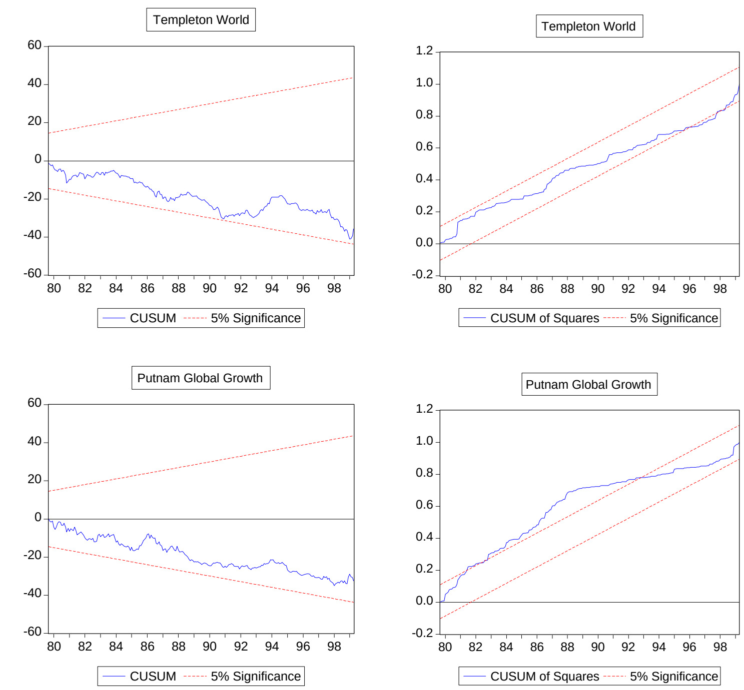


Figure 9: Exposure for the regional style Pacific for the Putnam Global Growth fund over the period 1982 to 1999. The parameters are estimated using the full sample, May 1979 to April 1999. The dotted magenta line marks the constant exposure estimated by OLS. The blue line marks the 36-month rolling window regressions. The red line marks the random walk model estimated by the Kalman filter, the dashed dark purple line marks the same model estimated by the Kalman smoother.

A Tests for coefficient stability



Two tests for coefficient stability, CUSUM and CUSUMSQ. If the line goes outside the confidence lines, this casts doubt on the stability of the parameters. The regression equation estimated is $R_t^p - R_t^f = \alpha + \beta_1 \left(R_t^{EUR} - R_t^f\right) + \beta_2 \left(R_t^{US} - R_t^f\right) + \beta_3 \left(R_t^{PAC} - R_t^f\right) + \varepsilon_t$.

Name of Fund	Jan-1985	Jan-1990	Jan-1995
Templeton World	0.088	0.000	0.000
Putnam Global Growth	0.000	0.880	0.090

Chow test for parameter stability. The table displays the p-levels associated with the F-statistic for the model $R_t^p - R_t^f = \alpha + \beta_1 \left(R_t^{EUR} - R_t^f\right) + \beta_2 \left(R_t^{US} - R_t^f\right) + \beta_3 \left(R_t^{PAC} - R_t^f\right) + \varepsilon_t$ at three breakpoints. A low p-level indicates parameter instability.