

# ***STYLE BREAKS***

## ***IN RETURN-BASED STYLE ANALYSIS***

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### **ABSTRACT**

Despite the wide acceptance of return-based style analysis, the method has several limitations. One important drawback is the underlying assumption that the style exposures do not vary over time. In general, little attention was devoted to examining whether this hypothesis is acceptable, although a number of studies have documented that time variation in style exposure does occur. We apply results on break tests established in Andrews and Ploberger (1994), Hansen (1997) and Bai and Perron (1998, 2001) to examine profoundly the possibility of style breaks. We find strong evidence against the hypothesis of constant time exposures in time in daily return data of European equity funds. All funds exhibit at least one break, while 60% of the funds exhibit even more than one break. The style breaks may be induced by economic motives or may be related to other factors such as changes in management structure. A comparison of the number of breaks in the standard style analysis and an extended model where one additional variable capturing an economic motive is added, reveals that the most promising pursuit for explaining (the majority of) style breaks is to be found in economic motives.

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## 1. Introduction

Return-based style analysis (RBSA hereafter) has become a popular tool in analyzing mutual fund returns and investment objectives. The method was introduced by Sharpe (1988, 1992) as a tool to determine the effective asset mix of a mutual fund. Originally, RBSA boils down to estimating a constrained regression in order to determine the exposure of the historical mutual fund returns to different factors (returns on asset classes). The principal goal of RBSA is to find the best mimicking strategy that is in accordance with the investment style of the mutual fund.

The interest in RBSA was fuelled by difficulties, faced by investors and the management companies distributing funds, in determining the actual mutual fund investment objective and investment behavior. Empirical evidence on misclassification reported by Brown and Goetzmann (1997), Kim, Shukla, and Thomas (2000) or diBartolomeo and Witkowski (1997), corroborate that deviations between the actual investment style and the one reported in the prospectus or by the data vendor do occur in a substantial amount of funds.

In comparison to characteristic-based style analysis, RBSA has a number of advantages to gain insight in the actual investment policy. As the former relies on actual portfolio holdings and thus analyses the stocks held in mutual fund portfolios [e.g. Daniel, Grinblatt, Titman and Wermers (1997), Chan, Chen and Lakonishok (1999) or Wermers (2000)], its main drawback is that mutual fund holdings are in most cases not readily available. Furthermore, they are generally only available on a quarterly basis and timely information on holdings may be difficult to obtain. Moreover, if mutual fund managers commit window dressing practices, inferences from reported portfolio holdings might be misleading. In contrast, by regressing fund return on returns of selected passive style indices, RBSA relies only on abundantly available historical return data, which makes it an attractive tool from a practical point of view. Chan, Chen and Lakonishok (1999) compare the two approaches and conclude that in general they give similar results on the fund's style. However, in the cases where the two approaches yield different results, the characteristics-based approach is better in predicting future fund performance.

RBSA has become a widely accepted analytic tool, both by academics and practitioners. Besides problems related to misclassification, RBSA has been employed to address issues concerning performance evaluation and object gaming of mutual funds [see for instance Sharpe (1992) or de Roon, Nijman and ter Horst (2000)], construction of diversified portfolios or efficient portfolios of mutual funds with specified factor loadings [de Roon, Nijman and ter Horst (2000)], short term risk assessment of a mutual fund manager [Sortino, Miller, and Messina (1997)] and hedge fund style and risk evaluation [e.g. Fung and Hsieh (2002), Schneeweis and Spurgin (1998) or

L'Habitant (2002)]. Object gaming refers to the practice of deliberately deviating from the stated objective to attain higher relative performance.

Despite this wide acceptance, RBSA has in its original form a number of drawbacks and limitations. The main problems can be traced to the choice of the asset classes, estimation of confidence intervals of style exposures, the restrictions imposed in view of the purpose of RBSA, and the underlying hypothesis of constant style exposures in time. While we discuss briefly the former potential pitfalls in section 2, the main focus of this paper is the assumption that style exposures are constant over the period studied. Indeed, a number of papers have documented that style changes over time do occur [see e.g. Chan, Chen and Lakonishok (1999), Kim, Shukla and Thomas (2000), or Swinkels and Van Der Sluis (2001)]. Style breaks may be motivated by economic reasons like market timing, herding or portfolio alteration in anticipation of changing economic conditions. They may also be induced by changes in the mutual fund management structure. When a new mutual fund is introduced, it will usually not have the critical size to justify a separate fund manager. As a consequence, managers will monitor a number of funds and will be lured into managing them in a similar fashion, despite divergent investment objectives. If a fund attains the critical size, it will be entrusted to a single manager who is better placed to follow a unique investment strategy for the fund in line with the investment objective. If a successful fund's size shrinks below the critical size, the process will be reversed. The switch in managers may induce a sudden style change.

In this paper, we contribute to the existing discussion on RBSA-methodology by conducting a profound analysis on the nature of the time variation in exposures. As preliminary descriptive statistics indicate that style exposures of European equity funds may be important, we formally test for breaks in the estimated style exposures by employing the testing framework described in Andrews and Ploberger (1994), Hansen (1997) and Bai and Perron (1998, 2001). This framework has the advantage that it enables testing for breaks at a priori *unknown* break dates. Moreover, the tests suggested by Bai and Perron enable us to test for multiple breaks quite easily. For every fund in our sample we find evidence of at least one style break, and for many funds (60%) even multiple breaks. Therefore, we try to gain insight in the motivation that drives these breaks. Due to a lack of data on mutual fund managers, we can regrettably not test the hypothesis that the style breaks are induced by changes in the management of the fund empirically. Given the aforementioned reasoning it is unlikely that a switch of managers occurs frequently. Therefore, a high number of significant breaks over the sample period is at least indirect evidence against the hypothesis that the style break(s) is (are) only motivated by substitutions in mutual fund management structure. In the spirit of Ferson and Schadt (1996) we therefore acknowledge that

fund managers rebalance their portfolios in anticipation of changing economic conditions. In our extended style analysis, we express style exposures as linear functions of information variables that proxy for changes in the investment opportunity set. This approach has two pitfalls. First, this formulation is probably too unsophisticated to be realistic. Second, due to data limitations we can include only one information variable at a time, and it is unlikely that a single variable is able to capture all the style breaks. Yet, we do find that when exposures are allowed to vary in such a simple way, a significant reduction in the number of breaks per fund is noticeable. This clearly indicates that an adequate style analysis should allow for time-varying exposures, a result consistent with the performance evaluation literature.

Besides the profound analysis of the style exposures, there are two noticeable features of our empirical analysis worth mentioning. Firstly, the set-up of the empirical part is distinct from other existing studies in that it uses daily input instead of generally applied monthly data. The higher frequency of the data opens up the opportunity to grasp a more detailed picture of the time varying nature in style exposures, given that we are able to pick up intra-month style variation. Secondly, we focus on funds with 'European equity' as investment objective and that are distributed in Belgium. By studying a sub-market of the European mutual fund industry we contribute to the sparse (but growing) empirical evidence on this industry. The European mutual fund industry is the second largest market after the American mutual fund market.

The remainder of this paper is organized as follows. Section 2 gives a short overview of RBSA and its pitfalls. In section 3 the testing procedure for structural breaks is described. Our dataset and selection procedures are introduced in section 4. The empirical results are presented in section 5. Finally, we conclude.

## 2. Literature Review, Methodology and Limitations of RBSA

The econometric model proposed by Sharpe is part of the general class of factor models and is often written as:

$$(1) \quad R_{jt} = \alpha_j + \sum_{i=1}^K \beta_{ji} R_{it} + \varepsilon_{jt} \quad \text{with } t = 1, \dots, T \text{ and } \mathbb{E}[\varepsilon_{jt} R_{it}] = \mathbb{E}[\varepsilon_{jt}] = 0 \quad \text{for } i = 1, \dots, K,$$

subject to:

$$(2) \quad \sum_{i=1}^K \beta_{ji} = 1 \quad \text{and}$$

$$(3) \quad \beta_{ji} \geq 0 \quad \text{with } i = 1, \dots, K,$$

where  $R_{ft}$  is the return on fund  $f$  for the period ending at  $t$ ,  $R_{it}$  denotes the return on asset class  $i$ ,  $K$  is the number of asset classes,  $\varepsilon_{ft}$  is the idiosyncratic noise term, and  $\beta_{fi}$  is fund  $f$ 's factor exposure w.r.t. factor  $i$ . Because of the first restriction (2), which is also called the portfolio restriction,  $\sum_{i=1}^K \beta_{fi} R_{it}$  can be interpreted as the return on a passive portfolio with the same investment style as the fund. The second restriction (3) represents the short-selling restriction in this model. A feature of the model is that it decomposes a fund's return into a component that is attributable to style, given by  $\sum_{i=1}^K \beta_{fi} R_{it}$ , and an idiosyncratic return component, given by  $\alpha_f + \varepsilon_{ft}$ . With respect to the implementation of the original model a number of prerequisites, shortcomings, and pitfalls have surfaced in the relevant literature. In the following paragraphs we will briefly sketch the main issues.

First of all, the proper implication of the original model asks for asset classes that are mutually exclusive, linearly independent and exhaustive (in the sense that the asset factor model should be able to span the fund's portfolio asset mix). [Sharpe (1992), Lobosco and diBartolomeo (1997), de Roon, Nijman and ter Horst (2000)]. Highly correlated asset classes should be avoided, since they capture essentially the same style characteristics. Moreover, Bueton, Johnson, and Runkle (2000) argue that the outcome of the style analysis is sensitive to the chosen asset classes. For instance, they report that the style exposures change substantially depending on whether the Russell 2000 Growth index or the BGI Small Cap Growth index is used in the model. Both indices are generally viewed as representing the same style and are strongly correlated (0.99), see also Brown and Mott (1997). Ideally, we would apply ordinary style analysis only if the fund's assets are indexed to well-prescribed indices [Bueton, Johnson, and Runkle (2000)], create fund specific asset classes [Bailey (1992a,b)] or combine RBSA with fundamental information on the securities in the fund's portfolio [Lucas and Riepe (1996)]. In all other instances, it is advisable to examine the extent to which the results are driven by factor choice by means of sensitivity testing. We implement this recommendation in our research by evaluating the impact of alternative indices on the results of the basic model. Furthermore, to ensure that our results are not determined by the data vendor's classification scheme [see Gallo and Lockwood (1997)], we employ the classification put forward by two different data vendors. The main conclusions remain unaltered, so the results of the sensitivity analysis are not presented to save space.

Secondly, because of the restrictions (2) and (3), the original RBSA-model is usually estimated by quadratic programming. This implies that exposure estimates are not necessarily unbiased. Biased estimates occur when not all asset classes the fund invests in are represented in (1) or when the

investments are inaccurately taken into account by the adopted asset class indices. In addition, confidence intervals are not readily available as in OLS-estimation. Although other papers have quantified the biases induced by the constraints [de Roon, Nijman, and ter Horst (2000)] or have proposed solutions to the statistical accuracy of the exposure estimates [Lobosco and diBartolomeo (1997), Kim, Stone and White (2000) and Otten and Bams (2000b)], we prefer in this paper not to impose the restrictions. By estimating the exposures freely, we want to avoid any interference with the focus of our paper, namely the potential time-variation of style exposures. The paper that is most closely related to our research, Swinkels and Van Der Sluis (2001), also endorses to this approach.

Indeed, the third potential drawback of the standard RBSA-model is the implicit assumption that the sensitivities to the factors remain fixed over the sample period. In reality, style changes in time have been documented [see e.g. Chan, Chen and Lakonishok (1999), Kim, Shukla and Thomas (2000), or Swinkels and Van Der Sluis (2001)]. To visualize the time-varying property of style coefficients, it is common practice to estimate Sharpe's model over rolling windows [Sharpe (1992), Lucas and Riepe (1996) and Buetow, Johnson, and Runkle (2000)]. It is then possible to graph the style exposures through time. This approach might help to establish a first impression of the time variation of style coefficients. Nevertheless, one still assumes that the sensitivities are constant over the arbitrarily chosen length of the rolling window. Besides, the approach of overlapping rolling windows and the fact that every observation is equally weighted cause a delay in the recognition of a style change. Swinkels and Van Der Sluis (2001) perform the CUSUM (CUSUMQ) and Chow tests for coefficient stability. However, the CUSUM (CUSUMQ) tests are based on residuals from recursive estimation and have been criticized of having low statistical power [e.g. Andrews, Lee and Ploberger (1996) or Greene (2000)]. For the Chow test the sample is split into two. Subsequently, the parameters are estimated for each sub-period and the equality of the two sets of parameters is tested using an F-test. A major drawback of this procedure is that it is only applicable if the break date is known a priori. Moreover, the procedures cannot be used to test simultaneously for multiple breaks. Swinkels and Van Der Sluis (2001) decide to model explicitly the time-varying exposures by applying a Kalman smoother. The approach is suited to model smooth changes in time. Nonetheless, there is no a priori reason to assume that only smooth changes take place. If the Kalman smoother technique is applied, the complete data sample is used to estimate the model, instead of a subset of historical returns (which is used in the rolling window approach). In the following section, we will discuss relatively recent test procedures that are able to test for multiple breaks as well as for breaks with unknown break dates. We will also introduce how we will model time-variation in style exposures.

### 3. Research Design and Methodology

The literature on issues related to structural breaks is comprehensive, primarily aimed towards the treatment of a single break (see e.g. Krisnaiah and Miao (1988) for a survey). Recent papers derive procedures to deal with a single break or multiple breaks at (an) *unknown* date(s) in various models. If we are faced with a single a priori unknown break date, the  $\chi^2$ -distribution cannot be used to assess statistical significance of the Quandt (1960) statistic. The Quandt-test selects the largest Chow statistic over all possible break dates. Appropriate test statistics and critical values are proposed by a number of authors including Andrews (1993) and Andrews and Ploberger (1994), while Hansen (1997) derives the approximate asymptotic p-values.

In the empirical part we report the results based on the Andrews and Ploberger (1994) Exp test as well as the Hansen (1997) p-values. In general, the Exp structural change test and distribution can be summarized as follows [Hansen (1997)]. Consider the standard (unrestricted) RBSA model (1) in matrix notation:

$$(4) \quad \mathbf{r} = \mathbf{R}\boldsymbol{\beta} + \mathbf{e},$$

where  $\mathbf{r} = (R_{f1}, \dots, R_{fT})'$ ,  $\mathbf{R} = (\mathbf{r}_1, \dots, \mathbf{r}_T)'$ ,  $\mathbf{r}_t = (1, R_{1t}, \dots, R_{Kt})'$ ,  $\boldsymbol{\beta} = (\alpha_f, \beta_{f1}, \dots, \beta_{fK})'$ , and  $\mathbf{e} = (\varepsilon_{f1}, \dots, \varepsilon_{fT})'$ .

The null hypothesis that will be investigated is that  $\boldsymbol{\beta}$  is constant through time. The alternative hypothesis is that there are  $m+1$  regimes during which fund exposures have values  $\boldsymbol{\beta}^{(j)}$ ,  $j = 1, 2, \dots, m+1$ :

$$(5) \quad \mathbf{r} = \mathbf{R}^* \boldsymbol{\beta}^* + \mathbf{e}, \quad t = T_{j-1} + 1, \dots, T_j,$$

where  $\boldsymbol{\beta}^* = (\boldsymbol{\beta}^{(1)'}, \dots, \boldsymbol{\beta}^{(m+1)'})'$  and  $\mathbf{R}^*$  diagonally partitions  $\mathbf{R}$  at the break dates  $(T_1, \dots, T_m)$ , i.e.  $\mathbf{R}^* = \text{diag}(\mathbf{R}_1, \dots, \mathbf{R}_{m+1})$  with  $\mathbf{R}_i = (\mathbf{r}_{T_{i-1}+1}, \dots, \mathbf{r}_{T_i})'$ . Note that by definition we set  $T_0 = 0$  and  $T_{m+1} = T$ .

The Quandt-test tests the hypothesis that the parameter vector  $\boldsymbol{\beta}$  is constant against the alternative that it changes at an unknown break date  $\tau$ , i.e. there are only two regimes ( $m=1$ ). It is the maximum Chow test over all possible break dates  $K+1 \leq \tau \leq T-K-1$ . Given that the single breakdate is a priori unknown, the  $\chi^2$ -distribution cannot be used to assess statistical significance of the Quandt (1960) statistic, the results of Andrews and Ploberger (1994) can be used to derive the distribution of the Quandt-test (the sup-test in the parlance of Andrews and Ploberger) as well as the distribution of the related Exp-test. Let  $F_T(\tau)$  connote any Wald, Lagrange multiplier, or likelihood ratio statistic of the hypothesis of no structural change ( $\boldsymbol{\beta}^{(1)} = \boldsymbol{\beta}^{(2)}$ ) for given break date  $\tau$ . When the break date lies in the range  $[\tau_1, \tau_2]$ , the sup-test is:

$$(6) \quad \text{Sup}F_T = \sup_{\tau_1 \leq \tau \leq \tau_2} F_T(\tau),$$

and the Andrews and Ploberger  $\text{Exp}F_T$  test is

$$(7) \quad \text{Exp}F_T = \ln \left( \frac{1}{\tau_2 - \tau_1 + 1} \sum_{\tau=\tau_1}^{\tau_2} \exp \left( \frac{1}{2} F_T(\tau) \right) \right).$$

The asymptotic null distribution is given by:

$$(8) \quad \text{Exp}F_T \xrightarrow{d} \text{Exp}F(\pi_0) = \ln \left( \frac{1}{\pi_2 - \pi_1} \int_{\pi_1}^{\pi_2} \exp \left( \frac{1}{2} F(\tau) \right) d\tau \right)$$

$$\text{with } F(\tau) = \frac{(\mathbf{W}(\tau) - \tau \mathbf{W}(1))' (\mathbf{W}(\tau) - \tau \mathbf{W}(1))}{\tau(1-\tau)},$$

where  $\mathbf{W}(\tau)$  is an  $m \times 1$ -vector Brownian motion,  $\pi_i = \tau_i/T$ . The asymptotic distributions are non-standard and depend upon the number of parameters tested and the range of the sample that is examined for the break date. Given the non-standard nature of the test statistics, an elegant way to make inferences on the significance of the break results is to rely on the convenient approximate asymptotic p-values derived in Hansen (1997). In the empirical part, we test whether there is a single break in the entire parameter vector associated with RBSA.

When the alternative hypothesis is that multiple breaks are possible, the procedure outlined in Bai and Perron (1998, 2001) can be used. Bai and Perron (1998) focus on estimating multiple structural changes in a linear model that is estimated by least-squares and the limiting distribution of estimators and test statistics are derived. The practical issues concerning the implication of the procedure are outlined in Bai and Perron (2001). The general idea is to estimate the model under the alternative hypothesis for every  $m$ -partition of the time period studied. The estimates of the parameters and the break dates are obtained for the partition that minimizes the sum of squared residuals. Bai and Perron use insights from dynamic programming to avoid the computational burden to actually estimate the regression for every  $m$ -partition.

In section 5 we estimate for every individual fund a pure change models. We employ two test procedures. First, we verify if at least one break is present. The first procedure tests the null hypothesis of no structural break against an unknown number of breaks, given some upper bound  $M$  using the  $UD\text{max}F_T(M, K+1)$  test:

$$(9) \quad UD\text{max}F_T(M, K+1) = \max_{1 \leq m \leq M} F_T(\hat{\lambda}_1, \dots, \hat{\lambda}_m; K+1) \text{ with } \hat{\lambda}_j = \hat{T}_j/T \quad (j=1, \dots, m).$$

The estimates of the break dates  $\hat{T}_j$  are obtained from the global minimization of the sum of squared residuals.  $F_T(\hat{\lambda}_1, \dots, \hat{\lambda}_m; K+1)$  is therefore equal to the  $\text{Sup}F_T$  test of Andrews and

Ploberger (1994). In our empirical applications, we set the upper bound to 5. Second, if we find evidence of at least one break based on the  $UD\max F_T(M, K+1)$  test, we examine the number of breaks based on the sequential test for  $m$  versus  $m+1$  breaks. The procedure boils down to applying  $m+1$  tests of the null hypothesis of no structural change versus the alternative hypothesis of a single change. The test is applied to each segment containing the observations  $\hat{T}_{i-1}$  to  $\hat{T}_i$  ( $i=1, \dots, m+1$ ). The model with  $m+1$  breaks is rejected in favor of the model with  $m$  breaks if the overall minimal value of the sum of squared residuals is sufficiently smaller than the sum of squared residuals from the model with  $m$  breaks. Bay and Perron denote this test by  $\text{Sup}F_T(m+1|m)$ .

If we do find evidence of style breaks, the next step is to investigate whether these are due to changing economic conditions. As indicated in the introduction, we do not have data on mutual fund managers to test if the style breaks coincide with changes in the management structure. Therefore we rely on a different approach that is inspired by Ferson and Schadt (1996) and Christoperson, Ferson, and Turner (1999). Their focus is on performance evaluation. They argue that measures of conditional performance such as Jensen's alpha are biased when fund managers change their portfolio composition in response of predictable changes in the investment opportunity set. They model these changes by making the fund's exposures to asset classes linear functions of public information variables. The way in which we implement the insights of their approach can best be illustrated as follows. Take one observation from model (4):

$$(10) \quad R_{jt} = \mathbf{r}'_t \boldsymbol{\beta}_t + \varepsilon_{jt},$$

where now the parameter vector has an explicit time index. We assume that time variation in the parameters is determined by an  $L \times 1$  information vector  $\mathbf{z}_t$ :

$$(11) \quad \boldsymbol{\beta}_t = \boldsymbol{\Gamma} \mathbf{z}_t,$$

where  $\boldsymbol{\Gamma}$  is a  $(K+1) \times L$  coefficient matrix and the first information variable is by construction a constant. Eq. (10) can then be rewritten as follows:

$$(12) \quad R_{jt} = \text{vec}(\boldsymbol{\Gamma})' (\mathbf{r}_t \otimes \mathbf{z}_t) + \varepsilon_{jt},$$

where  $\text{vec}(\cdot)$  stacks columns vertically and  $\otimes$  denotes the Kronecker product. Alternatively, as both  $\mathbf{x}_t$  and  $\mathbf{z}_t$  contain a constant, a reformulation is:

$$(13) \quad R_{jt} = \mathbf{r}'_t \boldsymbol{\gamma}^{(1)} + \mathbf{x}'_t \boldsymbol{\gamma}^{(2)} + \varepsilon_{jt},$$

where  $\mathbf{x}_t \equiv \mathbf{r}_t \otimes \tilde{\mathbf{z}}_t$ , and  $\tilde{\mathbf{z}}_t$  is  $\mathbf{z}_t$  without the constant term.

In a similar vein, we extend the traditional style equation by factors representing economic motives. If the style breaks are fuelled by economic considerations, the standard style coefficients

in the extended model should be free of breaks. This hypothesis can be tested by estimating a partial break model in which only the standard coefficients  $\gamma^{(1)}$  are allowed to vary. The testing procedure outlined above can be adopted for testing stability of a subset of coefficients in a straightforward manner. However, a practical problem that arises is that the number of regressors in the extended style analysis goes up quickly, due to the interaction terms taken up in the regression. Consequently, the multiple break tests by Bai and Perron (1998, 2001) are no longer estimable because the degrees of freedom of the regression model become insufficient when the sample is sequentially subdivided at the various break dates. Therefore we present several extended style analyses where only one extra economic variable and the interaction terms with the indices  $r_t$  are added.

#### 4. Data Description

Our empirical research on the time variation in style exposures is conducted on European mutual fund data. In doing so, our study complements other recent studies on individual European countries like Dermine and Röller (1992) [France], Shukla and Imwegen (1995), Blake and Timmerman (1998), Otten and Bams (2000b) [UK], Scherer (1994), Otten (2000), Stehle, and Grewe (2001) [Germany], Cortez, Paxson and Armada (1999) [Portugal], Koedijk, Schotman and Schweitzer (1998), de Roon, Nijman and ter Horst (1998) [The Netherlands], Casarin, Pelizzon, and Piva (2001) [Italy] or Grünbichler and Pleschiutschnig (1999), Annaert, van den Broeck and Vander Vennet (2001) [France, Benelux and Off-shore Territories], and Otten and Schweitzer (1999), Otten and Bams (2000a) who study the European mutual fund sector in general. Notwithstanding that the European mutual fund sector is the second largest (measured by assets under management) [Otten and Schweitzer (1999)], the understanding of the European mutual fund industry is still scanty compared to the vast amount of research carried out on the American fund industry. Moreover, to our knowledge we are the first study on the European mutual fund industry to use daily data. All other studies rely on lower-frequency data. The daily frequency of our sample data makes it possible to document intra-month time variation in style exposures and allows for more efficient estimates over a fixed time interval. In the United States, daily data have been used in some studies on mutual fund timing like Chance and Hemler (1999) or Bollen and Busse (2000), or for instance Busse (1999) who documents volatility timing in mutual funds. Other studies that rely on daily data include Edelen and Warner (1999) and Goetzmann and Massa (1999) who study the relationship between mutual fund flows and market returns at high frequencies and Chalmers, Edelen and Kadlec (2001) investigating trading opportunities in relation to NAV calculations. As far as we know, no study concerning RBSA relies on daily data.

The mutual fund data are taken from the *Vision*-database. This is a comprehensive database containing daily data on funds distributed in Belgium and the Netherlands. We opt to focus on European equity mutual funds. The selection of mutual funds labeled 'European equity' is founded on the classification applied by two different data vendors. The first selection is taken from the 'Financieel Economische Tijd (Fondsen-Tijd)', a leading Belgian financial newspaper. To ensure that our results are not driven by differences in data vendor's classifications [see Gallo and Lockwood (1997)], we construct a second selection that follows the classification employed by 'Efund' [<http://www.e-fund.be/>]. Efund is an internet mutual fund market specialized in funds distributed in Belgium. The initial selections are made based on data available on 17 July 2001. Furthermore, we impose the following selection rules: A selected mutual fund should

- be a capitalization fund;
- have daily observations during the total sample period;
- have at least one year of daily data;
- have an adjusted  $R^2$  and exposure coefficient of at least 50% in preliminary regression of mutual fund returns on the return of a general equity index [namely Stoxx TMI Europe].

The imposition of the second criterion allows us to fully exploit the daily frequency of the data. Besides funds that report daily, also semi-weekly, weekly and semi-monthly frequencies occur in the category of funds with investment objective 'European equity'. The daily data ensures that we have enough data points to estimate the style equation over shorter time periods than the windows that are usually applied. Moreover, we can embark upon investigating intra-month variation. The third argument ensures that we have enough data points to arrive at sensible results by estimating our model and conducting the statistical tests that were discussed in section 3. For instance, the sequential procedure splits up the sample at the break date and the model is re-estimated *if* the length of the split segment is sufficient. Finally, previous studies [Brown and Goetzmann (1997), Kim, Shukla, and Thomas (2000) or diBartolomeo and Witkowski (1997)] have documented that fund misclassification exists. This could be problematic to our tests on time variation in exposures. To prevent that our results are driven by misclassified funds, we preliminary regress the individual fund returns on the return of the general equity index Stoxx TMI Europe and eliminate all funds with an adjusted  $R^2$  and equity exposure beneath 50%. Let us take the example of balanced funds. We expect a priori that this type of mixed funds will alter more rapidly from predominant asset class, because their investment policy is defined more broadly. This kind of investment behavior will result in time-varying exposures. Consequently, if balanced funds are misclassified in the European equity category we will tend to overestimate the time-variation of exposures and probably the number of breaks associated with equity funds. A

second argument is that, if the selected funds are not European equity funds the set of factors is misspecified, and will no longer satisfy the properties outlined in section 2.

A preliminary analysis of the available data teaches us that the raw data are not free of error. Three types of problems occur. Firstly, the mutual fund data contain a number of faulty data points resulting in improbable daily returns. Secondly, it happens that data points are entered on the wrong date (e.g. one day later), causing a shift in the data series from this point onwards. Both errors can be traced efficiently by performing RBSA over very narrow rolling windows (e.g. 30 days). Problematic data points were subsequently spot checked against the daily quotes reported in the newspaper and corrected in the final sample. Thirdly, despite the fact that only funds that report daily quotes are withheld, the data samples are not balanced. In case of missing values, mutual fund returns are calculated based upon the available net asset values enclosing the missing value(s) [see eq. (14)], and appropriate benchmarks returns are calculated as well. Since mutual funds are typically well-diversified portfolios of stocks, mutual funds are not as susceptible to problems associated with nonsynchronous trading as individual stocks.<sup>1</sup>

$$(14) \quad R_{ft} = \frac{NAV_{ft} + D_{ft}}{NAV_{f,t-\eta}} - 1,$$

where  $R_{ft}$  is the return of fund  $f$  over period  $t$ ,  $\eta$  is the number of trading days with missing values of the resp. return period,  $NAV_{ft}$  the net asset value of mutual fund  $f$  at time  $t$ , and  $D_{ft}$  the cash distributions over period ending at  $t$ . Provided that our sample consists only of capitalization funds, no cash distributions take place. We end up with a final sample of 62 funds for the Fet-selection, while there are 53 funds in the Efund-selection meeting the selection criteria. 15 funds are only taken up in the Fet-selection, while 6 funds are solely part of the Efund-selection. 47 funds are in both selections. Data is available for the period 3 June 1991 up to 25 June 2001. Summary statistics for both samples are taken up in Table 1. Readers interested in the result of the selection rules on the intermediate sample sizes may consult Appendix 1.

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### Table 1: Summary Statistics for Mutual Fund Data.

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Returns are daily returns in %. Panel A and B provide yearly key statistics and statistics for the complete sample period for the two mutual fund selections. To save space the numbers for the Efund-selection are reported between brackets. The total sample period runs from 3 June 1991 until 25 June 2001. <sup>(c)</sup> The yearly statistics are calculated from 3 June of year  $t$  until 2 June of year  $t+1$ , except for the period 2000-01 where the sample runs from 3 June 2000 until 25 June 2001. The Efund-selection and Fet-selection consist of 53 and 62 mutual funds respectively, meeting the criteria outlined in Appendix 1. All mutual fund data are taken from the Vision database.

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<sup>1</sup> In a recent paper, Chalmers, Edelen and Kadlec (2001) demonstrate that with respect to the U.S. markets non-synchronous trading problems in relation with NAV calculations given cause to an option to trade these assets indirectly at stale prices. Previous research [e.g. Bhargava, Bose, and Dubofsky (1998)] has documented similar issues with respect to foreign mutual funds. It is unclear, if (and to what extent), these results carry over to the European mutual fund markets that have different institutional characteristics.

*Panel A* reports, for each selection, the average return for the equally weighted portfolio of all existing funds over the period. *Panel B* reports the cross-sectional statistics for all funds with a full track record during the reported period (the fund's starting date should fall before the 30th of the first month, and the ending date should be after the 1st of the last month in the reported period).

**Panel A: Descriptive Statistics for Daily Mutual Fund Return Data.**

<i>Period</i> <sup>(*)</sup>	<i># Funds</i>	<i>Average Fund Return</i>		<i>Period</i>	<i># Funds</i>	<i>Average Fund Return</i>	
1991-92	7 [7]	0.024	[0.024]	1996-97	16 [15]	0.126	[0.133]
1992-93	8 [8]	-0.018	[-0.018]	1997-98	27 [23]	0.178	[0.182]
1993-94	10 [9]	0.077	[0.077]	1998-99	37 [31]	0.036	[0.039]
1994-95	12 [11]	0.003	[-0.003]	1999-00	61 [51]	0.158	[0.143]
1995-96	14 [13]	0.095	[0.092]	2000-01	62 [53]	-0.070	[-0.062]
				1991-01	62 [53]	0.061	[0.061]

**Panel B: Cross-sectional Descriptive Statistics for Daily Mutual Fund Return Data.**

<i>Period</i> <sup>(*)</sup>	<i># funds</i>	<i>Average Return</i>		<i>Min</i>		<i>Max</i>		<i>Standard deviation</i>	
1991-92	5 [5]	0.022	[0.022]	-6.565	[-6.56]	7.838	[7.838]	0.257	[0.257]
1992-93	7 [7]	-0.023	[-0.020]	-4.520	[-4.52]	3.929	[3.929]	0.380	[0.377]
1993-94	8 [8]	0.074	[0.074]	-4.733	[-4.73]	5.128	[5.128]	0.443	[0.443]
1994-95	10 [9]	-0.004	[-0.010]	-4.186	[-4.19]	3.452	[3.452]	0.626	[0.521]
1995-96	13 [12]	0.096	[0.094]	-4.654	[-4.65]	4.866	[4.866]	0.527	[0.449]
1996-97	14 [13]	0.128	[0.129]	-6.779	[-6.78]	7.292	[7.292]	0.528	[0.480]
1997-98	17 [15]	0.182	[0.191]	-12.425	[-5.72]	13.696	[6.931]	0.761	[0.713]
1998-99	29 [25]	0.036	[0.040]	-7.691	[-8.20]	10.486	[13.27]	0.978	[0.962]
1999-00	37 [31]	0.160	[0.145]	-8.428	[-6.37]	14.617	[7.668]	0.890	[0.814]
2000-01	62 [53]	-0.070	[-0.06]	-12.345	[-8.08]	13.658	[7.922]	0.865	[0.805]

The mutual fund returns, as revealed in panel A and B of Table 1, are comparable for both selections. In general, the average daily fund return is positive, in three years the average daily yearly return is negative. The substantial positive return in 1995-96 and the subsequent returns mirror the bull market in that period. The last column of panel B shows further that, likely due to the increased volatility of the underlying markets, the cross-sectional standard deviation increases substantially over time.

The overall aim of our study is to investigate the time variation in the fund's exposures to general asset classes. For this purpose we decide to employ general equity and bond indices as factors in

our style analysis. More specifically, in our basic model we employ the following total return indices: the general and small cap equity indices labeled Stoxx Broad Europe Market Index (In2) and the Stoxx Small Europe Market Index (In4) respectively. The broad market index (In2) covers the largest 600 companies measured by market capitalization. The small cap index (In4) is constructed by ranking the stocks along the free float market capitalization. The companies between the 90 and 95th percentile make up the small cap index. If European equity funds are exposed to the government bond market, they may prefer the Belgian bond index. Before the European unification, this behavior could be driven by home bias. After the unification, a motivation often encountered is that a premium on the Belgian bond index could be earned. In a preliminary analysis, we estimate the RBSA-model with the Belgian or the German bond index. The specification with the Belgian bond index yields a bond exposure that is both significant and higher than the bond exposure to the German bond index, as well as a better goodness-of-fit. Thus, it appears from this preliminary analysis that mutual funds are indeed sensitive to the premium. As a consequence, the basic model is run with the Belgian total return government bond index (In5). The bond indices are taken from Datastream. In the sensitivity analysis, we have also run alternative regressions where the Stoxx Broad Europe Market Index is replaced with the Stoxx Total Market Index (In3) or the Euro Stoxx Blue Chip Market Index (In1). The total market index contains the largest 95% of companies sorted by free float market capitalization, while the blue chip market index consists of 50 stocks covering the market sector leaders in the Euro Stoxx index. Since results were not fundamentally altered, we do not report the results of these regressions to save space. Other studies like Chan, Chen and Lakonishok (1997)] have selected the Fama-French (1993) 3-factor model or Carhart (1997) 4-factor model. This choice is appropriate in style analysis when one is interested in evaluating relative excess performance of mutual funds consistent with an asset-pricing model constituted of 3 or 4 risk factors. The descriptive statistics are given in Table 2.

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**Table 2: Descriptives for Indices.**

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The average return and standard deviation over the complete sample period for the different indices are reported. The total sample period runs from 3 June 1991 until 25 June 2001. The correlations between the indices can be retrieved in columns 3 to 7. The indices are the Stoxx Total Return Indices Blue Chip Europe (In1) Broad Europe (In2) and TMI Europe (In3), as well as the size index Small Europe (In4). Furthermore, the Belgian and German total return government bond indices, labeled (In5) and (In6). The bond indices are taken from Datastream, The Stoxx indices are downloadable from the Stoxx-website.

<i>Return</i>	<i>Standard</i>	<i>Correlations</i>				
<i>Deviation</i>	<i>In1</i>	<i>In2</i>	<i>In3</i>	<i>In4</i>	<i>In5</i>	

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<i>In1 (Stoxx Blue Chip)</i>	0.065	1.057	1				
<i>In2 (Stoxx Broad Eur.)</i>	0.055	0.937	0.984	1			
<i>In3 (TMI Europe)</i>	0.056	0.909	0.918	0.936	1		
<i>In4 (Small Europe)</i>	0.013	0.728	0.811	0.867	0.835	1	
<i>In5 (Belgian Gov. Bond)</i>	0.031	0.196	0.126	0.125	0.130	0.087	
<i>In6 (German Gov. Bond)</i>	0.028	0.191	0.109	0.110	0.100	0.090	

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Surprisingly, the return and standard deviation of the small cap index are lower than those on the general equity benchmarks. Appendix 2 provides yearly summary statistics for the indices. With respect to equity indices we can notice that the variability of the average daily return increases substantially in the second half of the sample period. In 50% of the years the small cap index has a yearly average daily return that is negative. If we compare the characteristics of the two bond indices, we note that the average daily return on the Belgian government bond index is higher than the one of the German bond index, but this goes hand in hand with a higher standard deviation and higher correlations with the equity indices.

Finally, a set of extra variables proxying economic motives to be used in our extended style analysis has to be selected. We only know that these proxies should be related to future investment opportunities. An extensive literature studies the predictability of both expected returns and future volatility of asset classes. In our empirical analysis we use variables that are among the most powerful predictors. More specifically, we add a January dummy variable, measures of the lagged dividend yield of the European stock index, a lagged measure of the slope of the term structure, and a lagged measure of the short-term interest rate level. We do not include the quality spread in the corporate bond market because it is not readily available for the European market over the complete data sample. The slope of the term structure is proxied by the difference between the redemption yield of the 10-year German Government index and the one-month German interbank rate. The latter is used as the short-term interest rate. All data are taken from Datastream. In addition to these generally accepted information variables, we add a number of variables that prove to be sensible in our framework. More specifically, the daily data make it possible to pick up intra-month variation. We add a dummy variable to test if the exposure is different in the last week of the month. The results with respect to this dummy variable can be related to the documented turn-of-the month effect [Ariel (1987)]. The effect refers to the fact that the stock returns at the turn of the month are higher. Furthermore, if mutual funds are influenced by the previous actions of other mutual funds, we expect that mutual fund returns are positively correlated with lagged returns on an equally weighted portfolio of all

existing funds. We test this proposition by adding the average portfolio fund return from the previous week. If we introduce the lagged dividend yield and the lagged fund return with one lag the regressand and regressor we could run into simultaneity problems. To avoid this problem we add the dividend yield with a lag of 5, and measure the lagged average fund return from  $t-6$  up to  $t-2$ . Finally, we also add the (contemporaneous) index returns to the  $\mathbf{z}_t$  vector. Of course, these variables are no information variables, but as in Ferson and Schadt (1996) we include them to capture market timing in the spirit of Treynor and Mazuy (1966).

In our empirical analysis we estimate equation (4) with the three indices used throughout the analysis and a constant in  $\mathbf{r}_t$ . In view of the break tests (and accompanying data limitations) we estimate various models (13) where only a single information variable is introduced at a time.

## 5. Empirical Results

### 5.1 Preliminary Analysis

In this section we investigate the possibility of style breaks in detail. We begin by presenting the results of the RBSA over rolling windows. In studies with monthly data a three-year window is often chosen. There are no guidelines on the window to use, so the chosen window length is function of the kind of research questions addressed. Swinkels and Van Der Sluis (2001) report that in empirical work the window length lies mostly between 24 and 60 months. In Figure 1 the exposures are displayed using 180-days rolling regressions. Panel A presents the result based on cross-sectional average data. Apparently, the portfolio restrictions (2) and (3) would have been binding if included in the RBSA. Panel A teaches us that substantial variation of the exposures in time is present. Both smooth and abrupt changes do occur. Given that the mutual fund sample does not remain fixed over the sample period, the observed variation may be induced by variation in the sample selection (composition of the sample and number of funds). To shed some light on this issue, panel B provides the average factor exposures for the rolling regression of five funds that exist during the complete sample period. We obtain broadly the same picture. Consequently, we rule out the possibility that the observed exposure variation is due to alternation in the sample selection. Of course, the fact that the results in panel B are not based on cross-sectional data (over a large number of funds) results in even more erratic style shocks.

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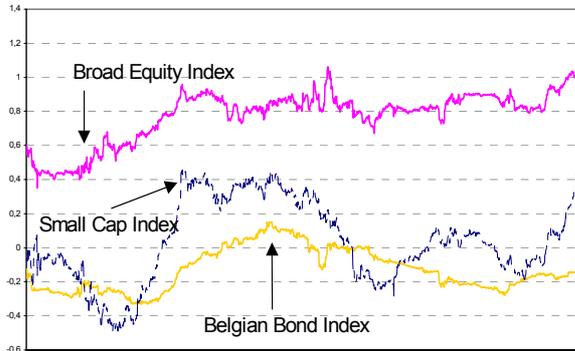
### Figure 1: RBSA over Rolling Windows.

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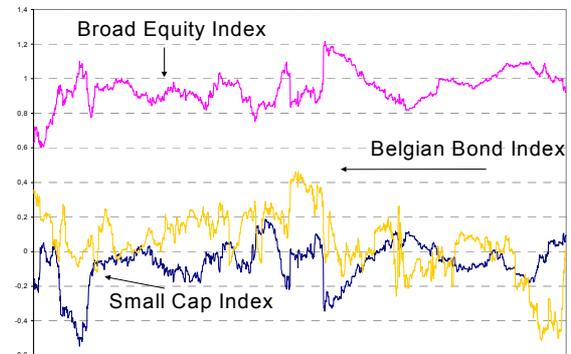
Panel A presents for the Fet-selection the results of RBSA [described by Eq. (1)] over rolling windows based on cross-sectional data. The window length is 180 days. The factors are In2, In4 and In6. See Table 1 for details on the indices. The total sample period runs from 3 June 1991

until 25 June 2001. Panel B provides the average factor exposures for the same type of analysis for the group of 5 funds that exists during the complete sample period.

Panel A: Cross-Sectional Data.



Panel B: Group of Funds (Complete Data Coverage).



The important message to remember from panel B is that variation of exposures in time continues to be present. A more rigid method of conduct is a decomposition of the variance due to Mundlak (1978). We can introduce the following types of variance (up to the constant  $N.T$ ). Let the total variance  $V$  of a generic fund characteristic (e.g. its bond exposure)  $v_{ft}$  be defined as  $\sum_{f=1}^N \sum_{t=1}^T (v_{ft} - v_{..})^2$ . Then part of it is due to variance between funds  $V_{bf} = T \sum_{f=1}^N (v_{f.} - v_{..})^2$  and to variance across time  $V_{bt} = N \sum_{t=1}^T (v_{.t} - v_{..})^2$ . The remaining part is residual variance  $V_{wft} = \sum_{f=1}^N \sum_{t=1}^T (v_{ft} - v_{.t} - v_{f.} + v_{..})^2$ . The average characteristic over time and funds is denoted by  $v_{..}$ , whereas the average over funds (time) is  $v_{f.}$  ( $v_{.t}$ ).

Table 3 reports, for the 5 funds with complete data coverage, this decomposition with respect to the exposures to the broad equity index (In2), the small cap index (In4) and the Belgian bond index (In5).

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**Table 3: Decomposition of Variance.**


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Table 3 reports the decomposition of variance [Mundlak (1978)] of the factor exposures  $V = V_{bf} + V_{bt} + V_{wft}$ . The factor exposures result from rolling RBSA over 180-days windows of individual mutual funds on the following factors In2, In4, In5. See Table 2 for description of the indices. The selected individual funds have data over the complete sample period. In total 5 funds meet this criterion.

	<i>Between Time Variance</i>	<i>Between Fund Variance</i>	<i>Residual Variance</i>
<i>In2</i>	42.4%	21.6%	36.0%
<i>In4</i>	36.6%	13.5%	49.9%
<i>In5</i>	70.7%	2.9%	26.4%

---

Despite the fact that we use a moving window to compute exposures, time-series variance is the main source of the total variance for exposures with respect to the general equity index (In2) and the bond index (In5) (with 42.2% and 70.7% respectively). Time-series variance with respect to the small cap index remains high (36.6%), but is no longer the prominent source. The decomposition provides corroborating evidence that there is variation over time in the factor exposures. Therefore, there is reason to doubt the underlying hypothesis made in RBSA of constant exposures over the entire sample period. We shall investigate this possible variation more formally by applying the results of the break tests established by Andrews and Ploberger (1994), Hansen (1997) and Bai and Perron (1998, 2001).

### 5.2 Testing for structural breaks

In this section we present the outcome of the structural break tests.<sup>2</sup> The results of the Andrews and Ploberger (1994) Exp-tests in Table 4 provide supportive evidence against the hypothesis that the style exposures are constant over the sample period.<sup>3</sup> Panel A shows the results for the cross-sectional data. The structural break test is significant at the 1%-level. Panel B lists the number of funds that exhibit a significant break at various confidence levels (99%, 95% and 90%). If the tests are conducted on the whole data sample, more than 95% of the selected funds have a significant break at the 1%-level. At the 5%-level only one fund does not display a structural break.

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**Table 4: Andrews and Ploberger (1994) Structural Break Tests.**

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Panel A shows the results for the Exp-test of Andrews and Ploberger (1994), see eq. (7). The Hansen (1997) p-values are reported between parentheses. The test is conducted on the cross-sectional data of both selections. In the first row the complete data sample period that runs from 3 June 1991 until 25 June 2001 is used. If a break date does occur based on the Exp-test, we used this date to split the sample into two. The second and third rows report the results on the two subsamples. Panel B states for both selections the number of funds displaying a significant break date according to the Exp-test at three  $\alpha$ -levels (1-5 and 10%). The column *Total funds* shows the total number of funds in the selected sample.

#### Panel A: Results for Cross-Sectional Data.

<i>Sample:</i>	<i>Fet-selection</i>	<i>Exp-test (p-values in parentheses)</i>
Complete	29.20	(0.000)
Start – Breakdate	7.67	(0.005)

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<sup>2</sup> We would like to thank B. Hansen and P. Perron for making the Gauss code for the structural break tests available through the internet.

<sup>3</sup> The main results are not sensitive to the choice of a particular test procedure from the ones suggested in Andrews and Ploberger (1994).

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Breakdate – End 7.99 (0.003)

Panel B: Summary Results for Individual Funds.

<i>Sample:</i>	<i>Fet-selection: rejection of no structural break (Exp-test)</i>			
	<i>Total funds</i>	<i>1%-<math>\alpha</math></i>	<i>5%-<math>\alpha</math></i>	<i>10%-<math>\alpha</math></i>
Complete	62	60	61	61
Start – Breakdate	61	42	52	55
Breakdate – End	49	44	49	49

---

In order to understand the reasons for structural breaks in the style exposures, it is important to know whether structural breaks occur frequently. To get a first idea, we split the sample into two at the break date and rerun the break test procedure. If the break date is near the beginning or end of the data sample, it is possible that there are insufficient data points to estimate the model on the split sample. Hence, the total number of funds for which the break test is conducted is smaller if we test on the split sample. The results indicate that the hypothesis of multiple break dates is not unrealistic. For the cross-sectional data the tests are significant at the 1%-level in all instances. With respect to the individual fund data, the number of funds with significant break dates (1%-level) lies between 69 and 89%. To test the existence of multiple breaks more formally, the test procedure of Bai and Perron (1998, 2001) is adopted. Since there is no a priori reason to presume that only a subset of the style exposures change, we estimate a pure break model. The results are presented in Table 5.

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**Table 5: Bai and Perron Multiple Break Tests.**

*Panel A* shows the results for cross-sectional data set of the test procedure for multiple breaks [Bai and Perron (1998, 2001)]. The null hypothesis of no breaks against an unknown number of breaks is tested by the  $UD_{max}$ -test. Critical values (5%-level) are displayed between parentheses. The number of breaks is tested by means of the  $SupF_T(m+1|m)$  test. *Panel B* reports the results for the individual funds (5%-level). The second column ( $\geq 1$  break) tests the hypothesis that there is at least one significant break. Columns 3 to 5 state the number of funds having 2, 3 or 4 significant break dates. The column *Total funds* shows the total number of funds in the selected sample.

Panel A: Results for Cross-Sectional Data.

$UD_{max}$  : 43001334.61 (16.37)

SupF (2|1) test: 45.55 (16.19)

SupF (3|2) test: 58.78 (18.11)

SupF (4|3) test: 23.46 (18.93)

## Panel B: Summary Results for Individual Funds.

<i>Total funds</i>	<i>Fet-selection</i>			
	$\geq 1$ break	2 breaks	3 breaks	4 breaks
62	62	15	9	13

All funds in the sample have at least one break during the sample period based on the  $UD_{max}$  test (5%-level). More than fifty percent of those funds have also more than one break (5%-level). This result are even more striking if we take into consideration that the number of breaks is limited by the time series length of the individual funds.

## 5.3 Time-variation in style exposures

What causes these style breaks? It appears unreasonable that a fund changes, for instance, three or four times from manager during the sample period. A more likely hypothesis is that the style breaks are induced by economic motives, such as herding, timing, or that style breaks result from anticipating changing economic conditions. Therefore we estimate the extended style analysis given by eq. (4). Because of lack of degrees of freedom in subsamples, we will only add one information variable at the time.

**Table 6: Extended RBSA.**

Table 6 shows the results of the extended RBSA [eq. (13)]. The average coefficient over the individual regressions is reported, the average value of the absolute t-statistics are given between parentheses. The White (1980) heteroskedasticity correction is used. The adjusted  $R^2$  is given in column 2. The first row reports the RBSA without extra variables added. The extra variable added in the other RBSA is indicated in the first column. The coefficient and t-statistic of this variable can be retrieved in the column *Extra*. The last three columns state the interaction terms with the three indices. The three indices are the Stoxx Broad Europe (In2), the size index Small Europe (In4), and the Belgian Government Total Return Index. The following variables are used: daily lagged measure of dividend yield (lag 5), The daily lagged (lag 1) measure of the slope of the term structure is proxied by the difference between the redemption yield of the 10-year German government index and the one month German interbank rate, the daily lagged (1 lag) measure of the one month German interbank rate is used as lagged short-term interest rate, average daily fund return from  $t-6$  until  $t-2$ . In addition, two dummy variables are introduced: a dummy variable for the last week of the month, and a January dummy variable.

	$\bar{R}^2$	$\alpha$	In2	In4	In5	Extra	InterIn2	InterIn4	InterIn5
	69%	-0.001	0.736	0.201	0.084				
		(0.26)	(13.75)	(3.81)	(2.03)				
<i>Div.Yield<sub>t,5</sub></i>	77%	-0.080	0.776	0.320	-0.022	0.035	0.053	-0.268	0.015

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		(1.30)	(8.04)	(3.01)	(0.11)	(1.19)	(1.32)	(5.06)	(0.12)
<i>Term Spread</i> <sub><i>t-1</i></sub>	72%	-0.010	0.703	0.108	0.149	0.005	0.158	-0.091	-0.117
		(1.96)	(33.53)	(3.30)	(2.61)	(1.12)	(9.99)	(3.97)	(3.72)
<i>Interest</i> <sub><i>t-1</i></sub>	62%	0.290	0.800	0.169	-0.491	-0.073	-0.177	0.135	0.093
		(2.67)	(21.62)	(1.40)	(1.24)	(2.65)	(6.65)	(2.34)	(0.99)
<i>D</i> <sub><i>January</i></sub>	64%	-0.004	0.762	0.076	0.159	-0.003	0.120	-0.041	-0.238
		(1.08)	(32.60)	(2.85)	(3.77)	(0.23)	(3.22)	(0.94)	(3.36)
$(In_2)^2$	63%	-0.002	0.754	0.091	0.148	-0.002			
		(0.29)	(33.80)	(3.64)	(3.69)	(1.08)			
<i>D</i> <sub><i>last week of month</i></sub>	63%	-0.007	0.747	0.096	0.095	0.011	0.094	-0.026	0.076
		(1.52)	(30.64)	(3.34)	(2.56)	(1.24)	(3.67)	(0.89)	(1.11)
<i>Av. Fund Ret.</i> <sub><i>t-6,t-2</i></sub>	64%	-0.009	0.759	0.103	0.144	0.024	0.073	-0.025	-0.345
		(-1.75)	(32.80)	(3.71)	(4.41)	(1.41)	(3.68)	(1.30)	(8.86)

---

As expected, the mutual funds are mainly exposed to the general equity index. With respect to the additional economic variables the results are somewhat mixed. In general, the results with respect to the effect of the extra economic variables on the general index (which is the main investment class of the mutual funds) are in line with expectations. Note that the additional terms do not necessarily result in a higher  $\bar{R}^2$ . Because all funds in the sample have 'European equity' as investment objective our main interest in the discussion goes out to the equity interaction terms. In the relevant literature a positive correlation between the lagged dividend yield and the stock market is put forward. The interaction term with  $In_2$  is positive but not significant, while the interaction term for the small cap index is significantly negative. The negative relation with the small cap interaction term seems somewhat odd. A possible explanation is that the mutual funds, as other institutional investors, are reluctant to invest heavily in stocks with low liquidity. The expected negative relation for the short-term interest rate is retrieved for the interaction term of the general index [see e.g. Ferson (1995)]. The short-term interest rate may be closely related to expected inflation. The results for the January dummy are puzzling. From previous studies [e.g. Keim (1983), Reinganum (1983)] one would expect that mutual funds would try to benefit from the 'small-cap-in-January' effect. One line of thought consistent with the results is that mutual funds receive considerable cash inflows from mutual fund investors at the start of the year, and that the strong influx force mutual funds to invest in more liquid stocks. However, without flow data the results remain a matter of conjecture. The dummy for the last week of the month provides evidence that there exists intra-month variation in style exposure. The significant

positive effect on the general index interaction term is in line with the documented turn-of-the-month effect [Ariel (1987)]. Fama and French (1989) have documented that the term spread predicts bond and stock returns. Fama and French (1993) mention that if anything the common variation captured by the term spread is, stronger for stocks than for bonds. Hence, it makes sense that mutual funds that change their exposure conditional on the term spread focus on their main investment category. Consistent with previous literature [e.g. Kon (1983), Chang and Lewellen (1984) and Hendriksson (1984)] we find no evidence of significant timing ability. For a discussion on the causes of the generally retrieved negative coefficient, we refer to Hendriksson (1984) and Jagannathan and Korajczyk (1986). Finally, mutual funds are influenced by the average previous behavior undertaken by other mutual funds.

More interesting to our central research question is whether the style breaks are induced by economic motives. If the answer is affirmative, no style breaks in the set of standard style exposures should show up if we conduct a partial break test on the extended model, where only the set of standard style exposures are allowed to vary. As mentioned before, the number of regressands becomes too large to conduct the break test procedure, if we estimate an extended model that includes all variables proxying economic motives. Therefore, we conduct the partial break test based on an extended model with one additional variable. The test could be conducted for 54 funds. Given the high explanatory power of the model with the lagged dividend yield, the results reported in Table 7 fall back on this particular model. We compare the number of breaks in a fund's style exposures in the traditional and extended style analysis. Because we only use one additional economic variable, it is unlikely that this variable captures all style breaks. Nevertheless, the reduction in the number of breaks is substantial. To investigate whether there is a significant reduction in the number of breaks, we apply the Wilcoxon matched-pairs signed-ranks test (1945). We test the null hypothesis that the median of the population of difference (between pairs of breaks with respect to the standard and extended model) is larger or equal to zero. The null hypothesis is rejected [p-value (0.00)]. The number of funds that exhibited a high number of breaks (3 or 4) is reduced from 7 (13) to 3 (1), respectively. Overall, the results are supportive for the hypothesis that most style breaks are induced by economic motives. Given that our model does not include all variables proxying economic motives simultaneously, it is likely that the number of breaks will decrease even more if more economic variables are introduced. To test this hypothesis we ran specifications where we do include more than one economic variable (to limit the number of regressors we include only one intercept and no bond index). The preliminary results stemming from this approach are consistent with the reasoning outlined above. Nevertheless, no definitive conclusions can be drawn from these experimental tests because we

have only results for a very limited group of funds for which a sufficient number of observations were present.

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**Table 7: Number of Breaks for Individual Funds in the Different Models.**

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The second and third column of the table displays, for the funds for which the tests could be estimated, the number of funds having 1, 2, 3 or 4 significant breaks based on the  $UD_{max}$  and the sequential test procedure based on  $\text{Sup}F_T(m+1|m)$  [Bai and Perron (1998, 2001)]. In case of the extended model a partial break model is estimated where only the standard style coefficients are allowed to change. The third column states the median reduction in breaks when the break tests are estimated based on the standard and extended model. The last column gives the number of breaks in the standard RBSA for the funds for which the break tests could not be estimated in the extended model.

<i>Number of breaks</i>	<i>Standard RBSA</i>	<i>Extended RBSA</i>	<i>Median Reduction</i>	<i>Missing funds</i>
		<i>With Dividend Yield</i>	<i>in # of breaks</i>	
1	21	40	0	4
2	13	10	1	2
3	7	3	2	2
4	13	1	2	0

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## 6. Conclusion

Despite the wide acceptance of RBSA, both by academics and practitioners, the method has several limitations. One important drawback is the underlying assumption that the style exposures do not vary over time. In general, little attention was devoted to examining whether this hypothesis is acceptable, although a number of studies have documented that time variation in style exposures does occur. We apply results on break tests established in Andrews and Ploberger (1994), Hansen (1997) and Bai and Perron (1998, 2001) to examine profoundly the possibility of style breaks. An advantage of these test procedures is that we can test for breaks at a priori unknown break dates, test for multiple breaks, and test for simultaneous breaks in a (sub)set of variables. We apply these test procedures to a set of daily return data of European equity funds distributed in Belgium. As such, we extend the empirical literature on the European mutual fund market, and the research relying on high-frequency data. The results confirm the indications on time varying style exposures that surfaced by the style analysis over rolling windows and the decomposition of variance. We find strong evidence against the hypothesis of constant time exposures in time. All funds exhibit at least one break [based on the test procedure

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of Bai and Perron (1998, 2001)], while 60% of the funds exhibited even more than one break. The style breaks could be induced by economic motives or could be related to other factors such as changes in management structure. A comparison of the number of breaks in the standard unrestricted style model and an extended model where one additional variable capturing an economic motive is added, reveals that the most promising pursuit for explaining (the majority of) style breaks is to be found in economic motives.

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**Appendix 1: Overview of Data Selection.**


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The table states the number of in Belgium distributed funds in the two data samples, taking into account the selection criteria. The number of funds not meeting the selection criterion in each step is reported in parentheses. The second column lists the number of funds for the selection based on the 'Financieel-Economische Tijd (Fondsen-Tijd)'. The third column gives the relevant sample sizes based on the 'Efund-database'. The initial selections were made based on data available on 17 July 2001. Fund data is taken from the *Vision* database that contains daily data (if reported by the fund) for all funds listed in Belgium and the Netherlands.

<i>Selection-criteria:</i>	<i>No. of funds in Fet-selection</i>		<i>No. of funds in Efund-selection</i>	
All funds labeled 'Europe equity'	260		292	
Deletion of distribution funds	167	(-93)	202	(-90)
Deletion of TAK23-funds	137	(-30)	162	(-40)
Deletion of funds with non-daily data	106	(-31)	129	(-33)
Deletion of funds with nobs. < 1 year	64	(-42)	82	(-47)
Deletion of non European equity funds based on RBSA	53	(-11)	62	(-20)
<b>Final sample</b>	<b>53</b>		<b>62</b>	

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**Appendix 2: Yearly Descriptives for Indices.**


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All return data are daily data expressed in %. The total sample period runs from 3 June 1991 until 25 June 2001. (\*) The yearly statistics are calculated from 3 June of year  $t$  until 2 June of year  $t+1$ , except for the period 2000-01 where the sample runs from 3 June 2000 until 25 June 2001. The table reports average return and standard deviation over the separate years and over the complete sample period for the different indices. The indices are the Stoxx Total Return Indices Blue Chip Europe (In1), Broad Europe (In2) and TMI Europe (In3), as well as the size index Small Europe (In4). Furthermore, the Belgian and German total return government bond indices, labeled (In5) and (In6). The bond indices are taken from Datastream. NOB indicates the number of observations.

*Blue Chip Europe (In1)*

Period(*)	NOB	Average Return	Standard Deviation
1991-92	260	0.041	0.766
1992-93	259	0.028	0.966
1993-94	261	0.070	0.725
1994-95	261	0.039	0.734
1995-96	258	0.081	0.572
1996-97	259	0.149	0.722
1997-98	250	0.148	1.271
1998-99	250	0.038	1.698
1999-00	255	0.143	1.345
2000-01	266	-0.073	1.232
1991-01	2579	0.065	1.057

*Broad Europe (In2)*

Period(*)	NOB	Average Return	Standard Deviation
1991-92	260	0.028	0.725
1992-93	259	0.013	0.928
1993-94	261	0.074	0.649
1994-95	261	0.023	0.644
1995-96	258	0.075	0.535
1996-97	259	0.130	0.648
1997-98	250	0.143	1.100
1998-99	250	0.019	1.494
1999-00	255	0.106	1.168
2000-01	266	-0.057	1.054
1991-01	2579	0.055	0.937

*TMI Europe (In3)*

Period(*)	NOB	Average Return	Standard Deviation
1991-92	108	0.107	0.734
1992-93	259	0.009	0.908
1993-94	261	0.069	0.626
1994-95	261	0.017	0.611
1995-96	258	0.074	0.513
1996-97	259	0.123	0.622
1997-98	250	0.142	1.041
1998-99	250	0.016	1.407
1999-00	255	0.100	1.113
2000-01	266	-0.061	1.031
1991-01	2427	0.056	0.909

*Small Europe (In4)*

Period(*)	NOB	Average Return	Standard Deviation
1991-92	260	-0.013	0.686
1992-93	259	-0.029	0.811
1993-94	261	0.087	0.541
1994-95	261	-0.027	0.488
1995-96	258	0.025	0.404
1996-97	259	0.055	0.499
1997-98	250	0.076	0.799
1998-99	250	-0.080	1.106
1999-00	255	0.072	0.895
2000-01	266	-0.037	0.769
1991-01	2579	0.013	0.728

*Belgian Government Bond Index (In5)*

Period(*)	NOB	Average Return	Standard Deviation
1991-92	262	0.034	0.086
1992-93	261	0.053	0.162
1993-94	261	0.017	0.249
1994-95	261	0.047	0.274
1995-96	260	0.040	0.206
1996-97	261	0.033	0.176
1997-98	261	0.031	0.144
1998-99	261	0.028	0.186
1999-00	262	-0.002	0.238
2000-01	276	0.028	0.171

*German Government Bond Index (In6)*

Period(*)	NOB	Average Return	Standard Deviation
1991-92	262	0.033	0.112
1992-93	261	0.049	0.156
1993-94	261	0.023	0.210
1994-95	261	0.036	0.223
1995-96	260	0.031	0.220
1996-97	261	0.030	0.177
1997-98	261	0.030	0.147
1998-99	261	0.027	0.217
1999-00	262	0.001	0.246
2000-01	276	0.024	0.158

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