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Time Variation in Mutual Fund Style Exposures*

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Abstract. Despite the wide acceptance of return-based style analysis, the method has several limitations. One important drawback is the assumption that style exposures are time-invariant. We apply results on break tests developed in Bai and Perron (1998, 2003) to test for style breaks. We find strong evidence against the hypothesis of constant time exposures in daily return data for European equity funds. All funds exhibit at least one break, and 60% exhibit more than one break. We show that the main reason for style breaks is the mutual funds' reliance on conditional investment strategies based on public information and volatility estimates.

JEL Classification: C22, C52, G11, G20

1. Introduction

Return-based style analysis (RBSA) 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.

RBSA has become a widely accepted analytic tool, both by academics and practitioners. Besides problems related to misclassification, RBSA is employed in addressing issues concerning performance evaluation and object gaming of mutual funds[1] (See, e.g., Sharpe, 1992; de Roon et al., 2004), construction of diversified portfolios or efficient portfolios of mutual funds with specified factor loadings (de Roon et al., 2004), short-term risk assessment

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[1] Object gaming refers to the practice of deliberately deviating from the stated objective to attain higher relative performance.

of a mutual fund manager (Sortino et al., 1997) and hedge fund style and risk evaluation (e.g., Fung and Hsieh, 1997; Schneeweis and Spurgin, 1998; Lhabitant, 2002).

Despite this wide acceptance, in its original form RBSA has 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 purpose-dependent restrictions to be imposed in RBSA, and the underlying hypothesis of constant style exposures over time. While we briefly discuss the former potential pitfalls in Section 2, this paper focuses mainly on the assumption that style exposures are constant over time. Indeed, a number of papers have documented that style changes over time do occur (see, e.g., Kim et al., 2000; Swinkels and van der Sluis, 2001; Chan et al., 2002). Style breaks may be motivated by economic reasons like market or volatility timing, herding or portfolio alteration in anticipation of changing economic conditions. They may also be induced by changes in the mutual fund management structure or by flow dynamics.

In this article, we contribute to the existing discussion on RBSA methodology by conducting a comprehensive analysis of the nature of time variation in exposures. Contrary to previous literature, we conduct formal and econometrically powerful tests to examine the occurrence of style breaks. Besides the econometric advantages, this approach makes it easy to assess the performance of extended style models that are introduced subsequently to capture this time variation. We also investigate if we can identify classes of funds that are subject to style breaks. By doing so, we relate our findings on style breaks to the literature on mutual fund investment strategies.

Since descriptive statistics indicate that changes in style exposures of European equity funds may be important, we formally test for breaks in the estimated style exposures by employing the framework described in Bai and Perron (1998, 2003). This framework has the advantage that it enables testing for multiple breaks at a priori *unknown* break dates, as well as investigating breaks in a subset of variables. For every fund in our sample we find evidence of at least one style break, and for 60% of the funds we document multiple breaks.

Our subsequent step is to investigate the economic behavior that drives these breaks, estimating a model for the time variation. In addition, we compare the number of breaks in the basic model, and in the extended models put forward to account for the time variation. By doing so, we can assess the performance of the extended models. We focus on the investment policy of mutual funds by testing whether mutual fund managers use conditional investment strategies based on publicly available information, like dividend yield or volatility estimates.[2] We also investigate the importance of the level of industry concentration of fund portfolios and past performance. We show that the first approach, based on conditional investment strategies of mutual fund managers, is the most fruitful approach, despite its limitations. Even though the extended models are probably too unsophisticated to be realistic (style exposures being expressed as linear functions of a single public information variable at a time), we do find that they imply a significant reduction in the number of breaks per fund. This clearly indicates that an adequate style analysis should allow for time-varying exposures, a result consistent with the performance evaluation literature.

The data used in our analysis have two features that are worth mentioning. First, differently from other existing studies, we rely on daily instead of monthly data. The higher frequency of the data offers the opportunity to grasp a more detailed picture of the time-varying nature in style exposures, by picking up intramonth style variation. Second, we analyze funds that focus on European equities as investment objective and are distributed in Belgium, thereby contributing to the growing empirical evidence on the European mutual fund industry, which is the second largest 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. We conclude in Section 6.

2. Literature Review, Methodology and Limitations of RBSA

The interest in RBSA is fuelled by the difficulties that investors and fund distributors face in determining the actual mutual fund investment objective and investment behavior. Empirical evidence on misclassification reported by Brown and Goetzmann (1997), Kim et al. (2000), and di Bartolomeo and Witkowski (1997) corroborate that deviations between the actual investment style and that reported in the prospectus or by the data vendor do occur in a substantial number of funds. As indicated in the introduction, RBSA has subsequently been applied to a number of mutual fund issues. A more detailed discussion of the various applications of RBSA can be found in Van Campenhout (2002).

[2] Due to a lack of data on mutual fund managers and fund flows, we can regrettably not test the hypothesis that the style breaks are induced by fund-specific factors (like changes in the fund management or flow dynamics) empirically.

In comparison to characteristic-based style analysis, RBSA has a number of advantages if one wants to identify a fund's actual investment policy. Since characteristic-based style analysis requires knowledge of mutual funds' actual portfolio holdings (e.g., Daniel et al., 1997; Wermers, 2000; Chan et al., 2002), it cannot be applied in the numerous cases where such information is not readily available. Furthermore, even when available, such information is only provided on a quarterly basis. Finally, if mutual fund managers implement window-dressing practices, inferences from reported portfolio holdings might be misleading. In contrast, by regressing fund returns 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 et al. (2002) 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.

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

$$R_{ft} = \alpha_f + \sum_{i=1}^{K} \beta_{fi} R_{it} + \varepsilon_{ft}. \tag{1}$$

where $t = 1, \ldots, T$, $E(\varepsilon_{ft} R_{it}) = E(\varepsilon_{ft}) = 0$ for $i = 1, \ldots, K$, R_{ft} is the return on fund f for the period ending at t, R_{it} is the return on asset class i, K is the number of asset classes, ε_{ft} is the idiosyncratic noise term, and β_{fi} is fund f's factor exposure with respect to factor i. 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 $\alpha_f + \varepsilon_{ft}$. In addition, the exposures are restricted to be positive and to add up to 1 in the original model. This could result in biased estimates when not all asset classes the fund invests in are accounted for, or when the investments are inaccurately taken into account by the adopted asset classes (de Roon et al., 2004). Therefore, in this paper we prefer not to impose these restrictions, which could affect our estimates on the time-variation of style exposures.

The proper implementation of the original model requires asset classes that are mutually exclusive, linearly independent and exhaustive (in the sense that the asset factor model should span the fund's portfolio asset mix) (Sharpe, 1992; Lobosco and di Bartolomeo, 1997; de Roon et al., 2004). Highly correlated asset classes should be avoided, since they capture essentially the same style characteristics. Ideally, we would apply ordinary style analysis only if the fund's assets are indexed to well-prescribed indices (Buetow et al., 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).

Gallo and Lockwood (1997) demonstrate that the data vendor's classification scheme could influence the outcome of the style analysis. To ensure that our results are not determined by the data vendor's classification scheme, we employ the classification put forward by two different data vendors. As the main conclusions remain unaltered, to save space, we do not present the results of this sensitivity analysis.

A potential drawback of the standard RBSA model that is directly related to the main issue in this article is the implicit assumption that the sensitivities to the factors remain fixed over the sample period. In reality, style changes over time have been documented (see, e.g., Kim et al., 2000; Swinkels and van der Sluis, 2001; Chan et al., 2002). 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; Buetow et al., 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. A paper that is closely related to our research is Swinkels and van der Sluis (2001), who model the time-varying exposures explicitly by applying a Kalman smoother and therefore, use the complete data sample to estimate the model, instead of a subset of historical returns as in the rolling window approach. The Kalman smoother approach is suited to model smooth changes in time. Nonetheless, there is no a priori reason to assume that only smooth changes take place. Some studies rely on the CUSUM (CUSUMQ) and Chow tests for coefficient stability to support a time-varying model. However, these tests, which are based on residuals from recursive estimation, have been criticized for having low statistical power (e.g., Andrews et al., 1996; Greene, 2000). Moreover, the implementation of the Chow test requires a priori knowledge of the break date, which is not the case in style analysis. Finally, such procedures cannot be used to test simultaneously for multiple breaks. In the next section, we discuss a test procedure that allows testing for multiple breaks at unknown break dates, and explain how we model time-variation in style exposures.

3. Research Design and Structural Break Methodology

The literature on structural breaks is quite large, and focuses primarily on the treatment of a single break (see, e.g., Krishnaiah and Miao (1988) for a survey). Recent papers derive methods to deal with a single break or multiple breaks at *unknown* dates in various models.

In general, the research design of our principal structural break tests can be summarized as follows. We want to test whether the coefficient matrix that consists of the fund's style exposures to the various benchmarks is constant over time, or alternatively, is subject to one or more structural breaks.

The standard unrestricted return-based style model (Equation (1)) is summarized in matrix notation by:

$$\mathbf{r} = \mathbf{R}\boldsymbol{\beta} + \mathbf{e}, \tag{2}$$

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

To consider the standard (unrestricted) RBSA model with m breaks in the coefficient matrix that captures the fund's style exposures to the various benchmarks, we rewrite Equation (2). There are $m + 1$ regimes during which fund style exposures have values $\boldsymbol{\beta}^{(j)}$, $j = 1, 2, \ldots, m + 1$:

$$\mathbf{r} = \mathbf{R}^{*}\beta^{*} + \mathbf{z}\delta + \mathbf{e}. \tag{3}$$

where $\boldsymbol{\beta}^{*} = (\boldsymbol{\beta}^{(1)\prime}, \ldots, \boldsymbol{\beta}^{(m+1)\prime})'$ and $\mathbf{R}^{*}$ diagonally partitions R at the break dates $(T_1, \ldots, T_m)$, i.e. $\mathbf{R}^{*} = diag(\mathbf{R}_1 \ldots, \mathbf{R}_{m+1})$ with $\mathbf{R}_i = (\mathbf{r}_{T_{i-1}+1}, \ldots, \mathbf{r}_{T_i})'$. Note that by definition we set $T_0 = 0$ and $T_{m+1} = T$. In our model, $\mathbf{z}$ is an $(T \times 1)$ identity vector. The coefficient matrix that is subject to change is $\boldsymbol{\beta}$, whereas the parameter vector $\boldsymbol{\delta}$ is not subject to change. In our setting, the factor style exposures to the benchmarks are stacked in $\boldsymbol{\beta}$, while the intercept is included in $\boldsymbol{\delta}$.

The null hypothesis to be tested is that $\boldsymbol{\beta}$ is constant through time, against the alternative hypothesis that (multiple) breaks occur. Depending on the specific test statistic used, there are two related alternative hypotheses, as we shall see later on. We test for multiple breaks by applying the break test methodology developed in Bai and Perron (1998, 2003). Bai and Perron (1998) focus on estimating multiple structural changes in a linear model that is estimated by least squares. They derive the limiting distribution of the estimators as well as the test statistics. The practical issues concerning the implementation of the procedure are outlined in Bai and Perron (2003). 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 that would arise from actually estimating the regression for every m-partition.

The break tests are estimated for every individual fund. The empirical results are presented in Section 5. 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 $UD\max F_T(M, K+1)$ test:

$$UD\max F_T(M, K+1) = \max_{1 \leqslant m \leqslant M} F_T(\hat{\lambda}_1, \ldots \hat{\lambda}_m; K+1), \tag{4}$$

where $\hat{\lambda}_j = \hat{T}_j T (j = 1, \ldots, m)$. The estimates of the break dates $\hat{T}_j$ are obtained from the global minimization of the sum of squared residuals. In our empirical applications, we set the upper bound at 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 subsample containing the observations $\hat{T}_{i-1}$ to $\hat{T}_i (i = 1, \ldots, m+1)$. 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. Bai and Perron denote this test by $\mathrm{Sup}F_T(m+1|m)$.

If one finds evidence of style breaks, the question that naturally arises is: which economic behavior could account for the pattern of style breaks present in the data? An explanation that we explore in Section 5.4 is that the style breaks are induced by the fact that mutual fund managers alter their market exposures conditioning upon publicly available information such as macroeconomic variables or volatility shocks. Our research method is inspired by the methodology applied in the conditional performance evaluation literature (Ferson and Schadt, 1996; Christopherson et al., 1999). They model a fund's exposures to asset classes as linear functions of public information variables to account for changes in portfolio composition made by the fund manager in response to predictable changes in the investment opportunity set. The way in which we implement the insights of their approach can best be illustrated as follows. Take one observation from Equation (2):

$$R_{ft} = \mathbf{r}_t' \boldsymbol{\beta}_t + \varepsilon_{ft}, \tag{5}$$

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 $\mathbf{z}_t$:

$$\boldsymbol{\beta}_t = \boldsymbol{\Gamma} \mathbf{z}_t, \tag{6}$$

where $\mathbf{\Gamma}$ is a $(\mathrm{K}+1) \times L$ coefficient matrix and the first information variable in $\mathbf{z}_t$ is by construction a constant. Equation (5) can then be rewritten as follows:

$$R_{ft} = vec(\mathbf{\Gamma})'(\mathbf{r}_t \otimes \mathbf{z}_t) + \varepsilon_{ft}, \tag{7}$$

where 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:

$$R_{ft} = \mathbf{r}_t'\boldsymbol{\gamma}^{(1)} + \mathbf{x}_t'\boldsymbol{\gamma}^{(2)} + \varepsilon_{ft}, \tag{8}$$

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 factors, 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 $\boldsymbol{\gamma}^{(1)}$ are allowed to vary. The testing procedure outlined above can be adapted in a straightforward manner if we want to test the stability of a subset of coefficients. 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 included in the regression. Consequently, the multiple break tests by Bai and Perron (1998, 2003) 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 in each of which only one additional economic variable and the interaction terms with the indices $\mathbf{r}_t$ are included.

In view of the literature on volatility timing (Busse, 1999), we also explore the extent to which this type of timing behavior by mutual fund managers could account for possible style breaks. We use an approach similar to that outlined above, where the interaction terms of the factors with the information variables is replaced by an interaction term capturing the daily volatility shock $(\sigma_{mt+1} - \sigma_{mt})$ and the broad market index. To model daily market volatility we estimate a GARCH(1,1) specification with t-distributed conditional errors:

$$\sigma_{mt}^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \vartheta_1\sigma_{mt-1}^2, \tag{9}$$

where $\varepsilon_t|\psi_{t-1} \sim t(0, \sigma_{mt}^2)$ and ψ_t is the filtration at time t.

4. Data Description

Our estimation is conducted on European mutual fund data. In doing so, we complement the growing body of empirical studies on European mutual fund markets (see, e.g., Walter and Weber, 2006, for Germany; Casarin et al., 2005, for Italy; Otten and Bams, 2000, for the UK; Annaert et al., 2003, for France, Benelux and off-shore territories; Otten and Schweitzer, 2002, and Otten and Bams, 2002, for European mutual funds in general). Even though the European mutual fund sector is the second largest in the world (measured by assets under management), 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, this is 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 data makes it possible to document intramonth time variation in style exposures and allows for more efficient estimates over a given time interval. In the USA, daily data have been used in studies on mutual fund timing (see, e.g., Busse, 1999; Chance and Hemler, 2001; Bollen and Busse, 2001) or studies on mutual fund flows (see, e.g., Edelen and Warner, 1999; Goetzmann and Massa, 2003).

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 mutual funds that invest in European equities. The initial selections are made based on data available on 17 July 2001. The selection of mutual funds labeled "European equity" is based on the classification applied by two different data vendors. The first selection, to be denoted by Fet 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 (Gallo and Lockwood, 1997), we construct a second selection that follows the classification employed by Efund (an Internet mutual fund market which specialized in funds distributed in Belgium at that time). Furthermore, we impose the following selection rules: to be included in our sample, a mutual fund must be a capitalization fund, and must have a daily quotation frequency during the whole sample period, at least 1 year of daily data, and an adjusted R^2 and exposure coefficient of at least 50% in a preliminary regression of its returns on the percentage change of a general equity index—the Stoxx Total Market Index (TMI) Europe.

We restrict attention to capitalization funds in order to avoid superfluous duplication in our sample: managers often set up capitalization and distribution funds to appeal to different types of investors, even though the investment policy of the two types of funds is identical (and most likely entrusted to the same fund manager). The requirement that funds have at least 1 year of daily data is imposed to investigate intramonth style variation and to ensure that the sequential testing procedure, which reestimates the style model over the subsamples if a break date is identified, can be applied properly.

The last prerequisite ensures that our results are not biased due to fund misclassification (Brown and Goetzmann, 1997; di Bartolomeo and Witkowski, 1997; Kim et al., 2000). Misclassified funds could increase the number of style breaks. For instance, if balanced funds are misclassified in the European equity category we will tend to overestimate the time variation of style exposures, because we expect a priori that this type of mixed funds switches more rapidly between broad asset classes like equity and bonds. Moreover, if the selected funds are not European equity funds, the set of factors will be misspecified, and will no longer satisfy the properties outlined in Section 2.

A preliminary analysis of the raw data reveals that they are not error free. Three types of problems occur. First, the data contain a number of faulty observations resulting in improbable daily returns. Second, some observations are entered on the wrong date (e.g., 1 day later), causing a shift in the data series from that point onward. Both errors can be traced efficiently by performing a RBSA over very narrow rolling windows (e.g., 30 days). Problematic data points were identified, checked against the daily quotes reported in newspapers and corrected in the final sample. Third, although we retain only funds that report daily quotes, the data samples are not balanced.

In case of missing values, mutual fund returns are calculated based upon the available net asset values (NAV) enclosing the missing value(s), according to the following equation:

$$R_{ft} = \frac{NAV_{ft} + D_{ft}}{NAV_{ft-1-\eta}} - 1, \tag{10}$$

where R_{ft} is the return of fund f over period t, η is the number of trading days with missing values of the return period under consideration, NAV_{ft} the NAV of mutual fund f at time t, and D_{ft} the cash distributions over the period ending at t. 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.[3] Given that our sample only consists of capitalization funds, no cash distributions take place.

We end up with a final sample of sixty-two funds based on the Fet selection, while there are fifty-three funds in the final Efund selection, with forty-seven funds in both selections. Instead, fifteen funds are chosen only using the Fet selection, while six funds are solely part of the Efund selection.

[3] In a recent paper, Chalmers et al. (2001) show that in the US market, nonsynchronous trading problems in relation with NAV calculations create an option to trade these assets indirectly at stale prices. Previous research (e.g., Bhargava et al., 1998) documented similar phenomena for foreign mutual funds. It is unclear if (and to what extent), these results carry over to European mutual fund markets, which have different institutional characteristics.

Data are available for the period 3 June 1991 up to 25 June 2001. Summary statistics for both samples are provided in Table I. Readers interested in the result of the selection rules are referred to the Appendix.

The table shows that mutual fund returns are very similar for the two selections. In general, the average daily fund return is positive, except for 2 years. The substantial positive return in the second half of the nineties reflects the bull market in that period. The last column of Panel B shows 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 a fund's exposure to general asset classes. To this purpose, we rely on general equity and bond indices as factors in our style analysis. More specifically, in our basic model we use total returns based on a general equity index (the Stoxx Broad Europe Market Index, to be denoted by In2) and a small cap index (Stoxx Small Europe Market Index, to be denoted by In4). If European equity funds are exposed to the government bond market, they might prefer the Belgian bond index. Before the European monetary 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, this preliminary analysis suggests that mutual funds are indeed sensitive to the premium. As a consequence, we run the basic model with the Belgian total return government bond index (In5). The bond indices are taken from Datastream. To perform sensitivity analysis, we have also estimated alternative regressions where the Stoxx Broad Europe Market Index is replaced with the Stoxx TMI (In3) or the Euro Stoxx Blue Chip Market Index (In1).[4] Since results were not fundamentally altered, to save space, we do not report the results of these regressions. The descriptive statistics are shown in Table II. The characteristics of the general equity market indices are quite similar, which is also reflected in the high correlation between these three indices. As to the two bond indices, the average daily return on the Belgian government bond index is higher than that of the German bond index, but this goes hand in hand with a higher standard deviation and higher correlations with the equity indices.

[4] Other studies, like Chan et al. (2002), have selected the Fama and French (1993) 3-factor model or Carhart (1997) 4-factor model, which is an appropriate choice in style analysis when one is interested in evaluating relative excess performance of mutual funds based on an asset-pricing model with three or four risk factors.

Table I. Summary statistics for mutual fund data

Returns are percent daily returns. Panels A and B provide key statistics for the two mutual fund selections for 12-month periods and for the complete sample period. The total sample period runs from 3 June 1991 to 25 June 2001. 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 fifty-three and sixty-two mutual funds respectively, meeting the criteria outlined in the Appendix. All mutual fund data are taken from the *Vision* database. 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 day 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 returns

Period	Number of funds		Average fund return	
Selection	Fet	Efund	*Fet*	*Efund*
1991–01	62	53	0.061	0.061
1991–92	7	7	0.024	0.024
1992–93	8	8	−0.018	−0.018
1993–94	10	9	0.077	0.077
1994–95	12	11	0.003	−0.003
1995–96	14	13	0.095	0.092
1996–97	16	15	0.126	0.133
1997–98	27	23	0.178	0.182
1998–99	37	31	0.036	0.039
1999–00	61	51	0.158	0.143
2000–01	62	53	−0.070	−0.062

Panel B: Cross-sectional descriptive statistics for daily mutual fund returns

Period	Number of funds		Average fund return		Minimum		Maximum		Standard deviation	
	Fet	Efund	Fet	Efund	Fet	Efund	Fet	Efund	Fet	Efund
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

Table II. Descriptive statistics for indices

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 are shown in columns 4 to 8. 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, statistics are provided for 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

Index	Return	Standard deviation	Correlations				
			In1	In2	In3	In4	In5
In1 (Stoxx Blue Chip)	0.065	1.057	1				
In2 (Stoxx Broad Europe)	0.055	0.937	0.984	1			
In3 (TMI Europe)	0.056	0.909	0.918	0.936	1		
In4 (Small Europe)	0.013	0.728	0.811	0.867	0.835	1	
In5 (Belgian Gov. Bond)	0.031	0.196	0.126	0.125	0.130	0.087	1
In6 (German Gov. Bond)	0.028	0.191	0.109	0.110	0.100	0.090	0.737

We also estimate the correlation of fund returns with the returns computed from sector indices to assess whether the level of industry concentration of fund portfolios is of importance in explaining time variation in style exposures. We take the Stoxx Supersector indices that have complete data coverage over the sample period. The 15 sector indices are Oil & Gas, Chemical, Basic Resources, Construction & Materials, Industrial Goods & Services, Automobiles & Parts, Food & Beverage, Health Care, Media, Telecommunications, Utilities, Banks, Insurance, Financial Services and Technology. Descriptive statistics are available upon request, because, as will be clear from subsequent analysis, industry concentration is not a significant determinant of time variation in style exposures.

Finally, we select a set of additional information variables that we will use in our extended style analysis. We only know that these proxies should be related to future investment opportunities, based on the extensive empirical literature that studies the predictability of 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, as well as a lagged measure of the 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. 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 1-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. To investigate the existence of intramonth time variation, we add a dummy variable to test if a turn-of-the-month effect (Ariel, 1987) is present in mutual fund returns.[5] Furthermore, if mutual funds' investment decisions are influenced by the previous performance of other funds, we expect mutual fund returns to be 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 we could run into simultaneity problems. To avoid this problem, we add the dividend yield with a lag of five, and measure the lagged average fund return from $t-6$ up to $t-2$. Finally, we also add the square of the (contemporaneous) index returns to the $\mathbf{z}_t$ vector to capture market timing (Treynor and Mazuy, 1966).

In our empirical analysis, we estimate Equation (3) 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 (Equation (8)) where only a single (information) variable at a time is introduced.

5. Empirical Results

5.1 PRELIMINARY ANALYSIS

We begin our analysis of time variation in style exposures by presenting the results of the RBSA over rolling windows. In Figure 1 the exposures are displayed using 180-days rolling regressions. Panel A is based on average cross-sectional data. Apparently, the portfolio restrictions imposed in the standard model would have been binding if included in the RBSA. Panel A reveals that substantial variation of the exposures over 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

[5] This effect refers to the fact that stock returns are higher at the turn of the month.

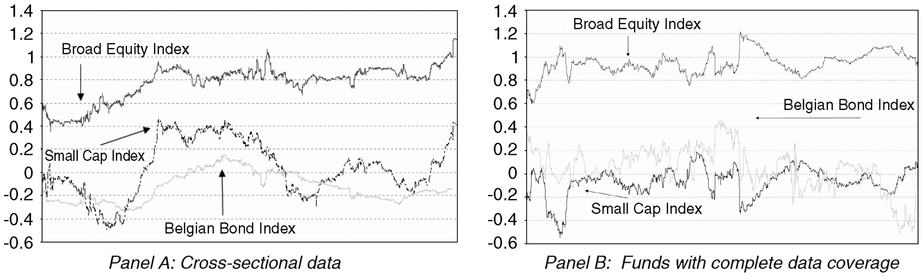


Figure 1. RBSA over rolling windows. Panel A presents the results of RBSA (described by Equation (1)) over rolling windows based on cross-sectional data, for the Fet fund selection. The window length is 180 days. The factors are In2, In4 and In5. See Table II for details on the indices. The total sample 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 five funds that exist during the entire sample period.

out the possibility that the observed exposure variation is due to changes in the composition of the sample.

The important point in Panel B is that variation of exposures in time continues to be present. This is confirmed by the more formal approach of the variance decomposition due to Mundlak (1978). 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 over 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 variance over time and funds is denoted by v, whereas its average over funds (time) is $v_{f.}$ $(v_{.t})$.

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

Even though we use a moving window to compute exposures, the 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). When we rely on the small cap index, the time-series variance remains high (36.6%), but is no longer the preeminent 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 the 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 in Bai and Perron (1998, 2003).

Table III. Decomposition of variance

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

	Between time variance (%)	Between fund variance (%)	Residual variance (%)
In2	42.4	21.6	36.0
In4	36.6	13.5	49.9
In5	70.7	2.9	26.4

5.2 TESTING FOR STRUCTURAL BREAKS

In this section, we present the results of the structural break tests.[6] Since there is no a priori reason to presume that a fund's exposure to one or more benchmarks is constant over time, we test for breaks in the matrix $\boldsymbol{\beta}$ of factor exposures to the various benchmarks.[7] Table IV presents the results of the *UD*max-test that examines the null hypothesis of no breaks against an unknown number of breaks.

It is clear from Panel B that all funds in the sample have at least one break during the sample period based on the *UD*max test (at the 5% level). Moreover, about 60% of those funds have more than one break (again at the 5% level): fifteen funds feature two breaks, nine funds have three breaks, and thirteen have four breaks. This result is 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 CLUSTERING OF STYLE BREAKS

In this section we take a closer look at the distribution of style breaks over time. The main question is whether style breaks are scattered over time or clustered in certain periods. The results are summarized in Table V. Style breaks clearly occur more frequently in the second part of the sample, particularly in the last quartile. About two-thirds of all style breaks are clustered in this last quartile

[6] We would like to thank P. Perron for making the Gauss code for the structural break tests available through the Internet.

[7] Because the structural break test could be sensitive to outliers we conduct an analysis of the presence of outliers and influential observations following the procedures and guidelines developed in Belsley et al. (1980).

Table IV. Bai and Perron multiple break tests

Panel A shows for the cross-sectional data set the results of the test procedure for multiple breaks (Bai and Perron, 1998, 2003). The null hypothesis of no breaks against an unknown number of breaks is tested by the *UD*max test. Critical values (at the 5% significance level) are displayed between parentheses. The number of breaks is tested by means of the Sup$F_T(m+1|m)$ test. Panel B reports the results for the individual funds (at the 5% significance level). The second column ($\geqslant$ 1 break) tests the hypothesis that there is at least one significant break. Columns 3 to 5 show the number of funds having 2, 3 or 4 significant break dates, respectively. The column *Sample size* 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

Sample size	$\geqslant$ 1 break	2 breaks	3 breaks	4 breaks
62	62	15	9	13

of the sample. Panel B of Table V provides further evidence on the clustering. We indicate the degree of clustering by listing the percentage of breaks that are clustered with breaks of v other funds (v is listed in the first row). Hence, the second column of this panel indicates the percentage of funds with a break that is not clustered, the third column denotes the percentage of funds that share a break date with one other fund, and so on. These statistics are presented for daily, weekly and monthly periods. This panel provides corroborating evidence that style breaks are clustered, except at the daily level, which of course is a very stringent level for analyzing clustering. The level of clustering rises rapidly when one moves to the weekly or monthly frequency. At the weekly frequency, more than half the breaks (55%) feature some clustering, while at the monthly frequency, 87% of the breaks are clustered. As expected from these results, χ^2tests reject the null hypothesis that the style breaks at daily, weekly, and monthly intervals are uniformly distributed over time (p-values lower than the 1% level in every instance).

All results indicate that clustering of style breaks is present in our sample. This could indicate that the style breaks are induced by the reaction of funds to a common factor. In the next section, we investigate this possibility by

Table V. Clustering of style breaks

Table V provides descriptive statistics for the distribution of style breaks over time. Panel B lists the percentage of breaks that cluster with breaks of v other funds in period ω, where v represents the number of funds listed in the first row. ω indicates a single day, week or month as stated in the first column. Hence, the second column represents the percentage of funds that display no clustering. Panel C states the results of a Kolmogorov–Smirnov test that tests the null hypothesis that the distribution of style breaks is drawn from a uniform distribution. Panel D illustrates the monthly clustering graphically. It displays the number of funds having a significant break in a particular month

Panel A: Clustering per quartile

Quartile	(%)	Quartile	(%)
1	4	3	19
2	4	4	74

Panel B: Descriptive statistics regarding the percentage of clustered style breaks

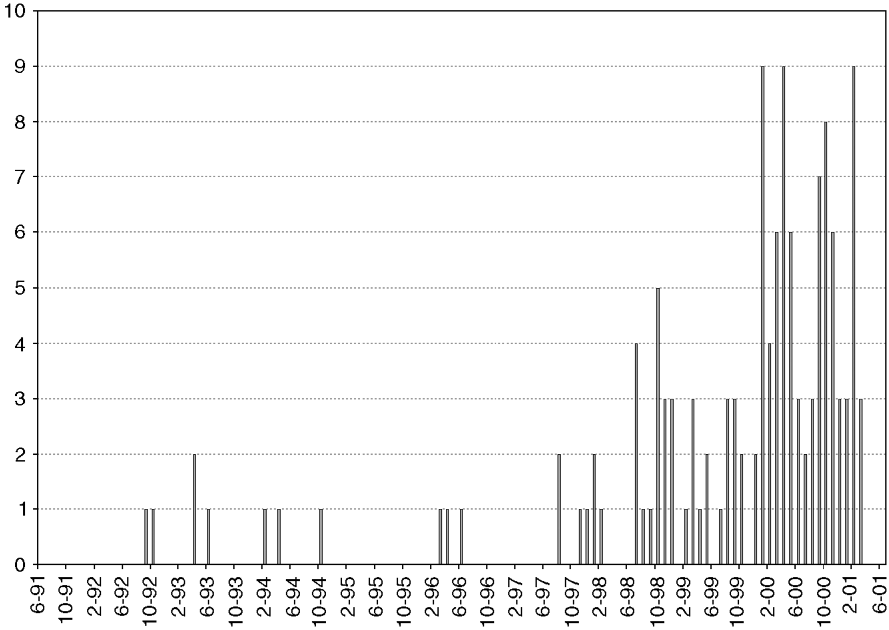
Clustered with breaks of v funds	0	1	2	3	4	5	6	7	8	Total
Daily clustering	75	21	4	—	—	—	—	—	—	100
Weekly clustering	45	19	22	6	7	—	—	—	—	100
Monthly clustering	13	10	22	6	4	13	5	6	20	100

Panel C: Kolmogorov–Smirnov test

	Monthly clustering	Weekly clustering	Daily clustering
Z-value	7.23	19.12	58.76
Significance	0.00	0.00	0.00

Table V. (Continued)

Panel D: Monthly clustering of style breaks



analyzing whether fund managers use publicly available information when they decide on their investment strategy.

5.4 DETERMINANTS OF TIME VARIATION IN STYLE EXPOSURES

In this section, we attempt to gauge the factors that drive the time-varying investment style of mutual funds. First, we explore whether the style breaks are induced by mutual fund managers engaging in conditional investment strategies based on (i) predictive information variables, and (ii) volatility estimates. Subsequently, we investigate the relation between style breaks and (iii) industry concentration of the investment portfolio, (iv) past performance, as well as (v) fund ownership (bank-owned versus independent).

Recall that more than 40% of the funds in our sample have even more than two style breaks. It appears unreasonable that such style breaks occur because the fund manager changes three or four times during the sample period. A more likely hypothesis is that the style breaks are induced by economic motives, such as herding, timing, or result from anticipating changes in economic conditions. To investigate this hypothesis, we estimate the extended style analysis given by Equation (8). For lack of degrees of freedom in subsamples, we add only one

Table VI. Extended RBSA

Table VI shows the results of the extended RBSA (Equation (2)). For each variable, the table reports the coefficient averaged across regressions, with the average value of the absolute t-statistics in 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 estimate and t-statistic of this variable is displayed in the column *Extra*. The last three columns show the coefficient estimates of the interaction terms with the Stoxx Broad Europe *(In2)*, the size index Small Europe *(In4)*, and the Belgian Government Total Return Index *(In5)*, respectively. The following variables are used: daily lagged measure of dividend yield (lag five), the daily lagged measure of the slope of the term structure (proxied by the difference between the redemption yield of the 10-year German government index and the 1-month German interbank rate), the daily lagged short-term interest rate (proxied by the 1-month German interbank rate), and the 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

Variables	$\overline{R}^2$	α	In2	In4	In5	Extra	InterIn2	InterIn4	InterIn5
	0.69	−0.00	0.736	0.201	0.084				
		(0.26)	(13.75)	(3.81)	(2.03)				
Div. yield$_{t-5}$	0.77	−0.008	0.776	0.320	−0.02	0.035	0.053	−0.268	0.015
		(1.30)	(8.04)	(3.01)	(0.11)	(1.19)	(1.32)	(5.06)	(0.12)
Term spread$_{t-1}$	0.72	−0.01	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)
Interest$_{t-1}$	0.62	0.290	0.800	0.169	−0.49	−0.07	−0.177	0.135	0.093
		(2.67)	(21.62)	(1.40)	(1.24)	(2.65)	(6.65)	(2.34)	(0.99)
D_{January}	0.64	−0.00	0.762	0.076	0.159	−0.00	0.120	−0.041	−0.238
		(1.08)	(32.60)	(2.85)	(3.77)	(0.23)	(3.22)	(0.94)	(3.36)
$(\text{In}_2)^2$	0.63	−0.00	0.754	0.091	0.148	−0.00			
		(0.29)	(33.80)	(3.64)	(3.69)	(1.08)			
$D_{\text{last week of month}}$	0.63	−0.00	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)
Av. Fund Ret.$_{t-6.-t-2}$	0.64	−0.000	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)

information variable at a time. Table VI shows the estimates of our extended style model.

As expected, the mutual funds in our sample are mainly exposed to the general equity index. In general, the estimated effects of the additional economic variables on the exposure to the general index (which is the main investment class of the mutual funds) are broadly—but not always—in line with expectations. The interaction term with the broad market index (In2) is positive—though not significant—in accordance with the well-documented positive correlation between the lagged dividend yield and the stock market.

But surprisingly, the interaction term for the small cap index (In4) is significantly negative. The highly significant interactions between all three market indices and the term spread accords with evidence by Fama and French (1989) and Fama and French (1993) that the term spread predicts bond and stock returns. Hence, it makes sense that mutual funds change their equity exposure conditional on the term spread. The negative interaction with the short-term interest rate (and therefore presumably to expected inflation) accords with the literature (see, e.g., Ferson, 1995). Surprisingly, the results indicate that mutual funds do not exploit the "small-cap-in-January" effect (see, e.g., Keim, 1983; Reinganum, 1983), possibly because funds receive considerable cash inflows at the start of the year, which force them to invest in more liquid stocks. However, without flow data the results remain a matter of conjecture. The significant positive interaction with the dummy for the last week of the month provides evidence that there is intramonth variation in style exposure, and is in line with the documented turn-of-the-month effect (Ariel, 1987). Consistent with previous literature (e.g., Kon, 1983; Chang and Lewellen, 1984; Henriksson, 1984) we find no evidence of significant market timing ability. Finally, the estimates in the bottom row indicate that mutual funds investment policies are influenced by the average performance of other mutual funds in the previous period.

More interesting to our central research question is whether style breaks are induced by economic motives. If the answer is affirmative, there should be no style breaks in the set of standard style exposures if we conduct a partial break test on the extended model, where only standard style exposures are allowed to vary. As mentioned before, the number of regressors becomes too large if we try to implement the break-test procedure by estimating an extended model with all the variables that proxy for economic motives. Therefore, we conduct the partial break test based on an extended model with a single additional information variable. Given the good fit of the specification with the lagged dividend yield, the results reported in Table VII refer to this particular specification. The test could be conducted for fifty-four funds.

Table VII. Number of breaks for individual funds in the different models.

Number of breaks	Standard RBSA	Extended RBSA with dividend yield	Median reduction in the number of breaks	Missing funds
1	21	40	0	4
2	13	10	1	2
3	7	3	2	2
4	13	1	2	0

We compare the number of breaks in a fund's style exposure 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 (1945) matched-pairs signed-ranks test. 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 with a p-value of 0.00. The number of funds that feature three breaks is reduced from seven to three, while the number of funds with four breaks shrinks from thirteen to one. Overall, the results are consistent with the hypothesis that a substantial number of style breaks are induced by the fact that mutual fund managers alter their portfolio composition based on information variables. Given that our model does not include all variables proxying economic motives simultaneously, it is likely that the number of breaks would decrease even more if more economic variables were introduced.[8]

Besides relying on macroeconomic variables, mutual funds have another way of exploiting public information. Busse (1999) demonstrates that mutual fund managers alter their market exposure as a function of market volatility. This strategy results in better risk-adjusted performance. To investigate whether volatility timing accounts for the observed style breaks, we estimate a partial structural break model that includes the volatility component, and where only the standard benchmark exposures are allowed to vary. Subsequently, we investigate the number of breaks in this model. We opt to model conditional volatility based on the GARCH(1,1) specification with t-distributed conditional errors as assumed in Equation 9.[9] It follows from the partial structural break model with the volatility component that volatility

[8] To test this hypothesis, we estimated specifications with more than one economic variable. The results stemming from this approach are consistent with the reasoning outlined above. Nevertheless, the sample of funds for which the tests could be performed is too limited to generalize these conclusions.

[9] A similar approach is applied in, for instance, Corhay and Tourani (1994) who investigate the statistical properties of daily stock indices for five European countries. To model the conditional volatility in this article, we estimate a number of GARCH specifications, including GARCH, exponential GARCH and threshold GARCH models. We also consider Gaussian, generalized Gaussian and the t-distribution for the error terms, and estimate GARCH(1,1) as well as GARCH(1,2), GARCH(2,1) and GARCH(2,2)-models. For the chosen model, the AIC and BIC test statistics are with −13,581.1 and −13,552.9 amongst the lowest values. With respect to the distribution of the errors, the t-distribution is preferred to the normal distribution based on the log-likelihood test. The generalized Gaussian distribution is rejected based on the Kolmogorov–Smirnov test (0.042, with a p-value of 0.001). The model fits the data well, as

timing accounts for a substantial number of breaks detected in the standard model. More than half the breaks (56%) are explained by this extended model, compared to 39% in case of the extended model with dividend yield. Thirteen funds are free of style breaks, while there are thirty-two, twelve and nine funds with one, two and three style breaks, respectively. This evidence is supported by the Wilcoxon signed-ranks test. The test statistic is statistically significant when we compare the number of breaks in (i) the standard model and the model with volatility timing (-5.31, with a p-value of 0.00) and (ii) the model with dividend yield, and the volatility model (-2.92, with a p-value of 0.00). We conclude that a substantial number of style breaks are induced by the fact that fund managers engage in volatility timing.

We investigate the relation between the style break patterns and the investment style of a fund further by relating our results to two other documented features on mutual fund investment strategies: tournaments and portfolio concentration. Brown et al. (1996) and other studies on mutual fund tournaments argue that mutual funds alter their investment strategy during the year conditioning upon their previous performance: mid-year losers have the tendency to increase fund risk.[10] This kind of investment behavior can be explained by the relative performance contracts that are common in the mutual fund industry. In the same spirit, we could raise the question whether some of the identified style breaks are related to tournament behavior. For instance, funds that want to decrease their risk could decrease their exposure to the equity factors and increase their exposure to the bond factor. To this purpose, we test the null hypothesis that the average performance of funds in the prebreak period (1 month or 6 months) is equal to the average performance of funds with no style break in that period. We find no evidence that relates style breaks with this type of tournament investment strategy. For instance, the mean difference in performance in the month preceding a style break between funds that have a style break and funds that do not have a style break equals -0.002 (with a p-value of 0.211).

Kacperczyk et al. (2005) document that industry concentration is a determinant of the investment policy and performance of mutual funds. Funds with concentrated portfolios achieve superior performance by overweighing growth and small stocks. We investigate whether the occurrence of style breaks is related to the level of industry concentration of a fund. Regrettably, we do not have data on mutual fund portfolio holdings, so we proceed in

shown by several tests of model misspecification (e.g., the ARCH-test (Engle, 1982) with one lag equals 0.09 with a p-value of 0.76).

[10] A view challenged by Busse (2001) based on daily estimates of fund risk instead of monthly estimates.

Table VIII. Industry concentration and number of funds

We form two portfolios of ten funds with the most extreme industry concentration measure. This measure is calculated as the sum of the squared deviations between the correlations of the fund's returns with sector returns, and the correlations of the broad equity index returns with sector returns. We test the null hypothesis that the median number of breaks for these two portfolios is equal by means of the Mann–Whitney U test.

		Standard model	Model with information variable	Model with volatility timing
Highest portfolio (4.14)	Maximum	2	2	4
	Median	1.00	1.00	1.50
	Minimum	1	1	1
Lowest portfolio (0.03)	Maximum	2	3	4
	Median	1.00	1.00	2.00
	Minimum	1	1	1
Mann–Whitney U test		46 (0.80)	33 (0.36)	32 (0.32)

an alternative manner. We calculate the correlation of mutual fund returns and fifteen sector returns based on indices taken from the Stoxx-website and ranging from Banking, Chemical to Media, Gas and Oil indices. We sort funds based on the sum of the squared deviations between the correlations of the fund return with sector returns, and the correlations of the broad equity index return with sector returns. If funds follow the same industry allocation as the broad index this measure should be low, and vice versa. If industry concentration is important to the time variation in style exposures, significant differences in the number of breaks should be evident if we compare the two groups consisting of the ten funds with the highest and lowest concentration measure. It follows from Table VIII that we do not find any relationship between industry concentration and the susceptibility of funds to style breaks.

Finally, we find that our results on style breaks do not depend upon the fact that funds are part of bank-related or independent fund groups. The χ^2-value for the contingency table testing this hypothesis equals 0.189 with a p-value of 0.664.[11]

[11] To relate our results further to the literature on mutual fund organization, and more specifically the literature on mutual fund families (see, e.g., Siggelkow, 2003; Elton et al., 2004), we test for style patterns at the fund family level to investigate whether investment strategies set at the fund family level might induce the documented style variation for individual funds. We find only weak support for this hypothesis. Although, we document that a number of funds within a family show the tendency to have (or not have) a reduction in the number of breaks after accounting for dividend yield or volatility timing, the hypothesis that all funds within a family follow an investment strategy based on dividend yield or volatility timing, and that this

6. Conclusions

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. We rely on break tests established in Bai and Perron (1998, 2003) to examine profoundly the possibility of style breaks. An advantage of these test procedures is that one can test for multiple breaks at a priori unknown break dates, and test for 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. 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 style exposures over time. All funds exhibit at least one break, while 60% of the funds exhibit even more than one break. An analysis of the distribution of breaks over time reveals that breaks are clustered, especially in the second half of the sample. This could indicate that the style breaks are induced by the reaction of funds to a common factor. Indeed we document that the patterns of style changes are mainly induced by the response of mutual funds investment strategies to publicly available information variables, and particularly to volatility shocks. Other variables like, for instance, industry concentration or past performance appear not to be related to the occurrence of style breaks.

Appendix

The following table shows the number of funds (distributed in Belgium) in the two data samples, depending on the selection criteria. The number of funds that do not meet the selection criterion at 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 are taken from the *Vision* database that contains daily data (if reported by the fund) for all funds listed in Belgium and the Netherlands.

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behavior causes a reduction in the number of style breaks is rejected at the conventional levels of significance. Results are available upon request.

Selection criteria	Number of funds in the Efund selection	Number of funds in the Fet selection
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 nondaily data	106 (−31)	129 (−33)
Deletion of funds with less than 1 year of observations	64 (−42)	82 (−47)
Deletion of non European equity funds based on RBSA	53 (−11)	62 (−20)
Final sample	53	62

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