Derivatives Use

Time lags in fund of funds

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Practical applications

Net asset value (NAV) of funds of funds (FoF) is based on the underlying funds NAVs. Due to the time of publication of the underlying funds NAVs as well as the underlying funds relating to different markets with different closing times, the NVA of FoF includes time lags and is therefore producing some noise. This noise makes it difficult to correctly estimate tracking error (TE). To minimise the impact of time lags, the authors suggest a measure to adjust the TE considering the problem of non-synchronous data. The paper constitutes an appropriate reading for risk managers as well as for investors needing to compare risk relevant factors using TE (ie information ratio) of funds of funds.

Abstract

The purpose of this paper is to analyse the impact upon tracking errors (TEs) of time lags in the calculation of fund of funds (FoF) net asset value (NAV). We examine how microstructure effects produce noise in the NAV of FoF and therefore noise in the TE. For that, we use simulations to calculate FoF NAVs at different closing dates. We then compare series of TEs to analyse the impact of time lags and formalise a relation adjusting the TE including error terms in the ratio.

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INTRODUCTION

Just as a mutual fund invests in a number of different securities, a fund of funds (FoF) holds

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shares of many different mutual funds. These funds were designed to achieve greater diversification than traditional mutual funds. An FoF typically diversifies its portfolio not only among hundreds or thousands of stocks, bonds and money market assets with a minimum investment but also across the entire industry, that is different regions, industries, managers, time horizons, etc. Thus, FoF can be an interesting solution for small and medium investors.

The first private equity FoF was raised in 1978. The development of the industry started only in the last couple of years. The FoF asset under management increased by more than 115 per cent during the last seven years, whereas asset under management of funds increased only by 20 per cent (see Figure 1b in Appendix A). The number of FoF increases each year and the proportion of this tool also increases (see Figure 1a and b).

In their paper , Agache and Huys[1] show that FoF makes sense. Based on fund database representative of European market, they conclude that FoF even performed significantly than their single fund counterparts over the period 2000–2004. The growing interest of institutional investors in the fields of alternative investments shows the need to understand the risk profile of FoF. Nevertheless, relatively little is known about the risk and the return of FoF until now.

The major aspects of investment strategies are to identify and select the most appropriate funds to use in an investor's portfolio FoF. This is true for both active and passive investment searches and selection. Investment advisors typically look at both qualitative and quantitative measures before making their decisions. Even though the qualitative tools are important, the manager will ultimately use some quantitative measures such as statistical ratio of risk adjusted measure of performance. Two of the most important quantitative measures traditionally used are tracking error (TE) and the information ratio (IR). When used properly, these tools give interesting information to make decisions.

One important problem recently advocated by Clarke *et al.*[2] and Rudolf *et al.*[3] concerns the difficulty to estimate TE. In this paper, we consider another source of bias to estimate TE relative to the analysis of FoF: the excess volatility of TEs due to microstructure effects. Although the problem of non-synchronous data has been already shown in mutual funds by previous studies (French and Roll,[4] Kadlec and Patterson,[5] Goetzmann *et al.*,[6] Chalmers *et al.*[7]), Ammann and Zimmermann[8] have found it more pronounced in FoF due to specific microstructure effects in FoF markets.

The remainder of this paper is set out as follows. The next section studies the related literature on TE. The third section presents the survey. First, we expose the problem of the excess volatility on TEs in FoF. Secondly, we develop the notion of time lags as an explanation of noise in the calculation of FoF NAV. Thirdly, we create simulations to demonstrate the problem. The fourth section presents the results. We show how time lags produce noise in the NAV and therefore noise in the TE. We study autocorrelation functions of simulated FoF and propose a correction term in TE formulas. The final section concludes the paper.

RELATED LITERATURE

Although there are a great number of risk measurement frameworks, the focus of the paper is the market risk of FoF relative to its benchmark. TE is a commonly used summary statistical measure of relative risk to provide an acceptable range of relative performance. TE was first defined by Tobe[9] as the percentage difference between the portfolio (in our application the FoF) and its benchmark index the fund was designed to replicate. TE is estimated as the annualised standard deviation of the difference in returns. For investment funds, it represents the percentage change in the net asset value (NAV) for each day of the whole time period required.

Percentage change in the *NAV*:

$$= \frac{NAV \text{ on day}(t) - NAV \text{ on day}(t-1)}{NAV \text{ on day } (t-1)} \tag{1}$$

Mathematically, the *TE* is:

$$TE = \frac{\sum_{t=1}^{n} (R_{FoF} - R_B)^2}{N-1} \tag{2}$$

where R_{FoF} is the return of *FoF*, R_B the return of the benchmark and N the number of return periods.

The annualised *TE* for daily observations is:

$$TE * 250 \tag{3}$$

Lower the *TE*, closer the returns of the *FoF* to that of the benchmark.

In the academic financial literature, the problem of how to minimise a TE objective starts with Roll.[10] The author solves the optimal asset allocation problem when the objective is to minimise the variance of the TE in a static (buy and hold) framework. He proves that, under most circumstances, the corresponding optimal portfolio is not mean–variance efficient. Clarke *et al.*[2] argue that the TE model should not be understood in terms of the standard Markowitz model but as a model involving aversion to regret. In the single-benchmark case, Rudolf *et al.*[3] investigate four different linear models for minimising TE. They show that these models are consistent with expected utility maximisation and thus provide a new explanation for the Roll's paradox. This methodology has been applied to the case of multiple benchmarks by Wang.[11] Rudolf *et al.*[3] investigated asymmetric extensions of the TE minimisation problem considering lower partial moment objectives and min–max functions with one-side deviations.

Instead of using TE optimisation problems, Jorion[12] derives analytical solutions in the mean variance plane subject to a TE constraint that forces the total risk of the portfolio to be no greater than the risk of benchmark.

The professional finance world has also studied this question in all aspects of portfolio management. Dynamic asset allocation advice is currently provided by most of the brokerage firms and financial advisors, and dynamic asset allocation strategies are carried out by active portfolio managers.

The main strategic asset allocation is to maximise expected alpha subject to a global TE constraint for the portfolio. Active managers and investors always expect to earn positive alpha, so expected alpha estimates are likely upward-biased measures of realised alphas. Expected alpha, however, may be an efficient way to rank investment opportunities, even if the numbers are biased.

Another problem concerns the difficulty to estimate TE. Ammann and Zimmermann[8] show that TE raises quickly as return correlations within an asset class fall. Bowen and Statman[13] discuss a psychological phenomenon called 'hindsight bias' that suggests the difficulty of accurately estimating one's own future performance. Many studies have tested the assumption relating the positive relation between TE and expected alpha. Gupta *et al.*[14] show that the number of quarters that managers outperformed their benchmarks is uncorrelated with TE for most asset classes, except

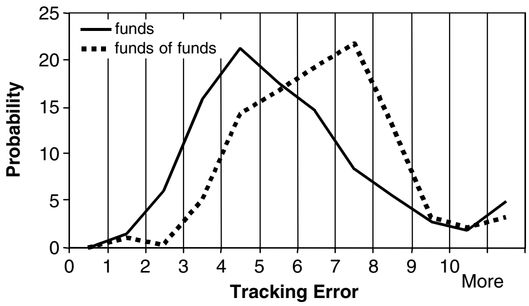

Figure 1: The distribution of TE

for emerging markets equity and international fixed income. They conclude that high TE does not indicate an ability to generate consistent positive alpha.

THE SURVEY

Excess volatility on TEs in FoF

The volatility on TE corresponds to the degree of risk an investment deviates from the average of his benchmark.

To analyse and compare the funds with the FoF markets, we dispose of 1,700 Funds and 280 FoF characterised by their benchmark: the MSCI World. The data come from Lipper.[15] We estimate TEs with regard to the MSCI World benchmark for all of these funds. For each asset class, we compute annualised TEs for the period of 28th February, 2005 to 28th February, 2006.

Several authors claim that the standard deviation is an inappropriate measure of risk due to the distribution of funds returns. This constraint is true for individual funds. But if we consider the market as a whole the standard deviation of historical funds should be reasonably a good measure of risk. Generally, the distribution of FoF has smaller tails and is less skewed than the underlying funds. Indeed, the main reason for investing in an FoF instead of a single fund is diversification. Investing in an FoF

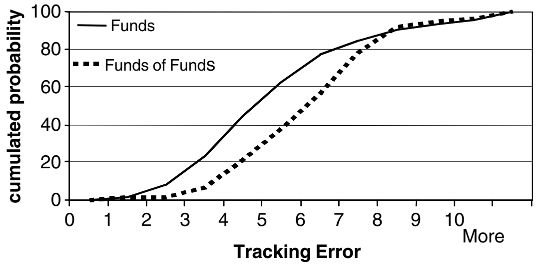

Figure 2: Comparison: FoF and funds

Table 1: TE statistics

	Funds	*Funds of funds*
Mean TE	4.80	5.69
Median TE	5	6
Standard deviation	2.65	1.93
Ratio	1.81	2.94

significantly reduces individual manager risk. Figure 1 shows the risk profile of FoF and Funds.

We observe an excess volatility on TE in FoF. If we compare the two distributions, we obtain a paradox. For example, 21.29 per cent of funds have TE equal to 4, whereas 21.70 per cent of FoF have TE equal to 7!

Figure 2 allows a comparison of the two asset class using descriptive statistics. The curve of Funds is located to the left of its FoF counterparts. This demonstrates that funds have lower TE than FoF on average. 1.067 per cent of FoF have a TE that is 1 or lower, 6.40 per cent that is 3 or lower 25 per cent of Funds have a TE until 4 against 5 for FoF and 75 per cent of assets have a TE until 6 for Funds and 7 for FoF. Finally, both curves show a similar pattern from the TE equal 8. The principal results are given in Table 1.

The mean, the median and the standard deviation offer different types of information. The median is much higher for FoF. This is because the FoF distribution is less skewed than the

Table 2: Kolmogorov–Smirnov test/bilateral test

D	0.285
p-value	<0.0001
Alpha	0.05

distribution of funds. The mean and the median are, however, close to each other, which imply relatively symmetric distributions. We calculate an average-risk ratio to measure the relative risk of the two assets. This ratio defined as mean TE divided by standard deviation is an appropriate measure to compare assets with different standard deviations. The ratio is higher for FoF indicating an excess of volatility gained per unit of risk.

Many causes can explain the excess of volatility of TE. First, the assumption of normality which is central in models where we use volatility as a risk measure. We apply the Kolmogorov–Smirnov test to assess whether the underlying distributions of the TE are normally distributed. If the calculated asymptotic significance is smaller than 0.05, the null hypothesis (the distribution is normally distributed) can be rejected. Table 2 shows the results of the test.

The test returns a *p*-value inferior to the significance value alpha. This validates that the distribution of funds and FoF are not normally distributed.

To compare statistical results between the two markets, one important question is to know if the two distributions are not significantly different. For that non-parametric tests are needed like the Mann–Whitney and the Wilcoxon tests (Table 3).

The results of tests reveal that the two samples of TE do not follow the same distribution (the *p*-value is inferior to alpha).

Table 3: Non-parametric tests

Mann–Whitney test	
U	24,142.000
Mean	39,480.500
Variance (U)	3,704,528.563
p-value (bilatéral)	<0.0001
Alpha	0.05
Wilcoxon test	
V	10,595.000
Mean	19,810.500
Variance (V)	1,858,881.625
p-value (bilatéral)	<0.0001
Alpha	0.05

Analysing these results, it seems difficult to explain excess volatility on TEs only by statistical properties of time series. Other sources like endogenous factors can explain one part of this volatility.

Time lags

Among stylised facts about volatility, several authors suggested to link asset returns to the flow of information arrivals. Concerning FoF, the process of greater diversification including different time zones can create time lags in the calculation of FoF NAV. Indeed, when the NAV of an FoF is calculated, the NAVs of underlying funds are not always available at the same market date. This lag is minimum (even null) when we dispose of all underlying NAVs at the same market day and is maximum when we have only 50 per cent of the available NAVs at one market day and 50 per cent at another market day. At the optimal situation, the most recent underlying NAVs are available for the day before the calculation day. This is usually the case when the FoF has a benchmark defined on a single market.

Nevertheless, every manager of FoF compares the return series of his FoF with the benchmark return series delayed by one day (the day before). This can be due to the time of publication of the underlying funds NAVs and also due to the fact that the funds relate to different markets with different closing times. The NAV of the FoF are therefore calculated using diverse market days. In practice, every manager of FoF compares the return series of his FoF at time t with the benchmark return series delayed by one day (at $t-1$). This strategy creates time lags.

A solution should be to use all NAVs available two days before ($t-2$) in place of some in $t-1$ and some in $t-2$. Nevertheless, managers do not use this solution because legal rules avoid arbitrage opportunity that can be generated by Late Trading or Market Timing.

Simulation

To isolate the problem of time lags noise, we use simulations in order to create all possible time lags situations. We create a FoF composed of 20 underlying funds for every market day during the period of May 2002 to March 2005. These funds are equally weighted, and we keep the number of parts of underlying funds unchanged during time without any buy and sell, avoiding by the way transactions costs. Our simulated FoF is presented in Table 4.

Table 4: The construction of funds of funds

Name		*Initial weight (%)*
1	Schroder ISF Japanese Equity C Acc	5
2	Pictet F-Emerging Markets-P	5
3	Pioneer Funds Top European Players A No Dis EUR	5
4	Ofima Cible	5
5	JPMF Europe Strategic Value A EUR	5
6	MLIIF US Focused Value A2 USD	5
7	Vanguard US Opportunities Institutional USD	5
8	Templeton Euroland A Acc	5
9	SGAM Fund Equities US Concentrated Core B	5
10	SGAM Fund Equities US Relative Value A	5
11	Fidelity Funds-European Aggressive Fund	5
12	CA Funds Emerging Markets I Cap (USD)	5
13	ACM Bernstein-European Value Portfolio A EUR	5
14	AXA Rosenberg Eurobloc Equity Alpha A EUR	5
15	Fidelity Funds-Japan Fund	5
16	Henderson HF Pan European Equity A2	5
17	INVESCO GT Pan European A	5
18	Gartmore CS Eurobloc	5
19	Franklin US Equity A Acc USD	5
20	GAM Star European Equity EUR Accumulation Class	5

About the benchmark definition, as the objective of the study is to analyse the impact of time lags on the FoF' TE, an interesting benchmark has to incorporate the larger possible range of international markets in order to maximise the overlapping effect induced by time zones. We choose the following benchmark with the proportion in the brackets: MSCI EMU (20 per cent), MSCI Europe ex-EMU (20 per cent), MSCI USA (20 per cent), MSCI Japan (20 per cent), MSCI Emerging Markets Free (20 per cent).

THE RESULTS

Let us assume that we calculate the NAV of our FoF at time *t*. At this time, the underlying funds have not yet published their own NAV. We create fictive situations starting from an optimal situation on which we dispose of every underlying NAV at time $t-1$ to the worst situation where all the underlying NAV are available only on time $t-2$. Between these two extreme situations, we have NAV available on both $t-1$ and $t-2$. As we have 20 underlying funds, we create 21 simulations. Table 5 describes the simulation

Table 5: Simulations results

Simulation	*Number of NAV in t-1 (in %)*	*Number of NAV in t-2 (in %)*	*Tracking error (%)*	*Beta*	*Correlation*	*Volatility (%)*
1	100	0	5.88	0.90	0.93	15.27
2	95	5	6.19	0.87	0.92	14.80
3	90	10	6.22	0.83	0.92	14.18
4	85	15	6.69	0.78	0.91	13.62
5	80	20	7.32	0.74	0.89	13.18
6	75	25	8.01	0.70	0.86	12.81
7	70	30	8.81	0.67	0.83	12.64
8	65	35	9.88	0.63	0.78	12.78
9	60	40	10.94	0.60	0.73	13.01
10	55	45	11.48	0.55	0.69	12.60
11	50	50	12.51	0.53	0.64	13.00
12	45	55	13.42	0.48	0.58	13.11
13	40	60	14.39	0.45	0.52	13.42
14	35	65	14.54	0.42	0.50	13.08
15	30	70	15.20	0.38	0.46	13.11
16	25	75	15.75	0.34	0.41	13.07
17	20	80	16.76	0.31	0.36	13.76
18	15	85	17.66	0.26	0.30	13.98
19	10	90	18.47	0.23	0.25	14.44
20	5	95	19.07	0.20	0.21	14.64
21	0	100	20.01	0.16	0.17	15.28

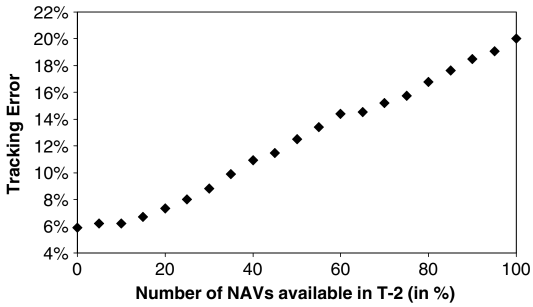

Figure 3: Influence on time lags on TE

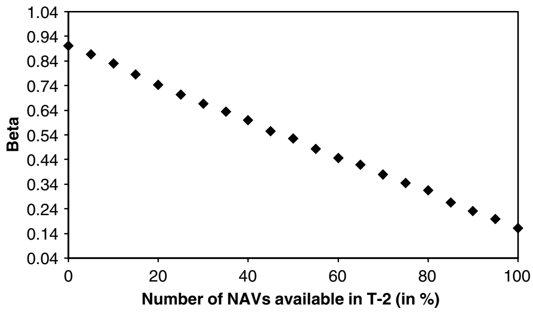

Figure 4: Influence on time lags on beta

procedure. For each simulation, we compute the returns series on a daily basis, the annualised TEs (from the benchmark return series delay by one day), the beta, the correlation and finally the total risk (the volatility). Table 5 shows the influence on time lags on measures of risk portfolio.

We can observe in Figures 3 and 4 linear relationships between them: the evolution of the TE is positively linear while the evolution of the beta is negatively linear.

Indeed, the higher the correlation between the benchmark and the FoF, the lower the TE. As NAVs available in $t-2$ increase, the correlation between the benchmark and the FoF falls and the TE increases exponentially.

To verify if the outcome of simulations is correlative to the choice of the benchmark, we compute the same simulations using different benchmarks and we obtain the same kind of behaviours with regard to time lags.

But due to our diversified benchmark, which maximises the overlapping effect induced by time zones, we observe the maximum microstructure effect in computing TE, beta and correlation for our simulations.

The next step in the analysis is the modelling of these linear dependencies within the FoF datasets. Indeed, time lags can create autocorrelation in series and then can explain one part of excess volatility in TE.

This phenomenon has already been observed in mutual funds. The goals of this step, however, are to determine the effects, if any, that such linear pre-filtering has on TE index.

We apply the Ljung Box statistics to test the autocorrelation in simulation series, in 250 FoF and 250 funds. The results of the tests on real series reveal that statistics is more often significant for FoF than funds.

The Ljung Box statistics reveal the presence of autocorrelation both in our simulations and the benchmark.

To take into account the autocorrelation effect, we pre-filter the original returns. This series is in effect an integrated series. More specifically, it follows an AR(1) or an AR(2) process. Thus, the elements of the processes must next be filtered out before the final, proxy series of returns could be obtained.

For the benchmark, the $I(1)$ elements is removed by taking the first differences within the series, leaving the following:

$$R_{B_t} - \underset{(0.036)}{0.1472} R_{B_{t-1}} = \eta_t \tag{4}$$

For our FoF series, the $I(1)$ or $I(2)$ elements is removed using the following regressions:

$$R_{FoF_t} - \rho_1 R_{FoF_{t-1}} - \rho_2 R_{FoF_{t-2}} = \varepsilon_t \tag{5}$$

where the parameters estimation of Equation (5) is given in Table 6:

Table 6: Regression estimations

Simulations	$\hat{\rho}_1$	$\hat{\rho}_2$
1	0.2488 (0.0358)	—
2	0.2739 (0.0356)	—
3	0.3223 (0.035)	—
4	0.3496 (0.0346)	—
5	0.3746 (0.0343)	—
6	0.4898 (0.0366)	−0.1338 (0.0366)
7	0.4892 (0.0366)	−0.1416 (0.0366)
8	0.4709 (0.0366)	−0.1314 (0.0366)
9	0.4709 (0.0366)	−0.1314 (0.0366)
10	0.5132 (0.0365)	−0.159 (0.0365)
11	0.522 (0.0364)	−0.1651 (0.0364)
12	0.6245 (0.0359)	−0.2337 (0.0359)
13	0.5957 (0.0361)	−0.2099 (0.0361)
14	0.6346 (0.036)	−0.2258 (0.036)
15	0.6319 (0.0362)	−0.2039 (0.0362)
16	0.5374 (0.0367)	−0.1145 (0.0367)
17	0.4994 (0.0367)	−0.1013 (0.0367)
18	0.4021 (0.0367)	
19	0.4354 (0.0368)	−0.0833 (0.0368)
20	0.3303 (0.0348)	—
21	0.299 (0.0352)	—

(.) Standard deviations.

It is the series of residuals from the models (4) and (5), which are $\hat{\eta}_t = R_B^{Proxy}$ and $\hat{\varepsilon}_t = R_{FOF}^{Proxy}$ that finally serves as the proxy series for returns.

The next step is to define an 'adjusted' *TE* from proxy returns of FoF:

$$\text{Adjusted } TE = \frac{\sum_{t=1}^{n} (\hat{\varepsilon}_t - \hat{\eta}_t)^2}{N-1} \qquad (6)$$

This indicator is based on a linear pre-filtering approach to estimate the TE ratio. In comparison with the traditional TE statistics, the adjusted TE pre-filters the original returns in order to avoid linear dependencies. The following picture compares the two indicators.

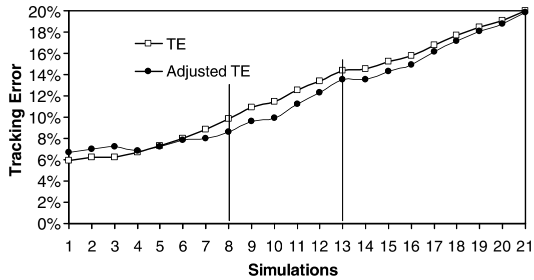

Figure 5: Comparison of TE and adjusted TE

We can observe a substantial improvement of our results from Figure 5: the correction of autocorrelation gives a better estimation of the TE that is more pronounced from simulation 8 to simulation 13 (12 per cent of correction on average).

These simulations incorporate the most important time lags problems as less than 35 per cent of NAV are available both at $t-1$ or at $t-2$.[16] Then our adjusted ratio filters, in part, the excess volatility of TE on FoF.

Linear filtering is, however, not sufficient. Indeed, even if the effect of time lags can be reduced by taking into account the autocorrelation of the series it seems that it cannot explain the excess of volatility observed in TE of FoF. Some other sources should be analysed like residual non-linear dependencies, or perhaps in the construction on FoF itself.

CONCLUSION

We have analysed another source of bias in the calculation of TE: time lags. We conclude that these microstructure effects create excess volatility in FoF TE. Moreover, we show that time lags in the NAV of FoF create autocorrelation in series and so induced a biased indicator of risk. We construct an adjusted TE formula estimated from autoregressive processes of returns. Our principal result is that taking into account the autocorrelation effect in NAV of FoF improves our risk estimation. The next step will be to ameliorate the quality of the correction of TE formula by improving the analysis of the residuals terms.

We suggest that you exercise caution with TE or derived measure as IR (excess return divided by TE) when these measures are used to compare FoF with funds. The effect of noise in the TE could lead to wrong conclusions with regard to the manager' skills.

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15 All our data in this paper come from Lipper (a Reuters Company).
16 In simulations 1 and 21, all NAVs are available at the same date and by the way, as time lags does not exist, the adjustment is close to zero.

Appendix A

See Figure 1A.

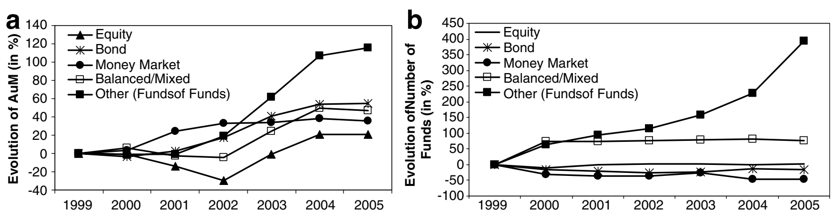

*Figure 1A: (**a**) Evolution of asset under management (in per cent): 1999–2005. Source: European Fund and Asset Management Association, 2005. (**b**) Evolution of number of funds (in per cent): 1999–2005. Source: European Fund and Asset Management Association, 2005*