Fund Performance Robustness
An Evaluation Using European Large-Cap Equity Funds

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Abstract

The paper revisits the issue of robustness of fund performance by evaluating European large-cap equity funds. For this fund category traditional market risk factor adjusted performance measures are expected to be fairly robust. However, for the sample of 65 European large-cap mutual equity funds, performance is shown to be very sensitive to the empirical estimation approach applied. Furthermore, the performance alphas are not robust over the conditional residual return distribution. This indicates that the performance is asymmetric with respect to the conditional outcome. A large part of the individual funds significantly underperform the benchmark in the lower tail of the conditional distribution. From a risk-averse investor's point of view, the results regarding the performance of an equally weighted fund of funds, is more comforting. On average the performance alphas are positive and highest in the lower part of the conditional distribution. As expected the market risk factor loadings are very robust for the sample of large-cap equity funds.

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1 - Introduction

In a recent paper Jha, Korkie and Turtle (2009) present a conditional alpha performance measure that is consistent with conditional mean-variance theory for monitoring the implied true conditional time varying alpha. In another paper Turtle and Zhang (2010) use a regime switching approach to model a state dependent conditional performance alpha. These approaches are interesting and need more elaboration.

The preset paper contributes to the discussion on conditional dynamic alphas by taking a slightly different empirical approach. Instead of explicitly modeling the risk adjusted returns over time we allow the risk adjusted returns to depend on the conditional residual return distribution using a quantile regression approach. Implicitly, if the risk adjusted return is varying over the conditional return distribution it is expected that a realized performance measure like alpha will explicitly exhibit a nonlinear and time-varying behavior. The advantage of this approach is that there is no need to explicitly neither define the economic state variables nor specify specific models for the time varying behavior. Furthermore, the paper also compares the estimated performance alphas of the quantile regression with those estimated by traditional OLS and Egarch techniques.

Using daily returns from January 1, 1996 to March 31, 2008 for 65 European Large-Cap mutual equity funds, the results show that performance is highly sensitive to the estimation technique. The Egarch technique produces more significant alphas than the other two methods: the OLS and the Quantile (Weighted Least Absolute Deviation (WLAD)) regressions. Furthermore, the results indicate that in many cases the performance to a high degree is a function of the realized outcome of the conditional residual return distribution. This last finding supports the findings of Jha et al. (2009) and Turtle and Zhang (2010) of the importance of accounting for time variability and state dependence when estimating alpha performance measures. The empirical evidence suggests that significant alphas are rare, if they exist at all. However, if the funds are combined to an equally weighted fund of funds, this fund of fund alpha is positive and highest in the lower part of the conditional distribution. This result indicates that fund managers collectively behave as risk averts.

The rest of the paper is set up as follows. Section 2 provides a brief literature review. Section 3 presents the empirical approach, the models and the estimation methods. Section 4 gives an overview of the data. Section 5 reports on the empirical results and Section 6 summarizes and concludes.

2 - Literature review

The discussion regarding fund performance measuring started with the concept of risk adjusted returns of Sharpe (1966). Jensen (1968) proposed a correction for market risk by testing the alpha of the traditional CAPM based single factor market model and a number of studies reported on short-term performance persistence (Hendricks, Patel, and Zeckhauser 1993, Goetzmann and Ibbotsson 1994, Brown and Goetzmann 1995, and Elton, Gruber, and Blake 1996). The results of Carhart (1997) indicate that this short-term performance persistence could be connected to the momentum effect. There is further development of the fund evaluation by Wermers (2000) who decompose the performance into different components to analyze the value of active fund management. However, most of the early performance studies are unconditional in their empirical approach. Do, Faff, and Veeraraghavan (2010) present a compact and comprehensive review of empirical findings on the short-term persistence.

A first step in the direction of a conditional approach is made by Ferson and Schadt (1996). They evaluate fund strategies and performance accounting for changing economic conditions. They advocate for conditional performance evaluation in which the relevant expectations are conditioned on public information variables. Several classical performance measures are modified and they find that the predetermined variables are both statistically and economically significant. Conditioning on public information controls for biases in traditional market timing models and makes the average performance of the mutual funds in their sample look better.

An alternative approach would be to explicitly model the time-variation in performance measures, the alphas, and /or the risk factor loadings of the risk adjusting asset pricing models. This approach is taken by Mamaysky, Spiegel, and Zhang (2008) who develop a Kalman filter to track the dynamics of the mutual fund factor loadings. They conclude that this approach is superior to OLS models employing macroeconomic variables in addition to fund returns.

Jha et al. (2009) develop a conditional alpha performance measure that is consistent with conditional mean–variance theory in line with the implied true conditional time-varying alphas in terms of magnitude and sign.

They show that the sequence of conditional alphas and betas are estimable from surprisingly simple unconditional regressions. A bootstrap analysis of Morningstar mutual fund returns demonstrates that the differences between existing conditional alphas and their proposed alphas are substantial for typical parameterizations.

Another explicit time-varying modeling approach is taken by Turtle and Zhang (2010). They use multivariate regime-switching modeling to study the portfolio performance benefits associated with the addition of emerging market and developed market mutual funds. The conditional performance measured by a state dependent Jensen's alpha varies with switching economic regimes. They argue that ignoring the existence of regimes could potentially misspecify mutual fund performance in some economic states. Their results are found to be robust to fixed or time-varying transition probability models, and to the use of either a one-factor market risk model, or a two-factor model with both market and foreign exchange risk factors included.

This study takes a different approach in accounting for conditional dependence of the fund performance measure. Using a quantile regression approach the alpha performance measure as well as the loadings on the adjusting risk factors are allowed to be dependent on the conditional residual return distribution of the mutual fund. This will impose no prior explicit time-varying pattern on the performance alpha. Instead the performance over different parts of the conditional residual return distribution will be monitored.

Jarrow and Protter (2010) show that a non-zero alpha can be the result if the wrong information set is applied for conditioning even if correct risk factors and time-varying loadings are used. The advantage of the approach in this paper is that we do not need to explicitly define any economic state variables nor specify any explicit model for the time varying behavior.

3 - Method

In order to simplify the presentation of our empirical evaluation we will base the presentation on a risk adjustment using the traditional CAPM framework and the single factor market model alpha in line with Jensen (1968). It is straight forward to expand the approach to a multifactor setting. We will first compare three different approaches for estimating the performance alpha. First, as benchmark we estimate a traditional OLS regression of the unconditional market model

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the return of mutual fund i at time t , $\left(r_{m,t} - r_{f,t}\right)$ is the market risk factor and $\varepsilon_{i,t}$ is assumed to be zero mean and i.i.d. normal. A correction for heteroskedasticity and autocorrelation (HAC) is applied to account for deviations from the i.i.d assumption.

The first partly conditional alternative is an Egarch(1,1) version of the single factor market model that accounts for the asymmetry and clustering of idiosyncratic volatility.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t} \tag{2}$$

$$\varepsilon_{i,t} \sim GED(0, h_t)$$

$$\log(h_t) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_1 \log(h_{t-1}).$$

The performance alpha estimates of OLS and Egarch(1,1) models will be compared to a more robust least absolute deviation (LAD) estimate of alpha. The LAD estimate is taken from a model where the variables are scaled with the Egarch standard deviations to ensure a constant variance in the regression (WLAD).

$$r_{it}^{e} = \frac{r_{i,t} - r_{f,t}}{\sqrt{h_t}} = c_i + \alpha_i \frac{1}{\sqrt{h_t}} + \beta_i \frac{\left(r_{m,t} - r_{f,t}\right)}{\sqrt{h_t}} + \frac{\varepsilon_{i,t}}{\sqrt{h_t}} \ . \tag{3}$$

The WLAD (weighted least absolute deviation) regression minimizes the sum of absolute residuals. A similar empirical approach is applied by Högholm, Knif, and Pynnönen (2011) for checking the robustness of weekday effects.

Using a quantile regression approach the alpha performance measures are made conditional upon the outcome of the conditional residual return distribution of the fund. The quantile regression approach was suggested by Koenker and Bassett (1978) and is in detail described in Koenker (2005). The quantile approach enables the monitoring and testing of the conditional regression slopes across different parts of the fund return distribution. Furthermore, as quantile regression is WLAD based it needs weaker distributional assumptions, and provides a distributionally more robust method of modeling the conditional distribution.

The quantile regression will minimize

$$\left[\sum_{t:r_{it}^{e}\geq \hat{r}_{it}^{e}(\Omega)} \tau |r_{it}^{e} - \hat{r}_{it}^{e}(\Omega)| + \sum_{t:r_{it}^{e}<\hat{r}_{it}^{e}(\Omega)} (1-\tau)|r_{it}^{e} - \hat{r}_{it}^{e}(\Omega)|\right] , \qquad (4)$$

where $\hat{r}_{it}^{e}(\Omega)$ is the estimated expectation of (3) and τ is the quantile parameter ranging from 0 to 1. The information set Ω consist of the conditioning regressors:1, $\frac{1}{\sqrt{h_t}}$ and $\frac{(r_{m,t}-r_{f,t})}{\sqrt{h_t}}$, that is the constant, the inverse of the Egarch standard deviation and the scaled market risk. In case of $\tau = 1$ the quantile regression will result in a WLAD regression for positive residuals. Correspondingly, in case $\tau = 0$ the result is a LAD regression for negative residuals. Setting $\tau = 0.5$ provides a WLAD median regression. Letting τ vary between 0 and 1, the quantile regression will monitor the regression relationship across the entire conditional excess-return distribution.

4 - Data

The data on European mutual equity funds was supplied by Morningstar Norway. The original data set contained information on 2,814 funds over the time period January 1, 1996 to March 31, 2008. However, for the analysis in this paper we only use funds with data available for the entire sample period. Furthermore, the sample is restricted to only contain funds classified to the large-cap category in order to obtain a homogeneous sample.

There are three main reasons for restricting the data. First, as the performance is dependent on general market conditions, it is beneficial to analyze the performance of the funds over a unified sample period. Still the sample period has to be long enough to cover a maximum variety of market conditions, such as bull as well as bear markets. Second, the Egarch technique and especially the Quantile regression require large samples. For Quantile regression a large sample is important in order to guarantee information for parameter estimation in all parts of the conditional distribution. Third, as the traditional CAPM derived market model is used to describe expected returns it is important that the market beta of the fund is robust. The market beta for the European Large-Cap equity funds are expected to be the most robust.

Accounting for the above restrictions the sample size shrunk drastically to only 80 funds. However, for four of the funds there were only weekly data available for some periods, especially in the first part of the sample period. For three of the funds the data contained obvious outliers like daily returns below -100% or long stretches of zero returns. From the data we also excluded eight large-cap funds with a statistically insignificant market model.

The final sample to be analyzed contains daily data for 65 large-cap European mutual funds starting January 1, 1996 and ending March 31, 2008. This large-cap category contains Large-Cap Growth, Large-Cap Value, and Large-Cap Blend funds as sub categories. The funds in the large-cap category are restricted to have at least 75% of the capital invested in European large companies with a market value above 8 billion euro. The names of the 65 funds are listed in Appendix in alphabetic order. The fund number used in the analysis and tables does not follow this alphabetic order.

Table 1 Descriptive statistics

	Average daily return	Max	Min	Standard deviation	Skewness	Kurtosis
Average among the 65 European large-cap mutual funds	0.024	6.694	-7.164	1.148	-0.315	7.046
Standard deviation among the 65 European large-cap mutual funds	0.007	1.533	1.526	0.136	0.132	1.249
MSCI Europe Large-Cap Index	0.032	5.778	-6.470	1.148	-0.258	6.421
One-month Frankfurt banks middle rate	0.012	0.019	0.008	0.003	0.230	2.305

Data contains 3195 daily total returns on 65 large-cap European mutual funds starting January 1, 1996 and ending March 31, 2008. As a proxy for market return the return on the MSCI Europe Large-Cap Index is used and the risk free rate is measured by the one-month Frankfurt banks middle rate.

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Descriptive statistics for the sample are presented in Table 1. The statistics are reported for the returns on an equally weighted portfolio of the 65 large-cap European mutual funds, the market return, and the risk free rate proxies, respectively. The equally weighted portfolio of the 65 funds can be interpreted as a fund of funds. Descriptive statistics for the 65 individual funds are available from the authors upon request.

Overall, the return distributions for the 65 large-cap European mutual funds are well behaved and as expected very similar. The average return on these funds over the sample period is 0.024% with an average standard deviation of 1.148, which in annual terms correspond to about 6% average return and 18% average volatility. The return on the MSCI European Large Cap Index is slightly higher, 0.032% (8% p.a.) with a standard deviation of 1.148 (18% volatility) which is in three decimal places the same as the average for the 65 equity funds. The average daily risk free rate is 0.012 (3% p.a.) with a standard deviation as low as 0.003 (0.8% volatility).

All of the 65 sample distributions are negatively skewed with an average skewness of -0.315 which is close to but slightly more negative than the skewness of the market index proxy. The return distributions for the 65 equity funds also show on average a higher kurtosis than the distribution for the returns on the market proxy.

5 - Empirical results

As a first step in the analysis of the robustness of fund performance, the market models (1), (2), and (3) are estimated for the 65 large-cap European mutual funds over the total sample period. The results are summarized in Table 2. In the OLS regression of (1) HAC (Newey-West) covariance matrices are used to account for the effect of heteroskedasicity. For model (3), the weighted quantile regression (WLAD) is estimated with a symmetric weighing of the absolute residuals, or with $\tau = 0.5$.

Although the return distributions for the 65 large-cap European mutual funds appear to be very similar the results for the performance alpha

Table 2 Market model alpha and beta estimates for 65 European large-cap mutual funds

	CAPM (HAC-OLS)			CAPM (EGARCH(1,1))			CAPM (WLAD(0.5))		
Nr	**Alfa**	**t-stat (NW)**	**Beta**	**Alfa**	**t-stat**	**Beta**	**Alfa**	**t-stat**	**Beta**
1	0.006	0.660	0.977	0.019	3.565	0.941	0.008	0.551	0.934
2	-0.006	-1.353	0.964	-0.011	-2.953	0.982	0.003	0.229	0.992
3	-0.007	-1.638	0.973	-0.020	-4.272	0.976	0.008	0.423	0.996
4	0.001	0.180	0.927	-0.016	-3.646	1.062	0.000	0.039	1.042
5	-0.011	-1.514	1.158	0.012	1.824	1.125	-0.026	-1.470	1.178
6	-0.005	-0.981	0.975	0.005	1.094	0.962	0.007	0.445	0.975
7	0.013	0.900	0.374	0.015	1.137	0.353	0.054	1.212	0.363
8	-0.003	-0.260	0.668	-0.011	-0.913	0.673	0.042	0.915	0.652
9	0.014	0.684	0.089	0.042	2.893	0.073	0.100	2.277	0.102
10	0.003	0.220	0.614	-0.003	-0.203	0.652	0.001	0.032	0.614
11	0.003	0.290	0.620	0.003	0.207	0.655	0.038	0.893	0.636
12	-0.009	-0.971	0.436	-0.008	-0.750	0.452	0.026	0.648	0.421
13	0.004	0.378	0.581	0.002	0.119	0.554	0.010	0.194	0.530
14	0.004	0.221	0.238	0.017	1.282	0.306	0.077	2.007	0.312
15	-0.005	-0.589	0.711	-0.010	-0.801	0.714	0.034	0.813	0.674
16	0.006	0.502	0.618	0.005	0.322	0.653	0.044	0.995	0.638
17	-0.003	-0.286	0.564	-0.013	-0.889	0.540	-0.009	-0.166	0.537
18	0.003	0.147	0.224	0.030	2.038	0.207	0.070	1.723	0.192
19	0.012	0.954	0.585	0.020	1.569	0.598	0.070	1.496	0.557
20	0.003	0.241	0.618	0.001	0.103	0.641	0.030	0.788	0.605
21	0.009	0.806	0.700	0.011	1.253	0.703	-0.005	-0.292	0.710

Table 2
Continued

22	-0.008	-0.946	0.685	-0.013	-2.581	0.952	-0.007	-0.661	0.963
23	0.009	0.626	0.378	0.019	1.422	0.554	0.034	0.926	0.525
24	-0.002	-0.170	0.723	0.004	0.552	0.906	0.018	1.351	0.910
25	0.005	0.514	0.697	0.018	1.839	0.755	0.037	1.217	0.741
26	0.002	0.102	0.328	-0.001	-0.063	0.431	0.035	0.945	0.385
27	0.004	0.303	0.385	0.009	1.363	0.821	-0.002	-0.147	0.765
28	-0.009	-1.413	0.774	-0.003	-0.672	0.741	0.000	-0.043	0.754
29	-0.010	-2.358	0.798	-0.015	-4.568	0.761	-0.012	-1.256	0.776
30	0.003	0.443	0.665	0.000	0.049	0.716	0.001	0.080	0.717
31	-0.012	-2.877	0.836	-0.016	-3.895	0.831	0.006	0.705	0.843
32	-0.009	-2.413	0.809	-0.010	-2.971	0.834	0.001	0.080	0.834
33	-0.004	-1.306	0.840	-0.008	-2.343	0.840	-0.005	-0.348	0.844
34	-0.011	-2.518	0.795	-0.022	-5.196	0.829	0.002	0.136	0.819
35	-0.008	-1.246	0.814	-0.004	-0.770	0.789	-0.010	-1.151	0.794
36	-0.015	-3.769	0.802	-0.022	-5.037	0.825	0.001	0.064	0.815
37	-0.004	-0.924	0.856	-0.008	-2.601	0.841	-0.004	-0.498	0.843
38	-0.019	-2.251	0.639	-0.016	-4.117	0.702	-0.001	-0.073	0.684
39	-0.013	-2.000	0.794	-0.002	-0.339	0.815	0.006	0.499	0.838
40	-0.009	-1.628	0.666	-0.014	-4.086	0.798	0.002	0.248	0.821
41	-0.014	-3.940	0.787	-0.004	-0.999	0.777	-0.003	-0.332	0.796
42	0.004	0.607	0.844	-0.007	-1.699	0.779	-0.003	-0.288	0.807
43	-0.004	-0.897	0.944	-0.009	-1.981	0.952	0.000	-0.018	0.972
44	-0.001	-0.125	0.681	-0.011	-2.772	0.996	-0.009	-1.087	1.000

Table 2
Continued

45	0.000	-0.038	0.647	0.003	0.333	0.668	-0.008	-0.284	0.636
46	-0.001	-0.134	0.804	-0.005	-0.513	0.823	-0.001	-0.022	0.871
47	0.001	0.094	0.510	-0.012	-2.753	0.993	-0.013	-1.743	0.986
48	0.013	0.938	0.412	0.004	0.686	0.939	-0.003	-0.337	0.957
49	-0.004	-0.221	0.525	0.019	1.502	0.493	0.022	0.792	0.466
50	0.002	0.345	0.722	0.004	0.598	0.732	0.021	0.850	0.745
51	-0.010	-1.716	1.002	-0.012	-2.351	1.021	0.000	0.014	1.021
52	0.004	0.390	0.600	0.006	0.984	0.921	0.001	0.122	0.924
53	0.011	0.649	0.210	0.022	1.735	0.585	0.031	0.903	0.570
54	0.031	2.676	0.478	0.050	6.556	0.677	0.021	1.003	0.655
55	0.010	0.578	0.212	0.032	2.159	0.401	0.037	0.903	0.432
56	-0.005	-0.762	0.997	-0.006	-1.058	1.012	0.001	0.070	1.022
57	-0.006	-0.984	0.995	-0.013	-2.197	1.009	-0.005	-0.258	1.019
58	-0.014	-2.207	0.975	-0.018	-3.387	0.983	-0.001	-0.057	0.994
59	0.006	0.736	0.736	0.017	1.774	0.791	0.052	1.500	0.751
60	-0.013	-2.793	0.801	-0.015	-5.180	0.800	-0.009	-1.097	0.831
61	-0.006	-1.297	0.806	0.003	0.596	0.799	0.000	-0.030	0.850
62	-0.003	-0.287	0.635	-0.011	-0.772	0.673	-0.017	-0.378	0.631
63	-0.011	-1.815	0.872	-0.007	-1.204	0.953	0.002	0.106	0.963
64	0.010	1.002	0.758	0.022	2.044	0.785	0.028	0.813	0.739
65	0.004	0.367	0.669	0.010	0.808	0.719	0.036	1.021	0.667
Average	**-0.001**		**0.685**	**0.001**		**0.751**	**0.013**		**0.748**

Models are estimated for 3195 daily returns on 65 large-cap European mutual funds starting January 1, 1996 and ending March 31, 2008. As a proxy for market return the return on the MSCI Europe Large-Cap index is used and the risk free rate is measured by the one-month Frankfurt banks middle rate. T-statistics for the OLS results use HAC(Newey-West) covariance matrices.

CAPM (OLS): $r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t}$

CAPM (EGARCH(1.1)): $r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t}$

$\varepsilon_{i,t} \sim GED(0, h_t)$

$\log(h_t) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_1 \log(h_{t-1})$

CAPM (WLAD): $r_{it}^{e} = \frac{r_{i,t} - r_{f,t}}{\sqrt{h_t}} = c_i + \alpha_i \frac{1}{\sqrt{h_t}} + \beta_i \frac{\left(r_{m,t} - r_{f,t}\right)}{\sqrt{h_t}} + \frac{\varepsilon_{i,t}}{\sqrt{h_t}}$

are very different. For the HAC-corrected OLS results 20% (13-out-of -65) of the alphas are statistically significant (at the 10% level of significance level or lower). Out of these 13 European large-cap equity funds 11 have a significant negative alpha. Hence, only two of the funds report a significant positive alpha. The average alpha is -0.001. For many of the funds the estimated betas are surprisingly low, on average 0.685, taken into account that these are large-cap European funds with at least 75% of the fund capital invested in very large European companies.

Even though the HAC-corrected OLS approach accounts for the heteroskedasticity, very different results appear when the Egarch(1,1) approach is used. For almost half, 48% (31-out-of-65), of the funds the alpha is now statistically significant. Of these 31 significant alphas 10 are positive and the average alpha is now also positive, 0.001. The beta estimates are also slightly higher using the Egarch(1,1) approach, on average 0.751, and closer to what would be expected for this fund category.

Switching to the more robust symmetric weighted least absolute deviation (WLAD) approach, the results again appear differently. Generally, many of the earlier negative alpha estimates are now positive. The average alpha (0.013) is now about 10 times higher compared to the Egarch(1,1) approach. However, the number of statistically significant alphas has dropped to 3. Interestingly, all three significant alphas (fund no. 9, 14, and 18) are positive and very high compared to the corresponding estimates using HAC-OLS or Egarch. There are also changes in the other direction. For fund no. 5 the significantly positive Egarch estimate 0.012 becomes negative for the WLAD approach, -0.26 and almost significant. The beta estimates using WLAD are on average at about the same level, 0.748, as the average betas of the Egarch approach.

The results above clearly indicate that the alpha estimates are not robust across different estimation approaches, not even for these fairly large equity funds. This picture is more evident from an analysis of the robustness across the conditional return distribution of the funds. Table 3 presents the results of the estimation using the WLAD quantile approach for nine values of the quantile weighting parameter τ, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9. These results are compared to the HAC- OLS, the Egarch, and the symmetric WLAD estimates in the first three columns of Table 3.

Table 3 shows that none of the 65 funds has a statistically significant alpha over the entire conditional residual distribution. For some of the funds the significant alpha is driven by outcomes in only one tail of the distribution (funds no. 1, 5, 22, 35, 40, 42, 47, 54, 55, and 60). In some cases the significant alpha is driven by extreme outcomes (funds no. 4, 11, 16, 17, 21, 30, 33, 34, 37, 43, 45, and 63). However, for some funds the significant alpha appears as the outcome of "normal" days in the middle of the conditional return distribution (funds no. 9, 14, and 18). Interestingly, for some funds the significant alpha changes sign as a function of the weighing parameter τ, (funds no. 2, 28, 32, 41, and 61). From a risk averse hedging point of view, it would be preferable to have a portfolio with significant positive alphas at least in the lower part of the distribution (for lower values of τ). This is the case for several funds (fund no. 9, 11, 16, 18, 21, 48, 55, 61, and 63). For other funds, however, the diversification fails when it would be mostly needed (funds no. 2, 5, 28, 30, 31, 32, 35, 37, 38, 41, 42, 44, 51, 56, 57, and 60). On the other hand, if this sample of 65 funds is regarded as an equally weighted fund of funds, Figure 1 shows that the fund of funds alpha is in fact positive in the lower part of the conditional return distribution. If the 65 funds are regarded as a random sample this average is positive and significant at the 10% level for τ values: 0.1, 0.3, 0.4, 0.5, 0.6, and 0.7. This could also be interpreted as sign of the alpha on average being more important for fund managers in the lower part of the conditional excess return distribution.

As expected, the market beta estimates are overall very robust across the conditional return distribution. The average beta for the 65 funds or the equally weighted fund of funds beta is presented in Figure 2 for the nine different τ values.

The market betas are on average slightly higher in the lower end of the distribution. Starting from 0.7772 for $\tau = 0.1$ and decreasing to 0.7303 for $\tau = 0.9$. This result indicates that the funds move more in line with the market in situations with low returns. One would perhaps have expected that the funds would use a possibility to drop the proportion invested in equity closer the limit 75% in cases of low expected returns. Figure 3 also indicates that the market model fits the data better in the left tail of the conditional residual distribution. The adjusted R-squares derived using the WLAD quantile approach are highest for the lowest τ values. One interpretation is that managers are risk averse and more concerned about market risk in the left tail of the conditional return distribution. On the other hand, the asymmetry of correlations among assets is well known and indicate a higher correlation in down markets. Furthermore, from a behavioural point of view more herding is expected among managers in bear markets.

Table 3 Comparison of performance alpha for OLS, EGARCH(1,1), and WLAD approaches

Fund	Alfa HAC-OLS	Alfa EGARCH(1,1)	Alfa WLAD(0.5)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	0.006	0.019*	0.008						+	+	+	
2	-0.006	-0.011*	0.003		-	-	-			+	+	
3	-0.007	-0.020*	0.008				-					
4	0.001	-0.016*	0.000									-
5	-0.011	0.012*	-0.026		-	-	-					
6	-0.005	0.005	0.007				+					
7	0.013	0.015	0.054									
8	-0.003	-0.011	0.042						+			
9	0.014	0.042*	0.100*	+	+	+	+	+	+	+		
10	0.003	-0.003	0.001									
11	0.003	0.003	0.038	+								
12	-0.009	-0.008	0.026									
13	0.004	0.002	0.010									
14	0.004	0.017	0.077*		+	+	+	+	+			
15	-0.005	-0.010	0.034									
16	0.006	0.005	0.044	+								
17	-0.003	-0.013	-0.009								-	

Table 3
Continued

18	0.003	0.030*	0.070*	+	+	+	+	+	+	+		
19	0.012	0.020	0.070				+					
20	0.003	0.001	0.03				+					
21	0.009	0.011	-0.005	+								
22	-0.008	-0.013*	-0.007							-	-	-
23	0.009	0.019	0.034							+		
24	-0.002	0.004	0.018				+					
25	0.005	0.018*	0.037									
26	0.002	-0.001	0.035						+			
27	0.004	0.009	-0.002									
28	-0.009	-0.003	0.000	-					+			
29	-0.010*	-0.015*	-0.012							-		-
30	0.003	0.000	0.001	-								
31	-0.012*	-0.016*	0.006		-							
32	-0.009*	-0.010*	0.001	-	-					+	+	+
33	-0.004	-0.008*	-0.005								-	-
34	-0.011*	-0.022*	0.002								-	-
35	-0.008	-0.004	-0.01		-	-	-					
36	-0.015*	-0.022*	0.001									
37	-0.004	-0.008*	-0.004	-	-							-

Table 3
Continued

38	-0.019*	-0.016*	-0.001		-							
39	-0.013*	-0.002	0.006							+		
40	-0.009	-0.014*	0.002							-	-	-
41	-0.014*	-0.004	-0.003	-	-	-			+	+	+	+
42	0.004	-0.007*	-0.003	-	-	-	-					
43	-0.004	-0.009*	0.000								-	-
44	-0.001	-0.011*	-0.009	-			-			-	-	-
45	0.000	0.003	-0.008								+	+
46	-0.001	-0.005	-0.001									
47	0.001	-0.012*	-0.013*					-	-	-	-	-
48	0.013	0.004	-0.003	+						-	-	-
49	-0.004	0.019	0.022									
50	0.002	0.004	0.021									
51	-0.010*	-0.012*	0.000		-	-	-					
52	0.004	0.006	0.001									
53	0.011	0.022*	0.031									
54	0.031*	0.050*	0.021						+	+	+	+
55	0.010	0.032*	0.037	+	+	+						
56	-0.005	-0.006	0.001		-	-	-					-
57	-0.006	-0.013*	-0.005		-	-	-					

Table 3
Continued

58	-0.014*	-0.018*	-0.001			-						
59	0.006	0.017*	0.052				+		+			
60	-0.013*	-0.015*	-0.009		-	-	-					-
61	-0.006	0.003	0.000	+							-	-
62	-0.003	-0.011	-0.017		+							
63	-0.011*	-0.007	0.002	+								
64	0.010	0.022*	0.028		+							+
65	0.004	0.010	0.036									

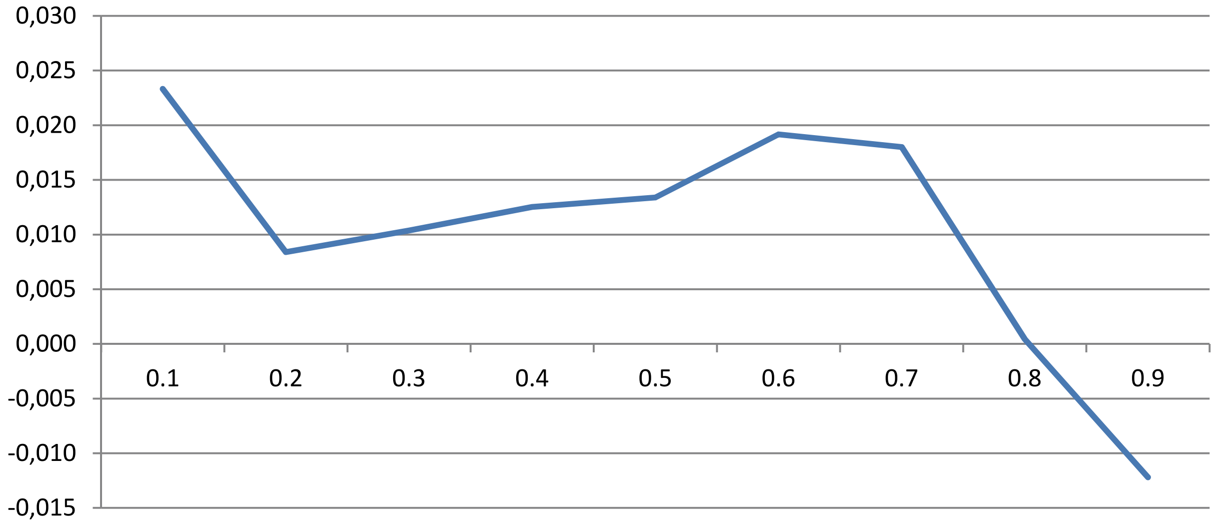

Figure 1 Average performance alpha for 65 European large-cap equity funds for different values of the quantile weighting parameter from 0.1 to 0.9.

Models are estimated for 3195 daily returns on 65 large-cap European mutual funds starting January 1, 1996 and ending March 31, 2008. As a proxy for market return the return on the MSCI Europe Large-Cap Index is used and the risk free rate is measured by the one-month Frankfurt banks middle rate.

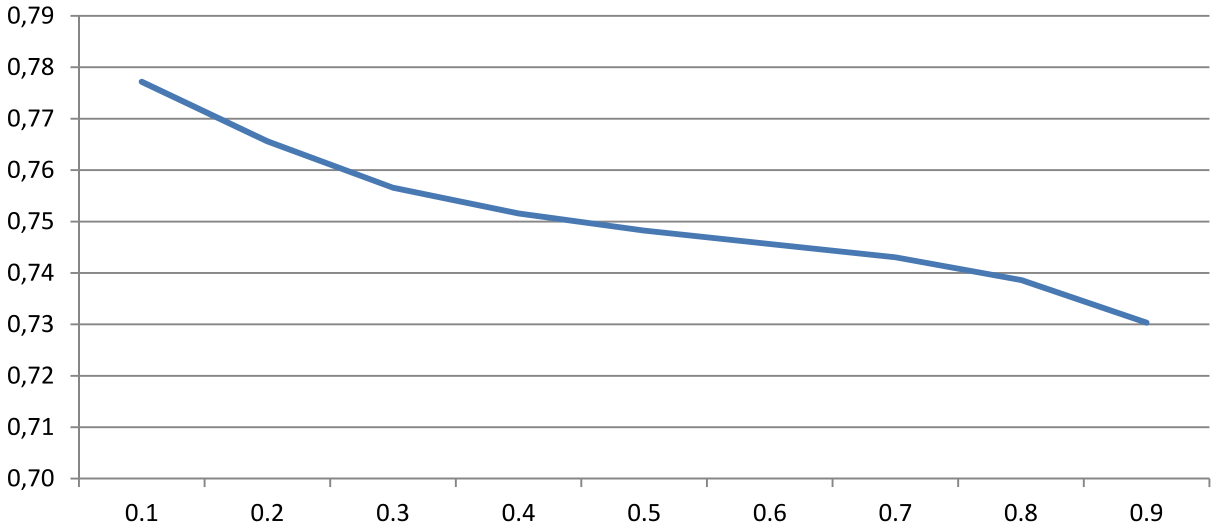

Figure 2 Average market beta for 65 European large-cap equity funds for different values of the quantile weighting parameter from 0.1 to 0.9.

Models are estimated for 3195 daily returns on 65 large-cap European mutual funds starting January 1, 1996 and ending March 31, 2008. As a proxy for market return the return on the MSCI Europe Large-Cap Index is used and the risk free rate is measured by the one-month Frankfurt banks middle rate.

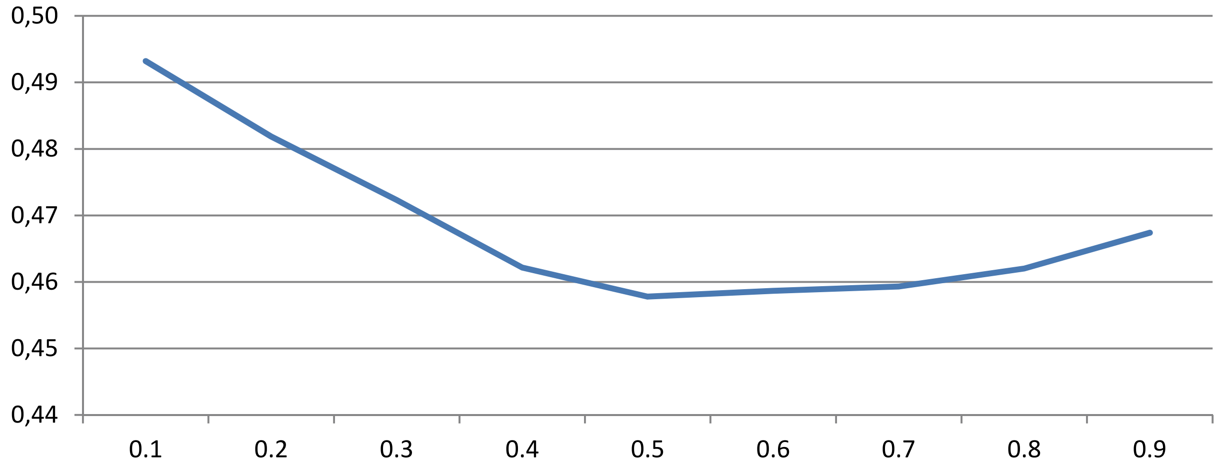

Figure 3 Average adjusted R-squares for 65 European large-cap equity funds for different values of the quantile weighting parameter from 0.1 to 0.9.

Models are estimated for 3195 daily returns on 65 large-cap European mutual funds starting January 1, 1996 and ending March 31, 2008. As a proxy for market return the return on the MSCI Europe Large-Cap Index is used and the risk free rate is measured by the one-month Frankfurt banks middle rate.

6 - Conclusion

The paper revisits the issue of robustness of fund performance by an evaluation of European large-cap equity funds using three different performance estimation techniques: a heteroskedasticity corrected ordinary least squares (HAC-OLS) approach, an exponential generalized autoregressive conditional heteroscedasticity approach (Egarch), and a robust weighted least absolute deviation (WLAD) quantile regression approach. The WLAD quantile approach enables a study of the performance robustness over the conditional residual return distribution.

For the studied fund category, European large-cap, traditional market risk factor adjusted performance measures are expected to be fairly robust. The unconditional return distributions appear to be very similar. However, for the sample of 65 European large-cap mutual equity funds, performance is shown to be very sensitive to the empirical estimation techniques applied. The Egarch approach reported more statistically significant performances than the HAC-OLS and the WLAD. Furthermore, the WLAD quantile approach shows that the performance alphas are not robust over the conditional residual return distribution. This indicates that the performance is asymmetric with respect to the conditional outcome. A large part of the individual funds significantly underperform in the lower tail of the distribution. From a risk-averse investor's point of view, the results regarding the performance of an equally weighted fund of funds is more comforting. On average, the performance alphas are positive and highest in the lower part of the conditional distribution. As expected the market risk factor loadings are very robust for the evaluated large-cap funds. According to the adjusted R-squares, the market risk adjusted asset pricing model also seems to fit the data best in the lower part of the conditional return distribution. An interpretation is that risk averse fund managers are more concerned about market risk in situations where outcomes are in the lower part of the conditional return distribution.

Appendix

Alphabetic list of the European large-cap equity funds included in the sample set

The alphabetic order is not the same as indicated by fund number in the analysis

ABN AMRO INV.FUNDS EU. EQUITY FUND
ACTIVEST LUX GLB.PRTF. EUROPEANEQUITY C
ALLIANZ AZIONI EUROPA L
ARCA AZIONI EUROPA
ARIDEKA
AXA L FD.EURO EQTIES.C
AXA L FD.EURO EQTIES.D
AZIMUT EUROPEAN TREND
BNL AZIONI EUROPA CRESCITA
CLARIDEN LEU GUE EUROPEAN EQUITY FUND
COMINVEST ASTMGMT. PUBLIKFD.ADIG FONDIROPA
CS EQ.FD.PRI.50 EUROPE
DEKALUX EUROPA TF
DEXIA EQUITIES L EUROPE CLC.C CAP.
DIT INDUSTRIA
DIT VERMOEGENS AUFBAU FONDS
DRBK.INV.MAN.KPL. VERSORGUNGSWERK FON.A
DWS INV.EUROP.AKN.TYP 0
DWS INVESTMENT EUPA.AKN.
DWS INVESTMENT EUROVESTA
EUROM.EUROPE EQ. FD.
FIDELITY FUNDS EUR.GW. FD.A GLB.CERT.
FONDERSEL EUROPA
FONDITALIA EQUITY EUROPE
FORTIS L FUND EQ.EU.THES
FRANKFURT TRUST INV. BHF TRUST PORTFOLIO FT
FRANKFURT TRUST INV. FT EUROPA DYNAMIK FON.
GARTMORE PAN EUR.FD.A
GENERALI EUROPA VALUE
GESTNORD AZIONI EUROPA
HANSAINVEST HANSEATISCHE INV.GESELL.HANSAEUROPA

HOLL EUROPE FD
IMI EUROPE
INVESCO KPL.EUROPA CORE AKTIENFDS
INVESCO PAN/EU.EQUITY FUND LUX A
INVESTEC ASTMGMT.INTL. AC.PAN EUR.
JPM FUND.JPM EUROPE EQ. FUND A DS.NAV
JPMORGAN ASTMGMT.I EU. SLT.MEGA CAP A AC.EO
JULIUS BAER MULTISTOCK EUROPE STOCK FUND B
KBC EQUITY FUND EU.CAP
KBC EQUITY FUND EU.DS.
LANDESBANK BERLIN INV. EUROPA INVEST
MEAG MUNICH ERGO KPL. EUROKAPITAL
MEDIOLANUM AMERIGO VESPUCCI
METZLER INVESTMENT AKN. EUROPA
MGST.DN.WITT.EUR.VAL.EQ. I
MUNCH.KAPITALANLAGE AG INV.FON.EUROAKTIV
NEXTRA AZIONI EUPA.DNMO.
OPPENHEIM KPL.EUR. EQUITIES
PAM EQUITIES EUROPE C
PIONEER AZIONARIO EUROPA
PIONEER AZIONARIO VALORE EUROPA DIS.
RAIFF.SCHWEIZ LX.FON. EUROAC A
RAIFF.SCHWEIZ LX.FON. EUROAC B
RAS LUX EQUITY EUROPE
SAI EUROPE
SCHRODER INV.MAN.LX.ISF EUR.EQ.SIGMA A DS.
SEB INVEST EUROPAFONDS
SWISSCA FONDSLEITUNG SWISSCANTO CH EQ.CONT.EU
UBS EQ.FD.MAN.CO.LUX EUR.OPPOR.B
UBS(CH)EQ.EUROPE
UNION INV.PRIVATFONDS BBV INVEST UNION
UNION INV.PRIVATFONDS BERLINER VB AKTIEN UNION
UNION INVESTMENT LX. UNIEUROPA T
VONTOBEL EU.EUR.EQ.A1 A1 AUS

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