Asymmetric Fund Performance Characteristics A Comparison of European and US Large-Cap Funds

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The paper focuses on asymmetric fund performance by comparing performance characteristics of European and US large-cap mutual equity funds. The quantile approach applied enables the monitoring of fund performance across different conditional outcome scenarios. For the sample of 31 European and 35 US large-cap mutual equity funds the performance is found to be sensitive to the empirical estimation approach applied. Furthermore, the performance alphas exhibit asymmetry across the conditional return distribution. This asymmetric performance behavior might be utilized for the construction of a portfolio of funds with suitable hedge characteristics. A large part of the US individual funds significantly underperforms the benchmark, especially in the lower tail of the conditional distribution. A few of the European funds, on the other hand, exhibit significant and positive performance alphas in the lower tail of the conditional return distribution.

Keywords: asymmetric fund performance; european equity funds; US equity funds

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I. Introduction

In recent literature on both mutual and hedge fund performance evaluation, different measures of performance have been proposed. A majority of this research is advocating for conditional performance measures instead of unconditional ones. Utilizing the conditional mean-variance theory, Jha, Korkie and Turtle (2009) present a new conditional alpha performance measure to monitor the implied true conditional time-varying alpha. Turtle and Zhang (2012), on the other hand, use a regime switching approach to model a state-dependent conditional performance alpha. The present paper builds on and expands the approach of Högholm, Knif and Pynnönen (2011b). Instead of trying to model explicitly the average risk adjusted abnormal performance (conditional alpha) over time, alpha is allowed to depend implicitly on the conditional residual return distribution using quantile regression. The quantile approach enables the monitoring of fund performance across different conditional outcome scenarios. If the performance measure is not robust over the conditional return distribution it implies that it is state dependent and time-varying. In such a case, it is expected that realized performance measures like alphas, Sharpe ratios, and information ratios will exhibit nonlinear and time-varying behavior. This would, furthermore, indicate poor performance persistence.

The advantage of this quantile regression approach is that it materially simplifies the modeling as there is no need to define explicit economic state variables, conditioning investment opportunity sets, nor econometric models for the time-varying behavior of the conditional alpha. Högholm et al. (2011b) found that performance alphas are very sensitive to the applied modeling and estimation techniques. They also confirmed that in many cases the performance alpha is a function of the conditional residual return distribution. This finding supports the argument for the importance of accounting for time variability and state dependence in the performance measures, i.e. a conditional approach.

Knowing the performance characteristics of funds across different outcome scenarios would help investors in choosing suitable targets for a desired portfolio profile, e.g. conservative or aggressive. Further interesting information would be whether the fund has been a good hedge in bad times and/or a boost of returns in good times, or the opposite.

In order to monitor the robustness and to compare the performance characteristics of a sample of large-cap European and US mutual funds, monthly returns from September 1998 to December 2012 is used. This specific category of funds is expected to exhibit more robust risk-factor adjusted performance. For the sample of 31 European and 35 US large-cap mutual equity funds, the performance is, however, found to be sensitive to the applied empirical estimation approach. Furthermore, the performance alphas exhibit asymmetry as they are not robust across the conditional return distribution. A large part of the US individual funds significantly underperforms the benchmark especially in the lower tail of the conditional distribution. A few of the European funds, on the other hand, exhibit significant and positive performance alphas in the lower tail of the conditional return distribution. Accordingly, from a risk-averse investor's point of view, investing in an equally weighted portfolio of European large-cap funds, the performance results are more comforting. This result is in line with that documented by Högholm et al. (2011b) for another data set and another return horizon. On average, the performance alphas are positive and highest in the lower part of the conditional distribution for the European funds. Unfortunately, this result does not hold for an equally weighted portfolio of US large-cap equity funds. The US portfolio of funds exhibits the lowest alphas in the left tail of the conditional return distribution and is in this sense a poor hedge against unexpected low returns.

The results of this paper combined with those of Högholm et al. (2011b) suggest that, even though the performance is state dependent and time-varying, the structure of the performance variability across the return distribution is robust over sample periods and return horizons. For investors this indicates that the asymmetric performance behavior can be utilized for the construction of a portfolio of funds with suitable hedge characteristics.

The rest of the paper is set up as follows. Section II provides a brief literature review. Section III presents the empirical approach, the models and the estimation methods. Section IV gives an overview of the data. Section V reports on the empirical results and Section VI summarizes and concludes.

II. Literature review

The study of fund performance goes back to the concept of risk-adjusted returns of Sharpe (1966). Jensen (1968) suggested a market-risk adjusted performance measure by testing the significance of the alpha of the traditional CAPM-based market model and a number of studies reported on short-term performance persistence (e.g. Hendricks, Patel, and Zeckhauser 1993, Goetzmann and Ibbotsson 1994, Brown and Goetzmann 1995, and Elton, Gruber, and Blake 1996). Carhart (1997) indicated that the short-term performance persistence might be an effect of momentum. Wermers (2000) on the other hand decomposed the performance into components to analyze the value of active fund management. However, most of the early performance studies are unconditional in their empirical approach. A compact and comprehensive review of empirical findings on the short-term persistence is found in Do, Faff, and Veeraraghavan (2010).

One of the earliest papers using a conditional approach is Ferson and Schadt (1996) by accounting for changing economic conditions. They find that conditioning on public information reduces biases in traditional market timing models and makes the average performance of mutual funds look better.

Mamaysky, Spiegel, and Zhang (2008) take an alternative approach by explicitly modeling the time-variation in performance measures, the alphas, and /or the risk factor loadings of the risk adjusting asset pricing models. They develop a Kalman filter to monitor the time-varying behavior of the risk factor loadings of the mutual fund. They show that this approach is superior to traditional OLS models with macroeconomic variables in addition to fund returns.

Jha et al. (2009) present 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 conditional alphas and betas can be estimated using surprisingly simple unconditional regressions. An empirical bootstrap analysis for Morningstar mutual funds shows that the differences between existing conditional alphas and their proposed alphas can be substantial for typical parameterizations. Turtle and Zhang (2012) take another explicit time-varying approach using multivariate regime-switching modeling to study the portfolio performance benefits of including both emerging and developed market mutual funds. The state dependent Jensen’s alpha is shown to vary with switching economic regimes and they argue that ignoring the existence of regimes could bias mutual fund performance measures in some economic states. Their results are shown 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 a market risk factor and a foreign exchange risk factor.

The results in Jarrow and Protter (2013) show that a non-zero alpha might origin from using the wrong information set for conditioning even in the case correct risk factors and time-varying loadings are used. The advantage of the quantile approach taken in this paper is that there is no need to explicitly define any economic state variables nor specify any explicit model for the time-varying behavior. Furthermore, by using the 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 measure. Instead, the performance will be monitored over different parts of the conditional residual return distribution.

Recent literature on mutual and hedge fund performance apply the Fama-French three- or four-factor models to measure the performance alpha, see e.g. Bodson, Cavenaile, and Sougné (2013), Shive and Yun (2013), Hunter, Kandel, Kandel, and Wermers (2014), Jordan and Riley (2015), Tsai and Wu (2015), Cuthbertson, Hayley, and Nitzsche (2016). González, Papageorgiou, and Skinner (2016) use the eight-factor model of Fung and Hsieh (2004) to show that top quintile portfolios formed on Sharpe ratios, alphas, and information ratios persistently outperform corresponding third quintile portfolios.

Jordan and Riley (2015) show that in the standard four-factor framework, mutual fund return volatility is a powerful predictor of future abnormal returns. However, the abnormal returns are shown to be eliminated by inclusion of an explicit volatility anomaly factor. They conclude that failure to account for the volatility anomaly, directly or indirectly, may lead to substantial mismeasurement of fund performance. The approach taken in this study explicitly scales the fund returns by their conditional volatilities. In this way, the information ratio is modeled as a part of the abnormal return equation.

Banegas, Gillen, Timmermann, and Wermers (2013) study the performance of both Pan-European, country and sector funds and report that country-specific funds give the best opportunities for fund rotation strategies with four-factor alphas of 12-13% per year for the 1993-2007 period. However, using monthly returns over the period 1990-2009, Cuthbertson and Nitzsche (2013) find, for a three-factor model, that at most 0.5% of German equity mutual funds have truly positive alpha-performance and about 27% have truly negative alpha-performance.

Generally, for the European large-cap funds evidence indicate that significant alphas are rare. However, Högholm et al. (2011b) find that if the funds are combined to an equally weighted portfolio of funds, the alpha is positive and highest in the lower part of the conditional distribution. That is, it can partly act as a hedge for unexpected negative returns.

This paper applies a modified version of the conditional approach taken in Högholm et al. (2011b) by accounting for a larger set of risk factors and using a new empirical material that allows a performance comparison of European and US large-cap equity funds.

III. Method

The study partly follow the approach taken by Högholm et al. (2011b) and starting the empirical investigation by first comparing the results of three different approaches for estimating the performance alpha. As a benchmark, the traditional Fama-French four-factor model using an unconditional OLS regression is estimated.

$$\begin{aligned} r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}\left(r_{m,t} - r_{f,t}\right) + \beta_{2,i} SMB_t \\ + \beta_{3,i} HML_t + \beta_{4,i} MOM_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $r_{i,t}$ is the return of mutual fund i at time t , $(r_{m,t} - r_{f,t})$ is the market risk factor, SMB_t is the size factor, HML_t is the value factor, MOM_t is the momentum factor, and $\varepsilon_{i,t}$ is assumed to be zero mean and i.i.d. normal. In order to account for deviations from the i.i.d assumption a correction for heteroskedasticity and autocorrelation (HAC) is used in the estimation.

As a second step, the partly conditional EGARCH (1,1) version of model (1) is estimated. This accounts for the asymmetry and clustering of idiosyncratic volatility.

$$\begin{aligned} r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i} SMB_t \\ + \beta_{3,i} HML_t + \beta_{4,i} MOM_t + \varepsilon_{i,t} \\ \varepsilon_{i,t} \sim GED(0, h_t) \end{aligned} \tag{2}$$

$$\log(h_t) = \gamma_0 + \gamma_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma_2 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3 \log(h_{t-1}).$$

The performance alphas of model (1) and (2) are then compared to a more robust least absolute deviation (LAD) estimate of alpha. The LAD alpha is estimated using a model where the variables are scaled with the EGARCH (1,1) standard deviations to explicitly account for the dynamic fund return volatility and to ensure a constant variance in the weighted least absolute deviation regression (WLAD).

$$\begin{aligned} r_{i,t}^{e} = \frac{r_{i,t} - r_{f,t}}{\sqrt{h_t}} &= c_i + \alpha_i \frac{1}{\sqrt{h_t}} + \beta_{1,i} \frac{\left(r_{m,t} - r_{f,t}\right)}{\sqrt{h_t}} + \beta_{2,i} \frac{SMB_t}{\sqrt{h_t}} \\ &+ \beta_{3,i} \frac{HML_t}{\sqrt{h_t}} + \beta_{4,i} \frac{MOM_t}{\sqrt{h_t}} + \frac{\varepsilon_{i,t}}{\sqrt{h_t}}. \end{aligned} \tag{3}$$

Note that the $\alpha_i / \sqrt{h_t}$ component of the model might be interpreted as a time-varying information ratio. The new intercept c_i in (3) is inserted for technical purposes, as the quantile regression requires an intercept to balance against the conditional expectation at different parts of the distribution in order to have a residual summing to zero. This intercept takes the characteristic S-shape over the range 0 to 1 of the quantile parameter τ. Högholm, Knif, and Pynnönen (2011a) also apply a similar empirical approach for checking the robustness of weekday effects of stock returns. Note that the regression approach in (3) explicitly accounts for volatility and implicitly allows for conditional time-variability of factor loadings. Bali, Engle, and Tang (2016) also recently suggest the importance of accounting for this latter characteristic.

The EGARCH is chosen to allow for asymmetry in volatility across the conditional return distribution. This will match the asymmetric characteristic of the quantile regression better than corresponding GARCH estimates. Furthermore, the EGARCH will produce positive volatility estimates for the scaling in (3) without parameter constraints.

The quantile regression approach allows the performance alpha to be conditional upon the outcome of the residual return distribution of the fund. The quantile regression was presented by Koenker and Bassett (1978) and is in detail described in Koenker (2005).

Through the quantile approach, it is possible to monitor and test the conditional regression slopes, in this case the performance alpha as well as the risk factor loadings 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. As discussed earlier, a further advantage of the quantile regression approach is that it materially simplifies the conditional modeling as there is no need to define explicit economic state variables, conditioning investment opportunity sets, nor econometric models for the time-varying behavior of the conditional alpha.

The quantile regression minimizes

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

where $\hat{r}_{i,t}^{e}(\Omega)$ 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: $1, \frac{1}{\sqrt{h_t}}, \frac{(r_{m,t} - r_{f,t})}{\sqrt{h_t}}, \frac{SMB_t}{\sqrt{h_t}}, \frac{HML_t}{\sqrt{h_t}}, \text{and} \frac{MOM_t}{\sqrt{h_t}},$ that is the constant, the inverse of the EGARCH standard deviation and the scaled market risk, the scaled size factor, the scaled value factor, and the scaled momentum factor. In case of τ=1 the quantile regression will result in a WLAD regression for positive residuals. Correspondingly, in case τ=0 the result is a LAD regression for negative residuals. Setting τ=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 of the fund.

IV. Data

The data sample consists of monthly fund returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream. For the European funds, the sample period partly overlaps the sample period used in Högholm et al. (2011b). For comparison purposes, we try to sample the same large-cap funds even though Högholm et al. (2011b) focused on daily returns. For the empirical analysis, only use funds with data available for the entire sample period are included. Furthermore, the empirical sample is restricted to only contain funds classified as large-cap in order to obtain a homogeneous sample for the comparison with US large-cap funds. This large-cap category contains Large-Cap Growth, Large-Cap Value, as well as Large-Cap Blend funds as sub categories. The funds in the large-cap category are further restricted to have at least 75% of the capital invested in European large companies with a market value above 8 billion euro. The final sample size of European large-cap funds is 31. The return on the MSCI Europe Large-Cap Index is used as a proxy for market return and the risk free rate is measured by the one-month Frankfurt banks middle rate.

The sample of US funds from the CRSP database contains funds that invests in the domestic market and are classified both as "growth" and "income". A total of 581 US funds fulfilled this criterion. However, of these we excluded funds that did not meet the criteria: "Lipper class name: Large Cap Core Funds", that is funds that could not be classified as large-cap funds. After this step, there were 345 funds in the US sample left. In order to match the sample size with the European funds the US funds with a representative investment strategy were randomly listed and the first 35 where chosen for the final sample. Högholm et al. (2011b) present 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. On the other hand, the sample period needs 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 Fama-French four-factor model is used to describe expected returns it is important that the market beta and the factor loadings are robust. These factor loadings for the European and US large-cap equity funds are expected to be the most robust.

Descriptive statistics for the samples of returns of the European and US large-cap funds and for the risk factors are presented in table 1. The returns on the risk factors are collected from Kenneth French's home page.

The returns are presented as the return on an equally weighted portfolio of 31 and 35 European and US funds respectively. The equally weighted portfolio of funds can be interpreted as a fund of funds. The average monthly return over the sample span on the European portfolio is –0.02% per month or –0.24% per annum. The corresponding values

TABLE 1. Descriptive statistics for monthly returns on a portfolio of European and US large-cap funds and corresponding risk factors

	Average montly return	Std. dev. of monthly returns	Min. of monthly returns	Max. of monthly returns
A. European funds				
Equally weighted portfolio of funds	–0.02 %	4.75 %	–14.52 %	11.79 %
Market risk premium	0.39 %	5.68 %	–22.14 %	13.78 %
Size	0.12 %	2.38 %	–6.94 %	9.31 %
Value	0.49 %	2.82 %	–9.57 %	10.96 %
Momentum	0.86 %	5.03 %	–25.96 %	13.80 %
rf	0.20 %	0.17 %	0.00 %	0.56 %
B. US funds				
Equally weighted portfolio of funds	0.37 %	4.32 %	–17.82 %	10.26 %
Market risk premium	0.36 %	4.77 %	–17.23 %	11.34 %
Size	0.45 %	3.70 %	–16.39 %	22.02 %
Value	0.23 %	3.62 %	–12.68 %	13.87 %
Momentum	0.32 %	6.11 %	–34.72 %	18.39 %
rf	0.19 %	0.17 %	0.00 %	0.56 %

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

for the US portfolio are 0.37% per month and 4.5% per annum. The standard deviation for the European portfolio and the US portfolio are very close, 4.74% and 4.43% respectively. The average returns on the risk factors are slightly different for the two markets. The return on the size factor is low for the European market, only 0.12%. The average return on the size factor is almost 4 times higher for the US market, 0.45%. On the other hand, the return on the momentum factor is as high as 0.86% for the European market but only 0.32% for the US market. The return on the value factor is more than twice as high on the European market, 0.49% compared to 0.23% for the US market. The average monthly values for the risk free rate is almost the same for both markets.

V. Empirical results

As a first step, the market models (1), (2), and (3) are estimated for the 31 large-cap European and the 35 large-cap US funds over the total sample period September 1998 to December 2012. 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 heteroskedasticity. For model (3), the weighted quantile regression (WLAD) is estimated with a symmetric weighing of the absolute residuals, or with τ=0.5. In these first benchmark regressions the WLAD is chosen to be symmetric for the comparison with the symmetric OLS and EGARCH regressions.

Although the return distributions for the large-cap European mutual funds and the corresponding US funds appear to be similar the results for the performance alpha is very different. The results for the European market are presented in table 2.

For the HAC-corrected OLS results, none of the 31 estimated performance alphas are statistically significant at the 5% level and only 10 have a positive sign. The average alpha is –0.2% (–2.4% per annum). The results for the EGARCH(1,1) is different. Here 18 alphas out of 31 have a positive sign and four of these are statistically significant. Only one of the funds has a significant negative sign. The average alpha for the EGARCH estimation is about 0%. The results for the WLAD (0.5) are more in line with the results of the HAC-OLS regression. However, a few more alphas are positive, 16 compared to 10, and two are statistically significant at the 5% level, one negative and one positive.

TABLE 2. Four-factor model alpha estimates for 31 European large-cap mutural funds

	HAC-OLS		EGARCH(1,1)		WLAD(0.5)	
Fund	Alpha	p-value	Alpha	p-value	Alpha	p-value
1	0.000	0.958	0.000	0.982	0.006	0.705
2	–0.002	0.277	–0.001	0.721	0.009	0.282
3	–0.002	0.407	–0.005	0.000	–0.020	0.032
4	–0.001	0.673	0.000	0.933	0.010	0.570
5	–0.004	0.118	–0.004	0.151	–0.020	0.334
6	–0.001	0.541	–0.002	0.462	–0.014	0.259
7	–0.002	0.488	–0.002	0.135	–0.008	0.419
8	–0.003	0.214	–0.002	0.388	–0.009	0.540
9	0.001	0.843	–0.003	0.001	–0.017	0.139
10	–0.001	0.574	0.000	0.901	0.003	0.853
11	–0.001	0.765	–0.001	0.649	–0.013	0.309
12	–0.003	0.139	–0.002	0.303	–0.005	0.734
13	0.003	0.269	0.004	0.042	0.008	0.598
14	–0.001	0.594	0.001	0.829	–0.001	0.955
15	–0.002	0.467	0.000	0.908	0.000	0.998
16	–0.002	0.442	0.000	0.951	0.001	0.933
17	–0.001	0.679	0.000	0.987	–0.006	0.591
18	0.000	0.870	0.001	0.725	–0.007	0.692
19	–0.003	0.161	–0.004	0.049	0.000	0.983
20	0.000	0.948	0.000	0.907	–0.007	0.452
21	–0.001	0.778	0.001	0.813	0.004	0.818
22	0.001	0.673	0.001	0.501	0.000	0.980
23	0.000	0.966	0.002	0.334	0.002	0.831
24	0.000	0.855	0.002	0.430	0.019	0.109
25	–0.001	0.645	–0.003	0.213	–0.002	0.888
26	0.000	0.898	0.000	0.879	–0.004	0.817
27	–0.002	0.401	–0.002	0.324	–0.032	0.097
28	–0.018	0.224	0.003	0.003	0.006	0.039
29	–0.018	0.223	0.003	0.000	0.005	0.117
30	0.001	0.793	0.001	0.682	0.002	0.844
31	–0.003	0.161	–0.002	0.277	0.002	0.881
Average	–0.002		0.000		–0.003	

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

The average alpha is –0.3% (–3.7% per annum).

Table 3 shows the robustness of the performance alpha across the conditional return distribution for the European funds. Overall, there are very few indications of statistically significant alpha estimates at the 5%

TABLE 3. Performance alpha robustness over the conditional return distribution for 31 European large-cap funds. The alphas are estimated using quantile regression (3) for quantile parameter τ ranging from 0.1 to 0.9. Significant positive and negative alphas are indicated by bold at the 5% level.

Fund	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	0.018	0.002	0.005	–0.005	0.006	0.001	0.010	–0.001	0.009
2	0.015	0.003	0.002	0.006	0.009	0.005	0.008	0.011	0.008
3	0.004	–0.021	–0.016	**–0.020**	**–0.020**	**–0.026**	**–0.029**	**–0.026**	–0.022
4	0.006	0.002	0.017	0.016	0.010	0.018	0.020	0.002	0.009
5	0.010	–0.001	–0.012	–0.009	–0.020	–0.023	–0.023	–0.045	–0.012
6	0.011	0.001	–0.002	–0.008	–0.014	–0.020	–0.015	–0.020	–0.008
7	0.011	0.000	–0.004	–0.004	–0.008	–0.010	–0.015	–0.006	–0.005
8	0.014	–0.005	0.001	–0.006	–0.009	–0.005	–0.005	–0.009	0.005
9	**–0.036**	**–0.023**	–0.019	–0.011	–0.017	–0.019	–0.019	**–0.025**	–0.014
10	0.011	0.010	0.015	–0.003	0.003	–0.013	–0.007	–0.014	0.014
11	0.030	0.006	0.003	–0.015	–0.013	–0.001	–0.010	–0.017	–0.017
12	0.003	0.018	0.002	0.002	–0.005	0.003	0.003	0.005	0.008
13	**0.057**	0.023	0.003	0.004	0.008	0.004	0.006	0.020	0.024
14	0.019	0.008	0.000	–0.014	–0.001	0.004	–0.012	–0.013	0.014
15	0.026	0.019	0.013	0.010	0.000	0.006	0.014	0.019	0.020
16	0.024	0.015	0.015	0.011	0.001	0.003	0.007	0.005	0.018
17	0.004	0.005	0.001	0.000	–0.006	–0.010	–0.001	–0.001	–0.022
18	0.014	–0.003	0.000	–0.005	–0.007	–0.018	**–0.036**	–0.020	–0.016
19	–0.002	–0.002	–0.003	0.001	0.000	–0.015	–0.009	**–0.023**	–0.020
20	0.005	–0.002	–0.009	–0.009	–0.007	–0.011	0.000	0.005	0.002
21	0.032	0.025	0.002	0.004	0.004	0.005	–0.005	0.008	0.001
22	0.001	0.004	–0.012	0.001	0.000	–0.021	–0.032	–0.016	–0.002
23	**0.021**	0.009	0.007	0.008	0.002	0.004	0.009	0.014	0.019
24	**0.026**	**0.026**	0.021	0.020	0.019	0.017	0.019	0.017	0.017
25	–0.013	0.011	0.004	–0.003	–0.002	–0.007	–0.011	–0.012	–0.011
26	0.006	0.003	–0.003	0.007	–0.004	–0.007	–0.028	–0.024	–0.010
27	–0.021	–0.012	0.006	–0.021	–0.032	–0.023	–0.021	**–0.033**	–0.012
28	0.005	0.006	**0.008**	**0.006**	**0.006**	0.005	0.005	0.005	0.003
29	0.001	0.004	**0.007**	0.005	0.005	0.003	0.003	0.005	0.002
30	0.008	–0.005	–0.004	–0.002	0.002	0.006	–0.008	–0.007	–0.007
31	0.016	0.018	0.001	–0.009	0.002	0.002	–0.012	–0.013	0.005

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

level. Most of the significances are negative and indicate an underperformance in the upper part of the distribution. However, a few of the funds outperform the benchmark in the lower part of the return distribution.

TABLE 4. Four-factor model alpha estimates for 35 US large-cap mutual funds

	HAC-OLS		EGARCH(1,1)		WLAD(0.5)	
Fund	Alpha	p-value	Alpha	p-value	Alpha	p-value
1	–0.002	0.066	–0.002	0.099	0.001	0.935
2	0.000	0.573	0.000	0.727	–0.002	0.167
3	0.000	0.742	–0.001	0.320	–0.007	0.231
4	0.000	0.835	0.001	0.349	0.003	0.632
5	–0.001	0.421	–0.002	0.034	–0.004	0.261
6	–0.001	0.062	–0.001	0.002	0.000	0.918
7	–0.002	0.028	–0.001	0.047	0.003	0.228
8	–0.003	0.026	–0.001	0.089	0.003	0.334
9	–0.002	0.004	–0.002	0.001	–0.004	0.218
10	–0.003	0.000	–0.003	0.000	–0.002	0.496
11	–0.003	0.003	–0.002	0.005	0.002	0.530
12	0.000	0.949	–0.002	0.072	–0.002	0.506
13	–0.001	0.173	–0.001	0.016	–0.007	0.024
14	0.000	0.859	–0.001	0.193	–0.004	0.203
15	0.000	0.875	–0.001	0.186	–0.004	0.258
16	–0.002	0.105	–0.002	0.020	0.000	0.935
17	–0.003	0.000	–0.003	0.001	–0.029	0.005
18	–0.002	0.009	–0.003	0.000	–0.007	0.000
19	0.000	0.569	0.000	0.674	0.003	0.371
20	–0.001	0.000	–0.001	0.000	–0.001	0.614
21	–0.002	0.018	–0.003	0.000	–0.006	0.135
22	0.000	0.805	–0.001	0.217	–0.003	0.266
23	–0.002	0.092	–0.002	0.197	–0.003	0.726
24	–0.003	0.022	–0.002	0.001	–0.004	0.184
25	–0.002	0.009	–0.001	0.003	0.000	0.830
26	–0.002	0.005	–0.002	0.000	0.000	0.915
27	–0.002	0.082	–0.001	0.045	0.000	0.944
28	–0.003	0.000	–0.002	0.000	–0.001	0.524
29	0.000	0.867	–0.001	0.182	–0.006	0.292
30	0.000	0.935	–0.001	0.086	–0.002	0.407
31	–0.001	0.454	–0.002	0.008	–0.003	0.223
32	0.000	0.806	–0.001	0.168	–0.002	0.442
33	–0.001	0.488	–0.002	0.009	–0.002	0.251
34	–0.001	0.487	–0.002	0.011	–0.002	0.277
35	–0.002	0.001	–0.002	0.000	0.000	0.880
Average	–0.001		–0.002		–0.003	

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

Table 4 presents the results for the 35 US large-cap mutual funds. The HAC-OLS estimation indicates 14 out of 35 statistically significant

TABLE 5. Performance alpha robustness over the conditional return distribution for 35 US large-cap funds. The alphas are estimated using quantile regression (3) for quantile parameter τ ranging from 0.1 to 0.9. Significant positive and negative alphas are indicated by bold at the 5% level.

Fund	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	–0.023	–0.010	0.000	0.006	0.001	0.003	0.005	0.004	0.008
2	0.003	0.001	0.001	0.000	–0.002	–0.002	–0.002	–0.001	0.000
3	–0.008	**–0.016**	–0.008	–0.010	–0.007	–0.005	–0.007	**–0.010**	0.000
4	0.011	0.007	–0.001	0.003	0.003	0.000	0.003	–0.003	0.004
5	**–0.011**	**–0.009**	**–0.008**	–0.005	–0.004	–0.004	–0.005	–0.002	–0.003
6	0.001	–0.001	–0.002	–0.001	0.000	0.000	–0.001	0.000	–0.001
7	0.000	–0.001	–0.001	0.000	0.003	0.004	0.002	0.001	–0.002
8	–0.002	0.001	0.001	0.003	0.003	0.005	0.005	**0.008**	0.006
9	–0.004	–0.003	0.000	0.001	–0.004	–0.006	**–0.007**	**–0.009**	**–0.011**
10	–0.001	0.000	–0.004	–0.003	–0.002	–0.001	0.000	0.000	–0.001
11	0.007	0.002	0.004	0.000	0.002	0.002	0.004	0.002	0.000
12	–0.002	–0.004	–0.004	–0.001	–0.002	–0.002	–0.001	0.000	–0.001
13	**–0.011**	–0.007	**–0.007**	**–0.007**	**–0.007**	**–0.008**	**–0.008**	**–0.009**	**–0.009**
14	0.000	0.001	–0.001	–0.005	–0.004	–0.005	–0.006	–0.004	–0.002
15	0.000	0.000	–0.001	–0.005	–0.004	–0.005	–0.006	–0.004	–0.002
16	–0.003	–0.007	–0.004	–0.001	0.000	–0.003	–0.004	–0.004	0.002
17	**–0.040**	–0.023	**–0.028**	**–0.028**	**–0.029**	**–0.021**	–0.015	–0.011	–0.020
18	–0.004	–0.003	–0.006	**–0.007**	**–0.007**	**–0.009**	**–0.008**	–0.005	–0.001
19	0.005	0.006	0.005	0.004	0.003	0.002	0.000	0.001	–0.001
20	0.000	–0.002	–0.003	–0.001	–0.001	–0.001	–0.001	0.000	0.001
21	–0.009	–0.006	–0.005	**–0.007**	–0.006	–0.005	–0.002	0.001	–0.002
22	–0.004	**–0.006**	–0.003	–0.003	–0.003	–0.002	–0.001	–0.002	0.000
23	0.007	0.002	–0.003	–0.006	–0.003	–0.002	–0.003	–0.004	0.003
24	–0.001	–0.003	–0.004	–0.004	–0.004	–0.003	–0.001	–0.001	0.000
25	–0.001	–0.002	–0.001	0.000	0.000	–0.001	0.000	–0.001	–0.002
26	–0.007	0.000	–0.003	0.000	0.000	0.002	0.001	0.001	0.000
27	0.002	0.003	0.000	0.000	0.000	–0.003	–0.001	0.000	0.004
28	0.001	–0.001	–0.002	–0.002	–0.001	–0.001	0.001	–0.001	0.001
29	–0.007	–0.011	–0.005	–0.006	–0.006	0.000	–0.003	–0.002	–0.006
30	–0.003	–0.002	–0.003	–0.004	–0.002	–0.001	0.000	–0.001	0.001
31	–0.004	–0.002	–0.003	–0.004	–0.003	–0.001	–0.001	–0.002	0.001
32	–0.003	–0.002	–0.003	–0.003	–0.002	–0.001	0.000	–0.001	0.002
33	–0.004	–0.002	–0.003	–0.005	–0.002	–0.002	–0.001	–0.002	0.001
34	–0.003	–0.002	–0.004	–0.005	–0.002	–0.002	–0.001	–0.002	0.001
35	–0.002	–0.002	–0.001	0.000	0.000	0.000	0.000	0.000	0.000

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

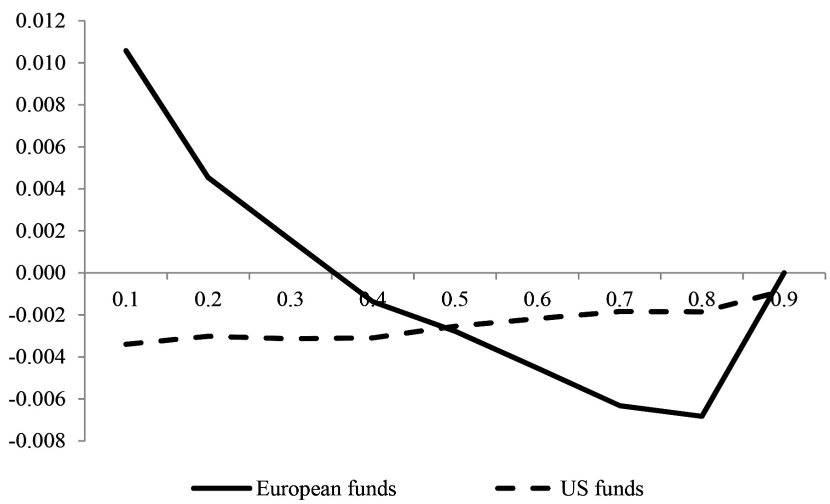

FIGURE 1.— Average performance alpha for European and US large-cap equity funds for different values of the quantile weighting parameter from 0.1 to 0.9

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

performance alphas at the 5% level and they are all negative. The average monthly alpha is –0.1% (–1.2% per annum). As for the European funds the EGARCH(1,1) results for the US market show several more significant alphas than the HAC-OLS: 21 out of 35, and they are all negative. The average monthly alpha is –0.2% (–2.4% per annum). For the WLAD(0.5) estimation only three alphas are significant and they are all negative. The average alpha is here –0.3% (–3.7% per annum).

Table 5 shows the robustness of the performance alpha across the conditional return distribution for the US funds. Of those alphas that are statistically significant at the 5% level only one is positive and only for τ=0.8.

Overall, these results suggest that a simple HAC-OLS estimated constant alpha may not be accurate enough for performance analysis. Allowing for volatility dynamics produces several more significant alphas as a base for the evaluation. Furthermore, the quantile regression approach with an EGARCH volatility correction enables the monitoring

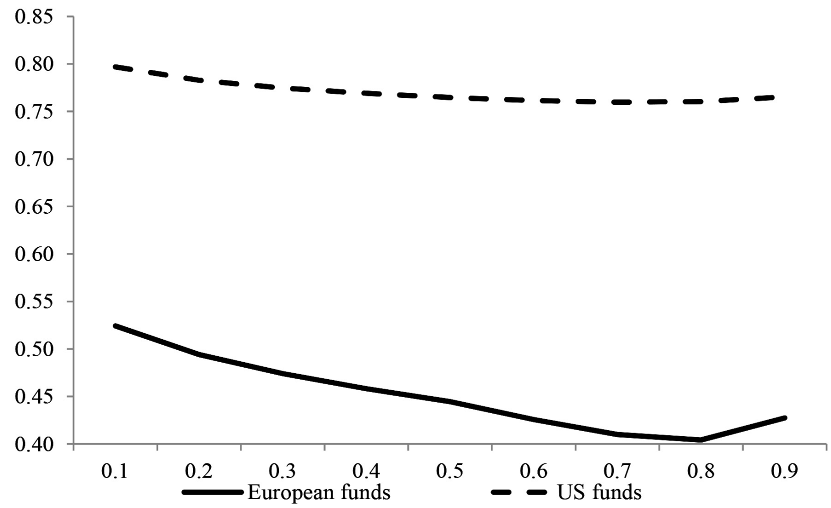

FIGURE 2.— Average adjusted R-squares for European and US large-cap equity funds for different values of the quantile weighting parameter from 0.1 to 0.9

Note: Monthly returns for the period September 1998 to December 2012 sampled from Thomson Reuters Datastream and CRSP databases. The returns on the risk factors are collected from Kenneth French's home page.

of the performance alpha across the conditional return distribution and reveals asymmetric performance for many funds. Often the behavior differs in the upper part of the distribution form that of the lower part. For investors this indicates that the fund performance might be state dependent. On the other hand, if this asymmetric behavior is persistent it can be utilized for the construction of a portfolio of funds with suitable hedge characteristics.

Figure 1 presents the average performance alphas for the European and US funds. This alpha can be interpreted as the alpha of an equally weighted portfolio of large cap-funds for both markets. For the US portfolio, the alpha is on average negative for all quantile levels from 0.1 to 0.9 and is more negative at the lower end of the risk-adjusted return distribution. For the European portfolio the variation in alpha over the distribution is more pronounced and on average it is positive in the lower part of the distribution for a quantile parameter lower than 0.35. This indicates that for the studied sample period an equally weighted European portfolio of large-cap funds had been a good hedge for more negative returns than expected.

Figure 2 shows the variation of the average adjusted R-squares over the different quantiles. It is obvious that the risk-factor model fits the US large-cap fund market much better than the European market. The estimated R-squares are about 1.5 to 1.9 times higher for the US market. For both markets, it seems like the risk-adjustment factor model fits better in the lower part of the return distribution. The R-squares reported here are very close to the ones reported for European large-cap funds for daily returns for the period January 1, 1996 to March 31, 2008 in Högholm et al. (2011b).

VI. Conclusion

The paper compares the performance of large-cap European and US funds using monthly risk-adjusted returns. It provides an example of how quantile regression can be applied to monitor the risk-adjusted performance over different parts of the return distribution. The results are also compared to the corresponding results when using traditional heteroscedasticity corrected ordinary least squares (HAC-OLS) and exponential generalized autoregressive conditional heteroskedeasticity (EGARCH(1,1)) estimation. The WLAD quantile approach enables a study of the performance robustness over the conditional residual return distribution.

For the studied fund categories, European and US large-cap mutual funds, risk-factor adjusted performance measures are expected to be fairly robust. However, the estimated performance alphas appears to be very sensitive to the estimation approach applied. For both the European and the US market the EGARCH(1,1) technique reported several more statistically significant performance alphas compared to the HAC-OLS or the WLAD(0.5). Furthermore, the WLAD(τ) quantile approach for different quantile parameters indicates that the performance alphas vary over the risk-adjusted return distribution. The consequence is that the performance is asymmetric and time varying and is, furthermore, dependent on the unpredictable realization of the conditional residual distribution. For investors this suggests that the fund performance might be state dependent. On the other hand, if the structure of this asymmetric behavior is persistent, as the results in this paper compared to Högholm et al. (2011b) indicate, it can be utilized for the construction of portfolios of funds with suitable hedge characteristics.

On average the US funds underperformed the risk adjusted benchmark across the entire return distribution and more so in the lower part of the distribution. A few of the European funds, on the other hand, exhibit significant and positive performance alphas in the lower tail of the conditional return distribution. From a risk-averse investor's point of view, investing in European large-cap funds, the results regarding the performance of an equally weighted portfolio of funds, is more comforting. On average, the performance alphas are positive and highest in the lower part of the conditional distribution for the European funds. However, the European funds underperform in a higher degree than the US funds in the upper part of the distribution. According to the adjusted R-squares, the risk-adjusted asset-pricing model seems to fit the data best in the lower part of the conditional return distribution. An interpretation could be that risk averse fund managers are more concerned about risk factors in situations where outcomes are found in the lower part of the conditional return distribution.

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