ECONOMIC ANNALS, Volume LXVI, No. 230 / July – September 2021
UDC: 3.33 ISSN: 0013-3264

https://doi.org/10.2298/EKA2130007B

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MUTUAL FUND PERFORMANCE: SOME RECENT EVIDENCE FROM EUROPEAN EQUITY FUNDS

ABSTRACT: *This paper studies the performance of mutual funds that specialise in equity investment. We use a sample of the top sixteen actively managed European equity funds operating in the United States between July 1990 and November 2020. Using standard factor models, we show that none of our sample funds generated a positive and significant alpha. The observed funds could not outperform a simple passive strategy that involves tradeable European benchmark portfolios in the longer run. As a rule, the funds in our sample did not exploit the known asset pricing anomalies.*

KEY WORDS: *investment funds, active strategy, European stocks, Fama-French factors, momentum*

JEL CLASSIFICATION: G12, G15, G23

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1. INTRODUCTION

Active mutual funds aim to manage investment portfolios in a way that reflects their competitive edge. This edge may consist of more profound knowledge and understanding of the market, available technology, and economies of scope; investment talent, instinct, and mental effort; or at very least the time and costs associated with selecting appropriate financial instruments through careful analysis. In brief, we expect actively managed funds to provide value to their investors through delivering returns higher than any alternative with similar risk. If successful, their active investment strategies should provide excess returns above and beyond the market risk premium or other known risk factors.[1]

Nevertheless, studies so far have shown quite the opposite: actively managed mutual funds provide predominantly lower returns than the market portfolio (see, for example, Fama & French, 2010; Berk & van Binsbergen, 2012). Historically, only a fraction of funds has been able to generate abnormal returns when trading friction is taken into account (Wermers, 2000; Kosowski et al., 2006). There is a compelling body of empirical evidence that 'top' mutual funds (irrespective of the ranking criteria) are unable to generate persistent returns and that their performance is mainly ephemeral (Mateus et al., 2019). Only the 'losers' tend to exhibit persistent losses (Carhart, 1997).

The mutual fund industry in the U.S. is significantly larger than in any other region or country, accounting for almost half of global assets under management. It is also one of the vital investment vehicles for a typical U.S. family: in 2018, more than 43% of households held mutual fund investment units (Elton & Gruber, 2020). Therefore, it is not surprising that the vast majority of research focuses on U.S. mutual funds and their performance measures. On the other hand, although individually smaller in market capitalisation than their U.S. counterparts, European stock markets attract many global institutional investors. However, very few studies on the performance and persistence of mutual funds

[1] With around 55 trillion U.S. dollars of assets under management in 2019 and projections of over 100 trillion U.S. dollars by the end of 2027 (Goswami et al., 2020), the global mutual fund industry is at the forefront of active investment efforts. In 2019 the management fees charged by the active funds were more than five times larger than the average compensation required by the passive funds: despite both having a declining tendency, the ratio of compensation for active and passive mutual funds continues to increase (PwC, 2020).

specialise in European stocks. Some notable exceptions, such as Otten & Bams (2002), Vidal-García (2013), and Graham et al. (2019), focus on European mutual funds. The literature on the performance of U.S. or international funds that concentrates on European asset markets is scarce at best.

Motivated by this research gap, we investigate the performance of actively managed European equity funds operating in the United States. The U.S. European equity funds hold at least three-quarters of their assets in European stocks. They primarily invest in developed European markets such as Germany, France, the United Kingdom, Switzerland, and the Netherlands. Some funds are also exposed to the emerging markets of Eastern Europe. We focus on the top sixteen mutual funds, based on their U.S. News Mutual Fund Score. We use monthly fund returns between July 1990 and November 2020 and regress them on European Fama & French portfolios and momentum. None of the funds in our sample generated a positive and significant alpha. Therefore, even the top funds could not outperform a simple passive strategy that uses tradable portfolios or exploits well-known market anomalies.

The paper contributes to the literature on mutual fund performance in several ways. First, it is one of the rare empirical studies related to the performance of U.S. European equity funds. Consistent with the general literature on fund performance, we verified that the observed funds provide no abnormal returns beyond what can be easily explained by the ordinary risk premia. Second, the paper hints at some of the investment strategies applied by the observed funds. Third, we find that two persistent anomalies in Europe are currently not exploited by the sample funds.

The remainder of this paper is organized as follows. In Section 2 we provide a brief review of the relevant literature on measures of mutual fund performance. This review sets the core methodology used in this research, presented in Section 3. Section 4 describes the data and presents preliminary results based on descriptive statistics. Section 5 presents and analyses the regression results. Concluding remarks are given in Section 6.

2. LITERATURE REVIEW

The research on mutual fund performance dates back to the 1960s and the seminal work by Jensen (1969). One of the main questions it tries to answer is whether excess returns of funds come from expertise or luck. Later, Carhart (1997) further refined this issue by introducing the notion of return persistence, which studies whether the funds can keep their good track record over significant periods. Good entry points to the literature on mutual fund performance are Cuthbertson et al. (2010) and Elton & Gruber (2020).

Traditionally, the main idea behind portfolio performance measurement is whether an investor can systematically achieve an abnormal return. The 'abnormal' in this context refers to any return beyond the investment portfolio's risk premium. This logic immediately invokes the use of an asset pricing model that relates the expected return to an observable risk factor. Historically, Jensen (1969) applied the Capital Asset Pricing Model (CAPM) previously formalised by Sharpe (1963, 1964), Lintner (1965, 1969), and Mossin (1966). The abnormal return in CAPM was captured by a statistically and economically significant intercept ('Jensen's alpha').

The main idea of CAPM, that the risk premium can be explained through a single-factor beta which captures the co-movement between the asset return and the market portfolio return, was revisited in the light of evidence of apparent 'anomalies'. For example, Fama & French (1992) found that between 1960 and 1990, companies with relatively smaller market capitalisation paid a significantly larger premium than larger companies. Also, companies with a higher book-to-market ratio paid a substantially larger premium than stocks with a lower ratio. Neither the 'size' nor the 'value–growth' anomaly could be explained by the market beta alone. These findings prompted the extension of CAPM to multifactor models. The Fama & French (1993) three-factor model, which includes two additional factors that 'explain' the anomalies – the 'small minus big' (SMB) and the 'high minus low' (HML) factors – eventually became the standard benchmark model for measuring asset pricing and performance. Thus, the definition of 'alpha' was modified to account for the premium earned by exposure to all three factors.

Over time, it turned out that even the three-factor model could not explain the cross-section of stock returns. For example, it exhibits poor performance when stocks are grouped by industry (Fama & French, 1997). It also cannot explain the persistent abnormal returns of momentum portfolios formed by buying recent winner stocks and selling loser stocks (Carhart, 1997). The latter anomaly is successfully captured by adding the fourth factor—the 'winners minus losers' (WML) – to the existing three. The only issue with this factor is related to relatively low values of R^2 in cross-sectional regressions compared to the time-series regressions used to obtain the corresponding factor loadings (Cochrane, 1999).

The number of anomalies reported in the academic literature over the past three decades is substantial. Hou et al. (2017) were able to identify as many as 447 different average-return anomalies. Mateus et al. (2019) provide a thorough overview of the known anomalies in the context of fund performance and persistence measurement. Titman et al. (2004), Novy-Marx (2013), and many other authors have since pointed out that a possible reason why the three-factor model is incomplete is the lack of variation in average returns that originate from company profitability and investments. To account for these effects, Fama & French (2015) suggest a five-factor model that expands the three-factor model with a profitability factor ('robust minus weak', RMW) and an investment factor ('conservative minus aggressive', CMA). The two additional factors can also explain several other anomalies, such as the high average returns associated with a low market beta, share repurchases, and low stock return volatility (Fama & French, 2016).

Despite the lack of an obvious link with fundamental macroeconomic variables or other systemic risk factors, the five-factor model can explain average returns for North America, Europe, Asia, and the Pacific (Fama & French, 2017). More specifically, average returns for most global markets increase with book-to-market ratio and profitability and decrease with the level of investment.[2] One of the crucial known drawbacks of the five-factor model is its inability to explain the low returns of companies with small market capitalisation whose stock prices behave like the prices of companies with low profitability that invest aggressively.

2 Among the rare exceptions to this stylized fact is the Japanese market, where average stock returns are positively associated with the HML factor but exhibit very weak correlations with RMW and CMA factors (Fama & French, 2017).

3. METHODOLOGY

We measure fund performance using the standard asset pricing models. We run a time-series regression of excess returns for each sample fund i on the set of risk factors f_{kt}:

$$r_{it} - r_t^f = \alpha_i + \sum_{k=1}^{K} \beta_{ik} f_{kt} + \varepsilon_{it}, \tag{1}$$

where ε_{it} is the usual regression residual. The least-square estimates of the coefficients give factor betas as loadings and alpha as the regressional intercept α_i. We use the Huber-White robust estimates of standard errors. An estimate for the risk premium of factor k can be obtained as the time-series average of the returns f_{kt}. The factors represent tradable mimicking portfolios for the actual sources of non-diversifiable economy-wide risks.

The asset pricing models used for performance measurement are the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model. In the CAPM, the only factor is the excess return on the value-weighted portfolio of European stocks. In the Fama and French (1993) three-factor model, the additional factors are the size (SMB) and the value (HML) portfolios. The Carhart (1997) four-factor model also includes the momentum (WML) portfolio. Finally, the Fama and French (2015) five-factor model extends the three-factor version to include the profitability (RMW) and investment (CMA) portfolios for the European market.

Each model applies the same null hypothesis of the absence of abnormal returns, captured by alpha. Since we run a time-series regression for each sample fund separately, we therefore test

$$H_0 : \alpha_i = 0$$

versus the alternative hypothesis

$$H_A : \alpha_i \neq 0.$$

If the null hypothesis is rejected in favour of the alternative, then there are two possibilities. If $\alpha_i > 0$, this indicates abnormal return by the fund i given the risk factors f_{kt}. On the other hand, if $\alpha_i < 0$, fund i provides a suboptimal premium with respect to the standard risk factors.

Even though this approach is well established in the empirical asset pricing literature, it is prone to the usual econometric challenges. Collot & Hemauer (2021) show that the two most important ones in this context are omitted-variable bias and errors-in-variables bias. The omission of some relevant pricing factors from Equation (1) will introduce bias and inconsistency in the OLS estimators for betas and alphas, especially for individual assets. A common approach in the empirical asset pricing literature to obtaining more precise coefficient estimates is to run factor regressions of portfolio returns rather than individual asset returns.

The imprecision resulting from omitted factors can further lead to errors-in-variable bias in the two-stage procedure of Fama & MacBeth (1973). This procedure uses the estimated coefficients from the first stage as explanatory variables in the second stage to obtain market prices of risk factors. Since we only run time-series regressions, there will be no errors-in-variable bias in our results. The issues with omitted-variable bias are alleviated by the fact that the explained variables are excess returns on equity funds, which by construction represent well-diversified portfolios rather than individual stocks.

4. DATA

The set of our explained variables consists of monthly stock returns on the top sixteen U.S. European equity mutual funds, based on their U.S. News Mutual Fund Score. The Mutual Fund Score represents an equally weighted score of the most popular fund rating services: CFRA, Lipper, Morningstar, TheStreet.com, and Zacks. The stocks for all of the top sixteen funds were traded on NASDAQ in U.S. dollars between July 1990 and November 2020. For each fund, we used the most extensive series available from Thomson Reuters Eikon (Refinitiv).

The data are summarised in Table 1. The columns show the fund ranking, name, ticker symbol, net assets under management, holdings turnover, and Morningstar overall rating. Our sample funds vary significantly in their asset size, ranging between 4.1 million and 1.2 billion U.S. Dollars. They also differ in the degree of active portfolio management, captured by the holdings turnover rate. This rate represents the fraction of portfolio investment holdings that change annually due to active trading. In general, most actively managed funds have double-digit turnover rates. There are several funds with three- and even four-digit rates in our sample, indicating an overly aggressive approach.

As described in Section 3, we use the usual benchmark portfolios for European stocks as explanatory variables: the excess return on the market portfolio, the Fama-French factors (SMB, HML, RMW, and CMA), and the momentum factor (WML). The monthly returns on these portfolios, available from Kenneth French's Data Library,[3] cover the same period as the mutual fund returns. All returns are in U.S. dollars and are adjusted for dividends and capital gains. The benchmark portfolios are constructed using stocks from the following countries: Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, and Sweden.

The market factor is the U.S. dollar return on the European value-weighted market portfolio, net of the yield on a U.S. one-month T-Bill. The SMB, HML, RMW, and CMA factors are constructed by the standard sorting algorithm, based on the companies' size, book-to-market ratio, operating profitability, and investment at the end of each June. The momentum factor (WML) is the difference in the average returns on the top and bottom 30% of European stocks based on their lagged momentum. The lagged momentum represents a stock's cumulative annual return ending a month before the month of observation.

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html

Table 1: Overview of funds

Rank	Name	Ticker	Net Assets (USD million)	Holdings Turnover (%)	Morningstar Overall Rating
1	Morgan Stanley Europe Opportunity Fund Inc. Class A	EUGAX	205.7	13.00	★★★★★
2	T. Rowe Price European Stock Fund	PRESX	1,170.0	75.40	★★★★
3	Columbia Acorn European Fund Class A	CAEAX	108.8	30.00	★★★★★
4	Janus Henderson European Focus Fund Class A	HFEAX	392.7	160.00	★★★
5	Brown Advisory WMC Strategic European Equity Fund Inst. Shares	BAFHX	363.2	53.00	★★★★
6	Fidelity Advisor Europe Fund Class A	FHJUX	990.2	39.00	★★★★
7	BlackRock EuroFund Investor A Shares	MDEFX	122.9	39.00	★★★
8	Virtus Vontobel GreaterEuropean Opportunities Fund Class A	VGEAX	7.3	51.00	★★★★★
9	DFA Continental Small Company Portfolio Institutional Class	DFCSX	683.3	1.68	★★★★
10	Vanguard European Stock Index Fund Investor Shares	VEURX	20.0	3.00	★★★
11	Invesco European Small Company Fund Class A	ESMAX	238.5	N/A	★★★★
12	JPMorgan Europe Dynamic Fund Class A	VEUAX	541.2	159.00	★★★
13	Invesco European Growth Fund Class A	AEDAX	1,100.0	27.00	★★★
14	Franklin Mutual European Fund Class A	TEMIX	792.8	12.16	★★
15	ProFunds Europe 30 Fund Investor Class	UEPIX	4.1	1,122.00	★
16	DoubleLine Shiller Enhanced International CAPE Class I	DSEUX	43.0	48.00	★★★★

Sources: Thomson Reuters Eikon (Refinitiv), Kenneth French's Data Library, U.S. News Mutual Fund Score

All Fama-French factors are originally denominated in U.S. dollars. To convert them into euros or another non-USD currency, one can follow the methodology described in Glück et al. (2021). When applying the conversion, an important caveat is related to the difference in formulas between long factors such as the market portfolio, and long–short factors such as SMB or HML. As Glück et al. (2021) further argue, the currency of the factor returns has to be adjusted when working with non-U.S. samples from a non-USD perspective. However, in this paper we use the U.S. dollar as a base currency, as all the funds are located in the U.S. and are USD-denominated. Hence, conversion to local currencies is unnecessary, and the exchange rates have no impact on the results.

Table 2: Descriptive statistics

Rank	Fund/portfolio	Number of observations	Average excess return (%)	St. dev. of excess return (%)	Sharpe ratio
1	EUGAX	280	0.47	5.28	0.09
2	PRESX	365	0.51	5.46	0.09
3	CAEAX	111	0.94	5.19	0.18
4	HFEAX	230	1.04	6.64	0.16
5	BAFHX	85	0.54	5.07	0.11
6	FHJUX	80	0.39	5.30	0.07
7	MDEFX	313	0.51	6.16	0.08
8	VGEAX	139	0.90	6.51	0.14
9	DFCSX	365	0.58	6.20	0.09
10	VEURX	365	0.47	5.06	0.09
11	ESMAX	243	0.96	7.49	0.13
12	VEUAX	300	0.61	5.66	0.11
13	AEDAX	277	0.72	5.63	0.13
14	TEMIX	289	0.63	4.89	0.13
15	UEPIX	260	–0.03	6.49	0.00
16	DSEUX	47	0.70	5.75	0.12
	Value-weighted portfolio	365	0.35	3.85	0.09
	Market portfolio	365	0.50	4.97	0.10
	SMB	365	0.07	2.13	0.03
	HML	365	0.21	2.53	0.08
	WML	365	0.90	3.99	0.23
	RMW	365	0.38	1.59	0.24
	CMA	365	0.11	1.80	0.06

Source: Author's estimations.

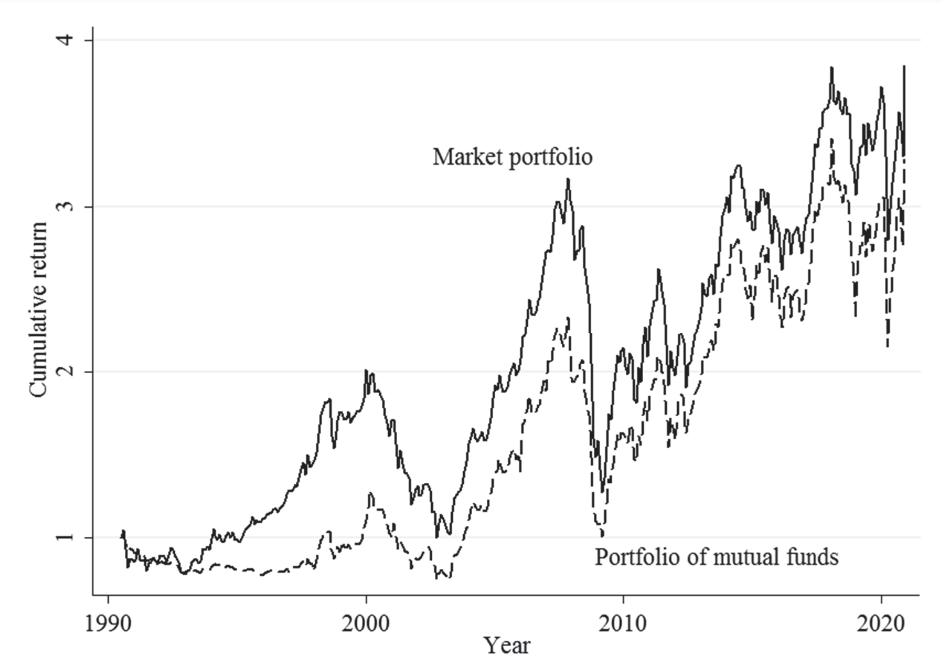
Table 2 shows the descriptive statistics for the dataset. The statistics are compiled for 16 mutual fund returns, the return on the value-weighted portfolio of these funds, and the 6 benchmark portfolios. The columns show the number of monthly observations in each series, the average excess return (as a percentage), the standard deviation of excess return, and the monthly Sharpe ratio. The Sharpe ratio suggests that the value-weighted portfolio performed worse than the market in terms of the risk–return trade-off.

This result becomes even more apparent in Figure 1, which compares the cumulative excess returns for the market portfolio and the value-weighted portfolio. The graphs represent the value of a dollar invested in the two zero-cost portfolios. Given that the value-weighted portfolio has lower volatility than the market portfolio, we adjust for the risk by scaling the former's excess return by the ratio of volatilities.[4] Even with the risk adjustment, the market portfolio is consistently above the portfolio of funds over the entire three decades. It gives an over 17% higher risk-adjusted cumulative return and an over 41% higher raw cumulative return. As the figure verifies, most of this difference comes from the relatively weak performance of the funds during the 1990s, when their active stock selection process did not pay off. From 2000 onwards the cumulative value of the fund portfolio correlates with the movement of the market portfolio of European stocks.

The key to understanding why the 'top' mutual funds performed worse than the most straightforward passive strategy is the choice of these funds. They are only the top sixteen funds ex-post, i.e., at the end of the sample. Their performance at an arbitrary moment may have little in common with their overall historical performance. Also, their past behaviour may not be consistent over time. This simple line of thought points to another conclusion: the top current performance of a fund is not necessarily the outcome of a consistent investment strategy.

4 We multiply the excess return of the value-weighted portfolio by the volatility of the market portfolio and divide it by the volatility of the value-weighted portfolio.

Figure 1: Risk-adjusted cumulative returns of a value-weighted portfolio of the top sixteen U.S. European equity funds vs. the European market portfolio.



Source: Thomson Reuters Eikon (Refinitiv) and Kenneth French's Data Library
Note: Monthly data, July 1990 – November 2020. U.S. European equity funds = solid line and European market portfolio = dashed line.

At the individual level, nine funds appear to 'beat the market' in terms of the Sharpe ratio shown in Table 2. However, in Section 5 we will determine whether this implies actual abnormal returns, both statistically and economically. Every one of the top sixteen funds markedly underperformed two benchmarks, the momentum portfolio (WML) and the 'robust minus weak' portfolio (RMW), implying that any investor would be better off following either of these two simple strategies.

5. RESULTS

5.1. Overview

We begin our analysis by running a simple CAPM time-series regression of the following form:

$$r_{i,t} - r_t^f = \alpha_i + \beta_i \left(r_{M,t} - r_t^f \right) + \varepsilon_{i,t}, \quad (2)$$

where $r_{i,t}$ is the return of fund i in month t, as a percentage, r_t^f is the yield on the U.S. one-month T-Bill, $r_{M,t}$ is the return on the European market portfolio in month t, and $\varepsilon_{i,t}$ is the error term. The results are summarised in Table 3. The columns show the intercept (α), the market beta (β), and the fraction of variation in excess returns explained by the variation in the market excess return (R^2). The parameters are estimated using an ordinary least square estimator with robust standard errors.

Several results become immediately apparent from Table 3. First, the alphas are either insignificant or negative for individual funds. For the value-weighted portfolio the alpha is insignificant. Put differently, the average monthly return for the mutual funds that performed the best at the end of our sample was not significantly better than the return of a passive strategy: for one of the funds (UEPIX) it was 49 basis points worse than the return on the market portfolio. Second, all sixteen funds and their value-weighted portfolios have highly significant betas. The highly significant betas imply that their exposure to systemic risk can explain the funds' excess returns. Third, the regressions have relatively high R^2, which is usual for time-series factor regressions of returns (see, for example, Cochrane, 1999). The market risk factor alone is responsible for 73% of fund return variation on average. The variation in individual fund returns explained by this factor is above 90% in some cases (VEURX and DSEUX).

If we compare the results in Tables 2 and 3, it becomes apparent that the cross-sectional differences in average returns cannot be explained by only the differences in individual betas. This finding, illustrated in Figure 2, is prevalent in the literature and originates from high errors in beta estimates obtained from time-series regressions. Some of our sample funds were active for only a couple of years, implying that they have a relatively short time series and imprecise beta estimates in individual regressions.

Table 3. Time-series regressions of fund excess returns on market excess return

Rank	Fund/portfolio	α	β	R^2
1	EUGAX	0.06	0.84***	0.71
2	PRESX	0.05	0.93***	0.72
3	CAEAX	0.32	0.99***	0.83
4	HFEAX	0.38	1.01***	0.65
5	BAFHX	0.12	1.01***	0.80
6	FHJUX	0.03	1.03***	0.78
7	MDEFX	0.01	0.91***	0.55
8	VGEAX	0.28	0.79***	0.39
9	DFCSX	0.11	0.95***	0.58
10	VEURX	–0.02	0.99***	0.94
11	ESMAX	0.61	0.76***	0.30
12	VEUAX	0.09	0.94***	0.72
13	AEDAX	0.27	0.90***	0.71
14	TEMIX	0.28	0.65***	0.48
15	UEPIX	–0.49**	0.84***	0.68
16	DSEUX	–0.14	1.08***	0.91
	Value-weighted portfolio	0.02	0.66***	0.73

Source: Author's estimations.

Note: * – p-value < 0.10; ** – p-value < 0.05; *** – p-value < 0.01.

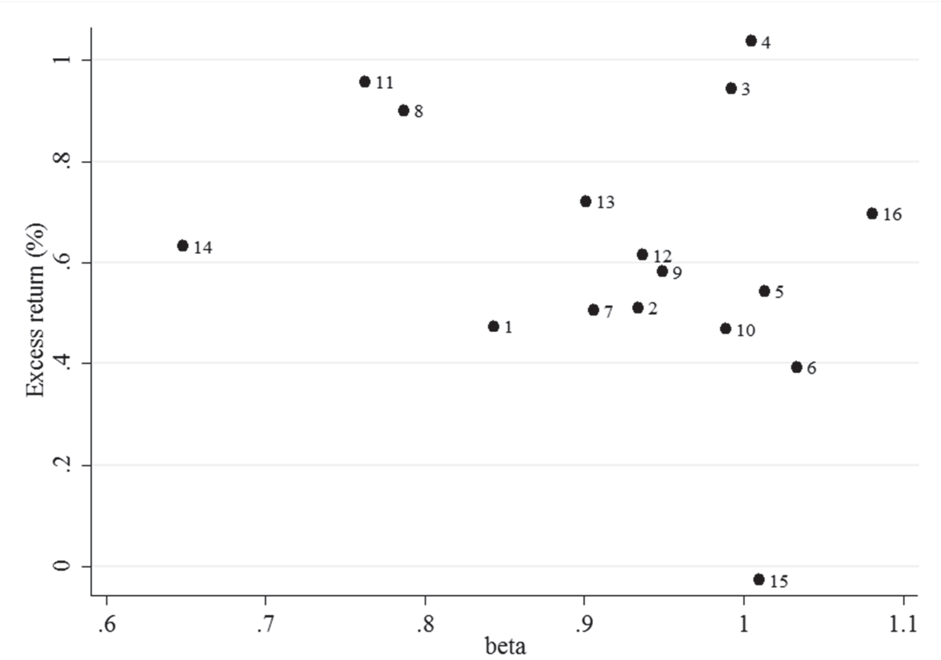
Notwithstanding the high correlations between fund returns and the market portfolio, Figure 2 also shows that the vertical dispersion is very high: individual average monthly excess returns differ by an entire percentage point. This difference implies that average fund returns vary in a range comparable to individual stocks. For funds that were actively trading during the entire sample (2 – PRESX, 9 – DFCX, and 10 – VEURX) the time series are relatively long, and the interpretation of the dispersion by the estimation errors in betas alone is implausible.

To capture the other possible sources of risk that drive the individual fund returns, we run a regression using the three-factor model of Fama & French (1993):

$$r_{i,t} - r_t^f = \alpha_i + \beta_i \left(r_{M,t} - r_t^f \right) + b_{SMB,i} SMB_t + b_{HML,i} HML_t + \varepsilon_{i,t}, \tag{3}$$

where we include the European SMB and the HML factors. The regression results are summarised in Table 4. All alphas are now insignificant. Since the Fama-French factors represent tradable portfolios, the insignificance of alphas implies that none of the funds could beat a simple passive strategy of investing in a combination of the three factors.

Figure 2: Average monthly excess returns of the top sixteen U.S. European equity funds vs. their market beta.



Source: Author's estimations.

Note: The numerical labels correspond to the fund ranking in Table 1.

Again, all the funds have statistically significant market betas, while fourteen funds have at least one additional significant factor. Only five funds have statistically significant coefficients associated with all three factors. This result indicates the possibility that some of the funds in our sample may have insufficiently diversified portfolios that are not able to buffer any extreme variation in returns. If this interpretation is correct, the implication is that even the best funds follow strategies that rely too much on particular speculative choices, i.e., 'stock picking' or 'market timing', rather than some elaborate investment strategy.

It is worth noting that the majority of funds have negative coefficients corresponding to the HML factor. Table 2 shows that both the SMB and the HML portfolio considerably underperformed the market. In particular, the European HML portfolio exhibited a substantial downturn after the Global Financial Crisis (Figure 3). Most of the funds successfully exploited this fact: significant negative coefficients b_{HML} indicate that they predominantly took short positions in value stocks and long positions in growth stocks.

Table 4: Time-series regressions of fund excess returns on three Fama-French factors

Rank	Fund/portfolio	α	β	b_{SMB}	b_{HML}	R^2
1	EUGAX	0.08	0.87^{***}	0.02	-0.19^{***}	0.72
2	PRESX	0.05	0.95^{***}	0.12	-0.09^{**}	0.73
3	CAEAX	–0.06	1.10^{***}	0.74^{***}	-0.52^{***}	0.93
4	HFEAX	0.15	1.07^{***}	0.69^{***}	-0.31^{***}	0.70
5	BAFHX	–0.09	1.10^{***}	0.02	-0.35^{***}	0.83
6	FHJUX	–0.26	1.13^{***}	0.08^{***}	-0.42^{***}	0.82
7	MDEFX	–0.05	0.89^{***}	0.23	0.18^{*}	0.56
8	VGEAX	–0.04	0.95^{***}	–0.01	-0.59^{***}	0.44
9	DFCSX	–0.02	0.97^{***}	1.03^{***}	0.29^{***}	0.71
10	VEURX	–0.02	0.98^{***}	-0.08^{**}	0.03	0.95
11	ESMAX	0.33	0.80^{***}	1.28^{***}	–0.22	0.42
12	VEUAX	0.05	0.97^{***}	0.36^{***}	–0.10	0.74
13	AEDAX	0.26	0.97^{***}	0.36^{***}	-0.43^{***}	0.77
14	TEMIX	0.22	0.65^{***}	0.27^{**}	0.08	0.50
15	UEPIX	–0.36	1.04^{***}	-0.35^{***}	-0.34^{***}	0.72
16	DSEUX	–0.09	1.08^{***}	–0.13	0.05	0.91
	Value-weighted portfolio	–0.00	0.68^{***}	0.35^{***}	–0.05	0.76

Source: Author's estimations.

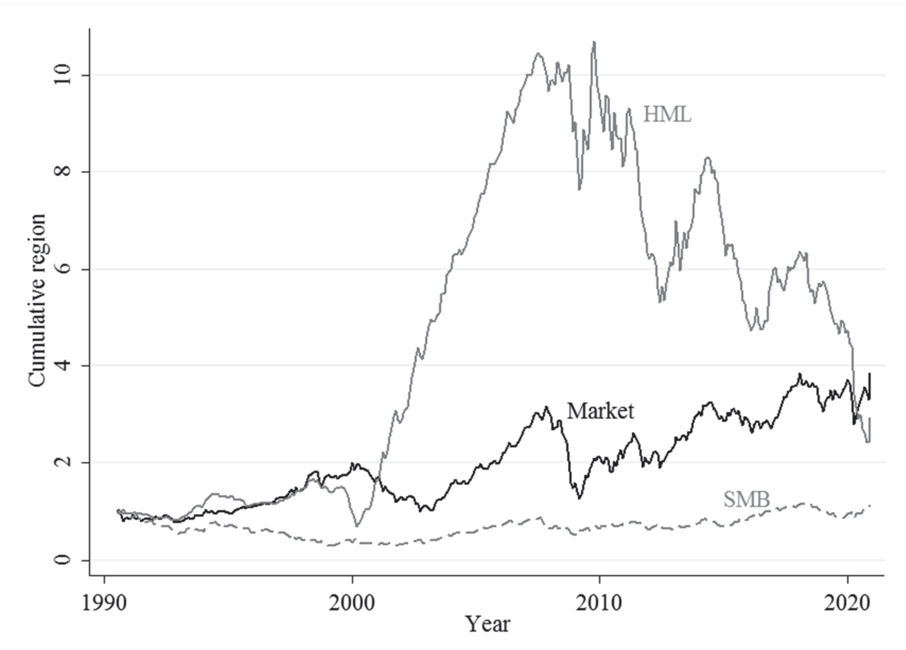
Note: * – p-value < 0.10; ** – p-value < 0.05; *** – p-value < 0.01.

Surprisingly, most of the top funds were not able to exploit the momentum anomaly. We can see this in Table 5, which summarizes the results of the four-factor regression:

$$r_{i,t} - r_t^f = \alpha_i + \beta_i \left(r_{M,t} - r_t^f \right) + b_{SMB,i} SMB_t + b_{HML,i} HML_t + b_{WML,i} WML_t + \varepsilon_{i,t}. \quad (4)$$

The regression given by Equation (4) includes the Carhart (1997) momentum factor WML for the European stocks. Again, all alphas are insignificant and all market betas remain highly significant, while the significance of the value-growth factor is somewhat reduced in favour of the momentum factor. All four factors are significant in only two funds. A puzzling result is that only two mutual funds (VEUAX and AEDAX) had positive momentum factor loadings, despite the WML portfolio's spectacular performance, with a monthly Sharpe ratio of 0.23 (Figure 4). It remains unclear why the remaining funds did not exploit this publicly available information. Three of the sample funds had a negative WML coefficient.

Figure 3: Risk-adjusted cumulative returns of the three Fama-French factors



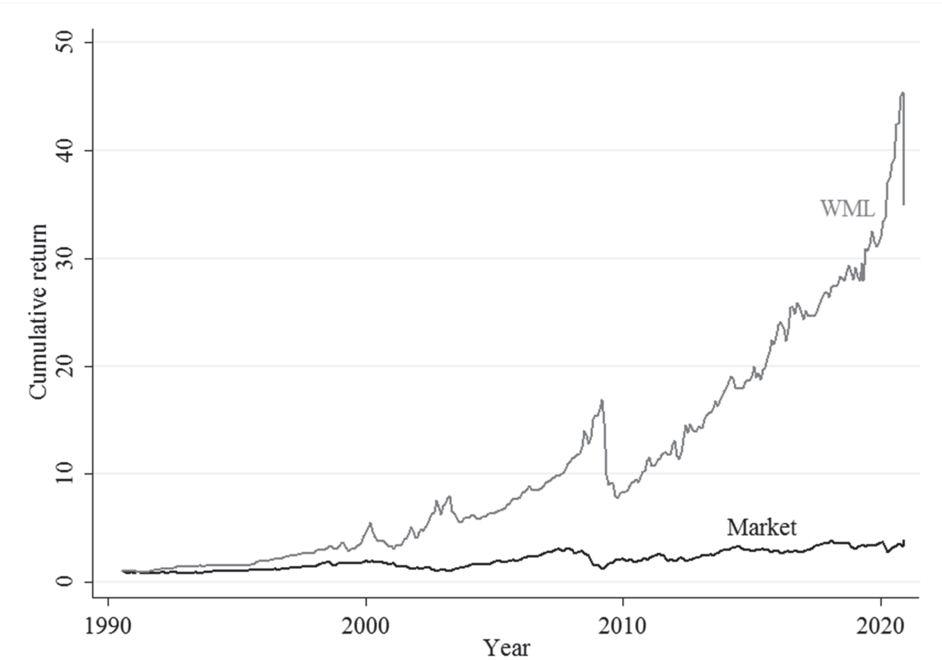
Source: Kenneth French's Data Library
Note: Monthly data, July 1990 – November 2020.

Equally perplexing are the results for the five-factor model of Fama & French (2015):

$$r_{i,t} - r_t^f = \alpha_i + \beta_i \left(r_{M,t} - r_t^f \right) + b_{SMB,i} SMB_t + b_{HML,i} HML_t + b_{RMW,i} RMW_t + b_{CMA,i} CMA_t + \varepsilon_{i,t}. \quad (5)$$

They are summarised in Table 6. The conclusions regarding alphas and market betas remain. The variance explained by the regressors represents an improvement over the CAPM, while the significance of HML coefficients is reduced. There are only two funds that had a negative HML factor loading at the 0.05 significance level. Similar to the momentum factor in Table 5, only one fund (AEDAX) had a significant positive coefficient corresponding to the RMW factor. The remaining funds had insignificant coupling with this factor, thereby entirely ignoring its monthly Sharpe ratio of 0.24 (Figure 5).

Figure 4: Risk-adjusted cumulative returns of the European momentum factor (WML) compared to the market portfolio



Source: Kenneth French's Data Library

Note: Monthly data, July 1990 – November 2020.

Table 5: Time-series regressions of fund excess returns on four Carhart factors

Rank	Fund/portfolio	α	β	b_{SMB}	b_{HML}	b_{WML}	R^2
1	EUGAX	0.11	0.86***	0.03	−0.20***	−0.02	0.72
2	PRESX	0.05	0.95***	0.12	−0.09*	−0.00	0.72
3	CAEAX	−0.06	1.10***	0.74***	−0.52***	−0.05	0.93
4	HFEAX	0.34	1.02***	0.73***	−0.39***	−0.19***	0.71
5	BAFHX	−0.01	1.05***	0.06	−0.48***	−0.18*	0.84
6	FHJUX	−0.22	1.10***	0.10	−0.50***	−0.12	0.82
7	MDEFX	0.09	0.86***	0.24	0.13	−0.12**	0.57
8	VGEAX	0.12	0.91***	−0.03	−0.74***	−0.24	0.45
9	DFCSX	0.02	0.96***	1.03***	0.23***	−0.03	0.71
10	VEURX	0.01	0.97***	−0.08**	0.02	−0.03**	0.94
11	ESMAX	0.46	0.76***	1.30***	−0.25*	−0.13	0.42
12	VEUAX	−0.09	1.00***	0.35***	−0.05	0.12**	0.75
13	AEDAX	0.03	1.03***	0.33***	−0.34***	0.22***	0.79
14	TEMIX	0.23	0.65***	0.27**	0.08	−0.01	0.50
15	UEPIX	−0.28	1.03***	−0.34***	−0.36***	−0.05	0.72
16	DSEUX	−0.09	1.09***	−0.14	0.06	0.01	0.91
	Value-weighted portfolio	−0.00	0.70***	0.35***	−0.07	−0.01	0.77

Source: Author's estimations.

Note: * – p-value < 0.10; ** – p-value < 0.05; *** – p-value < 0.01.

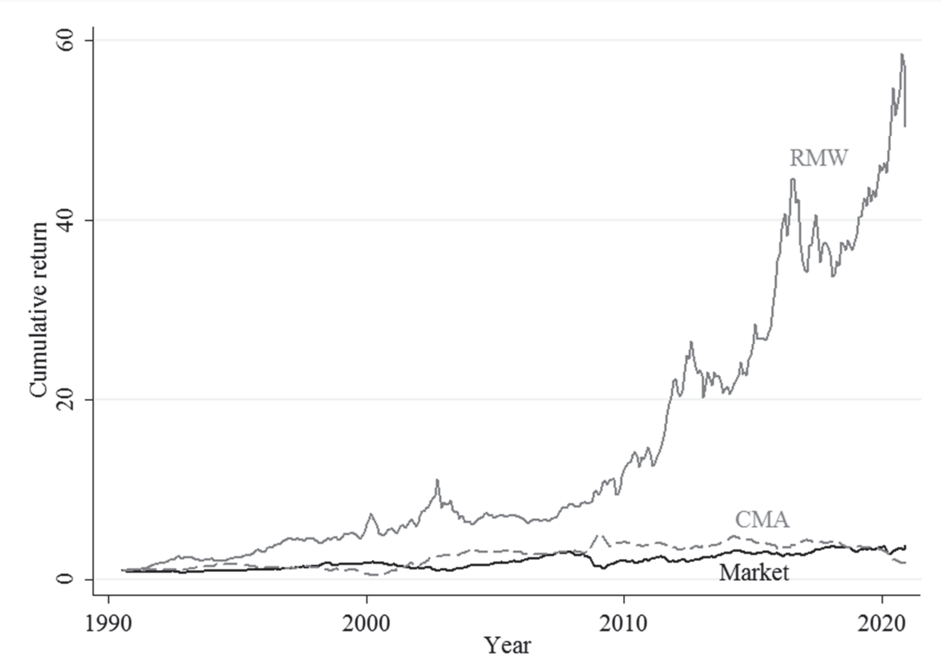
Table 6: Time-series regressions of fund excess returns on five Fama-French factors

Rank	Fund/portfolio	α	β	b_{SMB}	b_{HML}	b_{RMW}	b_{CMA}	R^2
1	EUGAX	0.16	0.84***	0.02	–0.20**	–0.16	–0.09***	0.73
2	PRESX	0.10	0.93***	0.11	–0.08	–0.09	–0.08	0.73
3	CAEAX	–0.10	1.10***	0.74***	–0.40**	0.21	–0.04	0.93
4	HFEAX	0.27	0.97***	0.60***	–0.03	–0.06	–0.72**	0.71
5	BAFHX	–0.11	1.08***	0.01	–0.25	0.18	–0.05	0.83
6	FHJUX	–0.24	1.14***	0.06	–0.52*	–0.27	–0.06	0.82
7	MDEFX	0.04	0.88***	0.23	0.13	–0.20	–0.01	0.56
8	VGEAX	–0.06	0.94***	–0.01	–0.53	0.08	–0.07	0.44
9	DFCSX	0.05	0.99***	1.03***	0.12	–0.17	0.14	0.72
10	VEURX	0.00	0.96***	–0.08***	0.07*	–0.03	–0.11*	0.95
11	ESMAX	0.47	0.70***	1.20***	0.06	–0.06	–0.62	0.43
12	VEUAX	0.05	0.93***	0.35***	0.02	0.03	–0.23	0.74
13	AEDAX	0.18	0.91***	0.33***	–0.12	0.29**	–0.46***	0.79
14	TEMIX	0.12	0.65***	0.26**	0.23*	0.27*	–0.13	0.50
15	UEPIX	–0.28	0.99***	–0.38***	–0.18	–0.04	–0.33*	0.72
16	DSEUX	–0.20	1.05***	–0.22	0.28	0.09	–0.47	0.92
	Value-weighted portfolio	0.02	0.66***	0.34***	0.02	–0.02	–0.17**	0.77

Source: Author's estimations.

Note: * – p-value < 0.10; ** – p-value < 0.05; *** – p-value < 0.01.

Figure 5: Risk-adjusted cumulative returns of the European RMW and CMA factors compared to the market portfolio



Source: Kenneth French's Data Library
Note: Monthly data, July 1990 – November 2020.

5.2. Discussion

The perplexing nature of our findings can be understood in the following simple manner. On the one hand, we know with absolute certainty that there are simple, commonly known investment strategies that investors could easily follow. These strategies could be fully implemented automatically to achieve a better risk–return trade-off than the market. Therefore, how is it possible that actively managed funds struggle to outperform even the market portfolio itself?

An alternative way of looking at these results is to not necessarily expect that all mutual funds will follow strategies that provide the best risk–return trade-off. However, what should be indisputable is that the performance of a typical equity fund should be reasonably close to the market portfolio. Table 2 shows that a value-weighted portfolio of even the top funds has a Sharpe ratio slightly below the market. When we consider the known trading anomalies, the inability of funds to generate positive and significant alphas becomes truly abstruse. The service that actively managed funds offer is careful investment selection: it remains unclear why they consistently fail in that effort, as the past three decades of research indicate (Cuthbertson et al., 2010; Fama & French, 2010).

Undoubtedly, some mutual funds will outperform the market, while others will underperform, even if we track their performance over extended periods. The idea is not to separate 'good' from 'bad' funds but to understand whether successful funds perform well merely as a coincidence or as a result of their skill and knowledge. A possible way to answer this question is to determine a measurable property or at least a criterion (even a qualitative one) that can be used to sort funds into portfolios. Such a metric or criterion would have to separate the funds ex-ante and track their performance over time. One metric commonly applied in the literature is the false discovery rate proposed by Barras et al. (2010). If investment skills positively influence performance, funds that are better according to the selection criterion will beat the market continuously and systematically.

Nevertheless, the vast majority of findings so far point to the same conclusion: there is no apparent relationship between the two, and mutual funds do not exhibit persistent returns. There is also no measurable causal link between good past and current performance. A typical mutual fund underperforms the market portfolio, while the fund returns show no predictability. Active investment strategies are not providing higher returns than passive investment strategies. They most likely provide lower returns when considering the typical transaction cost of 66 basis points per annum for global actively managed funds (PwC, 2020).

Another curious phenomenon is that the momentum and the profitability anomaly remain largely unexploited and continue yielding high Sharpe ratios. The momentum anomaly has been known since 1997 and the profitability anomaly since 2015. Nevertheless, they still significantly outperform the market, even when we consider the risk, as shown in Figures 4 and 5. This observation contrasts with the U.S. stock market, where benchmark portfolios became stagnant after a continuously increasing trend. The strong coupling with the benchmark portfolios is one of the usual explanations of why mutual funds fail to outperform the market in the longer run: only the equilibrium risk premia survive for decades. Otherwise, it would be difficult to understand why mutual funds do not perform better. However, such an explanation does not seem to be supported by the evidence we obtained for the European stocks.

Our findings for U.S.-based European equity funds are consistent with previous studies on the performance of mutual funds that invest in the United States (see, for instance, Mateus et al. 2019 for an overview). As we pointed out in Section 1, not many studies focus on the performance of European equity funds. Otten & Bams (2002) conduct an overview of 506 mutual funds from five European countries. They find that in four of these countries the funds outperform the market portfolio. They also report strong evidence of return persistence for U.K. funds. Vidal-García (2013) finds a similar persistence pattern for funds traded in six European markets between 1988 and 2010. These findings deviate from most studies for U.S.-based funds and are also in stark contrast to our evidence of underperformance for even the top-performing funds. Graham et al. (2019) report that both U.S. and European equity funds achieve high profits under very similar conditions, which could be a possible clue regarding their comparable lack of performance.

6. CONCLUSION

In this paper we have studied the performance of actively managed U.S. mutual funds specialising in investing in European stocks. Our sample consisted of monthly returns on the top sixteen mutual funds ranked by the U.S. News Mutual Fund Score between July 1990 and November 2020. We measured the performances of our sample funds through their abnormal returns, captured by the regressional intercept (i.e., alpha) in the standard factor models. We used four benchmark models: CAPM, the three-factor model of Fama & French (1993), the four-factor model of Carhart (1997), and the five-factor model of Fama & French (2015). We detected no abnormal positive returns for any of the funds: the CAPM model gave either insignificant or negative alphas. By contrast, all three multifactor models had systematically insignificant alphas for all the funds. Therefore, the top European equity funds' returns can be trivially explained by the known risk factors.

We found that the sample funds did not exploit some of the well-known market anomalies that could have significantly improved their performance. Only two funds had significant exposure to the European momentum factor (WML), and only one fund had significant exposure to the stocks of highly profitable companies (the RMW factor). Exposure to either of these two portfolios would have resulted in a considerable improvement in the Sharpe ratio of the observed funds. On the other hand, the funds successfully exploited the downturn of the value stocks, i.e., the negative average return on the HML factor during the previous six years.

An overly simplistic interpretation of the lack of exposure to WML and RMW factors is that the fund managers were unaware of the evidence regarding the market anomalies. Despite the naivety of such a conclusion, this is what the results seem to imply. Of course, we should take it with a grain of salt. The consistently high significance of market betas and the short positions in the HML factor together illustrate that the funds track the performance of at least two crucial benchmark portfolios.

Since at least two known anomalies persist in Europe, we show they represent significant potential to improve the risk–return trade-off of funds that focus on European stocks. This potential is currently used sub-optimally. Therefore, our findings present some relevant explorable avenues that investors and academic researchers alike can investigate. A possible limitation of our results relates to the relatively small cross-sectional dimension of the sample. Expanding the scope of the funds is a relevant avenue for further research.

ACKNOWLEDGEMENT

This research was financially supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia. I am thankful to the anonymous reviewers of this manuscript for their valuable comments and suggestions. The usual disclaimer applies.

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Received: January 26, 2021
Accepted: August 23, 2021