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The persistence of European mutual fund performance☆

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ABSTRACT

This paper examines the performance and persistence in performance of style-consistent European equity mutual funds between 1988 and 2010. Using a large survivorship bias-free sample for six European countries, we document strong evidence of persistence in benchmark-adjusted returns over 1-year time periods as well as over longer periods. We find statistically and economically significant performance persistence for time horizons of up to 36 months, although persistence is much more pronounced for the top and bottom performers. Thus, past performance of European mutual funds have explanatory power for future performance and investors can obtain useful evidence from past performance data.

1. Introduction

Despite the economic importance of the European mutual fund industry, due to the integration of European financial markets in the last decade, European-registered funds are an under-research topic. There is no study which has examined the performance of equity funds investing in the main European financial markets over a long time period. This is an important area of research, investors

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can easily compare the performance of mutual funds investing in different European countries since the introduction of the common Euro currency.

Our paper investigates the performance of monthly returns for mutual funds having a European equity focus over the January 1988 to December 2010 period. Our research aims to provide evidence on whether countries and investment styles are segmented in European financial markets. Heston and Rouwenhorst (1994) study the impact of industry and country factors on stock returns and show that the country factor has a strong influence. Recently, Sonney (2009) finds that stock analysts who are focused in certain countries have an informational advantage over sector specialists due to their better knowledge about country-specific factors and the geographical proximity with the companies they research.

Research into fund performance persistence has a long history, the literature agrees that performance persistence is a relevant issue but disagrees on whether and to what degree persistence is present. Jensen's (1968) early research on mutual funds states that funds do not have abnormal performance. Some later papers contradict this conclusion and show that relative performance persists over short and long periods. Bollen and Busse (2005), Avramov and Russ (2006), and Kosowski et al. (2006) show predictability in fund performance even after accounting for momentum. In costrast, Carhart (1997) using a survivorship-free sample of U.S. equity funds shows that persistence disappears after accounting for momentum in stock returns. Henriksson (1984), Barras et al. (2010), Fama and French (2010), and Busse et al. (2010) show little to no evidence of persistence over long time horizons.

Our main contribution is to determine whether an investor can actively select European mutual funds with a persistent performance objective, relative to European risk factors. Most studies that have considered this question have focused on U.S. equity mutual funds. It is important to find out if this conclusion applies to other markets, in order to corroborate the U.S. results and to see how the macroeconomic characteristics affect the performance of equity mutual funds in Europe.

Our results have economic and practical implications for investment management. From an economic perspective, if previous return performance can be used to forecast future returns, this is an important challenge to market efficiency. From a practical perspective, if there is no persistence in performance, then investors can engage in completely passive asset management. Although taking into account agency problems, entirely passive asset management is an unlikely result. Thus, some degree of active management should exist.

A successful trading strategy would be of interest to many investors in European equity funds. Considering funds whose investment objectives focus on a specific country and investment style, we could allow for a potential investment strategy to generate abnormal returns by timing countries and investment styles, or by identifying funds with superior stock selection in each of our categories. Our results can determine whether country-specific or specialist style funds outperform generalist funds that invest more broadly across countries and investment styles in Europe. Further, our models determine whether macroeconomic factors are most useful in identifying superior European mutual funds.

The paper is organised as follows. Section 2 describes the data, and the variables used in the study. Section 3 reviews the basic models and the methodology. Section 4 presents the main empirical results. Section 5 provides additional empirical results. Finally, Section 6 offers concluding remarks. Tables, figures and details on data sources are provided in Appendix A.

2. Data and summary statistics

2.1. Data

Our main dataset consist of monthly returns of 1050 actively managed equity mutual funds. We focus on the six largest European mutual fund markets, as they account for almost 90% of total mutual fund assets in Europe. The funds are registered in United Kingdom, France, Italy, Spain, Germany and Netherlands.[1] All returns are in local currency, include any dividend paid, and only the primary share

[1] See European Fund and Asset Management Association (EFAMA) 2011 annual statistics. We exclude Luxemburg as it is considered an offshore centre, as a result of fiscal advantages.

class is included. The returns are net of fund operating expenses, this means that include management and distribution fees, although not sales loads. We obtain this data from Lipper mutual fund database.[2] Furthermore, we use fund investment styles, which we obtain from Morningstar Direct database. We employ fund names and ISIN codes to identify and link fund data across the different databases. Our time range is a 22-year period starting on January 1, 1988 and ending on December 31, 2010. We cross-check the number of mutual funds with two other similar databases, Datastream and Morningstar. The data coverage of Lipper is better than other alternatives data sources. In addition to returns, the Lipper database contains descriptive information. We obtain cross-sectional information on its trading currency, performance fee, initial charge, and redemption charge. From Morningstar Direct, we also extract time-series information on its investment sector, assets under management, and fund size.

We have applied several simple filters on the initial set of data. First, we have restricted our selection to domestic equity funds as we are interested in European-domiciled mutual funds. We include merged and liquidated funds in the sample. Second, we restrict our sample to equity funds with at least 24 months of data. A mutual fund needs a long enough return history to reliably estimate a factor model regression. We exclude index funds, sector funds (e.g. technology or health care), equity funds that invest internationally, funds that contain non-equity components such as convertible debt, or funds that became one of these types in a subsequent year during the sample period. Finally, we remove all funds that do not have style identification information. The Morningstar equity fund styles included are the following: Small Growth, Small Blend, Small Value, Mid Blend, Mid Growth, Mid Value, Large Value, Large Blend and Large Growth.

The percentage of dead funds during the sample period was 24% for (Germany), 29% (Spain), 17% (United Kingdom), 45% (Italy), 22% (France) and 22% (Netherlands). We specify the overestimation by survivorship bias for all our European countries, and find that restricting our sample to surviving funds yields to overestimate average returns by 0.31% (Germany), 0.24% (Spain), 0.40% (United Kingdom), 0.17% (Italy), 0.33% (France) and 0.12% (Netherlands) per year. Thus, survivor bias is an important issue in mutual fund research (see Elton et al., 1996a,b; Carhart, 1997). We include dead fund in the sample until they disappear. Afterwards, the portfolios are re-weighted with the surviving funds. The survivorship bias is a property of the sample selection method and is the consequence of including in a sample only funds that survive until the end of the study period. Another relevant property to consider in our test methodology is the look-ahead bias. This bias results from eliminating funds from the sample that do not survive a minimum period of time after the ranking period. Tests of performance persistence need funds to survive during both the ranking and evaluation periods. In our study, look-ahead bias may influence our results, as we require at least 20 time-series observations to estimate the parameters in regression (1). We impose a full look-ahead bias methodology on our sample, that means we eliminate disappearing funds before the ranking process starts. According to Carpenter and Lynch (1999), partial look-ahead biases are more pronounced than the full look-ahead in both cases, on a single-period criterion and on a multi-period criterion. Thus, we have implemented the full look-ahead methodology in our sample construction and impose a multi-period elimination criterion, eliminating observations when there is less than 20 months worth of data.

In our study, we use data for all selected mutual funds irrespective of whether they change manager. It is possible that survivorship bias is more important in mutual funds with the same manager, as mutual fund companies who retained the same fund manager are likely to have been satisfied with the fund manager's performance record. Thus, eliminating this survivorship bias from our sample, we are more likely to find true persistence.

We end up with a total of 137,956 monthly observations, the average life of a fund in our database is 9 years. Our sample is, to our knowledge, the largest and most complete database for European mutual funds currently available. Although Otten and Bams (2002) and Banegas et al. (2011) use similar databases to study European mutual funds. Otten and Bams (2002) use monthly returns of pure domestic equity funds for the five largest mutual fund countries in Europe covering 85% of total assets, from January 1991 through December 1998, whereas our data set uses a larger and longer time period and covers a slightly larger percentage of total assets. Banegas et al. (2011) use data obtained from

[2] *Source*: Lipper, a Thomson Reuters company.

Lipper, monthly observations from June 1988 to February 2008. Although they use European-domiciled equity mutual funds with a European investment focus, their data set also includes Pan-European[3] or sector specific as well as specialist funds with a more passive investment objective, as the authors acknowledge their data is limited in some respects and suffer from some selection bias. Our data set mitigates these problems as we obtain monthly total returns for actively managed funds for each of the main European markets.

2.2. Benchmarks

In each country, we construct a European version of the Carhart 4-factor and Fama–French 3-factor models, we consider all stocks included in the Worldscope database (Thomson Financial Company) for each country. Worldscope includes over 98% of total market capitalization per country. We restrict our selection to only primary quotes of major securities, the prices are adjusted and we also include dead and suspended stocks. The market excess return is calculated as the difference between the MSCI country total return index and the 1-month Treasury Bill rate for each country. For the SMB factor, we rank all stocks based on size, then we estimate the return of the bottom 30% of stocks less the return of the top 30% ranked by market capitalization. For the HML factor all stocks are ranked based on the book-to-market ratio. We estimate this factor subtracting the return of the bottom 30% of stocks from the return of the top 30% of stocks with high book-to-market ratios. We create a momentum factor portfolio by ranking all stocks on their previous 6-month returns. We estimate the momentum factor as the difference in returns between the top 30% and the bottom 30% ranked by market capitalization.

2.3. Descriptive statistics

Table A.1 presents the descriptive statistics of the sample for each investment style. Style classifications are based on investment focus (growth, blend, and value) and mutual funds' market capitalization (small, mid, and large cap). Table A.1 shows the Morningstar investment styles represented in our sample.

The second column of Table A.1 shows the number of mutual funds for each investment style, the third column presents the number of active funds from 1988 to 2010, and the fourth column shows the number of funds that discontinued operations prior to December 31, 2010. For our sample period, the largest number of mutual funds investing in domestic equity is domiciled in the UK (582), while the smallest number is in the Netherlands (27). Large capitalization funds represent 73% of the total fund sample, while mid capitalization accounts for 15% and small capitalization for the 12%. By the end of 2010, 78% of mutual funds still continue operations. Mean returns (shown in column 5) vary slightly among countries, from 0.65% for France to the 1.04% for UK.

The sixth column presents average assets sizes (in millions). Overall, average asset sizes are bigger for large cap mutual funds, total asset sizes per country range from 279 million for Spain to 1631 million for Germany. There is also significant variation in management fees across investment styles and countries (see column 7). Generally, small and mid cap mutual funds present the highest fees, while large cap funds have the lowest fees. Considering countries, UK has the lowest fees (1.17%), and Spain has the highest fees (1.93%). Management fees are normally constant during the time period of our research, fluctuating no more than 10 basis points over the whole sample period. The seventh and eighth columns show the initial and redemption charges (load fees) as a percentage of the investment. Considerable variation also exists in both charges across countries, varying from 0.01% (Spain) to 4.6% (Germany) for the initial charge, and from 0.01% (UK) to 0.87% (Italy) for the redemption charge. Thus, European mutual funds have a higher initial charge (2.42% in average), and a significantly lower redemption charge (an average of 0.35%). Load fees are also generally stable over the time period of our paper, varying in line with the management fees.

[3] Funds that are allowed to invest across all the developed European stock markets.

3. Models of performance measurement

We measure the persistence of fund performance by examining whether funds that have performed well in the past can repeat this in the following periods. We examine the consistency in performance of a specific investment style, we measure the performance across all the funds within that investment style. Each investment style consists of value-weighted returns from all the mutual funds included in that category. We weight by fund size, because fund managers give a better service and put more effort into managing bigger funds, since if fees are based on the value of assets under management, the bigger mutual funds pay a higher fee to the fund manager. Funds are weighted by assets under management at the beginning of each month.

We focus on persistence in 1-year period, as investors usually examine performance over annual periods, and researchers most often find evidence of persistence for 1-year horizons. We measure performance persistence using benchmark-adjusted returns, as we have monthly returns for existing and liquidated European mutual funds, and the quality of this benchmark adjustment is equal across investment styles, thus all European mutual funds can be analysed with well-researched multifactor models.

Following convention in the mutual fund literature, we will use performance-ranked portfolio strategies. Performance-ranked portfolio tests classify funds each period into portfolios according to past performance. After an initial ranking period, the performance of funds is compared and ranked. Our ranking period is one year. Funds are ranked on the basis of their average return in the ranking period, and style portfolios are classified on the basis of this ranking, with different number of funds in each portfolio. The top portfolio includes funds with the highest average abnormal returns in the ranking period, and the bottom portfolio consists of those funds with the lowest average abnormal returns.

Mutual fund performance is measured as the average abnormal return on the funds under management in every investment style portfolio, and the abnormal returns for each mutual fund are calculated from an asset pricing model. Our primary approach to measuring performance is to calculate factor models with time-series regressions. We form aggregate measures of performance using value-weighted portfolio returns of all mutual funds for that year, our purpose is to gauge cross-sectional variation in performance. Our main model of performance measurement is Carhart (1995) four-factor model due to its common acceptance in the literature, although we also present results for Fama and French (1993) model because of its ability to explain cross-sectional variation in returns:

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + m_i\,\mathrm{MOM}_t + e_{it} \quad (1)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + e_{it} \quad (2)$$

where R_{it} is the return on fund i for month t, R_{ft} is the risk-free rate and R_{Mt} is the market return over the same period, SMB_t and HML_t are the Fama–French (1993) size and book-to-market factors and MOM_t is the period t value of the Carhart (1997) momentum return, e_{it} is the regression residual, and α_i is the average return unexplained by the model. Regression (1) is Carhart's four-factor model, and regression (2), excluding the MOM_t factor, is the Fama–French three-factor model. To estimate each fund t-statistic, we use the Newey and West (1987) heteroskedasticity and autocorrelation consistent estimator of the standard deviation. The regression intercept measures the average return gained by a fund in excess of the return on a passive portfolio. The slopes on the explanatory variables on the left replicate the exposures of each mutual fund to a portfolio of passive benchmarks. The residual e_{it} is the part of the model that cannot be explained by the factors. The part of the variance in the portfolio returns that can be explained by the multifactor models is measured by the coefficient of determination R^2.

Carhart (1997) shows that a four-factor model can account for differences in the performance of past winners and past losers, and the momentum factor explains most of this difference. He states that Jegadeesh and Titman's (1993) 1-year momentum in stock returns explains the persistence of fund returns as these funds hold relatively larger positions in last year's wining stocks. Wermers (1997) points out that it is the momentum strategies followed by the outperforming mutual funds that generate short-term persistence.

The risk factors of Carhart's (1997) model are included in order not to reward fund managers for taking advantage of stock market systematic anomalies. As our funds are classified into specific investment styles by holding specific asset classes, the four factor model is the most relevant with the purpose of measuring fund performance.

We also obtain benchmark-adjusted returns by subtracting a benchmark return from the annual raw return:

$$R_{xt} = R_{it} - R_{bt} \tag{3}$$

where R_{it} is the return on fund i for month t, R_{bt} is the benchmark return, and R_{xt} is the excess return. Most investors and fund managers focus on benchmark-adjusted returns as performance measure, since the investment alternative is an index fund which replicates the stock index return, and beating this index is their investment objective. Furthermore, if the index already represents most of the style differences across mutual funds, then an extensive model may not be necessary to account for the style differences. We use MSCI style indices as benchmarks based on the investment style of each portfolio to adjust raw returns. Thus, we include individual country style indices among the benchmarks, allowing for partial market segmentation.

3.1. Ranked portfolios approach

We follow the methodology of Hendricks et al. (1993) and Carhart (1997) and use lagged 1-year returns. Each 1st of January, we create value-weighted portfolios of mutual funds for each investment style, net of management fees but before deducting any sales charges, we hold these portfolios for one calendar year, and then portfolios are created again the next year. We use annual intervals, as if the evaluation period is too short the signal of superior performance due to skill will get lost in the noise from chance factors. Mutual funds that are merged or liquidated during the year are included in the value-weighted average until they disappear, and then the portfolio weights are rebalanced accordingly.

We sort mutual funds into a ranking based on annual mean returns over the past year, then we create value-weighted style portfolios that we hold over the next year and calculate their monthly returns. This procedure is repeated at the end of each year, we obtain a time-series of monthly returns for each style portfolio from January 1988 to December 2010.

In contrast to Carhart (1997), we create a style portfolio ranking following benchmark-adjusted returns instead of raw returns. This is mainly because classifying on raw returns could distort the rankings with some investment style portfolios always being sorted into winner and loser positions. Using benchmark-adjusted returns, we create a ranking based on the abnormal returns of the portfolios rather than the abnormal returns of their asset class.

At the end of 1988, we rank investment style portfolios according to the prior annual benchmark-adjusted return. Then, we calculate the value-weighted return for each portfolio over the following year. We roll forward, creating a set of post-ranking annual returns. We obtain a time-series of post-ranking returns for each portfolio, we then compute estimates of abnormal performance from these time-series. Note that alphas are not multiyear alphas, an alpha in a given year corresponds to the performance of the portfolio in that year after ranking, and not the performance over the previous years.

3.2. Contingency tables

We also analysed the persistence of mutual funds investment style performance through contingency tables. The non-parametric contingency table analysis is a common test for persistence to examine the frequency with which winners or losers funds maintained that category over consecutives time periods. Additionally, the contingency table analysis let us examine the effects of changes in the methodology.

Contingency tables sort funds as winners or losers in each time period, and the different combinations are counted: winner–winner (WW), winner–loser (WL), loser–winner (LW), and loser–loser (LL). Winning and losing funds are classified according to the median fund return for each year.

Winner–winner (WW) refers to a fund which presents abnormal returns above the median return in each period, Winner–loser to a fund which obtained returns above the median in the prior period and below the median in the next period, and so on. Thus, contingency tables present the frequency with which winners and losers repeat. There is performance persistence if statistical evidence shows a significantly larger number of observations in the WW/LL categories than in the other two. The strength of the contingency table method is based on the way in which it tracks the fluctuation of individual funds and evaluates their transitional probabilities. We calculate annual percentage returns for each investment style portfolio for the period 1988 to 2010, we use benchmark-adjusted returns for the reasons mentioned previously.

The use of contingency tables is straightforward and easy to understand by private investors, especially if benchmark-adjusted returns are used. Contingency tables are preferred to other methods when there is a limited sample of funds. The contingency tables show the probability of a fund in a ranking position being in the same rank in the following period. If performance was completely random, investors would expect an equal chance of a top ranked fund ending up in any of the ranking positions in the next investment period as the past evaluation period has no influence on the subsequent period. To avoid the possibility that a high proportion of funds remain in the top ranks by chance, we test all available data and also use different statistical tests. Previous contingency table analysis of fund performance show quite different results depending on the type of returns used in the study, raw or risk-adjusted. The use of raw returns usually reveals performance reversals, while the use of risk-adjusted returns suggests the existence of performance persistence. To the best of our knowledge, there is no study of contingency tables that examines performance persistence in benchmark-adjusted returns.

The performance persistence could simply show the differential return between high risk and low risk funds and not consistency due to management skills. In order to account for this effect we have evaluated the contingency tables considering benchmark-adjusted alphas.

We use several statistical tests to establish the robustness of the possible performance persistence effect. Even in the case of no persistence, we could find a number of funds that repeat good performance or bad performance by chance alone. If we find statistical evidence that winners in 1 year remain winners in the subsequent year the null hypothesis of no persistence will be rejected. To test for independence in the results from year to year the contingency table estimates were examined by the use of the repeat winner approach (Malkiel, 1995), the odds ratio (Brown and Goetzmann, 1995), and the Chi-square statistic (Kahn and Rudd, 1995).

The first test is the repeat winner strategy proposed by Malkiel (1995). This test presents the percentage of repeat winners (WW) to winner–losers (WL). He uses a binomial test of $p > 1/2$ to check the significance of the proportion of WW to (WW + WL):

$$Z = \frac{(y - np)}{\sqrt{np(1-p)}} \tag{4}$$

where Z is the statistical variable with a normal distribution (0,1), y is the number of repeat winners (WW), n is the number of repeat winners and winner/losers (WW + WL). A percentage of winner portfolios to the number of repeat winners and winner/losers above 50%, and a Z-statistic above zero show performance persistence.

In a second test statistic, we calculate the cross-product ratio (CPR), also mentioned as the odds ratio (see Brown and Goetzmann, 1995). The CPR is calculated as (WW × LL)/(LW × WL), the ratio of the product of repeat winners (WW) and repeat losers (LL) divided by the product of winner–losers (WL) and loser–winners (LW). Under the null hypothesis of no persistence the CPR equals 1. A CPR greater than one indicates persistence, and a value below one shows a reversal in performance. The statistical significance of the CPR can be determined by a Z-statistic, which equals the ratio of the natural logarithm of the CPR and the standard error of the natural logarithm of the CPR. Using large samples it is normally distributed with mean log CPR, while for small sample sizes results about CPRs may be misleading.

The final statistical test is the Chi-square statistic, introduced by Kahn and Rudd (1995). The Chi-square statistic is calculated as:

$$\text{Chi} = \frac{(\text{WW} - \text{D1})^2}{\text{D1}} + \frac{(\text{WL} - \text{D2})^2}{\text{D2}} + \frac{(\text{LW} - \text{D3})^2}{\text{D3}} + \frac{(\text{LL} - \text{D4})^2}{\text{D4}} \tag{5a}$$

where

$$\text{D1} = \frac{(\text{WW} + \text{WL}) \times (\text{WW} + \text{LW})}{N} \tag{5b}$$

$$\text{D2} = \frac{(\text{WW} + \text{WL}) \times (\text{WL} + \text{LL})}{N} \tag{5c}$$

$$\text{D3} = \frac{(\text{LW} + \text{LL}) \times (\text{WW} + \text{LW})}{N} \tag{5d}$$

$$\text{D4} = \frac{(\text{LW} + \text{LL}) \times (\text{WL} + \text{LL})}{N} \tag{5e}$$

N is the number of funds. We adjust for small sample bias with Yates's continuity correction, a recommended correction particularly when sample size is small. With the Chi-square test is not possible to detect reversals in performance, as it is always positive. However, Carpenter and Lynch (1999) showed that the Chi-squared test is well specified, powerful, and more robust to the presence of survivorship bias when compared to other tests of performance.

We do not have information on the behaviour or preferences of investors. As we do not know if some types of investors always select top-ranked funds while others buy low-performance funds. Thus, our results are based on a random re-investment rule, and we do not adopt a rule that investors re-invest in the same fund rank as they initially chose.

3.3. Bootstrap tests

If there is persistence in ability for a portfolio of funds, the alphas and returns for a given fund will be correlated to the alphas and returns estimated over other months. Thus, there is a potential problem with the post-ranking tests of return significance as the independence assumption, required for a parametric test, may be violated.

To address this issue, we use the bootstrap procedure of Kosowski et al. (2006). We bootstrap the returns of mutual funds under the null of zero alpha and then base their inference on the whole cross-section of simulated alphas and their t-statistics. We use the three-factor and four-factor models to implement this experiment, and we use alphas and t-statistics in the simulation implementation. We do this for all months, then we calculate a single bootstrap mean alpha. We repeat this procedure 1000 times and obtain the empirical distribution of the alpha mean. In each table, we show each style portfolio ranked according to their simulated (averaged across 1000 simulations) alphas and t-statistics.

4. Results

4.1. Aggregate performance

Table A.2 presents results of aggregate measures of performance. We report benchmark-adjusted returns for all investment styles portfolios in the six countries, we also show estimates of the Fama–French and Carhart factor models. The second column of Table A.2 shows benchmark-adjusted returns. If an investor evaluates the performance of mutual fund portfolios using simple style benchmarks, then on average the investment style portfolios present a positive performance.

Table A.2 presents summary statistics for the explanatory returns in regressions (1) and (2) from January 1988 through December 2010, the period considered in our study, and it shows that both factor models account for variation in returns. The three-factor and four-factor intercepts for value-weighted returns are negative, the value-weighted Fama–French alpha ranges from −1.95 for Italy

to −0.27 for Spain, while the value-weighted Carhart alpha ranges from −1.59 for Italy to −0.23 for Germany. Our results are in line with previous work for U.S. equity mutual funds (e.g. Malkiel, 1995; Gruber, 1996; Fama and French, 2010). However, it differs from the results of Otten and Bams (2002). They research European mutual fund performance and find positive alphas for all European countries except Germany. In their results only UK funds present significant out-performance, the majority of alphas from all other countries are insignificantly different from zero.

Controlling for momentum makes a substantial difference, suggesting that mutual funds have significant exposure to the momentum factor. Instead, *R*-squares are similar in both models, which means that the momentum factor is only able to explain a relatively small proportion of the variability of the excess returns on our mutual funds. On average, large funds present bigger benchmark-adjusted returns than small funds, furthermore alphas are also more positive for large capitalization funds than for the smaller ones. On aggregate, our investment style portfolios do not deliver benchmark-adjusted excess returns.

4.2. Performance persistence

Table A.3 presents results of Fama–French and Carhart models in Panels A and B, respectively. We estimate alphas for every investment style portfolio in the six countries. Persistence is important from a practical and economic perspective, as it implies a violation of market efficiency and a value-increasing opportunity for investors.

Performance estimates from the Fama–French present significantly different sizeable abnormal returns for the previous year's top-ranked and bottom-ranked portfolios of funds. The difference in terms of annual percentage in each country: Germany (−1.58), Italy (−1.30), Spain (−1.21), Netherlands (−0.40), France (−1.25) and UK (−2.91). The top-ranked portfolios appear to have more small stocks than the bottom-ranked. The size factor is significantly positive in all countries with the exception of UK, while the book-to-market is also significantly positive except for UK and Netherlands. The average alphas across the different portfolio rankings are negative. This is in line with the majority of the previous mutual fund literature showing poor performance to be more persistent (e.g. Carhart, 1997), and the reason why it is considered that normally active management do not create value.

The four-factor model accounts for a larger cross-sectional variation in expected returns on portfolios of mutual funds sorted on lagged one-year return. This model presents a larger difference in abnormal returns between the previous year's top-ranked and bottom-ranked funds, expressed in monthly percentage: Germany (−0.52), Italy (−1.30), Spain (−1.53), Netherlands (−2.75), France (−2.69) and UK (−2.30). Sensitivities to the factors are similar to the 3-factor model, with book-to-market and momentum factors being significant for a larger number of portfolios. The 1-year momentum factor presents a stronger positive correlation with the returns on the bottom rank than with the returns on the top rank. Hence, the momentum factor seems to explain the observed persistence. Persistence is still a significant characteristic of the data set even after allowing for momentum in individual funds. Controlling for momentum, alpha estimates are slightly more negative relative to the Fama–French model. This reversion could be due to look-ahead issues in non-survivorship biased samples. As poorly performing mutual funds are more likely to discontinue operations, the number of funds that will disappear in the bottom-rank is higher than in the top-rank. Carhart (1997) points out that momentum has an important role in persistence. Portfolios in the top ranks are more likely to have winner stocks and this creates persistence among winner portfolios.

One year after the creation of our ranking, the three-factor alphas for the top winner portfolios are highly negative and statistically significant. After controlling for momentum, alphas do not change dramatically and still are highly statistically significant. Thus, the results suggest that the 1-year horizon presents strong aggregate persistence in overall performance as measured by alpha. Furthermore, contrasting to other previous studies (see Brown et al., 1992), which have shown that persistence is mainly due to the bottom-ranked funds ongoing underperformance, this is not our case, although we also find persistence in the bottom rank, the top-performing funds also present significant underperformance.

Table A.4 reports a non-parametric contingency table of the performance persistence of mutual fund winners and losers from 1988 to 2010. The results show repeat wining and repeat losing percentages as well as its significance, and those that are winning fund portfolios in one of the two periods and loser fund portfolios in the other period. The contingency table results, as summarised in the tests figures, are not very different from what we find previously in the regression estimates and reveal that persistence is universally significant for all mutual fund investment style portfolios across countries. Thus, it is clear that winners will possibly remain winners, and losers will possibly remain losers or disappear, as the number of funds repeating as winners or losers is larger than the number of funds that change their status. The ranks of all of the top and bottom mutual fund portfolios persist. This means that the results obtained by mutual funds during the second period are dependent on those obtained in the previous period. As can be observed, we reject the hypothesis of no persistence, at the 5% level, for all fund portfolios in each European country. This result is a strong evidence, suggesting that investors could benefit from past performance information.

Significant performance persistence results are also confirmed from statistical tests, which are robust under non-normality of the fund return distribution. Note that the contingency table tests are only valid asymptotically and some adjustment for possible small sample bias may be needed. To account for this, the last column of Table A.4 incorporates the use of Yates's continuity correction for the Chi-square test. The repeat winners test shows a probability above 50% for most winners and losers in a rank position being in the same raking in the following period. The cross-product ratio is significantly different from unity, except for few fund portfolios, with all of them being statistically significant at the 5%. And the Chi-square test on independence is clearly rejected for all fund portfolios, confirming the existence of persistence. The percentage of repeat winners varies from 43% to 89.4%, with an average above 60% for most fund portfolios. While the proportion of repeat losers varies from 46.6% to 84.5%, with an average also above 60% in most cases. Overall, the highest persistence is found for Italian funds and the lowest for Spain. Thus, in contrast to the conclusion of previous studies that persistence is concentrated mainly in the poorly performing funds, we find that persistence is due to both good performing funds and poor performing funds. Our results are in line with the findings of Carpenter and Lynch (1999), who state that, in general, contingency tests are robust and powerful.

We can conclude that the there is a strong phenomenon of performance persistence for European mutual funds. Consequently, previous fund performance information is useful for potential investment strategies in order to achieve higher returns.

4.3. Robustness of the evidence

Standard measures of performance suffer from a number of biases, relying on unconditional models may lead to unreliable inference about mutual fund returns performance. Using instruments for the time-varying expectations, we control for predetermined information and reduce this source of bias. The expected returns and risks are conditioned on publicly available information. In this sense, Lynch et al. (2008) state that conditional performance of mutual funds moves with the business cycle, while Kosowski et al. (2006) shows that unconditional performance models underestimate the value created by actively managed funds in recession periods. Conditional asset pricing models are able to explain the cross-section of returns better than unconditional models (e.g. Cochrane, 1992; Jagannathan and Zhenyu, 1996). In unconditional multifactor models, both the betas and the alphas are constant over time but they may change across funds. In conditional models, betas are time-varying, but abnormal performance is reflected by fixed alphas.

Ferson and Schadt (1996) create conditional models of the standard mutual fund performance regressions, and find that using public information influences the average performance in a sample of open-ended mutual funds. They state that conditional performance evaluation is interesting for two reasons. First, traditional performance measures are not able to deal with the dynamic behaviour or returns. Second, the trading behaviour of fund managers implies more complex patters than those of the underlying assets they trade. They argue that the benchmark parameters should be conditioned on economic variables, the authors suggest that fund managers' market timing skills should be evaluated

and the predictable component of market movement should be removed. They find that conditioning information is both statistically and economically significant, introducing information variables changes the estimated performance of many funds. They also find evidence that mutual fund betas are correlated with their public information variables.

Christopherson et al. (1998) present evidence of investment performance persistence for institutional equity managers. They state that a conditional approach is better able to detect this persistence and to predict the future performance of the funds than traditional methods. They prefer conditional performance measures as they think that plan sponsors condition their expectations taking into account the state of the economy. Furthermore, unconditional performance indicators may be biased when plan sponsors use trading strategies that react to changes in market conditions.

We estimate conditional version of the three-factor and four-factor models:

$$R_{it} - R_{ft} = a_i + b_i(Z_{t-1})(R_{Mt} - R_{ft}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + m_i\,\mathrm{MOM}_t + e_{it} \quad (6)$$

Z_t is a vector of instruments for the information available at time t and $b_i(Z_t)$ are time t conditional betas, following Ferson and Schadt (1996) we approximate their function linearly:

$$b_i(Z_t) = b_0 + B'z_{t-1} \quad (7)$$

where $z_{t-1} = Z_{t-1} - E(Z)$ is a vector of the deviation of Z from the unconditional means. We assume that market prices reflect available public information, as measured by the vector of predetermined variables, Z_t. We use four publicly available conditioning state variables in our analysis: (1) dividend yield, (2) a Treasury Bill spread (the difference between long- and short-term government bond yields), (3) the yield on a 3-month Treasury Bill, and (4) a corporate bond yield spread (the difference between low- and high-quality corporate bonds).

Table A.5 shows conditional alphas for the persistence tests based on three-factor (Panel A) and four-factor (Panel B) models, where the conditioning variables include lagged macroeconomic factors. The results based on conditioning variables reported in Table A.5 indicate that our variables are related to performance. Although, we find that fund ranking on performance persistence is not changed when the conditional measures are considered, our results show that mutual funds time the overall market factor based on lagged macroeconomic variables on the market portfolio. In contrast with Ferson and Schadt (1996), we find that the performance of mutual funds in our sample is slightly worse when evaluated using conditional measures instead of unconditional ones.

In Table A.5, we also report the contingency table of winners and losers based on the conditioning variables. The strong statistical significance of the test statistics supports the existence of persistence, the significance is more robust than the previously found with unconditional models. Similarly to the results found with the unconditional regressions, evidence is strong for most investment style portfolios in each of the countries (with significant Chi-square statistics at the 5% level).

Research on persistence tests has found that mutual fund performance is mainly influenced by macroeconomic variables instead of the past performance of funds. We can notice that the evidence of performance persistence increases slightly when conditional alphas are considered instead of unconditional alphas. Furthermore, we find that the average R-square presents a modest improvement from unconditional models, which motivates the use of conditional models to research performance. The incremental explanatory power of the conditioning variables is significant for all investment style portfolios. Thus, we can observe that time-varying betas jointly with the additional factors used in the conditional model are relevant to establish an evident relationship between past and future fund performance. Therefore, conditional models are able to capture returns across funds better than models which assume that betas are constant. The stronger evidence on persistence for the conditional abnormal returns implies that the unconditional factors do not reveal the fund managers' true abilities, so relying on conditional alphas will produce better investment decisions.

In summary, whatever measure of performance used and considering regression analysis and contingency tables methodology, a robust consistency in performance is found for all fund portfolios in each country. We find, in line with Ferson and Schadt (1996), that using conditioning information

models have a greater impact on performance results than moving from the three-factor to the four-factor model.

It might seem puzzling that investors still invest in poor performing funds. In this sense, Gruber (1996) explains that this fact may be the consequence of the existence of two types of investors, a sophisticated clientele and a disadvantaged clientele. He points that the first type of investors makes investing decisions taking into account fund performance information, while the second type does not. This latter group includes uninformed investors, usually influenced by marketing and recommendation from brokers.

5. Longer-term persistence in mutual fund portfolios

As we find robust evidence of persistence performance, we would like to know whether the results hold when persistence is measured over a longer period. Few studies detect persistence beyond the 1-year horizon. We repeat our regression analysis with longer-term measures of persistence and investigate time horizons of 2 and 3 years. The knowledge of longer-term performance persistence will add a great deal of value for investors.

Carhart (1997) argues that if manager skill exists, a 1-year return is probably a noisy measure. In order to reduce the noise in past-performance rankings, he creates portfolios of mutual funds on lagged 2- to 5-year returns. He then repeats his previous analysis to evaluate how much cross-sectional variation in mean return can be explained by the 4-factor model.

We show the results of the performance persistence tests in Table A.6, from a 4-factor model in which the coefficients in regression (1) have been estimated from the returns of the previous 24 and 36 months. As Carhart (1997) points out, sorting mutual funds on alphas from the same model should measure stock-picking talent more accurately. From our results, we can state that performance persistence is greater when the period of historical data increases, we also find significant negative persistence at longer horizons. The 4-factor model presents evidence of persistence at all periods considered. The coefficients of the regression evidence of persistence reveal that performance predicts future returns.

The overall results of our analysis of mutual funds suggest that the past performance of a fund is a reliable benchmark to future performance. We find that most mutual funds maintain their initial annual alpha ranking at longer periods. Funds in the top and bottom ranks maintain their positions more frequently than the other fund portfolios. Furthermore, results show that the information content of the performance history does not vary across the different fund investment styles, and is not influenced by the measurement methodology used or by the performance persistence horizon considered.

6. Conclusions

In this paper, we examine the performance and persistence in performance of European equity mutual funds between 1988 and 2010, and investigate whether the persistence effect is related to investment style. The performance of European equity mutual funds is an area of research with only a few significant articles. Using monthly data for the six largest European mutual fund countries, we find that past performance carries information about the future, we show alpha persistence of up to three years which is both economically and statistically highly significant. Thus, mutual funds that performed well in the past are likely to do well in the future on a benchmark-adjusted basis.

The main conclusion is that European mutual funds show strong evidence of significant performance persistence, which is constant across investment styles, on an annual basis and in the longer-term periods (2- and 3-year intervals). Both 2- and 3-year alphas convey information about future performance, although persistence is much more pronounced for the top and bottom performers. We have used two methodologies in order to evaluate the existence of the persistence phenomenon. First, a parametric approach consisting of regression analysis. Second, a non-parametric methodology based on contingency tables, and supported by the repeat winner, the odds ratio, and the Chi-square tests to estimate the statistical significance of the results. The statistical tests confirm that persistence is strongly significant, mostly at a confidence level

at the 99.9%. Thus, we can state that past performance of European mutual funds have explanatory power for future performance and investors can obtain useful evidence from past performance data. Multifactor models provide a useful discrimination of the winner and loser phenomenon in the European mutual fund market. Furthermore, our estimates of persistence are not sensitive to the choice of models, both three-factor and four-factor models show strong evidence of persistence.

We also use conditioning information in performance measurement and find that is both statistically and economically significant. Our results also show that conditional measures are more informative and present a stronger significance about future performance than unconditional measures. Comparing the results from conditional and unconditional models, we assert that conditional alphas lead to stronger evidence of performance persistence for all fund portfolios. This suggests that the conditional factors considered in the multifactor model and the time-varying betas drive some of the evidence that there is a relationship between past and future fund performance. This is in line with most of the previous studies for the US market, which find that performance persistence is more significant when conditional models are used. Finding that a conditional measure is useful to detect persistence in fund performance is consistent with the view that more advanced methodologies are needed to successfully evaluate mutual funds performance.

Our results show that average performance (Jensen's alpha) is negative for all fund portfolios at any time horizon considered, with poorer performance when conditional models are used. This suggests that in the European mutual fund market, the value added by active management does not cover its fees incurred. Overall, based on our results we can conclude that investment style consistency is indeed relevant and that the market values the ability of a fund manager to maintain a style-consistent portfolio.

We also investigate the influence of fund characteristics on benchmarks-adjusted performance. We find that expense ratio, portfolio turnover, and load fees are significantly and negatively related to benchmark-adjusted performance, while maximum load is positively related.

Finally, a few concerns about the methodology employed to obtain our results can be raised. We have addressed some concerns as the effect of fund size, investment style influence on persistence, or benchmark-adjusted results. Areas for future research include examining a larger sample size and the influence of fund characteristics such as management tenure on persistence.

Appendix A.

See Tables A.1–A.6.

Table A.1
Descriptive statistics. The table presents descriptive statistics on our sample of mutual funds. Live funds are those in operation at the end of the sample. Dead funds are those that stopped operations before this date. The sample period: January-1988 to December-2010. Asset size is expressed in millions of dollars, management fee includes total annual management and administrative expenses and is in percent per year. Initial charge and redemption charge are expressed as a percentage of the investment.

	Total number	By current status		Mean return	Average asset size	Management fee	Initial charge	Redemption charge
		Live funds	Dead funds					
Germany	**68**	**52**	**16**	**0.869**	**1631**	**1.437**	**4.668**	**0.044**
Large Blend	38	35	3	0.849	496	1.226	4.942	0.262
Large Value	15	4	11	0.808	661	1.173	4.420	0
Mid Blend	5	4	1	1.024	245	1.491	5.000	0
Mid Growth	2	1	1	0.963	143	1.575	5.251	0
Small Blend	5	5	0	1.033	17	1.362	4.434	0
Small Growth	3	3	0	1.102	69	1.811	4.678	0
Italy	**62**	**35**	**27**	**0.722**	**714**	**1.882**	**1.747**	**0.879**
Large Blend	3	0	3	1.117	55	2.026	1.000	2.000
Large Value	37	20	17	0.715	438	1.850	2.189	0.722
Mid Blend	4	1	3	0.639	133	1.938	3.500	1.625
Mid Value	7	4	3	0.800	33	1.811	2.357	0.928
Small Blend	8	7	1	0.525	55	1.875	1.437	0
Small Value	3	3	0	0.310	52	1.811	0	0
Spain	**114**	**80**	**34**	**0.689**	**279**	**1.934**	**0.013**	**0.567**
Large Blend	17	6	11	0.634	62	1.794	0	0.824
Large Growth	3	1	2	0.636	38	1.952	0	0.345
Large Value	71	54	17	0.722	62	1.863	0.078	1.063
Mid Blend	3	2	1	0.721	67	1.899	0	0.523
Mid Value	17	15	2	0.704	27	1.964	0	0.353
Small Value	3	2	1	0.781	23	2.233	0	0.667
Netherlands	**27**	**21**	**6**	**0.848**	**1221**	**1.171**	**0.933**	**0.348**
Large Blend	1	0	1	0.021	223	1.212	0.876	0.345
Large Value	18	13	5	0.842	448	1.003	0.881	0.035
Mid Value	1	1	0	0.536	21	1.251	0.512	0.500
Small Blend	2	2	0	0.841	189	1.125	2.752	0.843
Small Value	5	5	0	0.968	340	1.281	0.538	0.365
France	**197**	**153**	**44**	**0.650**	**1141**	**1.896**	**2.785**	**0.277**
Large Blend	24	9	15	0.463	71	1.588	2.473	0.260
Large Growth	2	2	0	0.417	465	1.611	2.500	0
Large Value	135	111	24	0.661	524	1.575	2.788	0.206
Mid Blend	9	6	3	0.515	21	2.113	2.968	0.031
Mild Value	21	20	1	0.561	41	2.128	2.762	0.444
Small Blend	3	2	1	0.530	5	1.882	2.833	0
Small Value	3	3	0	0.565	14	2.393	3.166	1
UK	**582**	**485**	**97**	**1.043**	**1434**	**1.305**	**4.401**	**0.005**
Large Blend	286	245	41	1.014	214	1.294	3.981	0.014
Large Growth	44	39	5	0.988	189	1.293	4.600	0.011
Large Value	77	50	27	1.053	250	1.346	3.936	0
Mid Blend	53	45	8	0.981	93	1.207	4.447	0.019
Mid Growth	20	18	2	1.170	196	1.342	4.822	0
Mid Value	20	18	2	1.013	161	1.409	4.912	0
Small Blend	43	37	6	1.143	124	1.290	4.285	0
Small Growth	28	24	4	1.175	95	1.241	5.008	0
Small Value	11	9	2	0.919	112	1.322	3.625	0

Table A.2
Performance measurement models summary statistics. The table reports summary statistics on the style portfolios. We present performance measures for mutual fund portfolios along with their adjusted *R*-square. We choose the benchmarks based on the country of the mutual fund portfolio to adjust raw returns. The sample period is January 1988 to December 2010. All alphas are annualised.

	Benchmark-adjusted returns	Standard deviation	Factor model alphas			
			3-Factor	Adj *R*-sq	4-Factor	Adj *R*-sq
Germany	**0.141%**	**1.553%**	**−0.954*****	**0.952**	**−0.230*****	**0.956**
Large Blend	0.121%	1.435%	−0.378***	0.995	0.491***	0.996
Large Value	0.079%	1.746%	−0.564***	0.846	−0.673***	0.846
Mid Blend	0.341%	2.511%	−0.612***	0.992	−0.803***	0.995
Mid Growth	0.321%	4.083%	−1.639***	0.855	−1.923***	0.861
Small Blend	0.414%	3.739%	−1.368***	0.767	−1.449***	0.767
Small Growth	0.436%	4.008%	−0.808***	0.937	−0.982***	0.938
Italy	**0.279%**	**2.263%**	**−1.955*****	**0.920**	**−1.599*****	**0.926**
Large Blend	0.388%	2.774%	−0.908***	0.777	−0.847***	0.788
Large Value	0.273%	2.206%	−1.914***	0.895	−1.645***	0.802
Mid Blend	0.296%	2.119%	−0.894***	0.944	0.556***	0.949
Mid Value	0.288%	2.513%	0.013***	0.836	0.675***	0.842
Small Blend	0.171%	2.808%	−0.100***	0.963	−0.227***	0.964
Small Value	0.487%	4.656%	−0.096***	0.794	−1.013***	0.799
Spain	**−0.077%**	**1.846%**	**−0.276*****	**0.962**	**−0.404*****	**0.963**
Large Blend	−0.147%	2.102%	−0.344***	0.947	−0.466***	0.947
Large Growth	−0.146%	3.031%	−1.426***	0.845	−2.329***	0.845
Large Value	−0.043%	1.725%	−0.969***	0.879	−0.072***	0.879
Mid Blend	0.110%	0.888%	−1.777***	0.894	−1.030***	0.895
Mid Value	−0.078%	2.237%	−0.932***	0.963	−0.151***	0.964
Small Value	0.032%	2.167%	−1.099***	0.825	−0.292***	0.826
Netherlands	**0.188%**	**2.510%**	**−0.779*****	**0.911**	**−0.883*****	**0.909**
Large Blend	−0.273%	6.056%	0.237**	0.887	−0.145**	0.891
Large Value	0.182%	2.431%	−0.780***	0.756	−0.919***	0.756
Mid Value	0.083%	3.652%	0.357***	0.939	−0.406***	0.938
Small Blend	0.842%	5.624%	−0.318***	0.895	−0.237***	0.895
Small Value	0.398%	3.737%	−0.528***	0.972	−0.490***	0.972
France	**−0.044%**	**6.524%**	**−0.976*****	**0.908**	**−0.439*****	**0.911**
Large Blend	−0.064%	6.321%	−0.999***	0.879	−0.449***	0.882
Large Growth	−0.132%	5.919%	−1.060***	0.942	−1.403***	0.943
Large Value	−0.032%	6.605%	−1.816***	0.924	−0.309***	0.928
Mid Blend	−0.034%	6.204%	−0.436***	0.870	0.809***	0.872
Mild Value	0.039%	5.923%	−0.421***	0.897	−0.808***	0.899
Small Blend	0.407%	5.417%	−1.255***	0.951	1.321***	0.951
Small Value	0.167%	5.517%	−0.062***	0.917	−0.493***	0.921
UK	**0.262%**	**1.656%**	**−1.243*****	**0.898**	**−1.295*****	**0.898**
Large Blend	0.222%	1.184%	−1.158***	0.925	−1.206***	0.925
Large Growth	0.237%	1.418%	−2.097***	0.825	−2.049***	0.826
Large Value	0.257%	1.365%	−0.353***	0.895	−1.404***	0.895
Mid Blend	0.267%	2.272%	−0.485***	0.878	0.541***	0.878
Mid Growth	0.256%	2.329%	−0.807***	0.895	−0.857***	0.895
Mid Value	0.266%	2.002%	−0.183***	0.898	−1.250***	0.899
Small Blend	0.367%	3.723%	−1.469***	0.946	−1.529***	0.946
Small Growth	0.425%	3.808%	−0.923***	0.937	−0.985***	0.939
Small Value	0.388%	4.253%	−2.579***	0.898	−1.676***	0.899

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table A.3
Performance persistence. Mutual funds are sorted on January 1 each year from 1988 to 2010 into investment styles portfolios taking into account their previous year's benchmark-adjusted return. The portfolios are value-weighted monthly. Rank 1 contains the best-performing funds, and rank 9 contains the worst-performing funds. Alpha is the intercept of the Model. The table shows average simulated alphas and their *t*-statistics. Panel A shows results for Fama–French regression (1), and Panel B presents results for Carhart regression (2).

Panel A: 3-Factor model

Performance rank		3-Factor model				
		Alpha	RMRF	SMB	HML	Adj *R*-sq
	Germany	**−0.621*****	**0.093*****	**0.138*****	**0.082*****	**0.750**
1	Small Growth	0.411***	−0.169***	0.006	0.030	0.622
2	Large Value	−0.583**	−0.040***	0.131***	0.022	0.768
3	Large Blend	−0.701***	−0.123***	0.102***	−0.002***	0.786
4	Mid Blend	−0.909***	−0.154***	0.024	−0.001	0.642
5	Mid Growth	−1.445**	−0.091***	0.003	0.010**	0.538
6	Small Blend	−1.875***	−0.064***	−0.002	0.013*	0.854
	Italy	**−0.207*****	**−0.006*****	**0.016*****	**0.102*****	**0.814**
1	Large Blend	−0.144***	−0.008**	0.018	0.126***	0.767
2	Mid Blend	−0.234**	−0.007**	0.014	0.132***	0.833
3	Large Value	−0.322***	−0.006***	0.018***	0.109***	0.789
4	Mid Value	−0.333**	−0.004*	0.013*	0.087***	0.628
5	Small Blend	−1.678***	−0.002***	0.006	0.035*	0.861
6	Small Value	−1.801***	0.001**	0.008	0.225***	0.954
	Spain	**−1.765*****	**−0.110*****	**0.017*****	**−0.002****	**0.781**
1	Small Value	−0.778***	−0.031**	0.004	−0.002***	0.670
2	Mid Blend	−0.867***	−0.050***	0.007	0.010*	0.785
3	Large Blend	−0.879***	−0.103***	0.018***	−0.006**	0.878
4	Large Growth	−1.777***	−0.112***	0.015	0.006***	0.903
5	Mid Value	−1.812***	−0.087***	0.012***	0.001**	0.861
6	Large Value	−1.866***	−0.122***	0.020***	−0.003	0.930
	Netherlands	**−0.688*****	**0.003*****	**0.015*****	**−0.092*****	**0.778**
1	Mid Value	−0.845***	0.066***	0.026**	−0.136**	0.856
2	Small Value	−0.900**	−0.032***	0.009**	−0.078***	0.665
3	Large Blend	−2.122***	0.095**	0.026***	−0.027**	0.988
4	Large Value	−2.209***	0.017***	0.017***	−0.098***	0.848
5	Small Blend	−1.332***	−0.019**	0.002***	−0.081**	0.894
	France	**−1.223*****	**−0.124*****	**0.009*****	**0.001*****	**0.860**
1	Large Blend	−0.987***	−0.091***	0.008**	0.006**	0.828
2	Small Value	−1.134***	−0.063***	−0.002**	0.006***	0.910
3	Small Blend	−1.207***	−0.058***	−0.001***	0.003**	0.898
4	Mid Blend	−1.176***	−0.094***	0.003	0.003***	0.703
5	Large Value	−1.178***	−0.130***	0.001***	0.003***	0.846
6	Mid Value	−1.278***	−0.106***	0.002**	0.006	0.734
7	Large Growth	−2.433***	−0.144***	0.007***	0.000**	0.889
	UK	**−0.656*****	**−0.086*****	**−0.007*****	**−0.147*****	**0.745**
1	Large Value	0.566***	−0.062***	0.007*	−0.141***	0.837
2	Small Value	−0.674***	−0.086***	−0.006**	−0.147***	0.765
3	Large Blend	−0.732**	−0.081***	0.003***	−0.152***	0.634
4	Mid Blend	−0.745***	−0.083***	−0.006***	−0.145***	0.667
5	Large Growth	−1.511***	−0.091***	−0.002*	−0.141***	0.525
6	Mid Value	−1.755***	−0.088***	−0.006**	−0.146***	0.840
7	Mid Growth	−1.765***	−0.086***	−0.007**	−0.135***	0.705
8	Small Growth	−2.787***	−0.136***	−0.004**	−0.171***	0.948
9	Small Blend	−2.866***	−0.115***	−0.002***	−0.137***	0.680

Table A.3 (*Continued*)

Panel B: 4-Factor model

Performance rank		4-Factor model					
		Alpha	RMRF	SMB	HML	PR1YR	Adj *R*-sq
	Germany	**−0.278*****	**0.086*****	**0.138*****	**0.100*****	**0.102*****	**0.774**
1	Small Growth	−0.688***	−0.169***	0.006	0.030**	−0.002**	0.699
2	Large Value	−0.833**	−0.024**	0.140***	0.028	0.029***	0.799
3	Mid Blend	−0.958***	−0.154***	0.023	−0.002	0.006*	0.899
4	Large Blend	−1.043***	−0.121***	0.102***	0.006***	0.039***	0.799
5	Mid Growth	−1.233**	−0.091***	0.002	0.016**	0.024**	0.638
6	Small Blend	−1.244***	−0.064***	−0.002	0.017*	0.015**	0.874
	Italy	**−1.978*****	**−0.006*****	**0.016*****	**0.107*****	**0.164*****	**0.851**
1	Small Blend	−0.833***	−0.002***	0.006	0.037**	0.070***	0.883
2	Mid Blend	−1.944**	−0.007**	0.014	0.137***	0.152***	0.869
3	Large Blend	−2.123***	−0.008**	0.018	0.132***	0.191***	0.775
4	Large Value	−2.144***	−0.007***	0.019***	0.115***	0.189***	0.798
5	Mid Value	−2.133**	−0.004**	0.014**	0.092***	0.163***	0.635
6	Small Value	−2.212***	0.005**	0.008	0.226***	0.133	0.956
	Spain	**−1.822*****	**−0.110*****	**0.018*****	**−0.002****	**0.002****	**0.820**
1	Mid Blend	−0.345***	−0.050***	0.007	0.021***	−0.066**	0.788
2	Small Value	−0.477***	−0.031**	0.004	0.005*	−0.044**	0.671
3	Mid Value	−1.577***	−0.088***	0.012***	0.008**	−0.045***	0.862
4	Large Blend	−1.889***	−0.102***	0.018***	−0.010***	0.023***	0.778
5	Large Growth	−2.066***	−0.112***	0.015	−0.005**	0.066*	0.904
6	Large Value	−2.108***	−0.122***	0.020***	−0.004	0.010***	0.963
	Netherlands	**0.406*****	**0.002*****	**0.014*****	**−0.085*****	**−0.067*****	**0.781**
1	Mid Value	0.532***	0.059***	0.024***	−0.120**	−0.165**	0.865
2	Small Value	−0.577**	−0.031***	0.009**	−0.072***	−0.063**	0.677
3	Large Value	−0.922***	0.013**	0.016***	−0.091	−0.071	0.871
4	Small Blend	−1.678***	−0.019***	0.001***	−0.076**	−0.046	0.914
5	Large Blend	−2.056***	0.093**	0.026**	−0.031**	0.058**	0.995
	France	**−1.977*****	**−0.113*****	**0.008*****	**0.005*****	**0.141*****	**0.867**
1	Small Value	−0.366***	−0.062***	−0.003**	0.002**	0.030	0.865
2	Small Blend	−0.578***	−0.056***	−0.002***	0.009**	0.050**	0.899
3	Mid Blend	−0.744***	−0.087***	0.002	0.006***	0.109***	0.776
4	Mid Value	−0.889***	−0.099***	0.002**	0.006**	0.120***	0.759
5	Large Blend	−1.855***	−0.077***	0.007**	0.006***	0.148***	0.825
6	Large Value	−1.933***	−0.119***	0.010***	0.005***	0.150***	0.854
7	Large Growth	−2.944***	−0.137***	0.007***	0.005**	0.132**	0.894
	UK	**−1.402*****	**−0.090*****	**−0.007*****	**−0.145*****	**−0.016*****	**0.846**
1	Large Value	−0.377***	−0.067***	0.009*	−0.139***	−0.015***	0.899
2	Small Value	−0.502***	−0.093***	−0.009**	−0.143***	−0.028***	0.844
3	Mid Blend	−1.697***	−0.088***	−0.006***	−0.142***	−0.021***	0.786
4	Large Blend	−1.766**	−0.086***	−0.008***	−0.149***	−0.015***	0.810
5	Mid Value	−1.788***	−0.092***	−0.006**	−0.144***	−0.015***	0.860
6	Large Growth	−1.801***	−0.095***	−0.007**	−0.139***	−0.013***	0.721
7	Mid Growth	−1.888***	−0.092***	−0.007**	−0.132***	−0.024***	0.801
8	Small Growth	−2.708***	−0.140***	−0.005**	−0.169***	−0.016***	0.850
9	Small Blend	−2.768***	−0.119***	−0.002***	−1.348***	−0.008***	0.781

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table A.4
Performance persistence based on contingency table. This table shows the percentage of funds that were winners in the two periods (WW), winners then losers (WL), losers then winners (LW) and losers in both periods (LL). We classify mutual funds as winners or losers for each of the consecutive annual periods. We apply the statistical tests of Malkiel, Brown and Goetzmann, and Kahn and Rudd. The last column presents the Chi-square statistic and the corresponding *p*-value considering the Yates correction for continuity.

Performance rank		RW							Chi-sq. Yates
		WW	WL	LW	LL	*Z*-Score	CPR	*Z*-Score	
	Germany	**68.6%**	**31.4%**	**28%**	**72%**	**4.56**	**4.32**	**5.38**	**60.67*****
1	Small Growth	65.5%	34.5%	34.5%	65.5%	3.43	2.33	3.45	40.34***
2	Large Value	60%	40%	40%	60%	2.85	4.54	2.74	6.98**
3	Mid Blend	63.9%	36.1%	40.6%	59.4%	6.34	1.80	5.34	78.4***
4	Large Blend	62.5%	37.5%	36%	64%	2.89	2.36	3.45	34.2***
5	Mid Growth	71%	0.29	30.5%	69.5%	4.34	0.95	4.67	19.34***
6	Small Blend	55.3%	44.7%	24.6%	75.4%	3.45	2.47	2.98	56.44**
	Italy	**68.1%**	**31.9%**	**35.5%**	**64.5%**	**3.45**	**8.58**	**3.23**	**39.00*****
1	Small Blend	72%	28%	32%	68%	2.67	11.08	2.98	26.56**
2	Mid Blend	67.2%	32.8%	32.7%	67.3%	3.34	2.10	4.34	35.56***
3	Large Blend	68.4%	31.6%	42.4%	57.6%	2.89	2.35	3.23	5.78***
4	Large Value	66.8%	33.2%	34.9%	65.1%	3.05	6.78	2.18	15.67**
5	Mid Value	67.8%	32.2%	35.9%	64.1%	3.78	2.32	3.34	77.45***
6	Small Value	71.2%	28.8%	29.7%	70.3%	3.45	5.68	4.12	24.45***
	Spain	**63.4%**	**36.6%**	**27.7%**	**72.3%**	**3.23**	**2.39**	**3.49**	**38.45*****
1	Mid Blend	54%	46%	31.6%	68.4%	3.44	1.22	3.67	7.45***
2	Small Value	63.5%	36.5%	30.7%	69.3%	2.89	3.04	2.93	18.45***
3	Mid Value	78.4%	21.6%	46.5%	53.5%	4.13	0.75	3.62	8.45***
4	Large Blend	43%	57%	35.7%	64.3%	2.35	1.67	1.98	8.45**
5	Large Growth	56.4%	43.6%	43%	57%	2.54	2.07	2.34	56.78***
6	Large Value	67%	33%	38.8%	61.2%	4.56	2.94	3.89	24.56***
	Netherlands	**78.4%**	**21.6%**	**43.3%**	**56.7%**	**3.67**	**3.41**	**3.45**	**75.56*****
1	Mid Value	65.4%	34.6%	23.5%	76.5%	4.12	2.43	5.67	60.45***
2	Small Value	67.6%	32.4%	54.4%	45.6%	2.67	4.01	2.45	35.67**
3	Large Value	54.6%	45.4%	21.6%	78.4%	3.12	1.19	3.56	23.56***
4	Small Blend	63.4%	36.6%	31.4%	68.6%	2.58	3.45	2.98	62.45***
5	Large Blend	74%	26%	18.2%	81.8%	2.64	2.56	3.45	36.43***
	France	**67%**	**33%**	**23.6%**	**76.4%**	**4.30**	**3.45**	**5.56**	**78.00*****
1	Small Value	89.4%	10.6%	34.6%	65.4%	4.98	2.78	4.57	56.67***
2	Small Blend	87.5%	12.5%	32.7%	67.3%	3.56	4.56	3.45	17.98***
3	Mid Blend	63.4%	36.6%	35.4%	64.6%	2.96	0.73	2.89	34.89***
4	Mid Value	68.2%	31.8%	45.7%	54.3%	3.88	2.30	3.35	17.45***
5	Large Blend	62.4%	37.6%	26.5%	73.5%	3.89	1.23	3.56	78.45***
6	Large Value	65.5%	34.5%	15.5%	84.5%	2.89	2.45	3.78	56.45***
7	Large Growth	67.5%	32.5%	37.7%	62.3%	4.90	2.12	4.56	82.12***
	UK	**68.5%**	**32.5%**	**32.6%**	**67.4%**	**4.45**	**3.45**	**5.67**	**56.45*****
1	Large Value	85.7%	14.3%	15.5%	84.5%	3.15	1.34	3.45	32.45***
2	Small Value	68.3%	31.7%	30.6%	69.4%	2.65	2.56	2.89	19.45***
3	Mid Blend	67.5%	32.5%	25.5%	74.5%	3.60	1.33	2.57	15.45***
4	Large Blend	64.3%	35.7%	16.6%	83.4%	4.56	0.45	5.21	67.34***
5	Mid Value	63.2%	36.8%	34.6%	65.4%	4.10	1.10	3.45	45.67***
6	Large Growth	76%	24%	31.6%	68.4%	3.67	2.45	3.32	5.345***
7	Mid Growth	67.4%	32.6%	33.33	66.7%	3.15	1.67	2.98	7.567***
8	Small Growth	65.7%	34.3%	31.1%	68.9%	3.89	2.45	4.56	8.908***
9	Small Blend	67.8%	32.2%	21.5%	78.5%	3.67	1.34	3.62	23.45***

** Significance at the 5% level.
*** Significance at the 1% level.

Table A.5
Conditional performance evaluation. Mutual funds are sorted on January 1 each year from 1988 to 2010 into investment styles portfolios taking into account their previous year's benchmark-adjusted return. The portfolios are value-weighted monthly. Rank 1 contains the best-performing funds, and rank 9 contains the worst-performing funds. Alpha is the intercept of the Model. The table shows average simulated alphas and their *t*-statistics, it presents results for the conditional model regression (10). The conditioning variables include the 3-month T-bill rate, dividend yield, the term spread, and the default spread.

Panel A: 3-Factor model

Performance rank		3-Factor model		RW			Chi-sq. Yates
		Alpha	Adj *R*-sq	*Z*-Score	CPR	*Z*-Score	
	Germany	**−1.024*****	**0.820**	**3.24**	**3.23**	**5.1**	**40.34*****
1	Small Growth	0.407**	0.674	3.74	2.55	3.55	26.15***
2	Large Value	0.004***	0.812	2.87	2.87	3.45	18.25***
3	Mid Blend	−0.107***	0.809	3.79	1.12	3.27	56.31***
4	Large Blend	−0.311***	0.723	3.12	5.45	2.30	57.23***
5	Mid Growth	−1.097**	0.623	4.87	3.15	2.89	32.56***
6	Small Blend	−1.767***	0.896	3.12	1.45	4.22	36.44***
	Italy	**−0.244*****	**0.847**	**3.13**	**2.13**	**3.24**	**39.34*****
1	Small Blend	−0.156***	0.816	2.83	1.34	3.89	18.34***
2	Mid Blend	−0.189**	0.867	3.22	2.34	2.78	38.35***
3	Large Blend	−0.204***	0.712	1.94	1.35	3.45	34.35***
4	Large Value	−1.356***	0.678	2.86	2.13	3.78	37.34***
5	Mid Value	−1.544***	0.896	4.12	1.45	3.44	58.72***
6	Small Value	−1.671***	0.963	2.96	1.23	1.80	54.67***
	Spain	**−0.089*****	**0.823**	**4.14**	**2.79**	**2.89**	**56.89*****
1	Mid Blend	0.406***	0.745	4.12	1.67	2.13	24.56***
2	Small Value	0.401***	0.825	4.44	2.05	3.78	34.19***
3	Mid Value	−0.345***	0.889	2.89	1.23	3.66	12.23**
4	Large Blend	−0.696***	0.921	4.56	3.03	2.80	18.33***
5	Large Growth	−1.023***	0.897	3.78	1.78	3.67	67.31***
6	Large Value	−1.275***	0.939	4.21	2.13	4.10	9.22***
	Netherlands	**−0.567*****	**0.798**	**3.17**	**1.21**	**4.23**	**38.32*****
1	Mid Value	0.334***	0.896	3.33	1.56	3.89	46.34***
2	Small Value	−0.387**	0.717	2.67	0.87	3.23	46.57***
3	Large Value	−0.394***	0.986	4.44	1.34	2.56	56.89**
4	Small Blend	−1.657***	0.865	2.67	2.34	3.56	56.28***
5	Large Blend	−1.832***	0.904	2.24	2.56	2.78	47.23***
	France	**−1.954*****	**0.897**	**3.11**	**2.78**	**3.86**	**45.17*****
1	Small Value	0.007***	0.876	2.88	3.23	2.85	45.33***
2	Small Blend	−0.013***	0.918	3.11	1.34	3.23	11.84***
3	Mid Blend	−1.703***	0.912	3.23	1.26	4.14	54.31***
4	Mid Value	−1.789***	0.785	2.48	2.67	3.66	32.19***
5	Large Blend	−1.840***	0.861	3.56	3.05	2.35	38.95***
6	Large Value	−2.934***	0.774	3.23	2.45	2.98	78.43***
7	Large Growth	−3.002***	0.912	3.04	1.14	3.45	23.11***
	UK	**−0.950*****	**0.765**	**3.87**	**1.07**	**3.33**	**48.13*****
1	Large Value	0.487***	0.864	3.21	2.23	2.87	7.34***
2	Small Value	0.344***	0.776	2.46	1.11	3.32	38.45***
3	Mid Blend	−0.844***	0.687	3.11	2.13	3.67	34.03***
4	Large Blend	−0.859**	0.687	2.66	0.89	4.22	45.89**
5	Mid Value	−1.967***	0.605	4.34	1.67	2.56	40.01***
6	Large Growth	−2.004**	0.865	3.34	1.56	3.23	19.22***
7	Mid Growth	−2.045***	0.754	3.55	2.34	2.23	33.23***
8	Small Growth	−2.123***	0.951	3.32	1.33	2.78	29.09***
9	Small Blend	−2.233***	0.697	3.11	1.87	3.13	40.41***

Table A.5 (*Continued*)

Panel B: 4-Factor model

Performance rank		4-Factor model		RW			Chi-sq. Yates
		Alpha	Adj *R*-sq	*Z*-Score	CPR	*Z*-Score	
	Germany	**−0.567*****	**0.787**	**4.12**	**6.78**	**4.22**	**50.77*****
1	Small Growth	0.740***	0.712	2.74	4.56	2.13	35.64***
2	Large Value	0.104**	0.823	2.97	3.66	3.45	21.45***
3	Mid Blend	−0.366***	0.923	4.67	2.44	3.22	67.41***
4	Large Blend	−1.870***	0.811	3.24	4.11	1.80	67.21***
5	Mid Growth	−1.920**	0.654	5.15	1.25	3.21	21.77***
6	Small Blend	−1.950***	0.912	3.45	3.55	2.60	34.54***
	Italy	**−0.934*****	**0.873**	**3.33**	**6.33**	**4.33**	**46.40*****
1	Small Blend	−0.740***	0.892	4.63	6.45	2.68	36.46***
2	Mid Blend	−0.816***	0.923	4.44	4.44	3.14	55.45**
3	Large Blend	−0.987***	0.794	6.14	3.35	2.99	14.58***
4	Large Value	−2.234***	0.812	3.45	5.38	3.21	17.21***
5	Mid Value	−2.076***	0.657	4.34	6.32	2.14	67.32***
6	Small Value	−2.106**	0.964	2.87	1.68	3.33	45.54**
	Spain	**−0.344*****	**0.854**	**4.45**	**4.39**	**2.31**	**41.23*****
1	Mid Blend	0.876***	0.812	6.24	3.22	5.22	11.32***
2	Small Value	0.765***	0.723	3.19	1.56	2.62	16.35**
3	Mid Value	−0.202***	0.869	3.23	2.75	3.13	6.49***
4	Large Blend	−0.314***	0.823	4.35	1.77	2.38	6.44***
5	Large Growth	−1.325***	0.923	2.58	4.77	3.14	78.21***
6	Large Value	−1.378***	0.865	5.36	0.94	3.49	17.12***
	Netherlands	**0.007*****	**0.881**	**2.67**	**2.41**	**3.45**	**53.33*****
1	Mid Value	0.655***	0.898	3.32	0.63	3.27	62.34***
2	Small Value	0.314***	0.723	4.37	3.33	2.33	55.77***
3	Large Value	−1.034***	0.896	3.42	2.39	2.55	35.88***
4	Small Blend	−1.240***	0.923	3.58	3.78	2.10	73.78***
5	Large Blend	−2.540***	0.896	2.64	3.56	3.11	64.33**
	France	**−0.546*****	**0.875**	**3.40**	**4.11**	**5.06**	**63.21*****
1	Small Value	0.534***	0.869	3.28	3.00	3.55	36.22***
2	Small Blend	0.008***	0.923	3.66	0.56	3.88	32.45***
3	Mid Blend	−0.296**	0.798	4.26	0.89	2.34	61.32***
4	Mid Value	−1.430***	0.805	3.48	3.30	3.23	24.65***
5	Large Blend	−1.485***	0.828	3.69	1.05	2.56	63.85***
6	Large Value	−2.498***	0.863	3.39	1.45	3.22	66.33***
7	Large Growth	−2.510***	0.912	2.90	0.78	4.14	72.33***
	UK	**−0.925*****	**0.867**	**4.25**	**1.45**	**3.17**	**49.33*****
1	Large Value	0.540***	0.956	5.15	0.80	2.45	43.22***
2	Small Value	0.410***	0.876	3.56	1.02	2.98	32.55***
3	Mid Blend	−0.806***	0.814	4.76	1.23	2.66	25.33**
4	Large Blend	−0.827**	0.834	3.76	2.15	3.21	56.33***
5	Mid Value	−1.905***	0.878	3.14	0.90	4.45	55.44***
6	Large Growth	−1.970***	0.732	2.90	3.01	3.88	24.45***
7	Mid Growth	−2.005***	0.844	4.35	2.37	2.81	34.57***
8	Small Growth	−2.067***	0.867	4.59	1.45	3.26	34.98***
9	Small Blend	−2.120***	0.812	4.66	1.44	3.29	34.44***

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table A.6
Longer-term persistence. On January 1 of each year, funds are ranked into value-weighted monthly portfolios based on their Carhart model alphas estimated over the previous 2-, and 3-year periods (we use benchmark-adjusted returns). The table shows average simulated alphas and their *t*-statistics. Rank 1 contains the best-performing funds, and rank 9 contains the worst-performing funds. The second column presents annual persistence performance ranking as previously reported in Table A.3. Alpha is the 4-factor model intercept estimate. We investigate performance persistence over non-overlapping time horizons of 24 months (Panel A), and 36 months (Panel B).

Panel A: 4-Factor model 2-year period

Performance rank	1-Year rank		4-Factor model					
			Alpha	RMRF	SMB	HML	PR1YR	Adj *R*-sq
		Germany	**−0.996*****	**−0.145*****	**−0.006*****	**−0.027*****	**0.019*****	**0.754**
1	(1)	Small Growth	−0.615***	−0.108***	−0.016	−0.070***	0.001***	0.663
2	(3)	Mid Blend	−0.645**	−0.136***	−0.014**	−0.042**	0.010***	0.883
3	(2)	Large Value	−0.815***	−0.024**	0.140***	0.028	0.029***	0.769
4	(4)	Large Blend	−1.820***	−0.090***	−0.012	−0.034	−0.003**	0.750
5	(5)	Mid Growth	−1.974**	−0.164***	−0.005**	−0.032***	0.024***	0.739
6	(6)	Small Blend	−1.970***	−0.047***	−0.007***	−0.033***	−0.001*	0.809
		Italy	**−1.104*****	**−0.007*****	**−0.008*****	**0.021*****	**0.063*****	**0.756**
1	(2)	Mid Blend	−0.914***	0.011***	−0.003	0.101***	0.031	0.789
2	(1)	Small Blend	−1.020***	0.008***	−0.001	0.082***	0.032***	0.842
3	(3)	Large Blend	−1.075**	0.005**	−0.003***	0.070***	0.031*	0.761
4	(5)	Mid Value	−1.104***	−0.016**	−0.006***	0.034***	0.019	0.815
5	(4)	Large Value	−1.162***	**0.003*****	−0.005***	0.156***	0.023***	0.729
6	(6)	Small Value	−1.987***	−0.001***	0.018	0.132***	0.191***	0.875
		Spain	**−1.175*****	**−0.113*****	**0.004*****	**0.006*****	**−0.028*****	**0.865**
1	(1)	Mid Blend	−0.715***	−0.027***	0.004	0.008***	−0.032***	0.765
2	(2)	Small Value	−1.810***	−0.041***	0.002**	−0.029***	−0.016	0.878
3	(3)	Mid Value	−1.923**	−0.099***	0.006*	0.048***	−0.038***	0.789
4	(6)	Large Value	−1.978***	−0.058***	0.002***	−0.035***	−0.019	0.944
5	(5)	Large Growth	−2.182***	−0.097***	0.003	−0.016***	−0.027***	0.790
6	(4)	Large Blend	−2.216***	−0.125***	0.005***	0.009***	−0.028***	0.752
		Netherlands	**−0.102*****	**−0.080*****	**−0.001**	**−0.051*****	**−0.008**	**0.718**
1	(2)	Small Value	0.414***	−0.066***	−0.003***	−0.058***	−0.006***	0.675
2	(1)	Mid Value	−0.178***	−0.106***	0.002***	−0.112***	0.005**	0.801
3	(3)	Large Value	−0.210***	−0.090***	−0.001**	−0.050***	−0.013***	0.893
4	(4)	Small Blend	−0.230***	−0.041***	−0.004***	−0.043***	0.023**	0.863
5	(5)	Large Blend	−1.213***	−0.027**	0.004*	−0.005	−0.023**	0.923
		France	**−1.210*****	**−0.096*****	**−0.000**	**0.003*****	**0.067*****	**0.864**
1	(1)	Small Value	−0.630***	0.420***	0.012***	−0.005***	0.113***	0.857
2	(2)	Small Blend	−0.650***	−0.045***	−0.002**	0.009	0.002	0.815
3	(5)	Large Blend	−0.705***	−0.032***	−0.002***	0.012***	0.019*	0.829
4	(4)	Mid Value	−1.984***	−0.078***	−0.003*	0.016**	0.033***	0.708
5	(3)	Mid Blend	−2.030***	−0.070***	−0.002***	0.033*	0.042***	0.700
6	(6)	Large Value	−2.174***	−0.086***	−0.001**	0.006***	0.073***	0.856
7	(7)	Large Growth	−2.183***	−0.100***	−0.002*	0.007	0.056**	0.874
		UK	**−1.178*****	**−0.115*****	**−0.006*****	**−0.062*****	**0.006*****	**0.818**
1	(1)	Large Value	−1.089***	−0.097***	−0.036***	−0.056***	0.004**	0.857
2	(3)	Mid Blend	−1.138***	−0.107***	−0.036**	−0.061***	0.005**	0.728
3	(2)	Small Value	−1.145***	−0.139***	−0.016***	−0.070***	0.007*	0.796
4	(6)	Large Growth	−1.167**	−0.123***	−0.006***	−0.062***	0.007***	0.713
5	(4)	Large Blend	−1.173***	−0.116***	−0.003***	−0.065***	0.007***	0.789
6	(5)	Mid Value	−2.184***	−0.103***	−0.005**	−0.055***	0.006***	0.845
7	(7)	Mid Growth	−2.196***	−0.120***	−0.056***	−0.063***	0.005***	0.821
8	(8)	Small Growth	−2.290***	−0.124***	−0.038**	−0.050***	0.004**	0.805
9	(9)	Small Blend	−2.430***	−0.093***	−0.046**	−0.143***	−0.028***	0.768

Table A.6 (*Continued*)

Panel B: 4-Factor model 3-year period

Performance rank	1-Year rank		4-Factor model					
			Alpha	RMRF	SMB	HML	PR1YR	Adj *R*-sq
		Germany	**−1.004*****	**−0.035****	**−0.103***	**−0.133*****	**1.020****	**0.792**
1	(1)	Small Growth	−0.420***	0.061***	−0.122	−0.170**	−1.033**	0.754
2	(5)	Mid Growth	−0.510**	−0.076***	−0.124***	−0.166***	0.067*	0.694
3	(2)	Large Value	−0.830***	−0.078**	0.034*	0.037	0.222	0.829
4	(4)	Large Blend	−0.840***	−0.190***	−0.112***	−0.124**	−0.145**	0.791
5	(3)	Mid Blend	−1.030**	−0.064***	−0.044***	0.162***	−0.134***	0.777
6	(6)	Small Blend	−1.078***	−0.123***	0.338***	−0.123***	−0.122*	0.842
		Italy	**−1.130*****	**−0.046*****	**−0.011*****	**0.045*****	**0.070*****	**0.766**
1	(1)	Small Blend	−0.730***	−0.231***	−0.045***	−0.131**	0.122*	0.693
2	(3)	Large Blend	−0.760**	0.128***	−0.022	0.182**	−0.145***	0.878
3	(2)	Mid Blend	−0.897***	−0.105***	−0.023	−0.172***	0.133*	0.790
4	(5)	Mid Value	−1.315***	−0.112**	−0.033***	−0.132***	−0.044**	0.867
5	(4)	Large Value	−1.416***	**−0.142*****	−0.021***	0.056	0.155*	0.693
6	(6)	Small Value	−1.596***	−0.133**	0.023***	0.062***	0.095***	0.812
		Spain	**−1.310*****	**−0.113*****	**−0.045*****	**0.133*****	**−0.553*****	**0.832**
1	(1)	Mid Blend	−0.640***	−0.034***	0.023***	0.168***	−0.157*	0.789
2	(2)	Small Value	−0.746***	−0.157***	0.111	−0.166	−0.112***	0.834
3	(3)	Mid Value	−0.849**	−0.122***	0.023***	0.165***	−0.189***	0.834
4	(5)	Large Growth	−0.887***	−0.113***	0.034***	−0.088*	0.215*	0.883
5	(6)	Large Value	−1.910***	−0.122***	0.012*	−0.167***	−0.127**	0.843
6	(4)	Large Blend	−1.997***	−0.023***	0.012***	−0.159***	−0.078***	0.789
		Netherlands	**−0.123*****	**−0.134*****	**−0.156*****	**−0.156*****	**−0.058****	**0.777**
1	(1)	Mid Value	−0.087***	−0.017**	0.044	−0.178***	−0.086*	0.694
2	(3)	Mid Value	−0.167***	−0.043***	−0.102***	−0.053	0.045***	0.877
3	(2)	Small Value	−0.189***	−0.173***	−0.134**	0.057***	−0.043***	0.824
4	(4)	Small Blend	−0.210***	−0.121***	−0.024**	0.143***	−0.123	0.823
5	(5)	Large Blend	−1.320***	−0.044***	0.134*	−0.122*	−0.143**	0.867
		France	**−1.520*****	**−0.145*****	**−0.016****	**0.134****	**0.155*****	**0.789**
1	(1)	Small Value	−0.480***	0.023***	0.132***	−0.122***	0.166***	0.834
2	(2)	Small Blend	−0.588***	−0.122***	−0.045**	−0.133*	0.034***	0.823
3	(3)	Mid Blend	−0.595***	−0.112***	−0.033**	0.067***	−0.155*	0.793
4	(4)	Mid Value	−0.610***	−0.174**	−0.153***	0.078	−0.167***	0.845
5	(7)	Large Growth	−0.670***	−0.033***	−0.132***	0.013**	−0.142**	0.893
6	(5)	Large Blend	−1.650***	−0.045**	−0.153**	0.176***	0.034***	0.845
7	(6)	Large Value	−1.687***	−0.108***	−0.033*	0.016*	0.126***	0.844
		UK	**−1.356*****	**−0.056*****	**−0.036*****	**−0.084*****	**0.046*****	**0.833**
1	(1)	Large Value	−0.986***	−0.088***	−0.144***	−0.022***	0.134***	0.823
2	(3)	Mid Blend	−1.120***	0.172***	−0.132**	−0.034***	0.035***	0.778
3	(2)	Small Value	−1.134***	−0.044***	−0.063***	−0.065***	0.127***	0.812
4	(4)	Large Blend	−1.159***	−0.045***	−0.126***	−0.034***	0.167***	0.778
5	(5)	Mid Value	−1.178***	−0.089***	−0.072***	0.037***	−0.177***	0.790
6	(8)	Small Growth	−1.220***	−0.004***	−0.032**	−0.139***	−0.186***	0.878
7	(6)	Large Growth	−1.245**	−0.155***	−0.152***	0.078***	0.185***	0.834
8	(7)	Mid Growth	−2.338***	−0.118***	−0.128**	−0.047***	0.154*	0.833
9	(9)	Small Blend	−2.450***	−0.103***	−0.122**	−0.044***	−0.058**	0.798

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

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