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On the robustness of persistence in mutual fund performance

Economics Department

Juan Carlos Matallín-Sáez
Amparo Soler-Domínguez
Emili Tortosa-Ausina

2014 / 01

Castellón (Spain)

UNIVERSITAT JAUME·I

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Juan Carlos Matallín-Sáez
Universitat Jaume I
Department of Finance and Accounting
matallin@uji.es

Amparo Soler-Domínguez
Universitat Jaume I
Department of Finance and Accounting
amparo.soler@uji.es

Emili Tortosa-Ausina
IVIE & Universitat Jaume I
Department of Economics
tortosa@uji.es

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Abstract

This paper analyzes persistence in US equity mutual fund performance over the period 2001–2011 for both net and gross returns. We apply commonly-used measures of persistence, which we test using a set of simulated passive funds. In the first stage we apply contingency tables and transition matrices in accordance with previous literature. Results show how these methodologies are biased towards finding evidence of persistence too easily. In the second stage, we take a recursive portfolio approach, which assesses the performance of investing by following recommendations based on past performance. Results show the importance of both estimating persistence by distinguishing among fund style groups, and considering the cross-sectional significance of recursive portfolios. In general, our results do not support evidence of persistence in mutual fund performance. Only very scarce evidence is found in some particular cases, but this is partly conditioned by whether net or gross returns are considered. We also find evidence supporting the relatively worse performance of non-survivor funds compared with that of survivor funds.

Keywords: mutual fund, performance, persistence

JEL classification: G23, G11

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Juan Carlos Matallín-Sáez† Amparo Soler-Domínguez† Emili Tortosa-Ausina‡

January 11, 2014

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Communications to: Emili Tortosa-Ausina, Departament d'Economia, Universitat Jaume I, Campus del Riu Sec, 12071 Castelló de la Plana, Spain. Tel.: +34 964387168, fax: +34 964728591, e-mail: `tortosa@uji.es`

*This study is part of the research projects P1.1B2012-07 supported by the Universitat Jaume I and Fundació Caixa Castelló-Bancaixa, and the Spanish Ministerio de Ciencia e Innovación (project ECO2011-27227). We thank Manuel J. Rocha-Armada and José L. Sarto-Marzal for their comments, and we are also grateful for input from Katja Ahoniemi and other participants at the International Conference of the Financial Engineering and Banking Society (FEBS) 2012, the International Risk Management Conference (IRMC) 2012 and the International Finance and Banking Society (IFABS) 2012. All errors are our own.

†Universitat Jaume I.

‡Universitat Jaume I and Ivie.

1. Introduction

For decades, the development of mutual fund industries has motivated a large body of literature that attempts to further understanding mutual fund performance, an important issue for both investors and managers because of its undeniable impact on wealth. In this important field of research, the question of whether mutual fund managers are skilled enough to beat the market is still under debate. However, while the issue of past performance is important, that of whether it might arise in the future is of even greater concern. Indeed, both individual and institutional investors have an interest in performance methods that can help them to select the funds that will provide the best future results. In this context, the objective of the present study is to analyze the performance and persistence of a sample of more than 3,500 US mutual funds, with particular interest in testing the robustness of the persistence methodologies commonly considered in the literature.

To assess performance we use the Carhart four-factor model (1997). This model arises from developments in the literature on performance and asset pricing models of Jensen's (1968) initial proposal and contributions such as those of Fama and French (1993). As with other multifactor models, this performance measure mitigates the bias due to the omission of factors or benchmarks related to the classes of assets in which the mutual funds invest (Sharpe, 1992; Elton and Gruber, 1996; Pastor and Stambaugh, 2002; Bertin and Prather, 2009; Matallín-Sáez, 2006). The Carhart four-factor model has been widely used in recent literature, such as studies by Kosowski et al. (2006), Busse et al. (2010), Fama and French (2010), or Vicente et al. (2011), among others. Concerning the evidence for mutual fund performance in the literature, some studies conclude that, in aggregate terms, it is impossible for funds to beat the market, while others find that a certain number of funds outperform, thereby justifying active management. Our results show that in general, abnormal performance estimated with net returns is close to zero, with a higher presence of negative values. As in studies by Carhart (1997), Wermers (2000), Fama and French (2010), among others, performance improves when it is estimated with gross returns. In short, although there are differences at the individual level, in aggregate and after considering management and operational expenses, mutual funds do not add value for final investors.

The main objective of the paper is to analyze the persistence of mutual fund performance. The evidence on this issue in the financial literature is not conclusive. Studies by Gruber (1996), Chen et al. (2000) and Cohen et al. (2005), Bollen and Busse (2004), Cremers and Petajisto (2009) find evidence of persistence. However some researchers point to underlying factors that could drive persistence. Carhart's (1997) influential paper shows how persistence could be caused by managers' costs and the momentum effect, rather than managers' ability. Gottesman and Morey (2007) attribute persistence to the expense ratio and more recently, in the same vein, Fama and French (2010) identify costs as the source of persistence. To estimate performance, we therefore include a momentum factor to capture any source of persistence from momentum behavior in the stocks in which the fund invests. We also estimate performance and persistence with both net and gross returns. In this way, we avoid mutual fund performance persistence being driven by persistence in mutual fund expenses.

Another significant aspect regarding the evidence found in the literature is the methodology used to measure persistence. The application of statistical measures such as contingency tables by Brown et al. (1992), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Malkiel (1995), Kahn and Rudd (1995), Allen and Tan (1999), Lunde et al. (1999), Droms and Walker (2001), Silva et al. (2005), Babalos et al. (2008) and Elyasiani and Jia (2011), has reinforced the persistence evidence mainly over short time horizons. Evidence of persistence is also found when the transition probability matrix approach is used, as in Brown et al. (1997) and Malkiel (1995). However Cuthbertson et al. (2010) point out some limitations of contingency tables, such as the fact that they are not easy for investors to interpret, and they take advantage of aggregate information presented as predictability whether or not this predictability is significant. Furthermore, Cortez et al. (1999) pointed out how results from contingency tables for small mutual fund samples should be interpreted with caution. We contribute to this literature by testing the robustness of these methodologies. To meet this aim, for all the mutual funds in the sample we generate a counterpart passive fund that mimics its style. The procedure of using passive and simulated funds has been applied in some studies on mutual funds, such as Hendricks et al. (1993) and Bollen and Busse (2001), among others. Therefore, as by definition passive funds do not have any value added by managers, abnormal performance should be zero and persistence will not exist.

When we apply contingency tables and transition matrices to measure mutual fund persistence, the results indicate generalized evidence supporting persistence. However, when we also apply these methodologies to the set of passive funds the results are very similar, that is, evidence of persistence in the performance of passive funds is found even though there is no active management. Therefore, these methodologies seem to be biased towards finding evidence to support mutual fund performance persistence.

Another methodology applied in the literature on performance persistence measurement is the *recursive portfolio* approach proposed by Grinblatt and Titman (1993), Hendricks et al. (1993) and Carhart (1997). This approach assesses persistence by estimating the performance of recursive portfolios that follow investment recommendations according to the past performance of mutual funds. If there is persistence one would expect that investing in the worst (best) mutual funds in the past would result in worse (better) performance in the future. More recently, Bollen and Busse (2004), Cohen et al. (2005), Busse and Irvine (2006), Kacperczyk et al. (2008), Busse et al. (2010), Fama and French (2010) and Benos and Jochec (2011) also apply a similar approach in different markets. However, Hendricks et al. (1993) and Brown and Goetzmann (1995) find that common investment strategies adopted by managers, but not captured by benchmarks or risk adjustment, could cause evidence of persistence. In this line, our contribution focuses on showing that artificial evidence of performance persistence could be found if abnormal performance between stock classes is persistent over time. First, our results reveal the importance of estimating persistence by considering a separate analysis for groups of mutual funds according to their style. When persistence is analyzed for all mutual fund styles, evidence of persistence might be due not to persistence in the value added by active management, but rather to the behavior of the underlying classes of stock in which the mutual fund invests. Second, we are concerned about the significance of abnormal performance of the recursive portfolios that invest according to dynamic strategies based on mutual funds' past performance.

Usually, if this abnormal performance is significant and negative (positive) for strategies that invest in the worst (best) past mutual funds, evidence of persistence has been found. However, it is necessary to correctly identify whether this abnormal performance is due precisely to a dynamic investment strategy based on past performance, or whether it is obtained *per se* by simply investing in a particular style group of mutual funds. With this aim, we contribute to the literature by proposing a cross-sectional test to control for significance of the recursive portfolios. Specifically, we generate synthetic portfolios in the same way as recursive portfolios, but with the difference that now the dynamic investment strategy is not based on the mutual funds' past performance, but that the mutual funds invested in are selected randomly. We then estimate the abnormal performance of these synthetic portfolios. Thus, for all recursive portfolios, we generate a set with a higher number of synthetic portfolios whose abnormal performances define a cross-sectional distribution with which to test significance. If there is persistence in the added value from managers, a recursive portfolio that invests in the worst (best) mutual funds should show a negative (positive) abnormal performance significantly different from that obtained by a random strategy that invests in the mutual funds without any criteria.

Next, we apply the recursive portfolio methodology to the sample of US mutual funds. As noted above, we analyze persistence considering both net and gross returns to avoid evidence driven by persistence in expenses. Robustness is also tested by comparing with the set of simulated passive funds. Finally, when controlling for the cross-sectional significance of the abnormal performance, our results do not find general evidence of persistence in mutual fund performance, corroborating the conclusions drawn by Carhart (1997), Cuthbertson et al. (2010), Busse et al. (2010) and Fama and French (2010). Only very scarce evidence of persistence is found in some cases, such as the worst Small Growth mutual funds, but this is also conditioned by whether net or gross returns are considered. Other studies have also found persistence in underperforming funds, such as Hendricks et al. (1993), Elton and Gruber (1996), Massa and Patgiri (2009), among others. In contrast, some evidence of reversal persistence is found: investing in past losers results in better future performance than investing in past winners. This evidence is found for simulated passive funds and groups of mutual funds with low active management such as index funds. This is due to a contrarian effect in the classes of stock in which funds invest. This result could explain the modest reversion also found by Busse et al. (2010) in the persistence of mutual fund performance.

The remainder of the paper is organized as follows: Section 2 proposes the methodological framework. In Section 3, the US market and US mutual fund data is described. Section 4 contains the empirical results for both performance and persistence, and finally Section 5 concludes.

2. Performance methodology

To add value to a particular portfolio, a mutual fund manager can implement a set of strategies Sj, for $j = 1, \ldots, J$. These strategies may vary widely, however. Some examples of different strategies may include investing in the risk free asset; investing in the stock market index; investing in microcap stocks; or exploiting an arbitrage opportunity.

Therefore, the return of a given portfolio p can be expressed as:

$$R_{p,t} = \sum_j E_{Sj,t}/A_{p,t-1} \tag{1}$$

where $E_{Sj,t}$ are the earnings obtained by following the Sj strategy, and $A_{p,t-1}$ is the value of the assets in which portfolio p invests at the beginning of the period $(t-1)$.

Computing the return for a given strategy $R_{Sj,t}$ as the quotient of $E_{Sj,t}$ and $A_{p,t-1}$, the return of the portfolio at time t may be expressed as the sum of the returns of the strategies, namely

$$R_{p,t} = \sum_j R_{Sj,t} \tag{2}$$

In the literature it is frequently the case that performance measures compare mutual fund returns with a set of *factors*, or *benchmarks*, in the context of a linear model. Likewise, the strategies may be assessed by a model such as

$$R_{Sj,t} = a_{Sj} + \sum_i \beta_{Sj,i} F_{i,t} + \upsilon_{Sj,t} \tag{3}$$

where a_{Sj} measures the value added by following strategy Sj to the performance measure defined by factors $F_{i,t}$, for $i = 1, \ldots, N$, and $\upsilon_{Sj,t}$ is the error term of the model. For instance, in the CAPM, only two factors $F_{i,t}$ would be considered in Equation (3), namely, the return of the risk free asset $r_{f,t}$ (assuming that $\beta_{Sj,f}$ is equal to one), and the excess return of the market $r_{m,t}$. Therefore, strategies will be assessed by means of

$$R_{Sj,t} = a_{Sj} + r_{f,t} + \beta_{Sj,m} r_{m,t} + \upsilon_{Sj,t} \tag{4}$$

Let us suppose there is a given fund with a particular strategy, Sf, which consists of investing in the risk free asset. Then, when it is assessed by means of Equation (4), and assuming $\text{cov}(r_{f,t}; r_{m,t}) = 0$, the abnormal performance a_{Sf} will be equal to zero since $R_{Sf,t} = r_{f,t}$. In other words, this strategy does not add any value when Equation (4) is used to measure performance. Also, it is well-known that a strategy on the Capital Market Line of the CAPM which combines the investment in the stock market and the risk free asset will show an abnormal performance equal to zero in (4).

Another example is a strategy based on arbitrage, which we refer to as *Sb*. If it is uncorrelated with respect to $r_{m,t}$, then the performance obtained when applying Equation (4) will be computed directly as $a_{Sb} = E(R_{Sb,t} - r_{f,t})$. In general, the last result will be expected for any strategy uncorrelated with the market factor.

Analogously, if a strategy Sj shows any level of dependence, part of the $R_{Sj,t}$ is captured by the factor, but another part will be priced by a_{Sj}. Therefore, a strategy based on investing in small cap stocks may yield a performance different from zero when Equation (4) is applied. However if a factor for small stocks is considered in Equation (3), it is very possible that the strategy will be correlated with the new factor, and then the performance a_{Sj} will be closer to zero.

At the mutual fund portfolio level, by substituting Equation (3) into (2) we can obtain the following expression:

$$R_{p,t} = \sum_j a_{Sj} + \sum_j \sum_i \beta_{Sj,i} F_{i,t} + \sum_j \upsilon_{Sj,t} \tag{5}$$

And, if we compare Equation (5) with the following expression:

$$R_{p,t} = \alpha_p + \sum_i \beta_{p,i} F_{i,t} + \varepsilon_{p,t} \tag{6}$$

we will obtain the following three expressions:

$$\alpha_p = \sum_j a_{Sj} \tag{7}$$

$$\beta_{p,i} = \sum_j \beta_{Sj,i} \tag{8}$$

$$\varepsilon_{p,t} = \sum_j \upsilon_{Sj,t} \tag{9}$$

Therefore, the *alpha* or abnormal performance of a p mutual fund, α_p, can be expressed as the sum of the performance a_{Sj} of the strategies implemented by the mutual fund manager. If a manager aims to achieve a positive performance, she must carry out strategies with a positive performance. In this task, the strategy will be, up to a certain level, uncorrelated with factors. On this question, Sharpe (1991, 1992) indicated that in order to beat the market or benchmark, a mutual fund will be differentiated from the benchmark, and then the residual variance of a model like that represented by Equation (6) will measure the level of active management of the mutual fund.

However, as noted above the relationship between *management skills* and *abnormal performance* may not be bi-univocal. In fact, as Berk and Green (2004) point out, no alpha does not imply no skill or, as Savov (2009) concludes, even negative alpha does not imply no skill. Therefore, according to our model it is possible that managers will follow a passive strategy, such as buy and hold, but that in Equation (4) a value of performance a_{Sj} will be obtained because, for instance, they invest in a class of stocks that is not perfectly correlated with the factors, or benchmarks in Equation (3). One solution might be to include relevant factors or benchmarks to ensure that all asset classes are considered in the performance model in order to avoid omitted benchmark bias (Elton et al., 1993; Pastor and Stambaugh, 2002; Matallín-Sáez, 2006). In this vein, the most recent literature on mutual fund performance has applied the following multi-factor model to the particular case of expression (6):

$$r_{p,t} = \alpha_p + \beta_{p,m} r_{m,t} + \beta_{p,smb} r_{smb,t} + \beta_{p,hml} r_{hml,t} + \beta_{p,wml} r_{wml,t} + \varepsilon_{p,t} \tag{10}$$

Five factors are considered in expression (10). The first one, analogously to expression (4), is the return of the risk free asset but on the left-hand side, and then $r_{p,t}$ is the excess return of the mutual fund portfolio. The next three are the Fama and French (1993) factors: excess market return $r_{m,t}$, the return of small stocks minus the return of big stocks $r_{smb,t}$, and the difference of the return between higher and lower book-to-market ratio stocks $r_{hml,t}$. The final factor is the momentum factor, the return of past winners minus past losers $r_{wml,t}$ proposed by Carhart (1997). This model has been widely applied in the recent mutual fund literature, by Kacperczyk et al. (2005), Kosowski et al. (2006), Kacperczyk and Seru (2007), Huij and Verbeek (2007), Fama and French (2010), Busse et al. (2010), Barras et al. (2009), Huij and Derwall (2011), or Hackethal et al. (2012), and Vicente et al. (2011), among others.

Following this literature, we applied model (10) to measure the performance of a sample of US equity mutual funds. As the factors are representative of US stock markets, the omitted benchmark bias is *a priori* lower. However, it is important to point out that, even so, a passive strategy, with low correlation with factors, could yield non-zero performance. This is especially relevant in the case of some classes of stocks which, during the sample period, perform differently from others. Thus, for instance, if $a_{S_{\text{value}}} > a_{S_{\text{growth}}}$ in Equation (3), i.e. if value stocks show better performance than growth stocks, then value style mutual funds will perform better than growth style funds, even though managers have not undertaken any particular active management in either case.

Analogously, "artificial" evidence of persistence could be found in the case where performance between stock classes is persistent over time. For this reason, we consider different groups of mutual funds to estimate persistence. But, even so, it is possible that in Equation (3) some other passive management strategy will obtain non-zero performance that persists over time. We therefore test for the robustness of the persistence measurement with a nonparametric approach in which performance and persistence results are benchmarked to the performance and persistence of *simulated* passive funds. This approach of building portfolios by mimicking style, or simulating strategies, has been documented in previous literature such as Bollen and Busse (2001), Bollen and Busse (2004), or Benos and Jochec (2011), among others.

The simulated funds are constructed following Sharpe (1992) methodology. In this approach, the passive management of a fund is identified by the weight invested in each asset class. Therefore, the set of weights will define the style of the fund. In contrast, the deviations from the style in each period are identified as the active management. Therefore, for each p fund in the sample we construct a simulated fund Sp that replicates its style. This procedure guarantees that the simulated funds will be diversified in the same way as the mutual funds are.[1] To form simulated funds, we applied the methodology proposed by Sharpe (1992) finding the weight $\omega_{Sp,b}$ invested in each benchmark b (for $b = 1$ to B benchmarks) that

[1]We also considered the possibility of totally random simulated funds, but these investments were highly variable in different classes of stocks. As a result, although they were passively managed funds, some performance and persistence were evidenced by the implicit effect of the performance and persistence of certain classes of stocks. For this reason we constructed simulated funds that replicate the style of each fund.

solve the following linear programming problem,

$$\begin{aligned}
&\text{Minimize} \sum_{t=1}^{T} \varepsilon_{Sp,t}^{2} \\
&\text{s.t.} \\
&\omega_{Sp,b} \geq 0, \\
&\sum_{b=1}^{B} \omega_{Sp,b} = 1.
\end{aligned} \tag{11}$$

(i.e. subject to conditions of non-negativity and convexity), taking also into account that:

$$r_{Sp,t} = \sum_{b=1}^{B} \omega_{Sp,b} r_{b,t} \tag{12}$$

and

$$\varepsilon_{Sp,t} = r_{p,t} - r_{Sp,t} \tag{13}$$

The mutual fund performance literature is usually concerned with analyzing whether managers add value from the investor's perspective (see, for instance Bär et al., 2011). To this end, net returns are used in models (10) and (11). Net returns are computed by comparing the NAV (the net asset value of the fund) on particular dates, and considering any distributed gain. The NAV is net of expenses, and for this reason it is a good proxy for the investor's return without accounting for subscription and redemption costs. However, we also show results using gross returns, since this is especially relevant for measuring persistence. In fact, if cross-sectional performance is explained, up to a significant level, by expenses, artificial evidence of persistence may be found if the differences in the expenses across the mutual funds are persistent over time.[2] We compute gross returns by adding expenses to net returns.

3. Data

We analyze the performance persistence of a large number of US domestic equity mutual funds with complete data for an extended period of time. Such a large sample allows us to draw inferences about the performance of the fund industry in general. In this way a sufficiently high number of funds can be included to analyze persistence in each different fund group. On the other hand, we are interested in mutual funds with complete data to assess performance over time. However, the number of mutual funds has increased notably in recent decades. There is therefore a trade-off between the number of funds and the length of the sample period i.e. the longer the sample period, the lower the number of mutual funds with complete data will be. However, if we select a more recent period, this number increases. In light of this trade-off, the sample period runs from March 1, 2001 to May 17, 2011. During this period, some funds were created, and others did not survive. Thus, since only mutual funds with complete data are selected, there could be a survivorship bias.

[2] This issue is especially important for the case of fixed income or cash mutual funds. Given that the return of the underlying asset does not show very much volatility and active management is lower, the main factor explaining performance is expenses. Although our sample is made up of equity funds and the impact of expenses is lower in cross-sectional terms, we show all the results for both net and gross returns.

To assess the performance of mutual funds in the industry and to avoid this bias, both new and non-survivor mutual funds could be considered. But, as our main objective is to analyze persistence, the inclusion of funds with limited data has several effects: (i) the low number of observations limits persistence measurement; (ii) there may be a bias if the mutual fund's performance is correlated with the period for which data are available (for instance, the performance could differ depending on the economic cycle); and (iii) in consequence, comparing funds with different periods of existence could add some noise to the estimations. Therefore, the sample used for the persistence analysis contains all US domestic equity mutual funds with complete data over the sample period. Nevertheless, previous research provides evidence of the effect of survivorship bias on persistence, especially if non-survivor are underperforming funds, as pointed out by Brown and Goetzmann (1995), Elton and Gruber (1996) and, more recently, Deaves (2004). But, as it is not possible to estimate the post performance of non-survivor funds, we analyze if there are performance differences (over matched sub-period samples) between survivor and not survivor mutual funds.

Specifically, we initially considered 5,719 multi-share mutual funds from the Morningstar database, 3,558 of which were survivors and 2,161 non-survivors. However, many of these funds have the same portfolios, the only difference being the expenses for investors for each type of share. Therefore, the performance from the NAV data, i.e. from net returns, will be slightly different for each type of share, even though the gross value added by managers is the same. The funds of a common portfolio show similar performances, and some results will thus be repeated. This convolutes the percentage of funds with good or bad performance in the aggregate and complicates the persistence analysis, making it difficult to identify the number of winner or loser funds over time. Therefore, using the Morningstar portfolio identification number, multi-share funds with the same portfolio were averaged and taken into account as one single unit, or mutual fund. Also, funds that did not report any investment objective or style were removed. The final sample consisted of 1,443 mutual funds with complete sample data, and 845 non-survivor mutual funds. The mortality rate of these funds is, on average, 5% per semester.

In the previous section we pointed out how in expression (3) we can find passive strategies that will provide non-zero performance, and how they are linked to the behavior of the different classes of stocks. To ameliorate the severity of this issue, mutual funds are grouped according to their investment style as defined by the Morningstar Style Box. Previous studies, such as Teo and Woo (2004) have also demonstrated the suitability of using the Style Box. These categories are useful to show performance results, but are also necessary to measure mutual fund persistence. If we evaluate the persistence for all funds as a whole, i.e. without grouping by style, it is likely that most of the persistence that we might find would not be attributable to managers, but to the persistence of the stock style classes in which the fund invests. Panel A of Table 1 shows some descriptive statistics of the mutual funds sample, and the varied behavior across the mutual fund style groups is noteworthy. This highlights the need to perform the persistence analysis within each group. For Table 1 and for the rest of the article, mutual funds' daily net returns are computed by comparing the NAV of the fund for daily dates and considering any distributed gain. Gross returns are subsequently estimated by adding daily fund expenses.

First, Panel A of Table 1 shows that the largest groups are those corresponding to Large styles; in fact 54.3% of the 1,443 funds in the sample belong to these groups. Moreover the assets managed by Large funds account for 74.4% of the total. This is important information because any results or conclusions drawn about these groups of funds have implications for most of the assets managed in the sample. Also notable is that, on average, Large and Index funds are the largest in terms of size, are cheaper, and show lower return and risk. In contrast, Mid and Small style groups only account for 14.1% of the assets managed and, on average, these funds are smaller in terms of size, are more expensive, and achieve higher levels of return and risk.

Second, we look at the data for the mutual funds in Panel A of Table 1 based on the characteristics of growth, blend and value. Note that the number of funds and the relative size of the group decrease as we move from growth funds to blend and value funds (within each set of Small, Mid and Large funds, respectively). In general, the relative size of the fund also decreases. This pattern is monotonically repeated for expenses, thus growth funds are more expensive than blend funds, which in turn are also more expensive than value funds. In contrast, return, on average, increases from growth to value funds, and in general, growth style funds are riskier than blend and value funds.

The above descriptive data tell us something about the characteristics of the mutual fund sample. However, a proper performance model must be applied to assess management. To apply model (10) we use the daily data of the returns of the three Fama and French factors and the Carhart momentum factor. This data—together with the data for the risk free asset, the one-month Treasury bill rate, to compute excess returns for mutual funds—was taken from French's website.[3] Panel B of Table 1 shows the annualized mean of daily return and risk (measured by the standard deviation of the returns) for these data.

Finally, we apply linear programming problem (11) to estimate the simulated mutual funds. To this end, we need to compute the returns, $r_{b,t}$ of each benchmark b. We use the Russell indexes for the US stock market as data for the benchmarks. These indexes represent a wide variety of stock style classes, which is very useful for developing simulated funds that replicate the style or investment objectives of the funds in the sample. Panel C of Table 1 shows the annualized mean of daily return and risk (measures by standard deviation of the returns) for these data.

4. Results

4.1. Performance

4.1.1. Funds with complete data

Model (10) is applied to measure the performance of the 1,443 funds in the sample with complete data. Table 2 shows a summary of the results: Panel A when performance is estimated from mutual fund net returns and Panel B for gross returns. Annualized performance from daily alpha is reported. In each

[3] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

panel, results are grouped by style type and the average of the all funds is reported at the bottom. From net returns, Panel A shows an average performance with a negative value of –0.78%, with the percentage of negative values twice that of positive values (68.14% negative to 31.86% positive) and with a much more compact degree of significant funds for the negative performance case: 16.21%, compared to 1.93% for the positive case. Figures 1 and 2 show the mean performance of the quintiles formed by the funds from worst to best performance for all fund style types.

This is a common result in the mutual funds literature: in general performance is not significant, and in any case it is negative and close to zero. However, if performance is estimated with gross returns, as reported in Panel B, positive performance increases. Hence, the aggregate performance has a positive value of 0.43%, and 45.72% of the alphas are negative (and 54.28 positive). Significance remains low but it clearly diminishes to 3.24% for negative performance and, in contrast, it increases to 6.90% in the positive case. In short, as documented widely in the literature, mutual fund expenses erode performance and, in aggregate, managers do not provide added value for final investors, as Sharpe's (1991) theoretical proposal indicated. In fact, the distance of the mean performance from gross returns, 0.43%, and that from net returns, -0.78%, in Table 2 is exactly the mean of the expense ratio 1.21% in Table 1.

However, as in the results of Payne et al. (1999), differences can be found in the performance across funds and type of funds. Panel A in Table 2 shows percentages of significant negative alphas in most of the fund styles, which are particularly relevant for the Large Capitalization funds (Large Growth, Large Blend, Large Value and Index). Figures 1 and 2 show how these funds achieve, in general, the worst performance and notably, they represent 85.9% of the sample funds' assets and are therefore driving aggregate results. In fact, when aggregated performance is computed weighting alpha by the relative size of the fund, it is lower, –1.04% in Panel A (Table 2) and –0.11% in Panel B (Table 2), than the simple mean.

The report for the Index funds is worth additional mention: in Panel A (Table 2), 84.16% of these funds present negative alphas of which 48.51% are significant, while only 15.84% are positive, but none is significant. This result sheds light on the efficient-market hypothesis debate. Index funds offer an investment alternative for less sophisticated investors because they are cheaper than other fund styles (see expense ratio data in Table 1), and the inefficiencies of stock selection can be avoided. However, the worst values are observed for Index funds (in theory, passive investments) in which, by definition, managers do not intervene very actively. Moreover, the results of Index funds' gross returns improve, but none of the funds show a significant positive performance. This result shows the perverse asymmetric behavior of Index funds: they are unable to achieve positive performance because they are unable to beat the market, but negative values may be achieved due to expenses and the impact of mimicking index rules in the context of a multifactor model like that in expression (10) for performance measurement.

In contrast, the positive values of performance reported for the Mid Value funds are particularly relevant. Hence, in Panel A (Table 2), 84.38% of alphas are positive, 18.75% significant, and the best average performance is achieved (1.85%). Considering gross returns in Panel B, these values are: 93.75% of positive alphas, 50% significant and an annual mean of 3.16%. Figure 1 also shows how Mid Value funds obtain higher performance. However, it should be noted that the Mid Value fund group is the least numerous in the sample: only 32 funds, representing only 1.19% of the assets managed by the US funds in the sample.

If we consider the patterns in the column of the mean annualized performance, we can see that within each group of three (small, mid and large), performance increases from growth, to blend and then to value funds. That is to say, regardless of the size characteristic of the fund, value funds obtain better performance than blend funds, which in turn perform better than growth funds. This pattern is seen in Figures 1 and 2, which display the plots of the quintile performance of the funds in each mutual fund group.

The differences in performance between each mutual fund style group indicated above highlight the relevance of estimating persistence for each group. Thus, if we analyze the persistence for all funds, we can find that persistence is not due to the fact that the value added by managers is persistent, but because the performance of the underlying type of stocks for any group of funds is persistent.

As stated in the methodology section, we will compare the performance and persistence results of the sample funds with those of passively managed funds that mimic their style. The style of each mutual fund is estimated by applying expression (11), which gives a simulated fund for each real mutual fund. This procedure is carried out for both net and gross returns.

Table 3 presents the results of applying model (10) to the simulated mutual funds' daily returns. Panel A shows the results when net returns were used in the style estimation. Funds with negative and positive performances are equally balanced: 53.72% of the simulated funds have a negative alpha, while for 46.28%, it is positive. What is most notable is the practical absence of significant alphas, specifically 0.34% for negative performance and none for positive performance. This result was to be expected because, by construction, simulated mutual funds are *passive*, and neither positive nor negative values may be added by active management. So, for all the fund style type groups the number of significant alphas is zero, except for the Small Growth type, for which it is 3.05% for negative alphas. That is to say, according to (3), a passive strategy Sj based on investment in small growth stocks may lead to negative performance. In other words, a small part of the negative performance found in Panel A of Table 2 for the Small Growth group funds could be due to the negative performance of the underlying stocks and not to active management.

In fact, a common pattern can be seen in the columns of the mean annualized performance in Panel A in Tables 2 and 3. Figures 3 and 4 show the mean performance of the quintiles formed by the simulated funds from worst to best performance for any style type. A comparison of these figures with their counterparts for the case of the mutual funds in Figures 1 and 2 reveal: (i) in general, the order of best to worst performance remains the same for the different fund types: from Mid Value to Small Growth. This result demonstrates the importance of analyzing funds according to style type, since on average, the underlying type of stocks perform differently; (ii) as simulated funds are passive, they show less performance dispersion than real mutual funds, so in Figures 3 and 4 the lines of the performance across quintiles are almost flat, whereas those for mutual funds in Figures 1 and 2 have more marked slopes. The distribution of the simulated funds for any style may be considered as a performance distribution under the null hypothesis of passive management; that is, zero value added and thus, zero performance.

We therefore run a test that only considers significant those mutual funds' alphas that fall outside the 95% of the distribution of the alphas from simulated funds. The results are shown in Table 4; specifically, the percentage of the number of funds with significant performance both in Table 2 and from the simulated funds performance distribution test. In general, the evidence found in Table 2 holds. This result is not surprising if we compare Figure 1 with 3 and 2 with 4. Specifically, mutual fund performance distribution is wider and many mutual funds with significant alphas are on the tails that are outside the range of the 95% of the simulated funds performance distribution. The most notable difference is seen in Panel A for the Index funds, where for –37.62% of the funds with significant and negative performance in Table 2, this is due to the investment characteristics of the fund.

In summary, the results show very slight evidence of performance. In any event, when performance is calculated from net returns, it takes a negative value close to zero. This result is due, to a large extent, to the expenses incurred by the fund, as can be seen in the improved performance when the estimation is based on gross results. In general, having compared performance with that of the simulated funds, we can conclude that the significant performance achieved by some mutual funds does not seem to be explained directly by the type of assets they invest in, but rather by the active management of the fund. Despite the scant evidence of performance found for the entire sample period, in the Section 4.2 we analyze whether this performance persisted over time.

4.1.2. Non-survivor mutual funds' performance

As stated above, non-survivor funds have been excluded from the persistence analysis. However, given the previous evidence found in the literature, we have compared non-survivor funds' performance with that obtained by survivor funds. In order to grant further robustness to the analysis, we only estimated performance for those funds with information for at least one semester. For each of these funds we estimated, using a non-overlapping half-year rolling window, the performance according to expression (10). Then we make a performance comparison between non-survivor funds and survivor funds in each of those semesters, in order to avoid any bias derived from comparing different periods. We do this separately for each investment style, but only for those semesters and investment styles for which the number of funds composing the non-survivor group is at least equal, or higher, than the 10% of the number of funds composing the survivor group. With this strategy we avoid making comparisons among heterogeneous groups of funds in terms of number of funds.

We compute the discrepancy between the average performance for the non-survivor and survivor funds for each semester and each investment style. Table 5 shows a summary of these results. Specifically, it reports the average performance discrepancies for the 20 semesters corresponding to our sample period, together with the percentage of semesters for which the value is either positive or negative, as well as the percentage of semesters during which it is significantly different from zero (its p-value ≤ 0). The

p-values corresponding to the performance differences for each group (non-survivor minus survivor), for each semester and style, were computed using bootstrap.

Results show that, in general, the performance discrepancies between the non-survivor and survivor funds are negative—i.e. favorable to the survivor funds. These discrepancies lie in the 0.17%–4.46% range, depending on the fund's style. For instance, for Small Growth funds, non-survivor funds' performance is 3.88% less than that corresponding to survivor ones. This occurs for 100% of the semesters under analysis, and for 81.25% of the semesters discrepancies are significant. We find this type of behavior for most investment styles, although the magnitude is slightly lower for Large and Index styles.

Therefore, although it is not possible to analyze the performance of a fund once it has disappeared, we find that non-survivor funds' performance before exiting the industry is comparatively worse than that corresponding to survivor ones. These results are in line with those obtained in the literature such Deaves (2004). By including these funds in the industry aggregate, funds' average performance would be even less than that shown in Section 4.1.1.

4.2. Persistence

As stated throughout the paper, the evidence on mutual fund performance persistence in the existing literature is inconclusive. This section aims to add further evidence to this literature, for which we will be using non-parametric methodology, first based on contingency tables as in Brown and Goetzmann (1995), Silva et al. (2005), and Elyasiani and Jia (2011), among others, and then transition probability matrices of the funds, grouped in quintiles, over two consecutive periods. Secondly, we analyze persistence by assessing the performance of investment strategies based on past performance.

4.2.1. Contingency tables and transition probability matrices

The two-way contingency tables rank funds as winners (losers) depending on whether the fund performance is above (below) the median relative performance of the group. The analysis considers semi-annual periods. We define as WW (winner-winner) the number of funds that are winners in both the current and the subsequent period. The inverse criterion is used to identify LL (loser-loser) funds. LW and WL correspond to funds with performance reversals. We then compare the number of cases observed with the theoretical values under the null hypothesis of independence. The non-parametric CPR (Cross Product Ratio) test by Agarwal and Naik (2000) is then applied, where the Z-Statistic tests the null hypothesis of absence of persistence for all funds in the group (Z total). However, the evidence of persistence could be non-symmetrical. It is therefore also pertinent to isolate the persistence of the winner funds from that of the loser funds. For instance, evidence from previous research suggests that persistence is mainly revealed in the worst mutual funds. Statistics are therefore computed to analyze only winners' persistence (Z WW) and losers' persistence (Z LL).

Panel A in Table 6 shows the results of these tests when net returns are considered to estimate performance. In general, the χ^2 test rejects the null hypothesis of independence between winners and losers in each pair of consecutive periods. From these results, and considering the distribution of the values of the categories WW, LL, WL and LW, we can infer strong positive persistence for most of the funds, mainly for those styles that include a higher number of funds, because this test is directly proportionate to the subsample size. Panel B shows the persistence results when performance is estimated with gross returns. The results are very similar to those from net returns. However, the Index funds reveal a strong influence of the impact of costs on the degree of persistence achieved and it is precisely these costs that cause the persistence phenomenon.

We also perform an analysis of five groups and the transition between them over two periods. Specifically, mutual funds are ranked by performance to form quintiles from $Q1$ (worst) to $Q5$ (best) in each period. The results are shown in the last columns on the left of Table 6. For virtually all the categories of mutual funds we find significant evidence of persistence. It is noteworthy that the three lowest values of the χ^2 test, and therefore lowest persistence, correspond to the three categories of mutual funds with the lowest number of funds, and in contrast, the highest value of the χ^2-statistic is found for the Index funds, precisely a type of fund that *a priori* will show the lowest level of active management.

To test for the robustness of the methodologies applied above, we analyze the persistence of the simulated mutual funds. In Table 7, Panel A and Panel B show the results when simulated funds were estimated from mutual fund net or gross returns, respectively. Given that, by definition, simulated funds are passive portfolios, significant evidence of persistence will not be expected. However, both panels in fact reveal persistence. In other words, methodologies based on contingency tables and transition probability matrices allow for the existence of persistence all too easily. This raises serious doubts about the results in Table 6. The previous evidence of persistence, therefore, may not in fact be due to fund manager activity, but rather, to the use of a methodology with questionable robustness. This finding leads us to the next section, in which we apply a methodology to evaluate the results of following investment recommendations based on past performance.

4.2.2. Portfolios based on past performance

In this section we assess persistence by analyzing the performance of portfolios that invest according to the mutual funds' past performance. This so-called recursive portfolio approach was initially proposed in the literature by Carhart (1997) and is one of the most commonly used methods in the literature, as in Bollen and Busse (2004) and subsequent papers, including Kosowski et al. (2006); Busse et al. (2010); Fama and French (2010) who have also proposed variations to this approach, in some cases related to the statistical significance of the alphas.

We have already highlighted the importance of estimating the persistence between each group of funds in terms of the funds' *style*. For instance, Table 2 shows that the *Small Growth type* mutual funds achieve the worst performance; if we analyze the persistence of all mutual funds, we can find persistence for the worst funds, not because of poor management, but because investing in small growth stocks was an Sj strategy that showed negative performance a_{Sj} in Equation (3) for the sample period. Then, when the persistence for any type of fund is analyzed, the number of funds in each group may be reduced and, for this reason, we use quintiles instead of deciles, following Carhart (1997) to differentiate from worst to best mutual funds. In order to develop a homogeneous analysis, we follow the same window period as in the previous approaches; that is, we analyze whether there is persistence between two consecutive six-month periods.

We first estimate the performance of the mutual funds by means of Equation (10) for the first semester of the sample period. Next, for each style group, we rank mutual funds in increasing order according to the performance they achieved in the period, to form quintiles. Then, for each style group, at the beginning of the next semester we form five equally weighted portfolios according to quintile past performance. Hence, the first portfolio, $Q1$, invests in the worst performing funds in the previous semester and, conversely, the last portfolio, $Q5$, invests in the previous best funds.

The same pattern is followed for the other quintiles. This procedure is repeated at the beginning of each semester, so that each portfolio represents a dynamic investment strategy that rebalances selected funds according to their previous performance. We therefore compute the daily return of 50 portfolios (5 for each of the 10 styles) and then we estimate the performance of the portfolio, also using model (10). We hypothesize that if there is persistence in mutual fund performance, a portfolio with investments based on a poor (good) past performance will show a negative (positive) performance. This procedure is performed for mutual fund performance from both net and gross returns.

Figure 5 shows the performance of these portfolios based on mutual funds' past performance when it is estimated from net returns. In some cases, the performance improves slightly from $Q1$ portfolios (that invest in past worst funds) to $Q5$ portfolios (that invest in past best funds); this pattern may be observed in Small Growth funds. In contrast, the lines for other types of funds are flatter, even showing a negative slope, as in the case of the Index mutual funds. Analogously, Figure 6 shows the performance across portfolios-quintiles when mutual fund performance was estimated from gross returns. The results are quite similar, although as seen in the panels of Table 2, the performance is higher when gross returns are used. In sum, in general there is no clear evidence of persistence.

Table 8 shows the values of the performance and statistical significance of the portfolios. Panel A presents the results when mutual funds net returns were used to estimate performance in model (10), and Panel B reports results for the case of gross returns. The panels show two p-values for the estimates. The first is the standard p-value from the regression model (10) with the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator. The second p-value, which we refer to as *cross-sectional p-value*, is the critical probability estimated by means of simulations in each style-type mutual fund group. This second p-value is necessary to differentiate between the performance *per se* of the portfolio and with the performance achieved by following a strategy of investing in past worst or best mutual funds.

Take, for instance, the case of Mid Value mutual funds. As seen in Table 2, these funds achieved the best performance, an annualized mean of 1.85% for net returns and 3.16% with gross returns. Thus, any portfolio that invests in these funds will probably show a good performance *per se*, simply because these were good funds. Therefore, a portfolio that invests in the past worst or best Mid Value mutual funds is also likely to show good performance. In fact, Figures 5 and 6 show that the best performance is that of the portfolios, from $Q1$ to $Q5$, based on the past performance of the Mid Value mutual funds. If we observe Panel B of Table 8, the performance for these portfolios varies from 2.36% for $Q1$ to 3.15% for $Q5$, and standard p-values are below 0.05 in all of the five portfolios; in other words, they show positive and significant performance. We then need to differentiate between the performance of the group of mutual funds and that achieved following a dynamic strategy based on past performance. To do this, we will form portfolios in the same way as the previous 50 portfolios based on past performance, but with the difference that now the funds invested in are not based on past performance, but selected randomly. If there is persistence in the added value from managers, worst or best mutual funds will repeat that ranking in the future and a strategy based on their past performance should achieve a better performance than a random strategy that invests in funds without any criteria.

For each of the 10 style groups of mutual funds in the sample, 2,000 synthetic equally-weighted portfolios were formed that invest randomly in a quintile of the group's funds. The daily return of the synthetic portfolios is computed and model (10) is applied to estimate performance. Consequently, for each style group of mutual funds a distribution of 2,000 alphas is formed to test for the significance of the performance of following investment recommendations based on past performance. Next, for each of the portfolios based on past performance, the *cross-sectional p-value* is computed as the percentage of synthetic portfolios which produce an alpha greater than the corresponding value for that past-performance-based portfolio. In sum, Table 8 shows *two p-values*, the first (the standard p-value) measuring whether the performance of the past-performance-based portfolio is significantly different from zero; the second, the *cross-sectional p-value* measures whether this performance is linked to investment in past worst or best mutual funds, and thus if it is significantly different from the result of any random investment in these funds.

As can be inferred from Figures 5 and 6, Table 8 provides no general evidence of persistence. The performance achieved by following past-performance-based investment strategies is only significant in some specific cases. In Panel A, from net mutual funds returns, the performance achieved from investing in the past worst ($Q1$) Small Growth mutual funds is significant. It provides an annualized alpha of –3.10%, the standard p-value is 0.010, and the *cross-sectional p-value* is 0.000. In this same mutual fund style type the performance for the $Q2$ case is also significant, achieving –2.20% annualized performance with p-values of 0.024 and 0.042, respectively. For Large Blend mutual funds, investing in the worst past funds ($Q1$) provides a significant performance of –1.38%. In these three cases, following a strategy of investing in the worst past mutual funds leads to a significant negative performance. In other words, we find persistence for the performance of the worst mutual funds.

However, for these cases, this evidence vanishes in Panel B (Table 8) when gross mutual funds are used to estimate mutual fund performance, i.e. the significant persistence found in Panel A is probably due to the effect of persistence in the expenses incurred by the fund. In Panel B, significant persistence is only found for the best mutual funds ($Q5$) for two categories of funds; specifically, Small Blend funds achieve a performance of 2.07% with a standard p-value of 0.024 and a cross-sectional p-value of 0.003 and for Mid Growth funds, with 2.29% performance and *p-values* of 0.038 and 0.009 respectively.

Index funds are a special case. The Index fund line in Figures 5 and 6 shows a negative slope. From Panel A of Table 8 the performance of these strategies ranges from –0.40% for $Q1$ to –2.06% for $Q5$; the latter is significant with a standard p-value equal to 0.024 and a *cross-sectional p-value* of 0.000. That is, strategies that invest in past best (worst) mutual funds exhibit worse (better) performance. This result contradicts the idea of mutual fund performance persistence. This pattern is repeated in Panel B, but for $Q5$ the significance is borderline. Next, when the persistence of the simulated funds is analyzed we show how this contrarian behaviour may be implicit for passive portfolios or low active management, as in the case of Index mutual funds.

Finally, to test the robustness of this methodology we analyze the persistence of the performance of the simulated mutual funds. Table 3 showed how simulated funds provide alphas close to zero and not significant except for one case. Because of this result, and because simulated funds are passive and in theory do not add any management value, we would not expect to find evidence of persistence of performance over time. Table 9 shows the performance of investment strategies based on past performance: Panel A when net mutual fund returns were used to estimate simulated funds and Panel B for the gross returns case. These panels show that the only result consistent, to some extent, with persistence is for the $Q1$ of Small Growth simulated funds in Panel B. Their annualized performance is –1.80%, with a standard p-value on the border equal to 0.050, and a cross-sectional p-value of 0.018. It should be remembered that precisely this type of fund, despite the reduced performance evidence in general in Table 3 for simulated funds, had the highest percentage of negative alphas (85.98% in Panel A and 95.73 in Panel B) and was significant (3.05%). For the rest of the simulated mutual funds no evidence is found in Table 9 of significant persistence, as was expected.

However, it is interesting to analyze the contrarian behaviour, in persistence terms, for the simulated mutual funds in Table 9, as commented above for Index funds in Table 8. Figures 7 and 8 help us show this behaviour. The figures show the performance achieved by investment strategies based on past performance: $Q1$ strategy invests in the worst simulated funds in the previous period and so on until the last strategy, $Q5$, which invests in the previous best simulated funds. These figures show how, except for small type funds, the slopes of the lines are negative, that is to say, investing in past best (worst) simulated funds lead to worse (better) performance. This behavior is also seen in Table 9, and it is significant in Panel A for $Q5$ for Large Growth and Index categories and in Panel B also for Large Growth $Q5$ and Small Blend $Q3$. In these cases the performance achieved is negative.

This evidence of contrarian behavior in terms of performance persistence is not attributable to active management because simulated funds are passive by construction. Thus, in order to explain this behavior several hypotheses were analyzed: (i) as the dynamics involve investing and dis-investing in different funds, the portfolio's parameters could vary over time; therefore all estimates were repeated considering time-varying parameters, but the evidence of contrarian behavior remained; (ii) we also ran regressions for different versions for model (10), for instance without including the momentum factor (since this contrarian behaviour goes against it), but results are also similar. In conclusion, the dynamics of the strategy itself might explain this result. In this vein, there is a large body of literature on contrarian investment strategy from De Bondt and Thaler (1985), Chan (1988), or Yao (2012), among others. De Haan and Kakes (2012) show how institutional investors tend to be contrarian traders, buying past losers and selling past winners, and how this behaviour may have a stabilizing impact on financial markets. The contrarian effect is the opposite of the momentum investment strategy: buy past winners and sell past losers, also well documented in the literature by Jegadeesh and Titman (1993), Griffin et al. (2003), or Wang and Wu (2011), among others.

Although an analysis of these issues goes beyond the scope of this study, our results from simulated funds support the existence of a contrarian effect. Remember that in Figures 7 and 8 and Table 9, $Q1$ is a strategy that invests in the past worst simulated funds and $Q5$ invests in the past best simulated funds. These funds allocate in different classes of stocks and are passive by definition. Therefore, our evidence of the contrarian effect is linked to a contrarian or reversal effect in the different style class of stocks. In a similar way, Teo and Woo (2004) find strong evidence that stocks in styles that performed poorly in the past, relative to other styles, tend to do well in the future. Thus, in our case, simulated funds that are winners (losers) in one period tend to be losers (winners) in the next period and for this reason $Q1$ performs better than $Q5$. However when strategies based on past performance are computed for the real mutual funds, this contrarian effect is not present in Figures 5 and 6 and Table 8, except for Index mutual funds. Thus, active management is what makes mutual funds differ from passive portfolios, and the performance across periods will not be reversed. Concretely, according to our evidence, the relationship of mutual fund performance between periods is in general flat and neither positive (persistence) nor negative (reversal or contrarian).

5. Conclusions

This paper has examined the performance and persistence of a sample of 1,443 US equity mutual funds. It tested the robustness of persistence measurement by comparing the performance and persistence obtained from simulated passive funds. Specifically, performance persistence was assessed by applying contingency tables, transition probability matrices, and recursive portfolio approaches.

Performance results presented in both net returns and gross returns follow the pattern established previously in the literature. Hence, from net returns, abnormal performance is close to zero in general, but the presence of negative values is more common than that of positive ones. However, performance improves when gross returns are considered. In short, although there are differences at the individual level, in aggregate and after considering management and operational expenses, mutual funds do not add value for final investors.

In the analysis of performance persistence, we first applied methodologies based on a winner-loser approach, namely, contingency tables, Z-tests and transition probability matrices. When comparing the persistence results of mutual funds with those achieved by simulated passive funds, the conclusion is that these methodologies are biased to show persistence much too easily. The skepticism surrounding the accuracy of previous methods was overcome by applying an approach to persistence measured from the performance achieved by recursive portfolios that invest according to past mutual fund performance. When we controlled for mutual fund group style type and considered cross-sectional significance, the results did not show evidence of persistence in general.

Only for a few cases, and depending on whether gross or net mutual fund returns were considered, did we find some evidence of persistence. When these results were compared with those achieved by investing according to the past performance of simulated mutual funds, active management was shown to compensate a reversal effect in the dynamic performance of passive portfolios.

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Table 1: Summary statistics for the mutual funds in the sample

PANEL A

Mutual fund style group	Number of multi-share funds	Number of mutual funds	Relative size of the style group	Average relative size of fund	Average expense ratio	Average annualized net return	Average annualized s.d.
Small Growth	402	164	2.80%	0.02%	1.44%	8.77%	24.08%
Small Blend	210	85	1.31%	0.02%	1.35%	10.81%	23.25%
Small Value	127	52	0.75%	0.01%	1.35%	11.26%	23.85%
Mid Growth	426	162	6.77%	0.04%	1.35%	7.78%	23.22%
Mid Blend	166	64	1.28%	0.02%	1.32%	8.88%	23.13%
Mid Value	89	32	1.19%	0.04%	1.31%	10.26%	22.35%
Large Growth	937	363	38.43%	0.11%	1.24%	4.77%	22.10%
Large Blend	587	249	20.90%	0.08%	1.14%	5.31%	20.99%
Large Value	465	171	15.11%	0.09%	1.13%	6.09%	21.07%
Index	133	101	11.47%	0.11%	0.50%	6.44%	22.67%
All funds	3542	1443	100.00%	0.069%	1.21%	6.82%	22.40%

PANEL B

Factors	Annualized mean return	Annualized s.d.
Market	6.49%	21.43%
Smb	5.23%	9.36%
Hml	3.92%	9.80%
Wml	1.25%	17.52%
Risk free asset	2.01%	0.11%

PANEL C

Benchmarks	Annualized mean return	Annualized s.d.	Benchmarks (cont.)	Annualized mean return	Annualized s.d.
Russell 1000® Growth Index	4.64%	21.82%	Russell Microcap® Growth Index	8.05%	24.19%
Russell 1000® Index	5.86%	21.55%	Russell Microcap® Index	10.18%	24.02%
Russell 1000® Value Index	7.04%	22.38%	Russell Microcap® Value Index	11.84%	24.42%
Russell 2000® Growth Index	9.08%	26.47%	Russell Midcap® Growth Index	8.87%	24.78%
Russell 2000® Index	10.62%	26.04%	Russell Midcap® Index	10.63%	22.83%
Russell 2000® Value Index	11.97%	26.32%	Russell Midcap® Value Index	11.50%	22.67%
Russell 2500™ Growth Index	9.58%	24.95%	Russell Small Cap Completeness® Growth Index	8.57%	25.51%
Russell 2500™ Index	11.08%	23.87%	Russell Small Cap Completeness® Index	10.03%	24.11%
Russell 2500™ Value Index	11.98%	23.90%	Russell Small Cap Completeness® Value Index	11.28%	23.91%
Russell 3000® Growth Index	4.94%	22.01%	Russell Top 200® Growth Index	3.44%	21.13%
Russell 3000® Index	6.18%	21.76%	Russell Top 200® Index	4.19%	21.31%
Russell 3000® Value Index	7.37%	22.52%	Russell Top 200® Value Index	5.20%	22.58%

Table 2: Mutual fund performance

The table presents the performance analysis results from model (11) considering daily net returns in Panel A, and from gross returns in Panel B for the sample period 2001-2011.

PANEL A: Performance estimated with mutual fund net returns

		Percentage of total number of funds in group				Annualized performance				
Style	Number of funds	< 0	p-value ≤ 0.05	> 0	p-value ≥ 0.05	Mean	Median	Min.	Max.	Average (by fund size)
Small Growth	164	74.39%	16.46%	25.61%	0.61%	-1.50%	-1.52%	-8.33%	4.62%	-1.61%
Small Blend	85	55.29%	10.59%	44.71%	2.35%	-0.13%	-0.30%	-6.13%	7.31%	0.14%
Small Value	52	57.69%	5.77%	42.31%	1.92%	-0.23%	-0.49%	-4.73%	3.57%	-0.15%
Mid Growth	162	51.85%	4.94%	48.15%	4.32%	-0.30%	-0.09%	-7.06%	5.91%	-0.60%
Mid Blend	64	42.19%	6.25%	57.81%	7.81%	0.34%	0.32%	-6.52%	5.68%	0.71%
Mid Value	32	15.63%	0.00%	84.38%	18.75%	1.85%	1.82%	-3.22%	6.80%	2.27%
Large Growth	363	78.51%	16.25%	21.49%	0.55%	-1.24%	-1.34%	-5.72%	6.95%	-1.29%
Large Blend	249	73.49%	24.10%	26.51%	1.20%	-0.96%	-0.99%	-5.81%	7.69%	-1.33%
Large Value	171	66.08%	8.19%	33.92%	0.58%	-0.44%	-0.39%	-4.64%	4.67%	-0.85%
Index	101	84.16%	48.51%	15.84%	0.00%	-0.94%	-1.06%	-3.61%	2.07%	-0.77%
All funds	1,443	68.14%	16.21%	31.86%	1.93%	-0.78%				-1.04%

PANEL B: Performance estimated with mutual fund gross returns

		Percentage of total number of funds in group				Annualized performance				
Style	Number of funds	< 0	p-value ≤ 0.05	> 0	p-value ≥ 0.05	Mean	Median	Min.	Max.	Average (by fund size)
Small Growth	164	53.05%	5.49%	46.95%	5.49%	-0.07%	-0.16%	-6.88%	6.75%	-0.33%
Small Blend	85	29.41%	4.71%	70.59%	11.76%	1.22%	1.14%	-4.09%	8.51%	1.33%
Small Value	52	25.00%	0.00%	75.00%	11.54%	1.12%	0.97%	-3.35%	4.80%	0.98%
Mid Growth	162	32.10%	0.62%	67.90%	16.67%	1.05%	1.30%	-5.92%	7.48%	0.57%
Mid Blend	64	21.88%	0.00%	78.13%	15.63%	1.64%	1.70%	-4.35%	6.55%	1.81%
Mid Value	32	6.25%	0.00%	93.75%	50.00%	3.16%	3.26%	-1.78%	8.19%	3.39%
Large Growth	363	56.47%	2.75%	43.53%	1.38%	0.00%	-0.23%	-4.42%	8.05%	-0.26%
Large Blend	249	51.41%	4.82%	48.59%	3.61%	0.18%	-0.03%	-5.11%	8.94%	-0.39%
Large Value	171	29.82%	0.58%	70.18%	4.68%	0.69%	0.72%	-2.83%	5.67%	0.13%
Index	101	80.20%	7.92%	19.80%	0.00%	-0.44%	-0.65%	-2.77%	2.23%	-0.54%
All funds	1443	45.72%	3.24%	54.28%	6.90%	0.43%				-0.11%

Table 3: Simulated funds performance

PANEL A: Performance of simulated funds estimated from mutual fund net returns

Style	Number of funds	Percentage of total number of funds in group				Mean annualized performance
		< 0	p-value ≤ 0.05	> 0	p-value ≥ 0.05	
Small Growth	164	85.98%	3.05%	14.02%	0.00%	-0.68%
Small Blend	85	78.82%	0.00%	21.18%	0.00%	-0.54%
Small Value	52	78.85%	0.00%	21.15%	0.00%	-0.55%
Mid Growth	162	32.10%	0.00%	67.90%	0.00%	0.37%
Mid Blend	64	28.13%	0.00%	71.88%	0.00%	0.50%
Mid Value	32	18.75%	0.00%	81.25%	0.00%	0.67%
Large Growth	363	41.32%	0.00%	58.68%	0.00%	0.11%
Large Blend	249	53.01%	0.00%	46.99%	0.00%	0.01%
Large Value	171	49.71%	0.00%	50.29%	0.00%	0.03%
Index	101	79.21%	0.00%	20.79%	0.00%	-0.36%
All funds	1,443	53.72%	0.34%	46.28%	0.00%	-0.05%

PANEL B: Performance of simulated funds from mutual fund gross returns

Style	Number of funds	Percentage of total number of funds in group				Mean annualized performance
		< 0	p-value ≤ 0.05	> 0	p-value ≥ 0.05	
Small Growth	164	95.73%	3.05%	4.27%	0.00%	-0.89%
Small Blend	85	85.88%	2.35%	14.12%	0.00%	-0.67%
Small Value	52	82.69%	1.92%	17.31%	0.00%	-0.62%
Mid Growth	162	16.05%	0.00%	83.95%	0.00%	0.71%
Mid Blend	64	15.63%	0.00%	84.38%	1.56%	0.83%
Mid Value	32	3.13%	0.00%	96.88%	0.00%	1.23%
Large Growth	363	26.72%	0.00%	73.28%	0.28%	0.23%
Large Blend	249	48.59%	0.00%	51.41%	0.00%	0.08%
Large Value	171	42.69%	0.00%	57.31%	0.00%	0.14%
Index	101	83.17%	0.00%	16.83%	0.00%	-0.37%
All funds	1,443	47.72%	0.55%	52.28%	0.14%	0.04%

Table 4: Comparative results from the significance test based on simulated funds' performance distribution[a]

PANEL A: Data from net mutual fund returns

Style	Number of funds	(1) Data from Table 2		(2) Simulated funds' performance distribution test		(2)-(1)	
		Performance < 0 and p-value ≤ 0.05	Performance > 0 and p-value ≤ 0.05	Performance < 0 and p-value ≤ 0.05	Performance > 0 and p-value ≤ 0.05	Performance < 0 and p-value ≤ 0.05	Performance > 0 and p-value ≤ 0.05
Small Growth	164	16.46%	0.61%	15.85%	0.61%	-0.61%	0.00%
Small Blend	85	10.59%	2.35%	10.59%	2.35%	0.00%	0.00%
Small Value	52	5.77%	1.92%	5.77%	1.92%	0.00%	0.00%
Mid Growth	162	4.94%	4.32%	4.94%	4.32%	0.00%	0.00%
Mid Blend	64	6.25%	7.81%	6.25%	7.81%	0.00%	0.00%
Mid Value	32	0.00%	18.75%	0.00%	18.75%	0.00%	0.00%
Large Growth	363	16.25%	0.55%	16.25%	0.55%	0.00%	0.00%
Large Blend	249	24.10%	1.20%	24.10%	1.20%	0.00%	0.00%
Large Value	171	8.19%	0.58%	8.19%	0.58%	0.00%	0.00%
Index	101	48.51%	0.00%	10.89%	0.00%	-37.62%	0.00%

PANEL B: Data from gross mutual fund returns

Style	Number of funds	(1) Data from Table 2		(2) Simulated funds' performance distribution test		(2)-(1)	
		Performance < 0 and p-value ≤ 0.05	Performance > 0 and p-value ≤ 0.05	Performance < 0 and p-value ≤ 0.05	Performance > 0 and p-value ≤ 0.05	Performance < 0 and p-value ≤ 0.05	Performance > 0 and p-value ≤ 0.05
Small Growth	164	5.49%	5.49%	5.49%	5.49%	0.00%	0.00%
Small Blend	85	4.71%	11.76%	3.53%	11.76%	-1.18%	0.00%
Small Value	52	0.00%	11.54%	0.00%	11.54%	0.00%	0.00%
Mid Growth	162	0.62%	16.67%	0.62%	16.67%	0.00%	0.00%
Mid Blend	64	0.00%	15.63%	0.00%	15.63%	0.00%	0.00%
Mid Value	32	0.00%	50.00%	0.00%	50.00%	0.00%	0.00%
Large Growth	363	2.75%	1.38%	2.75%	1.38%	0.00%	0.00%
Large Blend	249	4.82%	3.61%	4.82%	3.61%	0.00%	0.00%
Large Value	171	0.58%	4.68%	0.58%	4.68%	0.00%	0.00%
Index	101	7.92%	0.00%	6.93%	0.00%	-0.99%	0.00%

[a] The table shows the percentage of the total number of funds in the style-type group.

Table 5: Comparing performance of non-survivor and survivor mutual funds

PANEL A: Data from net mutual fund returns

Style	Number of funds		Mean annualized performance difference	Percentage of semesters according to the sign of the difference between the performance of non-survivor and survivor funds			
	Survivor	Non-survivor (max.)		< 0	p-value ≤ 0.05	> 0	p-value ≤ 0.05
Small Growth	164	75	-3.88%	100.00%	81.25%	0.00%	0.00%
Small Blend	85	37	-4.46%	76.47%	58.82%	23.53%	23.53%
Small Value	52	15	-2.18%	86.67%	26.67%	13.33%	13.33%
Mid Growth	162	92	-3.17%	100.00%	64.71%	0.00%	0.00%
Mid Blend	64	27	-3.12%	93.75%	50.00%	6.25%	6.25%
Mid Value	32	21	-3.36%	82.35%	47.06%	17.65%	17.65%
Large Growth	363	240	-2.23%	100.00%	81.25%	0.00%	0.00%
Large Blend	249	159	-1.47%	93.33%	80.00%	6.67%	6.67%
Large Value	171	98	-0.69%	82.35%	82.35%	17.65%	17.65%
Index	101	55	-0.17%	75.00%	6.25%	25.00%	25.00%

PANEL B: Data from gross mutual fund returns

Style	Number of funds		Mean annualized performance difference	Percentage of semesters according to the sign of the difference between the performance of non-survivor and survivor funds			
	Survivor	Non-survivor (max.)		< 0	p-value ≤ 0.05	> 0	p-value ≤ 0.05
Small Growth	164	75	-3.81%	100.00%	50.00%	0.00%	0.00%
Small Blend	85	37	-2.88%	70.59%	11.76%	29.41%	29.41%
Small Value	52	15	-2.11%	86.67%	13.33%	13.33%	13.33%
Mid Growth	162	92	-2.87%	100.00%	35.29%	0.00%	0.00%
Mid Blend	64	27	-3.04%	87.50%	0.00%	12.50%	12.50%
Mid Value	32	21	-3.26%	86.67%	13.33%	13.33%	13.33%
Large Growth	363	240	-2.10%	100.00%	43.75%	0.00%	0.00%
Large Blend	249	159	-1.33%	93.33%	26.67%	6.67%	6.67%
Large Value	171	98	-0.43%	82.35%	35.29%	17.65%	17.65%
Index	101	55	0.05%	68.75%	6.25%	31.25%	31.25%

Table 6: Performance persistence using winner-loser and transition matrix approaches

PANEL A: Performance estimated with mutual fund net returns

		Contingency table								Transition matrix	
Style	Number of funds	χ^2	p-value	Z total	p-value	ZWW	p-value	ZLL	p-value	χ^2	p-value
Small Growth	164	33.69	(0.000)	2.52	(0.006)	2.90	(0.002)	2.90	(0.002)	103.79	(0.000)
Small Blend	85	26.48	(0.000)	2.23	(0.013)	2.35	(0.009)	2.80	(0.003)	92.17	(0.000)
Small Value	52	1.96	(0.162)	0.61	(0.272)	0.70	(0.242)	0.70	(0.242)	34.88	(0.004)
Mid Growth	162	36.24	(0.000)	2.61	(0.005)	3.01	(0.001)	3.01	(0.001)	85.12	(0.000)
Mid Blend	64	5.26	(0.022)	1.00	(0.160)	1.15	(0.126)	1.15	(0.126)	52.33	(0.000)
Mid Value	32	2.13	(0.144)	0.63	(0.263)	0.73	(0.233)	0.73	(0.233)	21.97	(0.144)
Large Growth	363	29.75	(0.000)	2.37	(0.009)	2.60	(0.005)	2.85	(0.002)	141.95	(0.000)
Large Blend	249	13.31	(0.000)	1.58	(0.057)	1.68	(0.047)	1.97	(0.024)	172.89	(0.000)
Large Value	171	6.82	(0.009)	1.13	(0.128)	1.14	(0.126)	1.47	(0.071)	98.69	(0.000)
Index	101	84.57	(0.000)	3.96	(0.000)	4.40	(0.000)	4.79	(0.000)	361.80	(0.000)

PANEL B: Performance estimated with mutual fund gross returns

		Contingency table								Transition matrix	
Style	Number of funds	χ^2	p-value	Z total	p-value	ZWW	p-value	ZLL	p-value	χ^2	p-value
Small Growth	164	35.37	(0.000)	2.58	(0.005)	2.97	(0.001)	2.97	(0.001)	97.42	(0.000)
Small Blend	85	26.48	(0.000)	2.23	(0.013)	2.35	(0.009)	2.80	(0.003)	79.57	(0.000)
Small Value	52	2.33	(0.127)	0.66	(0.254)	0.76	(0.223)	0.76	(0.223)	40.59	(0.001)
Mid Growth	162	35.38	(0.000)	2.58	(0.005)	2.97	(0.001)	2.97	(0.001)	71.65	(0.000)
Mid Blend	64	7.58	(0.006)	1.19	(0.116)	1.35	(0.089)	1.40	(0.080)	49.36	(0.000)
Mid Value	32	2.13	(0.144)	0.63	(0.263)	0.73	(0.233)	0.73	(0.233)	28.23	(0.030)
Large Growth	363	24.73	(0.000)	2.16	(0.015)	2.38	(0.009)	2.60	(0.005)	170.76	(0.000)
Large Blend	249	7.07	(0.008)	1.15	(0.124)	1.19	(0.116)	1.47	(0.071)	174.78	(0.000)
Large Value	171	8.37	(0.004)	1.26	(0.105)	1.28	(0.099)	1.61	(0.054)	96.90	(0.000)
Index	101	4.29	(0.038)	0.90	(0.184)	0.80	(0.211)	1.27	(0.102)	292.31	(0.000)

Table 7: Simulated fund persistence using winner-loser and transition matrix approaches

Style	Number of funds	Contingency table χ^2	p-value	Z total	p-value	ZWW	p-value	ZLL	p-value	Transition matrix χ^2	p-value
PANEL A: Performance of simulated funds from mutual fund net returns											
Small Growth	164	55.54	(0.000)	3.23	(0.001)	3.71	(0.000)	3.74	(0.000)	221.74	(0.000)
Small Blend	85	34.14	(0.000)	2.53	(0.006)	2.70	(0.003)	3.14	(0.001)	148.68	(0.000)
Small Value	52	12.70	(0.000)	1.54	(0.061)	1.78	(0.037)	1.78	(0.037)	88.64	(0.000)
Mid Growth	162	49.42	(0.000)	3.04	(0.001)	3.51	(0.000)	3.51	(0.000)	162.15	(0.000)
Mid Blend	64	17.05	(0.000)	1.79	(0.037)	2.06	(0.019)	2.06	(0.019)	71.08	(0.000)
Mid Value	32	8.53	(0.004)	1.27	(0.103)	1.46	(0.072)	1.46	(0.072)	38.14	(0.001)
Large Growth	363	0.61	(0.434)	0.34	(0.367)	0.28	(0.391)	0.51	(0.307)	517.10	(0.000)
Large Blend	249	46.08	(0.000)	2.94	(0.002)	3.26	(0.001)	3.53	(0.000)	509.89	(0.000)
Large Value	171	1.00	(0.318)	0.43	(0.332)	0.33	(0.369)	0.66	(0.253)	351.20	(0.000)
Index	101	0.18	(0.668)	0.19	(0.426)	0.00	(0.500)	0.43	(0.333)	414.65	(0.000)
PANEL B: Performance of simulated funds from mutual fund gross returns											
Style	Number of funds	Contingency table χ^2	p-value	Z total	p-value	ZWW	p-value	ZLL	p-value	Transition matrix χ^2	p-value
Small Growth	164	66.73	(0.000)	3.53	(0.000)	4.08	(0.000)	4.08	(0.000)	234.30	(0.000)
Small Blend	85	59.80	(0.000)	3.34	(0.000)	3.63	(0.000)	4.10	(0.000)	140.87	(0.000)
Small Value	52	16.58	(0.000)	1.76	(0.039)	2.04	(0.021)	2.04	(0.021)	134.04	(0.000)
Mid Growth	162	44.48	(0.000)	2.89	(0.002)	3.33	(0.000)	3.33	(0.000)	220.02	(0.000)
Mid Blend	64	36.96	(0.000)	2.63	(0.004)	3.04	(0.001)	3.04	(0.001)	98.53	(0.000)
Mid Value	32	16.45	(0.000)	1.75	(0.040)	2.03	(0.021)	2.03	(0.021)	78.05	(0.000)
Large Growth	363	5.62	(0.018)	1.03	(0.152)	1.07	(0.142)	1.30	(0.097)	521.94	(0.000)
Large Blend	249	67.94	(0.000)	3.57	(0.000)	3.99	(0.000)	4.25	(0.000)	493.99	(0.000)
Large Value	171	12.92	(0.000)	1.56	(0.059)	1.62	(0.053)	1.98	(0.024)	435.10	(0.000)
Index	101	0.37	(0.542)	0.26	(0.396)	0.07	(0.473)	0.54	(0.293)	589.74	(0.000)

Table 8: Mutual fund persistence obtained by assessing performance of past-persistence-based portfolios[a]

PANEL A: Performance estimated with mutual fund net returns																
Style	Number of funds	$Q1$	p-value	Cross p-value	$Q2$	p-value	Cross p-value	$Q3$	p-value	Cross p-value	$Q4$	p-value	Cross p-value	$Q5$	p-value	Cross p-value
Small Growth	164	-3.10%	(0.010)	(0.000)	-2.20%	(0.024)	(0.041)	-1.09%	(0.234)	(0.918)	-0.72%	(0.408)	(0.991)	-0.76%	(0.444)	(0.991)
Small Blend	85	-1.53%	(0.083)	(0.009)	-0.49%	(0.578)	(0.485)	-1.49%	(0.070)	(0.014)	0.60%	(0.503)	(0.010)	0.60%	(0.510)	(0.010)
Small Value	52	0.07%	(0.949)	(0.090)	-1.48%	(0.142)	(0.104)	-0.29%	(0.767)	(0.765)	-1.39%	(0.157)	(0.131)	-0.63%	(0.557)	(0.566)
Mid Growth	162	-1.32%	(0.262)	(0.000)	-0.10%	(0.926)	(0.308)	0.90%	(0.405)	(0.012)	-0.11%	(0.920)	(0.304)	1.09%	(0.323)	(0.001)
Mid Blend	64	-0.46%	(0.683)	(0.166)	0.25%	(0.784)	(0.502)	0.79%	(0.371)	(0.197)	0.17%	(0.880)	(0.546)	0.33%	(0.768)	(0.464)
Mid Value	32	1.02%	(0.414)	(0.715)	1.80%	(0.078)	(0.390)	1.49%	(0.164)	(0.521)	1.57%	(0.136)	(0.493)	1.90%	(0.149)	(0.345)
Large Growth	363	-1.30%	(0.139)	(0.172)	-0.93%	(0.156)	(0.771)	-0.67%	(0.268)	(0.972)	-1.01%	(0.120)	(0.631)	-1.57%	(0.099)	(0.010)
Large Blend	249	-1.38%	(0.014)	(0.029)	-1.03%	(0.013)	(0.378)	-1.00%	(0.004)	(0.420)	-1.28%	(0.001)	(0.071)	-0.08%	(0.898)	(0.000)
Large Value	171	-0.62%	(0.399)	(0.388)	-0.62%	(0.364)	(0.397)	-0.42%	(0.525)	(0.709)	-0.84%	(0.180)	(0.114)	-0.27%	(0.734)	(0.887)
Index	101	-0.40%	(0.742)	(0.987)	-0.94%	(0.193)	(0.668)	-1.41%	(0.006)	(0.136)	-0.56%	(0.487)	(0.953)	-2.06%	(0.024)	(0.000)
PANEL B: Performance estimated with mutual fund gross returns																
Style	Number of funds	$Q1$	p-value	Cross p-value	$Q2$	p-value	Cross p-value	$Q3$	p-value	Cross p-value	$Q4$	p-value	Cross p-value	$Q5$	p-value	Cross p-value
Small Growth	164	-1.57%	(0.184)	(0.000)	-0.87%	(0.366)	(0.018)	0.20%	(0.828)	(0.168)	0.93%	(0.279)	(0.003)	0.60%	(0.553)	(0.021)
Small Blend	85	-0.06%	(0.947)	(0.020)	0.56%	(0.532)	(0.777)	0.17%	(0.831)	(0.945)	1.67%	(0.068)	(0.041)	2.07%	(0.024)	(0.003)
Small Value	52	1.24%	(0.285)	(0.160)	0.04%	(0.968)	(0.825)	1.10%	(0.254)	(0.218)	-0.15%	(0.878)	(0.100)	0.78%	(0.472)	(0.392)
Mid Growth	162	-0.05%	(0.968)	(0.000)	1.56%	(0.162)	(0.376)	2.04%	(0.056)	(0.046)	1.37%	(0.201)	(0.585)	2.29%	(0.038)	(0.009)
Mid Blend	64	0.83%	(0.462)	(0.821)	1.42%	(0.137)	(0.543)	2.51%	(0.006)	(0.076)	1.45%	(0.157)	(0.529)	1.39%	(0.232)	(0.560)
Mid Value	32	2.36%	(0.060)	(0.737)	3.15%	(0.003)	(0.385)	2.82%	(0.006)	(0.541)	2.83%	(0.009)	(0.535)	3.15%	(0.016)	(0.383)
Large Growth	363	0.09%	(0.915)	(0.580)	0.13%	(0.843)	(0.510)	0.55%	(0.355)	(0.032)	0.17%	(0.793)	(0.430)	-0.22%	(0.820)	(0.038)
Large Blend	249	-0.24%	(0.672)	(0.027)	0.22%	(0.591)	(0.441)	0.09%	(0.790)	(0.661)	-0.29%	(0.454)	(0.014)	1.12%	(0.058)	(0.000)
Large Value	171	0.63%	(0.405)	(0.430)	0.42%	(0.537)	(0.745)	0.48%	(0.475)	(0.665)	0.38%	(0.548)	(0.787)	0.93%	(0.226)	(0.078)
Index	101	0.48%	(0.696)	(0.000)	-0.81%	(0.274)	(0.233)	-0.61%	(0.236)	(0.452)	-0.18%	(0.830)	(0.900)	-1.78%	(0.054)	(0.000)

[a] For all styles, mutual funds are grouped in quintiles based on past performance. Portfolio $Q1$ consists of investing, over the next period, in the worst performing mutual funds, from the previous period, in the first quintile. The same pattern is followed by the rest of the portfolios up to Q5, which invests in the best mutual funds based on the performance achieved in the previous period.

Table 9: Simulated fund persistence obtained by assessing performance of past-persistence-based portfolios[a]

PANEL A: Performance estimated with mutual fund net returns

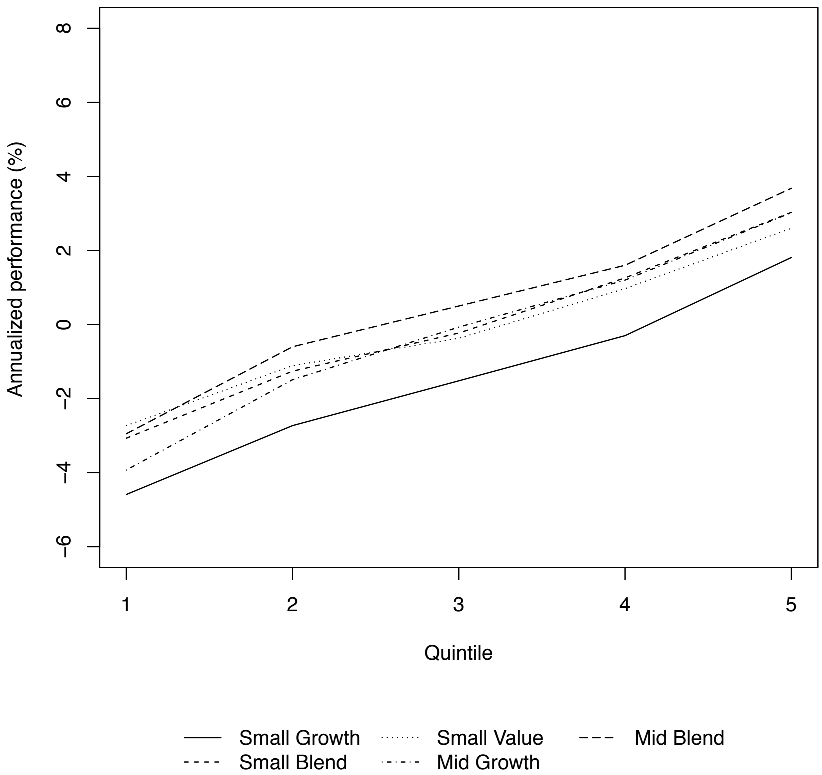
Style	Number of funds	$Q1$	p-value	Cross p-value	$Q2$	p-value	Cross p-value	$Q3$	p-value	Cross p-value	$Q4$	p-value	Cross p-value	$Q5$	p-value	Cross p-value
Small Growth	164	-1.18%	(0.219)	(0.750)	-1.46%	(0.048)	(0.162)	-1.19%	(0.049)	(0.732)	-1.21%	(0.081)	(0.702)	-1.47%	(0.065)	(0.155)
Small Blend	85	-1.46%	(0.102)	(0.268)	-0.82%	(0.225)	(0.893)	-1.39%	(0.022)	(0.334)	-1.30%	(0.060)	(0.427)	-1.28%	(0.198)	(0.458)
Small Value	52	-1.93%	(0.033)	(0.079)	-1.18%	(0.133)	(0.585)	-0.75%	(0.294)	(0.909)	-1.21%	(0.141)	(0.553)	-1.27%	(0.214)	(0.502)
Mid Growth	162	0.51%	(0.547)	(0.000)	0.55%	(0.384)	(0.000)	-0.29%	(0.631)	(0.325)	-0.37%	(0.547)	(0.199)	-1.40%	(0.105)	(0.000)
Mid Blend	64	0.07%	(0.925)	(0.323)	0.45%	(0.428)	(0.028)	0.13%	(0.823)	(0.240)	-0.09%	(0.886)	(0.433)	-0.77%	(0.320)	(0.003)
Mid Value	32	0.41%	(0.527)	(0.201)	0.59%	(0.326)	(0.081)	0.42%	(0.459)	(0.186)	-0.17%	(0.795)	(0.166)	-0.51%	(0.496)	(0.018)
Large Growth	363	0.17%	(0.820)	(0.000)	-0.03%	(0.946)	(0.000)	-0.32%	(0.448)	(0.952)	-0.78%	(0.088)	(0.015)	-1.64%	(0.015)	(0.000)
Large Blend	249	-0.24%	(0.720)	(0.994)	-0.56%	(0.284)	(0.589)	-0.63%	(0.161)	(0.383)	-0.53%	(0.254)	(0.683)	-1.02%	(0.113)	(0.001)
Large Value	171	-0.30%	(0.692)	(0.948)	-0.05%	(0.939)	(0.000)	-0.30%	(0.606)	(0.946)	-0.65%	(0.277)	(0.149)	-1.26%	(0.077)	(0.000)
Index	101	-0.01%	(0.994)	(0.000)	-0.97%	(0.186)	(0.480)	-1.22%	(0.032)	(0.180)	-0.60%	(0.464)	(0.901)	-2.06%	(0.018)	(0.000)

PANEL B: Performance estimated with mutual fund gross returns

Style	Number of funds	$Q1$	p-value	Cross p-value	$Q2$	p-value	Cross p-value	$Q3$	p-value	Cross p-value	$Q4$	p-value	Cross p-value	$Q5$	p-value	Cross p-value
Small Growth	164	-1.80%	(0.050)	(0.018)	-1.61%	(0.037)	(0.248)	-1.36%	(0.058)	(0.907)	-1.45%	(0.052)	(0.727)	-1.40%	(0.081)	(0.842)
Small Blend	85	-1.39%	(0.060)	(0.606)	-1.49%	(0.017)	(0.398)	-1.76%	(0.006)	(0.045)	-1.35%	(0.059)	(0.676)	-1.14%	(0.164)	(0.940)
Small Value	52	-1.72%	(0.035)	(0.072)	-1.56%	(0.052)	(0.264)	-1.34%	(0.101)	(0.646)	-1.07%	(0.219)	(0.948)	-1.40%	(0.142)	(0.541)
Mid Growth	162	0.74%	(0.425)	(0.001)	0.92%	(0.259)	(0.000)	0.39%	(0.639)	(0.090)	-0.09%	(0.908)	(0.029)	-0.97%	(0.310)	(0.000)
Mid Blend	64	0.34%	(0.627)	(0.429)	0.77%	(0.246)	(0.023)	0.46%	(0.502)	(0.242)	0.34%	(0.618)	(0.427)	-0.40%	(0.648)	(0.002)
Mid Value	32	0.78%	(0.247)	(0.424)	1.08%	(0.140)	(0.082)	0.85%	(0.253)	(0.327)	0.46%	(0.576)	(0.867)	0.51%	(0.548)	(0.822)
Large Growth	363	0.40%	(0.592)	(0.000)	0.20%	(0.713)	(0.000)	-0.22%	(0.641)	(0.974)	-0.86%	(0.078)	(0.000)	-1.49%	(0.029)	(0.000)
Large Blend	249	0.08%	(0.891)	(0.000)	-0.57%	(0.242)	(0.231)	-0.54%	(0.219)	(0.370)	-0.50%	(0.276)	(0.541)	-1.00%	(0.082)	(0.000)
Large Value	171	-0.07%	(0.922)	(0.999)	-0.08%	(0.902)	(0.999)	-0.25%	(0.698)	(0.919)	-0.54%	(0.392)	(0.043)	-0.99%	(0.148)	(0.000)
Index	101	-0.15%	(0.909)	(0.996)	-1.22%	(0.123)	(0.163)	-1.04%	(0.032)	(0.355)	-1.03%	(0.289)	(0.375)	-1.32%	(0.164)	(0.092)

[a] For all styles, simulated funds are grouped in quintiles based on past performance. Portfolio Q1 consists of investing, over the next period, in the worst performing synthetic funds, from the previous period in the first quintile. The same pattern is followed by the rest of the portfolios up to Q5, which invests in the best synthetic funds based on the performance achieved in the previous period.

Figure 1: Mutual fund performance estimated from net returns



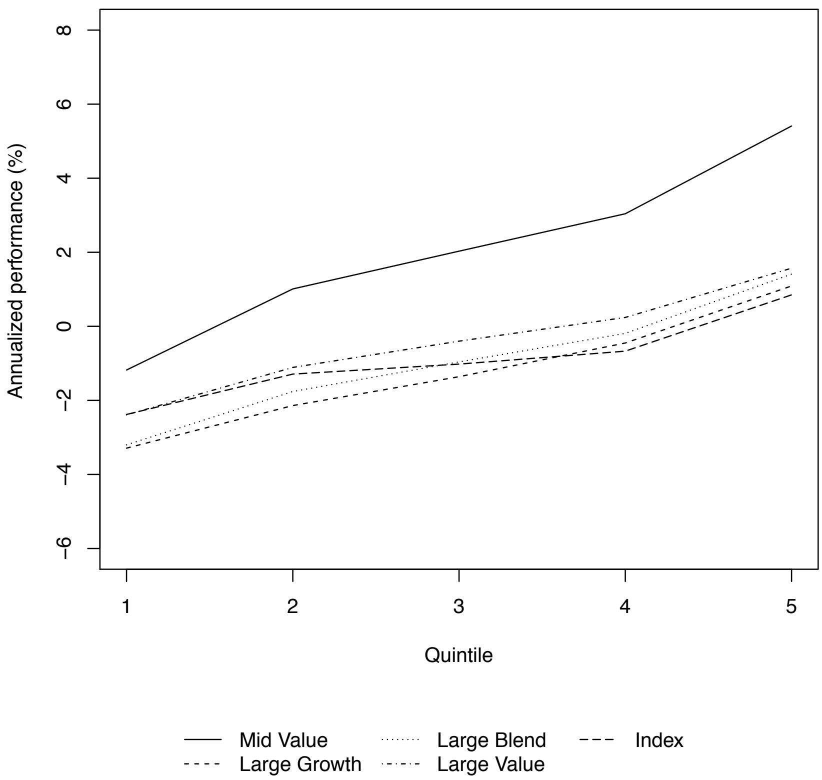
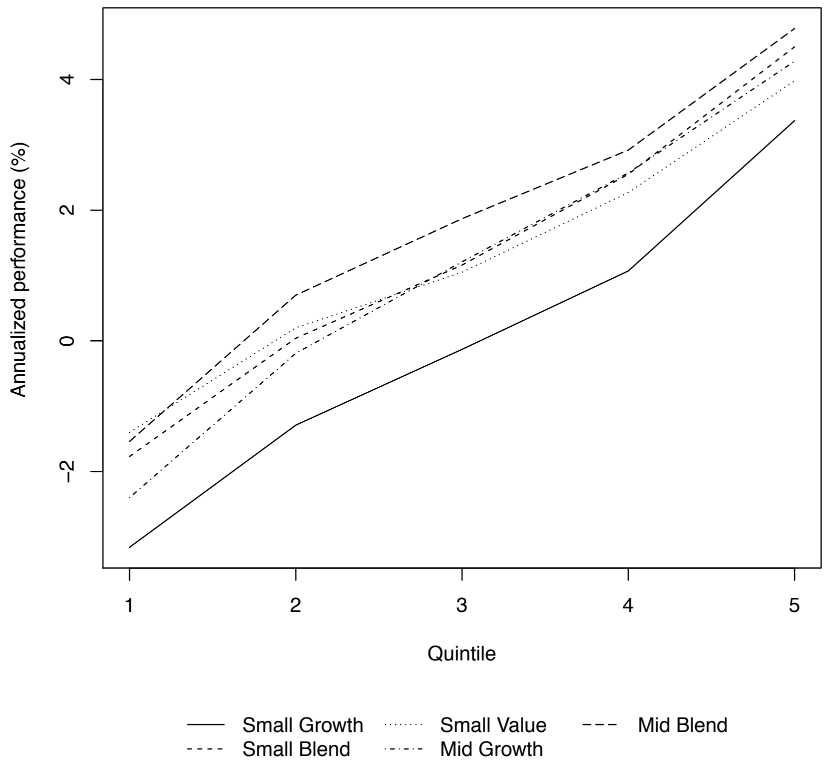


Figure 2: Mutual fund performance estimated from gross returns



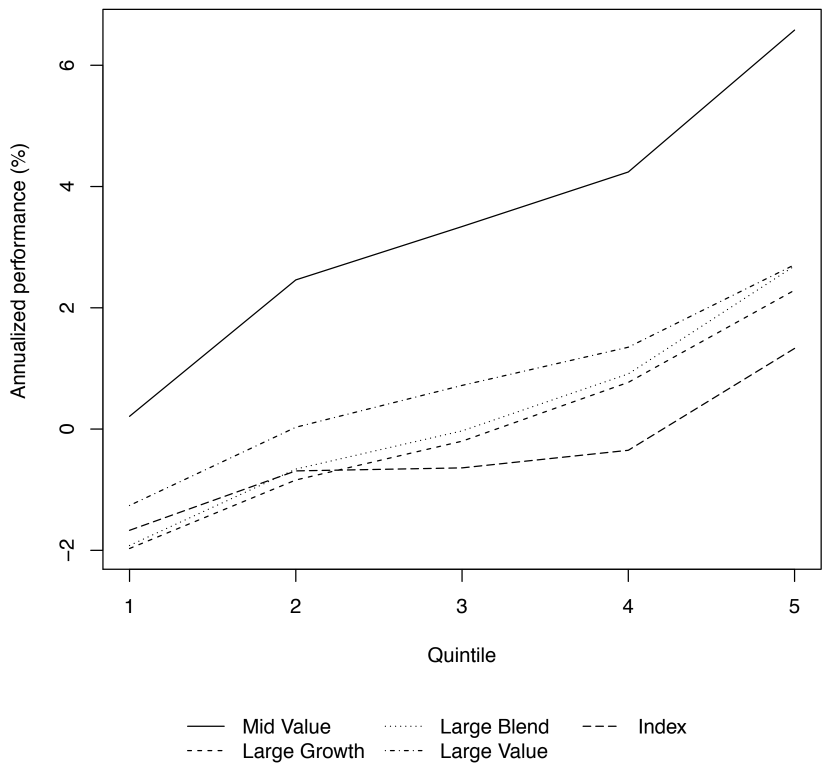
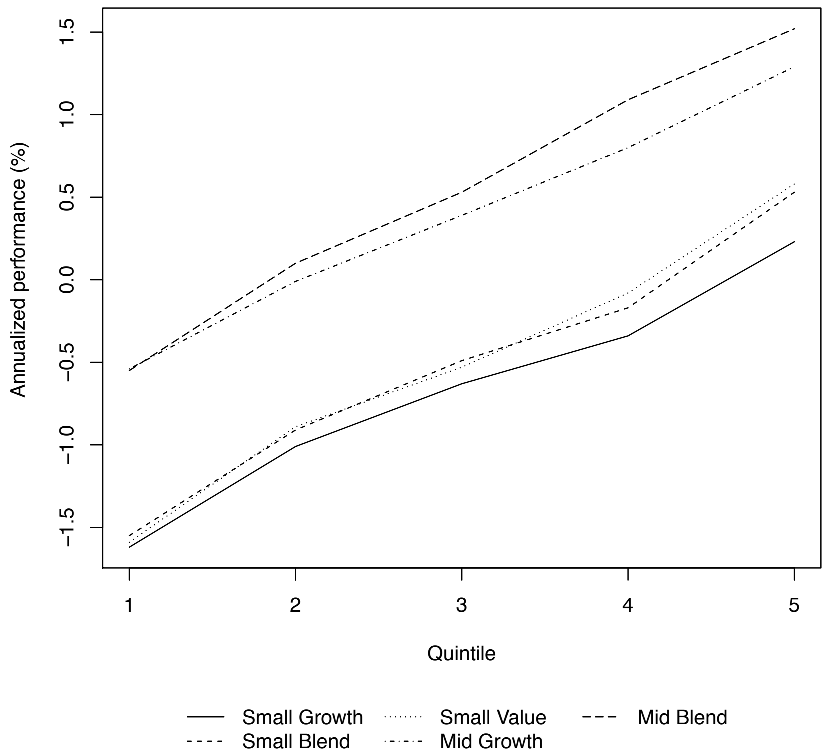


Figure 3: Simulated mutual fund performance estimated from net returns



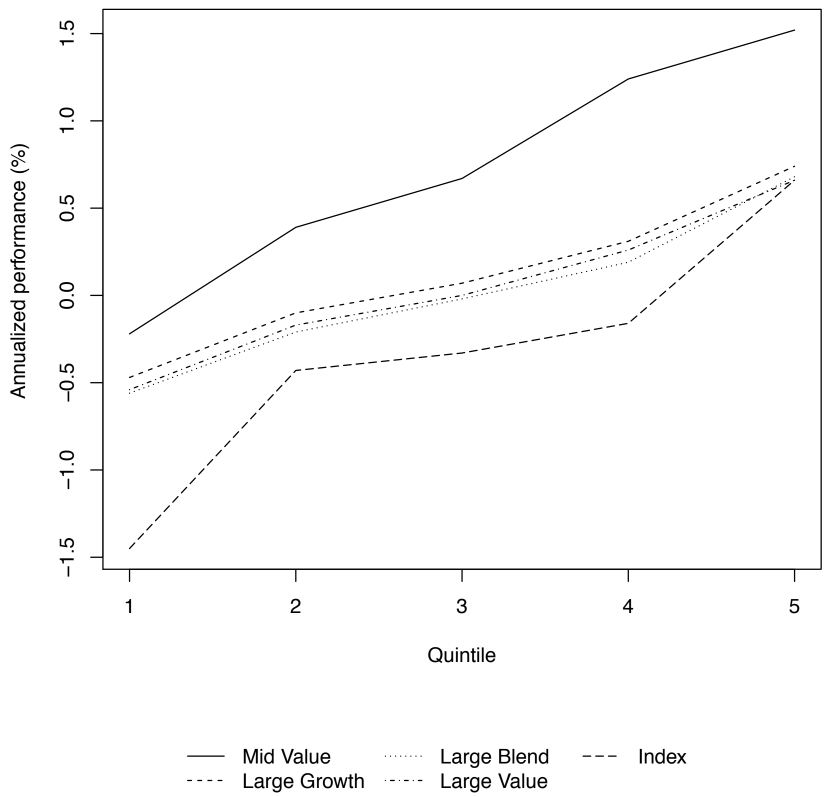
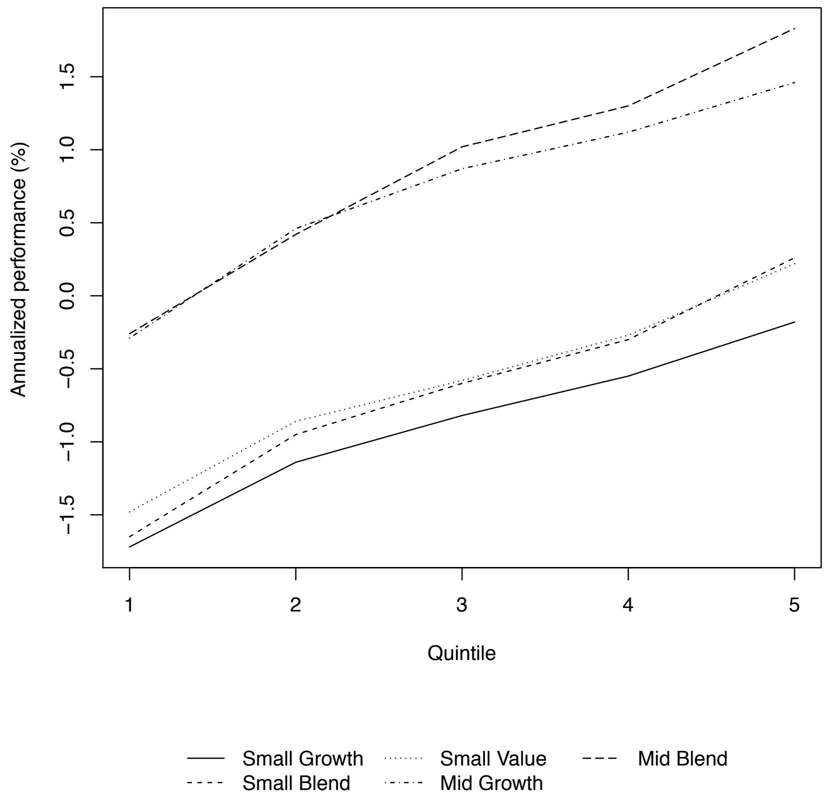


Figure 4: Simulated mutual fund performance estimated from gross returns



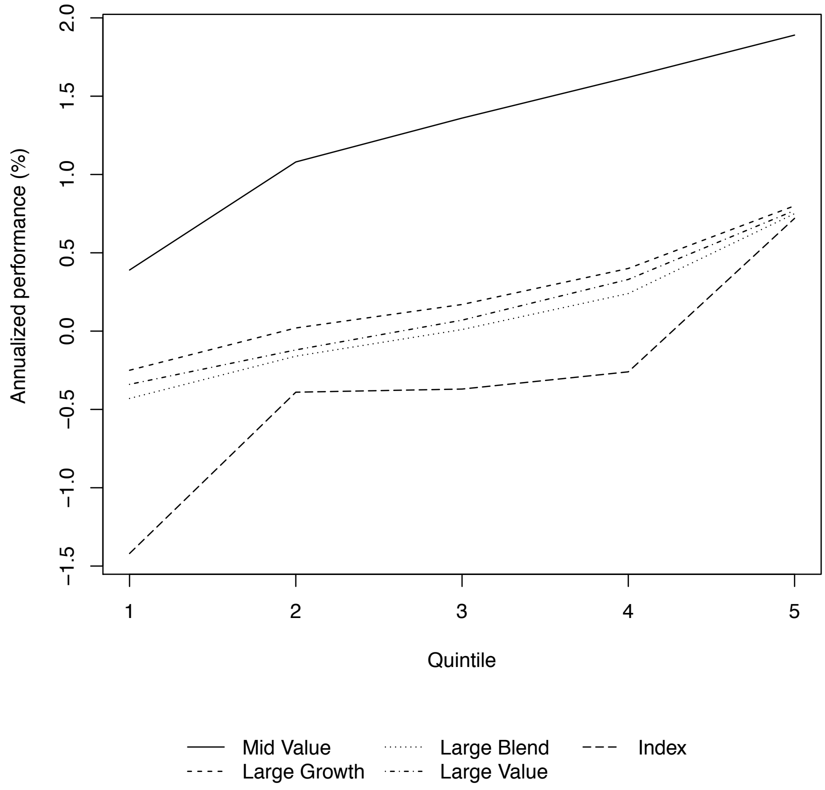
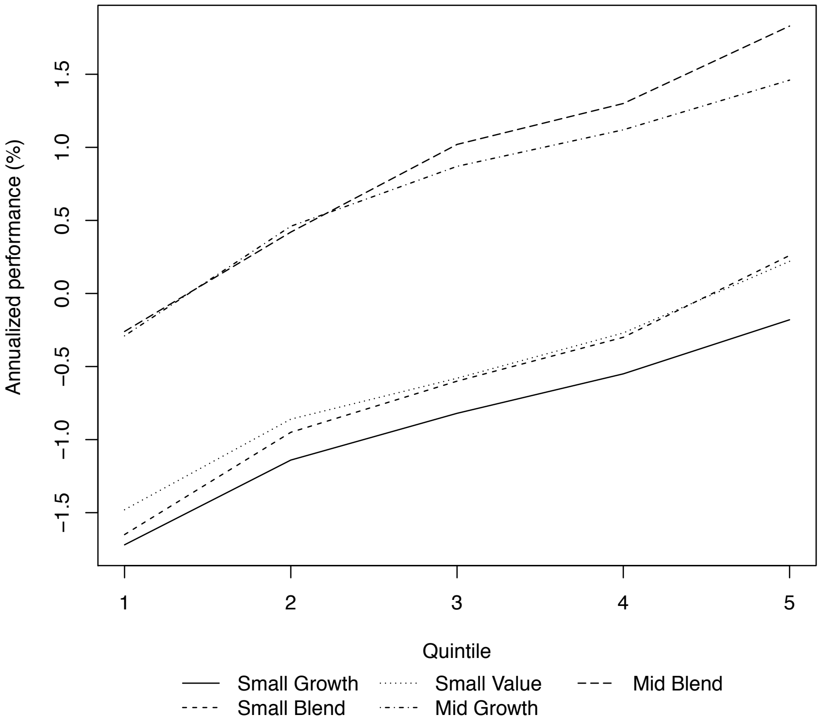


Figure 5: Performance of portfolios based on mutual fund past performance estimated from net returns



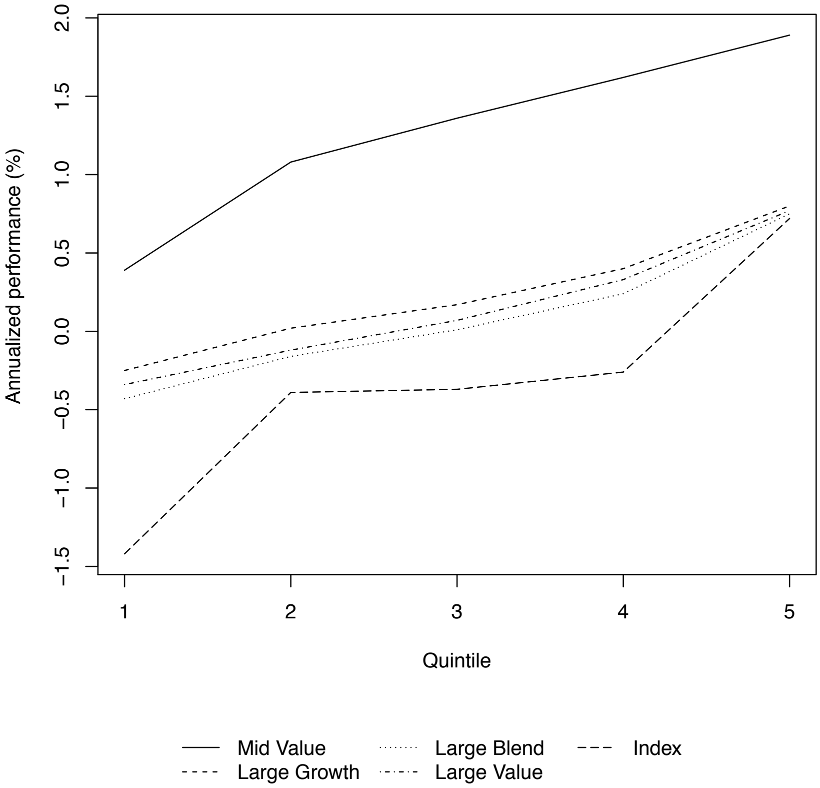
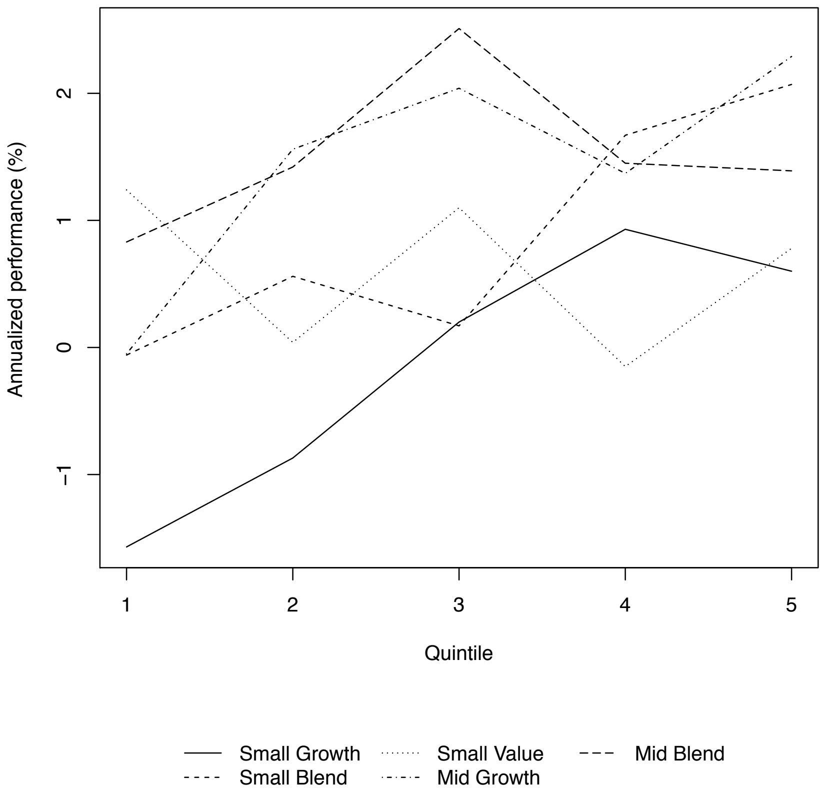


Figure 6: Performance of portfolios based on mutual fund past performance estimated from gross returns



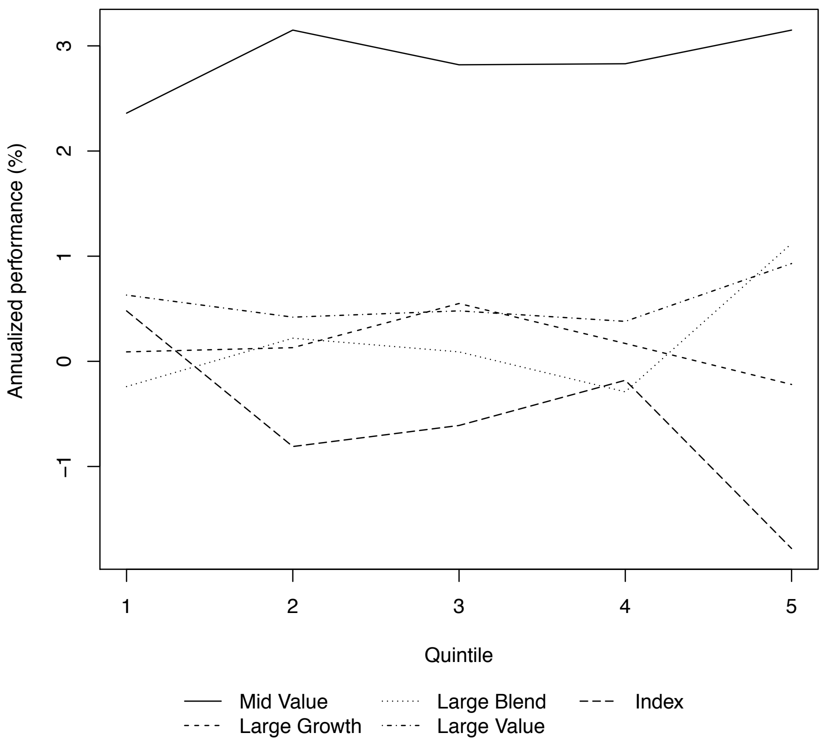
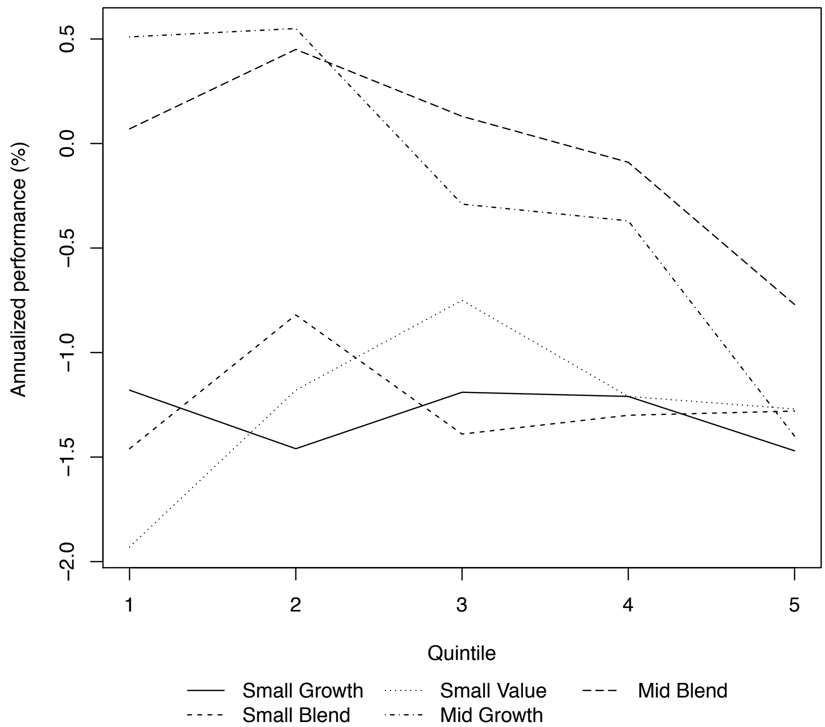


Figure 7: Performance of portfolios based on simulated fund past performance estimated from net returns



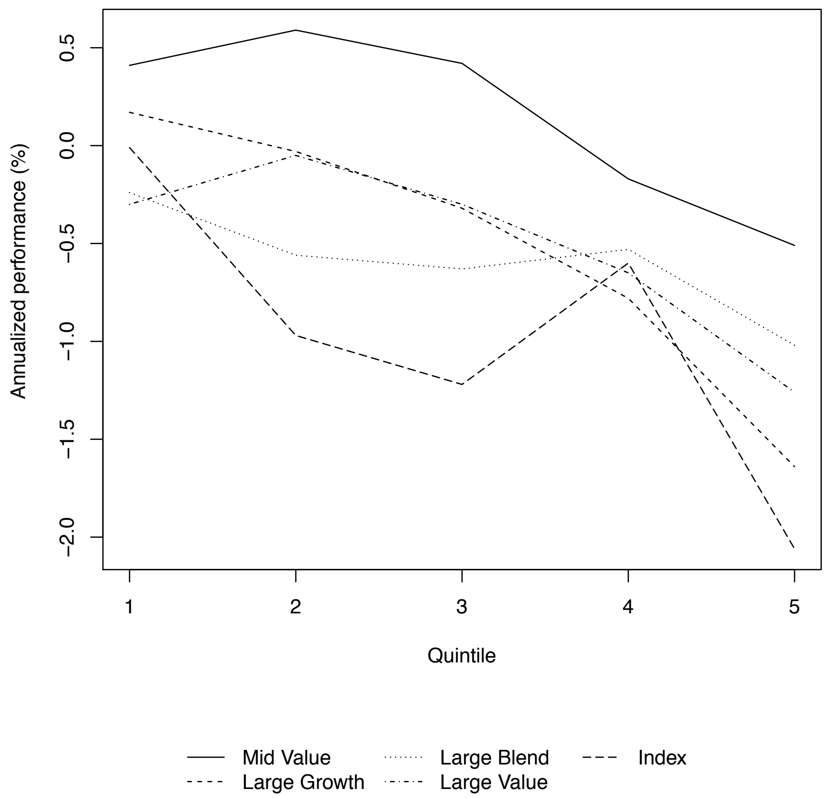


Figure 8: Performance of portfolios based on simulated fund past performance estimated from gross returns