Mutual Fund Performance Persistence: Factor Models and Portfolio Size

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Abstract:
We re-examine US mutual fund performance persistence. We investigate persistence (i) using both "academic" factor models and "practitioner" index models, (ii) using decile-size recursive portfolios and also portfolios formed from smaller numbers of funds, (iii) using nonparametric bootstrap p-values as well as conventional t-tests and (iv) using both net-of-fee fund returns (net alphas) and gross alphas. Our key result is that positive net alpha performance persistence can be found using small portfolios of funds together with a holding period of 6 months or less, for both practitioner index models and academic factor models.

Keywords: Mutual fund performance persistence, factor models, portfolio size.

JEL Classification: G11, G12, G14, C15.

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1. INTRODUCTION

The rationale for managed funds is that they “add value” by using private information and manager skill to produce “abnormal performance”. In turn, the question of performance persistence, i.e. whether past performance is an indicator of future performance, has attracted much attention. In this paper, we re-examine mutual fund performance persistence in light of recent literature discussion on factor models and furthermore we extend our understanding of persistence by investigating small portfolios of funds in the tail of the cross-sectional distribution of funds.

We investigate fund performance persistence using both academic factor models as well as practitioner index models. We follow Cremers, Petajisto and Zitzewitz (2013) and employ a seven-factor “index model” ("IDX7”) that uses commonly available easily tradeable indices. Unlike the Fama-French academic factors, these indices generally have zero alphas with respect to a wide range of passive indices and style-sorted stock portfolios. Academic factor models use “risk factors” which have explanatory power for the cross-section of average stock returns whereas practitioner-factors are chosen to more closely represent low-cost investible passive indices (which do not necessarily price stock portfolios).

In addition to reporting results for conventional decile portfolios, we investigate portfolios of smaller numbers of funds (e.g. top 2, 3, 5, 7, 10, 20, 35, 50 funds). This allows us to examine performance persistence within the tails of decile portfolios – which may not be revealed in larger decile portfolios.

The issue of non-normality in fund returns is important in the tails of the cross-sectional distribution of funds. It is especially problematic when forming recursive portfolios (deciles and smaller portfolios) of funds based on the t-statistic of alpha over some relatively short backward-looking formation period. We therefore implement a bootstrap procedure to construct a new nonparametric performance persistence test statistic.

We consider fund performance persistence based on both net-of-fee fund returns (net alphas) and gross returns (gross alphas). The extant literature rarely provides insight into persistence from the perspective of both fund managers as well as fund investors. Gross alpha persistence is potentially exploitable by managers who implement a trading strategy that switches between mutual funds. However, this persistence may not be exploitable by investors (when considering rebalancing costs). In other words, do fund management companies absorb abnormal performance or add value for investors in this regard?

We also examine the robustness of mutual fund performance persistence over alternative portfolio formation and holding periods (f,h). Winner portfolios are sorted on past t-alphas for $f=36$ or 60 months and held for holding periods of h = 1, 3, 6, and 12 months for both decile-sorted portfolios and for portfolios of a small number of funds $s_i, (i=2,3,5,7,10,20,35,50)$.

To our knowledge, there has not been an extensive recent study assessing the robustness of positive persistence in mutual fund portfolios, with respect to small versus large portfolios, different formation and holding periods, different factor models and with respect to standard t-test versus bootstrap t-values.

A key result is that investors can benefit from performance persistence in small portfolios of funds, using relatively short holding periods (of up to 6 months) and using bootstrap techniques. This may be a more parsimonious way of exploiting persistence in the tails of the cross-sectional distribution of fund performance compared to the extant study of decile portfolios. It may also be a more straight forward way to uncover positive net-alpha persistence than searching over many alternative sorting rules or using multiple sorting criteria, with the attendant problem of data-mining. Our findings are similar between academic factor models and practitioner index models.

We repeat the above analysis using gross (i.e. before fee) returns and the above results apply a fortiori. Hence the key to establishing relatively large statistically significant net-alphas to investors from a persistence strategy is to ensure effective competition amongst funds, which could lead to lower mutual fund fees, for investors in active funds. In the UK, the latter has been the focus of the UK Financial Conduct Authority's (FCA) Asset Management Markets investigation (FCA, 2017) which recommended greater transparency of fund performance measures, investigation into (internet) platform providers and a submission to the Competition and Markets Authority (CMA) to investigate the role of advisers in recommending mutual funds to pension trustees.

The rest of the paper is structured as follows. Section 2 provides a review of recent results from the asset pricing literature and their implications for factor models used in mutual fund performance evaluation. In section 3 we introduce our data sources and our empirical findings on net-alpha performance persistence are reported in section 4. Conclusions are presented in Section 5. Additional results on persistence in performance when using gross-of-fee alphas can be found in the Appendix.

2. PREVIOUS STUDIES

There are voluminous studies on the performance of individual mutual funds (MFs) and also on whether it is possible to form ex-ante sorts of MFs into portfolios based on fixed rules, which then show persistence in performance. Factor models applied to MFs are either based on academic risk factors that have been shown to explain the cross-section of average stock returns or on more ‘practitioner-factors’ which are chosen to more closely represent low-cost investible passive indices. When using academic factor models, the difficulty is in choosing the correct specification, since asset pricing studies provide a cornucopia of possible factors (see for example, Harvey et al 2015, Fama and French 2018).

The most frequently used academic-factor model in the MF performance literature is the Fama-French-Carhart (Carhart 1997) four factor model (FFC4), where in earlier studies the addition of a momentum factor dramatically changed one’s view of persistence in positive net-alpha performance. More recent papers use bootstrap techniques because of non-normality, especially in the extreme tails of the MF performance distribution, (Kosowski et al 2006, Fama and French 2010, Blake et al 2017, Huang et al 2019, Cuthbertson et al 2008).

The US and UK evidence, based on the FFC4 model, is that the *average* MF underperforms in terms of (after fee) net alpha. The evidence on *individual* fund performance is that it is difficult to find MFs with statistically significant positive net-alphas but there are a large number of “unskilled” (negative-alpha) funds (Fama and French 2010). For example, Barras et al (2010) after adjusting for the number of significant funds using the false discovery rate[1] and Kosowski et al (2006) and Fama-French (2010) after applying bootstrap p-values (using non-parametric order statistics), find that the proportion of truly positive-alpha US funds has declined over the 1990s and 2000s, while the proportion of statistically significant negative net-alpha funds has increased[2].

Using a non-parametric estimate of alpha based on the FFC4 model and allowing time variation in alpha, a similar conclusion is reached by Cai et al (2018) who find 32 funds (1%

1 Andrikogiannopoulou and Papakonstantinou (2019) using simulation, show that for US mutual fund returns, which have a low signal-to-noise ratio, relatively limited observations per fund and possible cross-sectional correlation across funds, estimates of the false discovery rate may be heavily biased and produce estimates of zero-alphas (non-zero-alphas) that are upward (downward) biased. Giglio et al (2018) propose an alternative FDR approach.

2 Another major strand in the literature is to use some form of shrinkage to adjust individual fund alphas. This may involve using Bayesian priors (Jones and Shanken 2005) or fund characteristics (Pastor and Stambaugh 2002) or information on the cross-section of performance (Chen et al 2017, Harvey and Liu 2018, 2019).

of all funds) have significantly positive (average) alphas and 229 funds (9%) have significantly negative alphas. Huang et al (2019) using the FFC4 model with time varying alphas and betas (Ferson and Schadt 1996, Christopherson et al 1998) find that up to 8% of US equity mutual funds have statistically significant positive alphas (after correction for false discoveries)[3]. Cross-section studies have also found that characteristics of funds such as expense ratios, fund size, board composition and characteristics of managers such as relative age and academic qualifications, influence *relative* (alpha) performance[4]. Broadly similar results suing the FFC4 model are found for UK equity funds (Blake and Timmermann 1998, Cuthbertson et al 2008, 2010).

Cremers (2017) and Cremers et al (2019) in a wide-ranging survey of US fund performance label the finding of few positive alpha funds as the "conventional wisdom" - but they argue that recent studies suggest that the conventional wisdom is "too negative".

2.1 Performance Persistence

There are typically two methodological approaches to measuring performance persistence: a multivariate regression approach and a recursive portfolio sorting approach. In the first, either a Fama-MacBeth (1973) cross-section rolling regression or a panel data approach is used. In the second, funds are typically sorted into fractiles (e.g. deciles) based on an attribute under examination (e.g. past performance) and periodically rebalanced over a specific holding period (e.g. monthly). Post-sort returns are then used to assess future performance. Alphas can be measured using *gross fund returns*[5] while investors earn *net returns* (i.e. gross returns after deduction of fund management fees)[6].

The multivariate regression approach can provide some indication of a number of key characteristics that may be important in deciding on appropriate "sorting rules" for the recursive portfolio approach. But actually implementing the latter approach is the only way to test whether a particular ex-ante strategy could have been successful (on past data), for investors switching between funds[7].

2.2 Fama-French-Carhart Factors

[3] Andrikogiannopolou and Papakonstantinou (2019) note the low power to detect nonzero-alpha funds when using the FDR approach on mutual fund data with a low signal-to-noise ratio and Ma et al. (2021) apply the functional FDR to improve power.

[4] See, inter alia Pastor et al (2015), Zhu (2018), Adams et al (2018), and Bai et al (2019). But compensation arrangements do not seem to influence FFC4 model net or gross alphas (Ma et al 2019).

[5] After transactions costs of buying and selling securities but before deduction of management fees.

[6] Net returns exclude any load fees and any income or capital gains taxes applicable to the individual investor.

[7] We discuss switching costs later in the paper.

Using the "academic" FFC4 model, persistence in MF alpha-performance uses a wide variety of sorting rules. These include, fund sorts based on past fund returns, benchmark-adjusted returns, alphas and t-alphas[8]. Other sorting rules include fund size (Cremers and Pareek 2016), active share (Cremers and Petajisto 2009, Frazzini et al 2016, Petajisto 2016), industrial concentration (Kacperczyk et al 2005), turnover (Pastor et al 2017), "unobserved actions" (Kacperczyk et al 2008), R-squared (Amihud and Goyenko 2013), 'word of mouth' (Hong et al 2005), 'commonality in holdings' (Cohen et al 2005), public information (Kacperczyk and Seru 2007), patient capital, (Cremers and Pareek 2016), gross profitability (Kenchington et al 2019), efficiency of trading desks (Cici et al 2018), herding behavior (Jiang and Verardo 2018) and past cash inflows (i.e. the smart money effect, Zheng 1999, Sapp and Tiwari 2004, Keswani and Stolin 2008, Akbas et al 2015)[9]. These are usually single sorts but sometimes double sorts on two attributes are used[10]. As the number of possible rules for predicting fund returns is very large, issues of data mining and data snooping come to the fore.

Kosowski et al (2006), for example, apply a cross-section bootstrap, ranking on past 36-month alpha. For the FFC4 model on US data they find the top decile exhibits persistence with annual rebalancing to give a net-alpha of 1% p.a. (bootstrap p-value = 0.05). At the bottom of the performance distribution, deciles 6-10 have significantly negative abnormal performance (of about -1% p.a. for deciles 6-9 and -3.5% for decile-10).

More recent US studies (Jordan and Riley 2016) have added the Fama and French (2015, 2016, 2017) pricing factors for profitability (RMW, "robust minus weak") and investment (CMA, "conservative minus aggressive") to the FFC4 four factor model, giving a six-factor model (FFC6). Using daily data (January 2000 - December 2014), sorting on the previous year's alpha and using a holding period of one year, they find that the move from the FFC4 model to the FFC6 model, leads to a dramatic change in the net-alpha of the top-5% US winner funds, from a statistically insignificant negative value to a positive 3.73% p.a. (t-alpha = 3.44).

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8 Past returns, alphas or t-alphas are perhaps the most widely used sorting rules in early work (e.g. Carhart 1997, Blitz and Huij 2012) and their use continues to today. For example, Choi and Zhao (2020) and Riley (2019) report a decline in top-decile alpha performance when using the Carhart (1997) 4-factour model as the data period is extended to 2018. Blake and Morey (2000) sort on Morningstar 5-star ratings.

9 In some of these studies only results for the future alphas (or returns) of the long-short sorted portfolios (i.e. top fractile funds minus bottom fractile funds) are reported. As mutual funds cannot be shorted, it is not clear if such results are exploitable by investors.

10 For example, Bessler et al. (2018) sort on the size of fund inflows ("external governance") and change in fund manager ("internal governance") while Cremers and Petajisto (2009) sort on active share and fund size.

It is also the case (Jordan and Riley, 2015) that sorting MFs based on their previous year's return volatility (and rebalancing each year) gives a positive (net of fees) alpha when using the FFC4 model, but the alpha "disappears" when using the FFC6 model. Hence, incorporating the profitability (RMW) and investment (CMA) factors in the FFC6 model, negates the so-called "volatility anomaly" found in the asset pricing literature (Frazzini and Pederson 2013, Novy-Marx 2014, Fama and French 2015, 2016). Fama and French (2018) also give qualified but relatively strong support to the FFC6 factor "base model" over several competitors, as providing a good empirical risk-based asset pricing model[11]. The evidence strongly implies that any tests of the abnormal performance of US mutual funds using academic factors should include the profitability (RMW) and investment (CMA) factors.

2.3 Non-Zero Passive Benchmark Alphas

In the MF performance literature, the problem of finding non-zero alphas when applying the academic FFC4 model with factors F to *passive* benchmark indices (e.g. $R_b =$ S&P500) has been addressed in two other ways. The first approach "adjusts" the estimated FFC4 alpha α_{FFC4} using the estimated non-zero benchmark-alpha α_b (where $R_b = \alpha_b + \pi F + v$) giving a true $\alpha = \alpha_{FFC4} - \alpha_b$ (Angelidis et al 2013, Chinthalapati et al 2017, Mateus et al 2016). Clearly, if the MF benchmark-alpha is positive (negative) then the true-alpha is smaller (larger) than the MFs standard FFC4 alpha. To implement this approach a 'true' benchmark needs to be chosen and as Sensoy (2009) demonstrates, a fund's self-declared benchmark is changed infrequently (in a fund's prospectus) and it rarely indicates the true exposure of a fund to common risk factors. Therefore, in our analysis we do not adjust our estimated fund alphas to take account of a somewhat arbitrarily chosen self-declared benchmark of the fund. Instead, we examine alternative multifactor models which have been shown to largely avoid non-zero benchmark alphas, with respect to a wide range of passive indices (Cremers et al 2013).

The second approach (Mateus et al 2016) to correct for non-zero benchmark alphas uses a constrained optimization procedure to alter the *time series* of the original FFC4 factors F to ensure that the *benchmark-alph*a α_b is zero. Although the method has the desirable property that it forces $\alpha_b = 0$, it implicitly assumes that the FFC4 model is the correct maintained hypothesis and the resulting time-series of adjusted-FFC4 factors constitute the 'true' factors. But each arbitrarily chosen single benchmark (eg. S&P500, or Russell 2000)

[11] Fama and French (2018) include a momentum factor "to satisfy insistent popular demand", even though it lacks "theoretical motivation".

will give a different adjusted FFC4 factor time-series and a different "true" fund-alpha. Hence the method does not obviate the need to find a set of true factors.

On US data, using either of the above two benchmark-alpha adjustments does not make a substantial qualitative difference to individual fund performance, compared to using the standard FFC4 factors. Overall, the adjusted US fund-alphas are mainly significantly negative, indicating unskilled managers.

2.4 Index Models

Investment practitioners interpret alpha primarily in terms of outperformance relative to passive index style-factors that can either easily be replicated by individual investors themselves or by purchasing index funds directly (Sharpe 1992). The problem in using the FFC4 academic factors is that mainstream passive portfolios (e.g. S&P500, Russell 2000) give non-zero alphas and also these academic factors are not net of transactions costs of replication incurred by investors (Cremers et al 2013).

Ideally, any passive index-based factors should represent tradable assets with returns measured net of any costs, payable by the investor (e.g. returns to ETFs which are net of any management and administrative fees). This is the approach behind the Cremers et al (2013) four factor and seven factor "index-based models" ("IDX4" and "IDX7") which use commonly available easily tradeable indices (except for the momentum factor). Unlike the Fama-French academic factors, these indices generally have zero alphas with respect to a wide range of passive indices and style-sorted stock portfolios (e.g. stocks sorted on size or BMV). These index models also have higher R-squared and lower tracking errors than the FFC4 model, for the time series of MF returns.

Hence, recent literature implies that the academic FF6 model is an improvement on the FFC4 factor model and the main alternative candidate practitioner index-based model is the Cremers et al (2013) IDX7 model.

The persistence literature cited above (mainly using decile portfolios and the FFC4 factor model) indicates at best a few statistically significant positive (net) alpha funds, when using short holding periods of up to one year. To our knowledge, there are no recent studies examining positive persistence in MF portfolios, with respect to small versus large portfolios, different formation and holding periods and different factor models, using bootstrap t-values.

2.5 Bootstrap Procedure

We use a bootstrap procedure to test for persistence in alpha performance given the non-normality in the residuals of our factor models (particularly those in the extreme tails of the performance distribution across funds). First, using actual data on all individual fund returns $R_{i,t}$ at time *t*, we sort funds into equally weighted portfolios of size-k based on the t-statistic of alpha estimated over the previous *f* months formation period. Each size-k portfolio is held for *h* month and the process is repeated on an h-month rolling basis. This gives a single time series of actual holding period returns $R_{k,t}\,(t=1,2,3...T)$ which are then used to obtain the estimated t-statistic of alpha $\hat{t}_k$ for each "persistence-portfolio" of size-k, from our factor models.

Bootstrap p-values are obtained as follows. First, we generate simulated returns for all funds $\tilde{R}_{i,t}^{(B=1)}$ $(i=1,2,3...n \text{ and } t=1,2,3...T_i)$ under the null of zero alphas. Using T_i observations on each fund we estimate the factor model and save the vectors $\{F_t, \hat{\beta}_i, e_{i,t}\}$. Next, for each fund-i draw a random sample (with replacement) of length T_i from the residuals $e_{i,t}$, (which may be non-normal). Use these *re-sampled* bootstrap residuals $\tilde{e}_{i,t}$ (and their corresponding F_t values), to generate a simulated return series $\tilde{R}_{i,t}^{(B=1)}$ for fund-i, under the null hypothesis α_i = 0 that is, $\tilde{R}_{i,t}^{(B=1)} = 0 + \hat{\beta}_i' F_t + \tilde{e}_{i,t}$. Hence the simulated returns for each fund-i have zero alphas and exhibit no "alpha-persistence" by construction. Next, using the simulated returns data, we sort funds into a "persistence-portfolio" of size-k (for a specific f, h combination) and roll over the portfolio every h-periods. This gives a single time series of simulated holding period returns $\tilde{R}_{k,t}^{(B=1)}\,(t=1,2,3...T)$ which are then used with our factor model to obtain a simulated t-statistic of alpha $\tilde{t}_k^{(B=1)}$ which represents sampling variation around a true alpha of zero (by construction) and is entirely due to 'luck'[12]. This process is repeated B = 1,000 times which gives a 'luck distribution' $f(\tilde{t}_k)$ for each size-sorted "persistence-portfolio" of funds, under the null of no alpha-persistence. We then compare the actual t-statistic of alpha $\hat{t}_k$

12 t_{α_i} is a "pivotal statistic" and has better sampling properties than α_i - the obvious reason being that the former 'corrects for' high risk-taking funds (i.e. σ_{ε_i} large), which are likely to be in the tails (Kosowski et al 2006, Fama-French 2010, Ayadi & Kryzanowski, 2011). If different funds have different distributions of idiosyncratic risk (e.g. different skewness and kurtosis) then we cannot say a priori what the distribution of $f(t_{\alpha_i})$ will be.

(using the *actual* returns data) with its ‘luck distribution’, $f(\tilde{t}_k)$. If $\hat{t}_k$ is greater than the 5% upper tail cut-off point of $f(\tilde{t}_k)$, we reject the null of no performance persistence (at 95% confidence) and infer that the sorting rule gives a true positive alpha-persistence.

A key element of the approach is that we do *not assume* the estimated alpha for each fund is normally distributed. Each fund’s alpha can follow any distribution (depending on the fund’s residuals) and this distribution can be different for each fund. Hence the distribution under the null of zero alpha-persistence $f(\tilde{t}_k)$, encapsulates the individual fund’s empirical ’luck distribution’.

3. DATA

Our US fund data set comprises 2,183 US equity mutual funds from Morningstar. These are US domiciled within the US investment area. Funds are categorised as small-cap, mid-cap and large-cap oriented funds and as value stock, growth stock and blend funds. Index tracking funds are excluded. Our sample includes 1,138 non-surviving funds. Returns are total monthly returns net of management fees. We include the oldest share class of each fund. Our sample period runs monthly from January 1990 to October 2021. The number of funds ranges from a low of 390 funds in January 1990 to a high of 2,113 funds in April 2007. The average month has 1,288 funds. The cross-sectional average fund return over time (i.e. an equally weighted portfolio of all funds) ranges from a low of -18.65% pm in October 2008 to a high of +13.5% pm in April 2020 with a standard deviation of 4.49%. The worst performing (raw return) fund has a time series average return of -2.81% over 33 monthly observations while the best performing fund has a time series average return of 2.00% over 23 monthly observations. There is a positive correlation coefficient of 0.64 between a fund’s time series average raw return and its history length (i.e., number of monthly observations). At the end of the sample period, the average fund management fee is 0.72%, the average annual net expense ratio is 1.18% and the average fund size is $4.85bn.

In our factor model estimation, we source the US Fama-French market, size, value, profitability, investment and momentum benchmark factors from Kenneth French’s data library[13]. Excess fund returns are calculated over the one-month Treasury bill rate. In the seven-factor index model we use returns on the S&P500 (S5), Russell Midcap (RM), Russell 2000 (R2), S&P500 Value (S5V), S&P500 Growth (S5G), Russell Midcap Value (RMV),

[13] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Russell Midcap Growth (RMG), Russell 2000 Value (R2V) and Russell 2000 Growth (R2G), respectively. The indices are sourced from Datastream.

4. Empirical Results

4.1 Decile Sorted Portfolios: (f,h) = (60,1)

In this section we report results for decile sorted portfolios for our two key models (FFC6 and IDX7) over the full data period January 1990 – October 2021.

Table 1 provides results for the FFC6 model, after sorting funds into deciles based on past t-alpha and using (f,h) = (60,1)[14]. Top decile funds (decile-1) have high factor weightings on small stocks and growth stocks relative to the bottom decile funds (decile-10) but the market return betas are similar across all deciles. The momentum factor (UMD) is statistically insignificant for all portfolios except for the top decile (in contrast to studies using data ending in 2000 or earlier). The profitability variable RMW is highly statistically significant except for decile-3 and the investment factor CMA is only statistically significant for the top three decile portfolios. The RMW beta for the top (decile-1) portfolio is -0.149 (t = -4.8) and for the bottom decile is 0.163 (t = 5.8) indicating that the upper deciles have a higher weighting on weak profitability stocks. For the FFC6 model there is a relatively small and just significant positive alpha of 1.07%pa (t=1.8) for the top decile and strongly statistically significant negative alphas for deciles 4-10, with the bottom decile having an alpha of -2.17 %pa (t = -3.9)[15].

[Table 1 here]

Decile results for the seven-factor index model (IDX7) in Table 2 (final column) show that the index-betas are statistically different for the top (decile-1) and bottom (decile-10) fund portfolios in all cases except for the S&P500 value minus growth index (S5V-S5G) and for some deciles for the momentum factor. The top minus bottom decile alpha of 3.0%p.a. (t = 4.2, Table 2, final column) is the result of 0.91%p.a. (t = 1.76) for the top-decile fund and -2.1%pa (t =-4.3) for the bottom-decile fund.

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14 Results for alternative values of (f,h) are discussed later.

15 Given the statistical importance of the omitted profitability factor RMW we are inclined to give more weight to the FFC6 model than for the FFC4 model and to avoid presenting too large a volume of results, we do not tabulate the latter results here. The FFC4 model results are broadly similar to the FFC6 model. The top decile FFC4 alpha is positive but insignificant. In the FFC6 model the RMW beta for the top (decile-1) portfolio is -0.122 (t = -3.8) and this results in a change in alpha as we move from FFC4 model to the FFC6 model. Full results are available on request.

As in previous studies, both the FFC6 and the IDX7 model provide weak evidence of positive persistence but strong evidence of negative alpha-persistence for past loser funds – although as you cannot short-sell MFs the latter result in not exploitable by investors[16].

[Table 2 here]

4.2 Small Portfolios: (f, h) = (60,1)

We now sort funds into alternative small fixed-size portfolios S_i (consisting of $i = 2, 3, 5, 7, 10, 20, 35, 50$ funds) for (f, h) =(60,1), based on the t-alpha of the top performing funds and repeat the above robustness tests – again presenting results for our two key models FFC6 and IDX7.

For the FFC6 model (Table 3), all the small-size fund portfolios have negative statistically significant profitability-betas (RMW) and investment-factor betas (CMA), reinforcing the additional explanatory power over original FFC 4-factor model. Based on bootstrap p-values there are statistically significant positive alphas (at the 5% significance level) for portfolios of top funds in the range 1.3-2.9% pa for all of these small-size portfolios. (except for sizes 5 and 7 which are significant at the 10% significance level).

[Table 3 here]

Similarly, the seven-factor index model IDX7 (Table 4) gives positive significant alphas, in the range 0.8-1.8%pa for all small-size portfolios with more than 5 funds in the portfolio. For the IDX7 model it is noticeable that the momentum (UMD) betas are all statistically zero for these small "winner portfolios".

[Table 4 here]

4.3 Formation/Holding Periods:
Top-Decile and Top-Small Portfolios. Net of (Management) Fee Alphas

Here we examine robustness results over alternative formation and holding periods (f, h). From Table 5, when using the *top-decile portfolio* sorted on past t-alphas, the bootstrap

[16] As the Cremers et al (2013) IDX4 model is largely a subset of the IDX7 model, we do not present the former results here in order to conserve space. In these results not shown, however, when the three value-minus-growth indices of the IDX7 model are subsumed into one value-minus-growth index in the IDX4 model, the results for the decile sorted portfolio alphas are qualitatively unchanged.

p-values indicate persistence at the 5% significance level for both the FFC6 and IDX7 models for most combinations of (f, h) with some evidence that shorter formation and holding periods give higher persistence-alphas than for larger values of (f, h) combinations. (The table presents the annualized alphas with statistical significance using bootstrap p-value at a 5% significance level indicated by **). Hence, for *decile sorted* portfolios we find evidence to support Cremers et al (2019) view that with more recent data it is possible to detect positive performance.

[Table 5 here]

When sorting into small portfolios there are 8 size portfolios x 8 combinations of (f, h) giving 64 combinations for any one factor model. For both the FFC6 model (Table 6) and the IDX7 index model (Table 7) we see positive persistence in the (net) alphas of small-size portfolios across many combinations of (f, h). Again, the tables report annualized portfolio alphas with bootstrap p-values at the 1%, 5% and 10% significance levels indicated by ***, ** or * respectively.

[Table 6 here]
[Table 7 here]

For the FFC6 model, there are 38 (out of 64) combinations (at a 10% significance level) that indicate positive persistence (Table 6) and 54 (Table 7) for the IDX7 index model. For both models a small-size portfolio (of around 5 or more funds) gives statistically significant net-alphas for most (f, h) combinations, (except for those portfolios with longer holding periods h=12).

Table 6 (FFC6 model) and Table 7 (IDX7 model) also indicate that for all of these small-size portfolios, point estimates of the alphas generally decline as the holding period increases from h = 1 month to h = 12 months, (for both formation periods f = 36 and f = 60). For example, for a size-5 portfolio the IDX7 model (Table 7) with for (f,h) = (36,1) has a statistically significant alpha of 2.059% p.a. but for (f,h) = (36,12) the alpha is 0.849%pa and not statistically different from zero. In fact for (f,h) = (36,12) and (f,h) = (60,12) many of the alphas are statistically zero for both factor models.

Finally, for both factor models the size of the alphas tends to decline as more funds are included in the portfolio (for any given f, h combination). For example, for the IDX7 model

(Table 7) for (f,h) = (36,1) the statistically significant persistence-alpha is 2.16% p.a. for a 2-fund portfolio and 1.52% for a size-50 portfolio.

Recursive Estimates: IDX7 Model

So far our analysis has used only the full data set. But investors in MFs should be concerned about the robustness over time of any potentially positive statistically significant (net) alphas, with respect to both different size portfolios and different combinations of formation and holding periods. This mitigates (although does not eliminate) the problem of false discoveries[17]. We illustrate these issues with the IDX7 model[18].

Figure 1 shows recursive estimates of alpha and t-alpha for the IDX7 model for a portfolio comprising the top-5 funds for various combinations of formation and holding periods. For the size-5 portfolio, over time the alphas are positive and becoming fairly constant (brown line) and are also becoming increasingly statistically significant (blue line) for all formation and holding periods, *f,h*.

[Figure 1 here]

We now take (f,h) = (36,1) for the IDX7 model and examine its performance as we alter the *number* of funds in the portfolio. Figure 2 shows constant alphas over time becoming increasingly statistically significant. Overall, these recursive estimates support the use of relatively small-size portfolios. The resulting alphas are reasonably constant over time and retain their statistical significance[19]. This information should be of use to investors looking to exploit persistence in performance using relatively simple yet robust sorting rules.

[Figure 2 here]

Switching Costs

As in extant studies, transactions costs of switching between funds at rebalancing periods is not explicitly covered in our analysis. For investors, switching funds may involve purchase and redemption fees (possibly reflected in the bid-ask spread), as well as

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17 There are insufficient estimates of alpha to calculate the false discovery rate.

18 In the interests of brevity we report these robustness variants only for the IDX7 model but results using the FFC6 model are qualitatively similar and are available on request.

19 Cai et al (2018, Table 5) using a non-parametric estimate of the average fund alpha (which varies over time), find evidence for very few positive alpha funds using the FFC4 factor model. But they only consider results from FFC4 and a CAPM model (using the Vanguard 500 index as the single benchmark) and find differing results for these two models (see their Table 5). Also, they examine at ex-post performance not ex-ante persistence in performance.

commissions (broker or platform fees) and "ticket fees" (commissions) - these costs are set out in each individual prospectus and on the specific platform used. There are also other potential switching costs (e.g. search costs, advisory fees) as well as potential capital gains taxes (e.g. in the US, via the 1099-DIV form). For some (but not all) retail investors and more so for institutional investors (e.g. pension funds and insurance companies), some of these switching costs may be relatively small.[20]

Given that our sorting rule uses only a small number of MFs, switching costs are likely to be lower than if decile sorts are used, where more funds are likely to be rebalanced each period. (Of course, any trading costs due to the fund manager are already taken care of in the returns series based on NAVs and our fund returns are also net of management fees).

Nevertheless, it is interesting to examine the degree of rebalancing within the different size portfolios and over alternative holding periods. In Table 8, for each size portfolio we report the number of switches Ns in the composition of the portfolio (figures are averages per year). Not surprisingly, for any given values of *f,h* the number of fund switches increases with portfolio size, Np. Also, for fixed portfolio sizes, the number of switches decreases over longer holding periods. These results are essentially the same in the case of both the FFC6 and IDX7 results in panel A and panel B respectively.

[Table 8 – here]
[Table 9 – here]

The alpha after switching costs (αASC, %pa), which accrues to investors, is αASC = alpha - c (Ns / Np). This depends on the pre-switching "alpha" and is also proportional to the number of fund-switches per year (Ns) relative to the number of funds held in the "persistence portfolio" (Np).[21] Table 9 reports the values of Ns/Np. This ratio falls relatively slowly as the number funds in the persistence portfolio Np increases. This implies that dollar switching costs will not vary substantially as the portfolio size Np increases for any given *f,h* combination.

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20 For example, for institutional investors and (retail) brokerage accounts, "breakpoint discounts" usually reduce front-end load charges as the size of MF purchase increases. For "fund-switches", load charges are zero if traded in an "advisory account" or if held in a brokerage account as load-waived A-class shares. For fund switches, "exchange fees" usually do not apply within fund families and No Transaction Fee ("NTF") platforms are increasingly common – see www.finra.org and www.investor.gov for details provided by the Securities and Exchange Commission, SEC).

21 αASC is calculated as follows: Consider an investment of NAV = $100,000 held in a portfolio of size Np = 5 funds. The dollar amount switched per fund is $20,000 (= NAV/Np) and for Ns = 10 funds switched per year, the dollar amount switched per year is $200,000 [= (NAV/Np) Ns]. If the cost per dollar switched c = 0.5% then the dollar switching cost per year is $1000 [= c (NAV / Np) Ns]. Hence given the estimated pre-switching cost alpha (% pa) then αASC = { alpha x NAV – c (NAV / Np) Ns } / NAV = alpha – c(Ns / Np).

As Table 8 shows, for any given fund size Np, the number of switches per year (Ns) declines as the holding period *h* increases from *h* = 1 to *h* = 12 (months). There is also a decline in Ns/Np (Table 9) which implies that switching costs will fall as the holding period lengthens.

[Table 10 – here]

In Table 10 we report the break-even costs c(bps) to achieve positive αASC for investors, for various fund sizes and fund holding periods[22]. To illustrate, for the IDX7 model, for *f* = 36 and *h* = 1,3 or 6, pre-switching alphas (Table 7) are statistically well determined for all of our small-size portfolios. For *h* = 1,3 and 6 (and all values of Np) switching costs less than 61 bps ensures positive αASC for all values of Np. Table 10 shows that for any fixed size portfolio (Np), break-even switching costs can be higher as the holding period *h* is extended from *h* = 1 to *h* = 6. For example, for Np = 5 funds, switching costs must be less than 98 bps for *h* = 1 but may be as high as 215 bps for *h* = 36. For (*f,h*) = (36,12) most of the pre-switching alphas are not statistically well determined and hence the corresponding break-even switching costs in Table 10 are not meaningful.

5. CONCLUSIONS

We have examined the robustness of positive persistence in mutual fund performance using monthly data (January 1990-October 2021) for different factor models, different size portfolios, different formation and holding periods (f,h) and using a bootstrap procedure for tests on alpha, which takes account of non-normality in mutual funds' specific risk.

As with previous studies we find a statistical difference in the net-alphas of top and bottom performing *decile-sorted* funds. As mutual funds cannot be short-sold, a long-short strategy cannot be implemented to exploit this difference in alphas and often the rather weak inference is for investors to avoid poor past performing funds. Hence, unless we can find persistent positive net-alpha funds, investors cannot benefit from a persistence strategy. In this paper we therefore focus on tests for positive persistence in performance for small-size portfolios of mutual funds.

We find that sorting funds (by t-alpha) into relatively small portfolios (of up to 50 funds), reveals substantial positive persistence with statistically significant positive net-alphas for many combinations (f,h). This evidence weakens slightly over longer holding periods,

[22] As αASC = alpha – c(Ns/Np), the break-even switching cost is, c = alpha x (Np/Ns).

particularly up to 12 months. Our findings are generally consistent between academic factor models and practitioner index models. We also report that switching costs of less than around 60 basis points ensures positive after-switching-cost alphas over all portfolio sizes.

Overall, our results provide support for positive net-alpha persistence for small portfolios of past winner funds (sorted on their t-alphas), with larger post-sort positive net-alphas for relatively small size portfolios and for relatively short holding periods of up to 6 months. Hence, forming persistence portfolios with a small number of funds provides a relatively simple way for investors to obtain positive net-alphas rather than searching over many alternative sorting rules or using multiple sorting criteria.

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Table 1: Performance Persistence: Decile Portfolios –Fama-French-Carhart Six-Factor (FFC6) Model, (f,h = 60,1)

This table presents the performance persistence results of decile sorted mutual funds. Each month funds are sorted into equally weighted decile portfolios based on the t-statistic of alpha from a Fama-French-Carhart six-factor (FFC6) model estimated over the previous 60 months formation period. Each decile portfolio is held for a one month holding period and the process is repeated on a one month rolling basis. A time series of holding period returns is generated for each decile and the FFC6 model is estimated in each case over the holding period returns. The table shows the alpha (%pa) and factor loadings (betas) for each of these decile regressions. Also shown are the alpha and betas of (i) an equally weighted portfolio of all funds, denoted “All Funds” and (ii) a portfolio of the top decile minus the bottom decile of funds, denoted “Decile 1 – 10”. t-statistics are shown in parentheses. In the case of decile alphas we also report the bootstrap p-value of the t-statistic of alpha in square brackets. Newey-West adjusted t-statistics are calculated throughout. Rm, SMB, HML, RMW, CMA and UMD refer to the market, size, value, profitability, investment and momentum risk factors respectively. Rm is measured in excess of the risk free rate. Also shown are the R^2 values as well as the Jarque-Bera (JB) test statistic of the null hypothesis that the regression residuals follow a normal distribution (p-values in brackets). Results relate to the sample period January 1990 – October 2021..

Portfolio	All Funds	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	Decile 1-10
Alpha	-0.480	1.070	0.266	-0.576	-1.117	-1.418	-1.584	-1.018	-1.640	-2.113	-2.172	3.240
	(-1.184)	(1.833)	(0.526)	(-1.099)	(-2.092)	(-2.533)	(-3.066)	(-1.868)	(-3.056)	(-4.049)	(-3.899)	(4.762)
		[0.007]	[0.167]	[0.778]	[0.978]	[0.988]	[0.998]	[0.935]	[0.999]	[1.000]	[1.000]	
Rm	0.978	0.993	0.989	0.985	0.983	0.982	0.983	0.977	0.976	0.982	0.978	0.014
	(86.061)	(65.651)	(75.634)	(74.268)	(69.604)	(62.010)	(64.767)	(64.255)	(63.844)	(65.340)	(62.856)	(1.010)
SMB	0.229	0.242	0.218	0.218	0.212	0.194	0.203	0.209	0.223	0.199	0.159	0.082
	(16.784)	(11.195)	(10.486)	(11.578)	(11.631)	(9.520)	(11.908)	(14.611)	(15.113)	(12.029)	(8.232)	(4.212)
HML	0.046	-0.099	-0.056	-0.016	0.029	0.060	0.083	0.098	0.122	0.149	0.162	-0.261
	(2.337)	(-4.236)	(-2.714)	(-0.736)	(1.283)	(2.467)	(3.375)	(3.802)	(4.371)	(5.060)	(5.488)	(-10.883)
RMW	0.033	-0.149	-0.075	-0.034	0.051	0.090	0.104	0.082	0.083	0.140	0.163	-0.313
	(1.999)	(-4.778)	(-2.875)	(-1.318)	(2.254)	(3.572)	(5.181)	(4.321)	(3.933)	(6.511)	(5.805)	(-12.011)
CMA	-0.052	-0.102	-0.085	-0.061	-0.029	-0.027	-0.013	-0.026	-0.020	-0.001	0.011	-0.113
	(-2.126)	(-3.036)	(-2.983)	(-1.926)	(-0.979)	(-0.867)	(-0.408)	(-0.948)	(-0.725)	(-0.054)	(0.373)	(-3.270)
UMD	0.006	0.039	0.013	0.004	0.001	-0.011	-0.010	-0.011	0.004	-0.007	-0.016	0.055
	(0.573)	(2.057)	(0.876)	(0.301)	(0.093)	(-0.756)	(-0.702)	(-0.870)	(0.303)	(-0.494)	(-1.000)	(4.695)
R^2	0.986	0.975	0.979	0.980	0.981	0.977	0.979	0.982	0.982	0.980	0.977	0.772
JB	325.00	58.60	40.85	74.24	73.99	83.16	83.24	166.30	165.10	58.28	88.66	54.56
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

For 77% of the funds, we reject the null hypothesis of normally distributed residuals.

Table 2: Performance Persistence: Decile Portfolios – Seven-Factor Index (IDX7) Model, (f,h = 60,1)

This table presents the performance persistence results of decile sorted mutual funds. Each month funds are sorted into equally weighted decile portfolios based on the t-statistic of alpha from the Cremers et al. seven-factor index (IDX7) model estimated over the previous 60 months formation period. Each decile portfolio is held for a one month holding period and the process is repeated on a one month rolling basis. A time series of holding period returns is generated for each decile and the IDX7 model is estimated in each case over the holding period returns. The table shows the alpha (%pa) and factor loadings (betas) for each of these decile regressions. Also shown are the alpha and betas of (i) an equally weighted portfolio of all funds, denoted "All Funds" and (ii) a portfolio of the top decile minus the bottom decile of funds, denoted "Decile 1 – 10". T-statistics are shown in parentheses. In the case of decile alphas we also report the bootstrap p-value of the t-statistic of alpha in square brackets. Newey-West adjusted t-statistics are calculated throughout. S5, RM, R2, S5V, S5G, RMV, RMG, R2V, R2G refer to returns on the S&P500, Russell Midcap, Russell 2000, S&P500 Value, S&P500 Growth, Russell Midcap Value, Russell Midcap Growth, Russell 2000 Value and the Russell 2000 Growth indices respectively. S5 is measured in excess of the risk free rate. UMD refers to the momentum risk factor. Also shown are the R^2 values as well as the Jarque-Bera (JB) test statistic of the null hypothesis that the regression residuals follow a normal distribution (p-values in brackets). Results relate to the sample period January 1990 – October 2021.

Portfolio	All Funds	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	Decile 1-10
Alpha	-0.132	0.914	0.504	-0.456	-0.336	-0.528	-0.744	-0.504	-1.788	-1.644	-2.136	3.048
	(-0.532)	(1.762)	(1.398)	(-1.224)	(-0.972)	(-1.569)	(-2.292)	(-1.438)	(-4.509)	(-3.741)	(-4.297)	(4.246)
		[0.003]	[0.009]	[0.723]	[0.630]	[0.843]	[0.958]	[0.762]	[1.000]	[1.000]	[1.000]	
S5	0.964	0.924	0.940	0.957	0.970	0.969	0.989	0.985	1.002	1.000	1.007	-0.083
	(129.531)	(75.166)	(123.266)	(106.357)	(93.408)	(106.681)	(116.154)	(106.978)	(101.352)	(82.095)	(90.954)	(-5.472)
RM-S5	0.578	0.671	0.630	0.594	0.578	0.585	0.588	0.574	0.548	0.500	0.455	0.216
	(35.132)	(17.635)	(28.965)	(23.552)	(22.873	(29.477)	(28.898)	(31.145)	(19.898)	(16.627)	(14.085)	(5.522)
R2-RM	0.224	0.292	0.289	0.215	0.204	0.221	0.173	0.177	0.160	0.148	0.148	0.144
	(14.757)	(9.584)	(16.228)	(10.922)	(10.887)	(14.449)	(9.443)	(12.068)	(10.338)	(7.157)	(8.020)	(4.621)
S5V-S5G	0.010	0.008	-0.000	-0.003	0.001	-0.005	-0.003	0.008	0.001	-0.008	-0.026	0.035
	(0.786)	(0.274)	(-0.020)	(-0.166)	(0.052)	(-0.299)	(-0.170)	(0.459)	(0.087)	(-0.405)	(-1.036)	(0.983)
RMV-RMG	-0.036	0.029	-0.039	-0.033	-0.019	0.005	-0.030	-0.030	-0.015	-0.028	-0.051	0.081
	(-2.122)	(0.766)	(-1.718)	(-0.936)	(-0.712)	(0.195)	(-1.531)	(-1.628)	(-0.637)	(-1.066)	(-2.072)	(1.947)
R2V-R2G	-0.037	-0.144	-0.075	-0.051	-0.017	-0.026	-0.004	-0.000	0.019	0.023	0.042	-0.187
	(-2.141)	(-3.983)	(-3.122)	(-1.964)	(-0.687)	(-1.336)	(-0.182)	(-0.014)	(0.712)	(0.859)	(1.297)	(-4.231)
UMD	0.009	-0.001	0.015	-0.009	0.001	0.019	0.017	0.017	0.005	-0.006	0.002	-0.003
	(1.812)	(-0.085)	(2.237)	(-0.951)	(0.185)	(2.286)	(2.576)	(2.426)	(0.631)	(-0.812)	(0.208)	(-0.222)
R^2	0.993	0.977	0.989	0.989	0.990	0.990	0.990	0.990	0.989	0.987	0.984	0.363
JB	26.83	31.43	9.75	86.11	25.34	39.40	40.28	33.80	37.95	136.18	196.37	87.47
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

For 73% of the funds, we reject the null hypothesis of normally distributed residuals

Table 3: Performance Persistence: Small Size Portfolios - Fama-French-Carhart Six-Factor (FFC6) Model, (f,h = 60,1)

This table presents the performance persistence results of portfolios of mutual funds sorted by various size portfolios. Each month funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from a Fama-French-Carhart six-factor (FFC6) model estimated over the previous 60 months formation period. Each size portfolio is held for a one month holding period and the process is repeated on a one month rolling basis. A time series of holding period returns is generated for each size portfolios and the FFC6 model is estimated in each case over the holding period returns. The table shows the alpha (% pa) and factor loadings (betas) for each of these size portfolios regressions. t-statistics are shown in parentheses. Newey-West adjusted t-statistics are calculated throughout. In the case of alpha we also report the bootstrap p-value of the t-statistic of alpha in square brackets. Rm, SMB, HML, RMW, CMA and UMD refer to the market, size, value, profitability, investment and momentum risk factors respectively. Also shown are the R^2 values as well as the Jarque-Bera (JB) test statistic of the null hypothesis that the regression residuals follow a normal distribution (p-values in brackets). Rm is measured in excess of the risk free rate. Results relate to the sample period January 1990 – October 2021.

Portfolio	Size 2	Size 3	Size 5	Size 7	Size 10	Size 20	Size 35	Size 50
Alpha	2.503	2.928	1.632	1.368	1.428	1.632	1.404	1.428
(t-stat)	(1.854)	(2.519)	(1.717)	(1.469)	(1.796)	(2.292)	(2.155)	(2.219)
[p-value]	[0.045]	[0.008]	[0.053]	[0.077]	[0.049]	[0.007]	[0.005]	[0.006]
Rm	1.050	1.011	1.010	1.004	0.999	0.990	1.000	0.995
	(27.447)	(34.079)	(35.925)	(37.926)	(44.334)	(45.907)	(52.963)	(54.492)
SMB	0.363	0.362	0.333	0.312	0.279	0.253	0.254	0.258
	(6.031)	(9.837)	(11.345)	(11.222)	(10.289)	(9.226)	(10.163)	(10.953)
HML	-0.249	-0.203	-0.181	-0.178	-0.148	-0.136	-0.135	-0.137
	(-4.637)	(-4.724)	(-4.862)	(-5.196)	(-4.789)	(-4.240)	(-4.815)	(-5.266)
RMW	-0.353	-0.365	-0.323	-0.283	-0.231	-0.188	-0.151	-0.152
	(-4.507)	(-7.150)	(-7.835)	(-7.232)	(-6.646)	(-4.634)	(-4.467)	(-4.530)
CMA	-0.258	-0.257	-0.219	-0.176	-0.180	-0.141	-0.103	-0.085
	(-3.001)	(-4.479)	(-4.418)	(-3.775)	(-4.401)	(-3.005)	(-2.278)	(-2.039)
UMD	0.135	0.132	0.097	0.073	0.048	0.025	0.031	0.040
	(3.904)	(4.747)	(4.308)	(2.847)	(2.288)	(1.267)	(1.561)	(1.843)
R^2	0.904	0.932	0.950	0.953	0.960	0.963	0.967	0.969
JB	106.44	47.02	28.27	54.91	42.23	43.94	124.80	81.79
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4: Performance Persistence: Small Size Portfolios – Seven-Factor Index (IDX7) Model, (f,h = 60,1)

This table presents the performance persistence results of portfolios of mutual funds sorted by various size portfolios. Each month funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from the Cremers et al. seven-factor index (IDX7) model estimated over the previous 60 months formation period. Each size portfolio is held for a one month holding period and the process is repeated on a one month rolling basis. A time series of holding period returns is generated for each size portfolios and the IDX7 model is estimated in each case over the holding period returns. The table shows the alpha (%pa) and factor loadings (betas) for each of these size portfolios regressions. t-statistics are shown in parentheses. Newey-West adjusted t-statistics are calculated throughout. In the case of alpha we also report the bootstrap p-value of the t-statistic of alpha in square brackets. S5, RM, R2, S5V, S5G, RMV, RMG, R2V, R2G refer to returns on the S&P500, Russell Midcap, Russell 2000, S&P500 Value, S&P500 Growth, Russell Midcap Value, Russell Midcap Growth, Russell 2000 Value and the Russell 2000 Growth indices respectively. S5 is measured in excess of the risk-free rate. UMD refers to the momentum risk factor. Also shown are the R^2 values as well as the Jarque-Bera (JB) test statistic of the null hypothesis that the regression residuals follow a normal distribution (p-values in brackets). Results relate to the sample period January 1990 – October 2021.

Portfolio	Size 2	Size 3	Size 5	Size 7	Size 10	Size 20	Size 35	Size 50
Alpha	1.191	1.034	1.789	1.784	1.363	1.146	0.991	0.800
(t-stat)	(0.883)	(0.841)	(1.526)	(1.755)	(1.488)	(1.513)	(1.644)	(1.422)
[p-value]	[0.176]	[0.172]	[0.050]	[0.038]	[0.056]	[0.040]	[0.018]	[0.024]
S5	0.935	0.912	0.924	0.912	0.911	0.917	0.918	0.917
	(22.297)	(32.299)	(33.170)	(37.841)	(44.563)	(54.315)	(64.568)	(67.637)
RM-S5	0.709	0.688	0.658	0.715	0.733	0.726	0.665	0.658
	(5.150)	(5.488)	(5.658)	(9.427)	(11.984)	(14.450)	(13.401)	(15.167)
R2-RM	0.283	0.328	0.339	0.329	0.340	0.304	0.306	0.313
	(2.781)	(4.967)	(5.572)	(5.625)	(7.719)	(7.726)	(8.507)	(9.511)
S5V-S5G	-0.092	-0.056	-0.075	-0.070	-0.066	-0.016	0.004	0.016
	(-0.974)	(-0.652)	(-0.915)	(-0.970)	(-1.077)	(-0.344)	(0.104)	(0.463)
RMV-RMG	0.263	0.221	0.233	0.164	0.127	0.090	0.053	0.013
	(1.556)	(1.509)	(1.768)	(2.018)	(2.078)	(1.906)	(1.050)	(0.310)
R2V-R2G	-0.229	-0.232	-0.250	-0.185	-0.159	-0.170	-0.152	-0.137
	(-1.916)	(-2.092)	(-2.445)	(-2.557)	(-2.622)	(-3.500)	(-3.427)	(-3.502)
UMD	-0.049	-0.031	-0.028	-0.025	-0.015	0.003	-0.007	-0.006
	(-0.873)	(-0.698)	(-0.665)	(-0.774)	(-0.557)	(0.153)	(-0.359)	(-0.402)
R^2	0.829	0.865	0.884	0.909	0.933	0.955	0.966	0.972
JB	250.47	404.03	392.60	118.76	62.61	45.68	60.77	55.15
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 5: Performance Persistence: Top Decile - various performance models and formation/holding periods.
This table presents the performance persistence results of mutual funds sorted by the top decile. Results relate to the Fama-French-Carhart six-factor (FFC6) model and the Cremers et al. seven-factor index (IDX7) model. At time *t*, funds are sorted into an equally weighted top decile portfolio based on the t-statistic of alpha from the performance model estimated over the previous *f* months formation period. The top decile portfolio is held for a *h* months holding period and the process is repeated on a *h* months rolling basis. A time series of holding period returns is generated for the top decile and the model is then estimated over the holding period returns. Newey-West adjusted t-statistics are calculated throughout. The table shows the alphas (%pa) over alternative values of *f-h* as indicated. Statistical significance by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. Results relate to the sample period January 1990 – October 2021. When funds with a minimum of 36 (60) observations are used, there are 2,081 (1,999) funds in the analysis.

Alpha (% p.a.)

	f-h							
	36-1	**36-3**	**36-6**	**36-12**	**60-1**	**60-3**	**60-6**	**60-12**
FFC6	1.312***	1.003**	0.038***	0.309	1.0740***	0.795**	0.576*	0.183
IDX7	1.284***	0.991***	0.955***	0.554***	0.914***	0.620**	0.499**	0.177*

Table 6: Performance Persistence: Small Size Portfolios - Fama-French-Carhart Six-Factor (FFC6) Model - various formation/holding periods.
This table presents the performance persistence results of portfolios of mutual funds sorted by various size portfolios. At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from the Fama-French-Carhart six-factor (FFC6) model estimated over the previous *f* months formation period. Each size portfolio is held for *h* months and the process is repeated on a *h* months rolling basis. A time series of holding period returns is generated for each size portfolio and the FFC6 model is then estimated over the holding period returns. Newey-West adjusted t-statistics are calculated throughout. The table shows the alphas (%pa) over alternative values of *f-h* as indicated. Statistical significance by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. Results relate to the sample period January 1990 – October 2021.

Alpha (% p.a.)

	f-h							
Size	**36-1**	**36-3**	**36-6**	**36-12**	**60-1**	**60-3**	**60-6**	**60-12**
2	1.273	1.929*	0.999	-0.890	2.503**	1.642	1.752	-0.949
3	0.747	1.110	0.604	-0.225	2.928***	1.905**	0.319*	0.086
5	2.017**	1.928**	1.345	-0.100	1.638*	0.768	1.063	0.759
7	1.728**	1.642**	1.185	-0.108	1.368*	0.764	1.185*	1.242*
10	1.806**	1.552**	1.338*	-0.048	1.436**	1.177**	1.332*	0.988*
20	1.752***	1.330**	1.213*	0.478	1.636***	1.207**	1.322**	0.626
35	1.332**	1.294**	1.218**	0.394	1.405***	1.143**	0.855*	0.427
50	1.548***	1.426***	1.249**	0.423	1.437***	1.035**	0.784*	0.279

Table 7: Performance Persistence: Small Size Portfolios - Seven-Factor Index (IDX7) Model - various formation/holding periods.
This table presents the performance persistence results of portfolios of mutual funds sorted by various size portfolios. At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from the Cremers et al seven-factor index (IDX7) model estimated over the previous *f* months formation period. Each size portfolio is held for *h* months and the process is repeated on a *h* months rolling basis. A time series of holding period returns is generated for each size portfolio and the IDX7 model is then estimated over the holding period returns. Newey-West adjusted t-statistics are calculated throughout. The table shows the alphas (%pa) over alternative values of *f-h* as indicated. Statistical significance by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. Results relate to the sample period January 1990 – October 2021.

Alpha (% p.a.)

				f-h				
Size	**36-1**	**36-3**	**36-6**	**36-12**	**60-1**	**60-3**	**60-6**	**60-12**
2	2.161**	2.004**	2.952**	1.914*	1.191	1.890*	1.684	1.185
3	2.258**	2.030**	1.754*	0.854	1.034	1.934*	2.030*	0.777
5	2.059***	1.406**	1.933**	0.849	1.789**	1.945**	2.366**	1.627*
7	1.539**	0.732	1.489**	0.010	1.784**	1.915**	2.052**	1.677*
10	1.395**	0.908*	1.227**	0.554	1.363**	1.468*	1.974***	1.916**
20	1.602***	1.090**	1.334**	0.892*	1.146**	0.898*	0.994*	0.894*
35	1.730***	1.178**	1.508***	0.726**	0.991**	0.652*	0.608*	0.627*
50	1.520***	1.065**	1.275***	0.613**	0.800**	0.626*	0.468*	0.432*

Table 8: Performance Persistence: Small Size Portfolios Rebalancing – average number of fund switches per annum (Ns)
This table reports the average number of fund switches per annum Ns, for small portfolios of funds of size Np, for alternative formation and holding periods as indicated. Results relate to the Fama-French-Carhart six-factor (FFC6) model (Panel A) and the Cremers et al. seven-factor index (IDX7) model (Panel B) At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha estimated over the previous *f* months formation period. Each size portfolio is held for *h* months and the process is repeated on a *h*-month rolling basis

Panel A: Fama-French-Carhart six-factor (FFC6) model

Np=Size	36-1	36-3	36-6	36-12	60-1	60-3	60-6	60-12
2	5.8	3.4	2.2	1.3	4.9	2.9	2.0	1.3
3	7.5	4.6	3.0	1.9	6.2	4.0	2.8	1.8
5	13.3	7.9	5.0	3.1	9.5	5.9	3.8	2.9
7	17.1	10.2	6.8	4.2	12.7	7.5	5.2	3.6
10	21.5	13.3	9.2	5.9	16.6	9.9	6.9	5.0
20	37.4	23.5	16.2	10.5	27.6	17.5	13.0	9.4
35	60.5	37.4	26.2	17.5	44.3	27.8	20.5	14.9
50	81.5	49.3	35.4	23.9	61.6	38.8	27.8	19.3

Panel B: Cremers et al. seven-factor index (IDX7) model

Np=Size	36-1	36-3	36-6	36-12	60-1	60-3	60-6	60-12
2	5.7	3.1	2.2	1.3	4.2	2.7	1.9	1.2
3	7.1	4.0	3.0	1.8	5.8	3.7	2.5	1.7
5	10.6	6.3	4.6	3.0	9.4	5.7	3.9	2.7
7	15.0	8.5	6.1	4.1	11.5	7.2	5.1	3.7
10	20.1	11.8	8.3	5.5	16.8	10.2	7.1	5.0
20	37.9	22.7	15.8	10.6	27.7	17.2	12.8	9.2
35	57.3	35.1	24.8	17.2	44.6	28.1	20.2	14.4
50	76.7	47.1	33.6	23.6	59.8	37.6	27.7	19.3

Table 9:

Performance Persistence: Small Size Portfolios Rebalancing – average annual number of switches as a proportion of portfolio size (Ns/Np)

This table reports the average number of switches per annum Ns, (Table 8) as a proportion of portfolio size Np, for alternative formation and holding periods as indicated. Results relate to the Fama-French-Carhart six-factor (FFC6) model (Panel A) and the Cremers et al. seven-factor index (IDX7) model (Panel B). At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha estimated over the previous *f* months formation period. Each size portfolio is held for *h* months and the process is repeated on a *h*-month rolling basis.

Panel A: Fama-French-Carhart six-factor (FFC6) model

Np=Size	36-1	36-3	36-6	36-12	60-1	60-3	60-6	60-12
2	2.9	1.7	1.1	0.7	2.5	1.5	1.0	0.7
3	2.5	1.5	1.0	0.6	2.1	1.3	0.9	0.6
5	2.7	1.6	1.0	0.6	1.9	1.2	0.8	0.6
7	2.4	1.5	1.0	0.6	1.8	1.1	0.7	0.5
10	2.2	1.3	0.9	0.6	1.7	1.0	0.7	0.5
20	1.9	1.2	0.8	0.5	1.4	0.9	0.7	0.5
35	1.7	1.1	0.7	0.5	1.3	0.8	0.6	0.4
50	1.6	1.0	0.7	0.5	1.2	0.8	0.6	0.4

Panel B: Cremers et al. seven-factor index (IDX7) model

Size	36-1	36-3	36-6	36-12	60-1	60-3	60-6	60-12
2	2.9	1.6	1.1	0.7	2.1	1.4	1.0	0.6
3	2.4	1.3	1.0	0.6	1.9	1.2	0.8	0.6
5	2.1	1.3	0.9	0.6	1.9	1.1	0.8	0.5
7	2.1	1.2	0.9	0.6	1.6	1.0	0.7	0.5
10	2.0	1.2	0.8	0.6	1.7	1.0	0.7	0.5
20	1.9	1.1	0.8	0.5	1.4	0.9	0.6	0.5
35	1.6	1.0	0.7	0.5	1.3	0.8	0.6	0.4
50	1.5	0.9	0.7	0.5	1.2	0.8	0.6	0.4

Table 10: Performance Persistence: Small Size Portfolios Rebalancing – breakeven switching costs, c (bps)

This table reports the breakeven switching costs c (bps), for investors to achieve positive after-switching-cost alphas, for alternative formation and holding periods as indicated, where c (bps) = alpha (Table 7) x Ns (Table 8) / Np. Results relate to the Fama-French-Carhart six-factor (FFC6) model (Panel A) and Cremers et al. seven-factor index (IDX7) model (Panela B). At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha estimated over the previous *f*-months formation period. Each size portfolio is held for *h*-month before the process is repeated on an -months rolling basis. The table shows c (bps) = alpha (Table 7) x Ns (Table 8)/ Np. The statistical significance of the corresponding alpha by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. (see Table 6 and Table 7).

Panel A: Fama-French-Carhart six-factor (FFC6) model

Np=Size	36-1	36-3	36-6	36-12	60-1	60-3	60-6	60-12
2	44	113*	91	-127	100**	109	175	-136
3	30	74	60	-38	139***	147**	35*	14
5	75**	121**	135	-17	86*	64	133	127
7	72**	109**	119	-18	76*	69	169*	248*
10	82**	119**	149*	-8	84**	118**	190*	198*
20	92***	111**	152*	96	117***	134**	189**	125
35	78**	118**	174**	79	108***	143**	143*	107
50	97***	143***	178**	85	120***	129**	131*	70

Panel B: Cremers et al. seven-factor index (IDX7) model

Np=Size	36-1	36-3	36-6	36-12	60-1	60-3	60-6	60-12
2	75**	125**	268**	273*	57	135*	168	198
3	94**	156**	175*	142	54	161*	254*	130
5	98***	108**	215**	142	94**	177**	296**	325*
7	73**	61	165**	2	112**	192**	293**	335*
10	70**	76*	153**	92	80**	147*	282***	383**
20	84***	99**	167**	178*	82**	100*	166*	179*
35	108***	118**	215***	145**	76**	82*	101*	157*
50	101***	118**	182***	123**	67**	78*	78*	108*

Figure 1: Recursive Estimation of Top-5 Portfolio: Seven-Factor Index (IDX7) Model, alternative f,h periods.
The figure plots the recursive estimates of alpha and t-statistic of alpha of portfolios of the top 5 funds. Each month funds are sorted into equally weighted portfolios of size 5 funds based on the t-statistic of alpha from the seven-factor index (IDX7) model estimated over formation periods of 36 months and 60 months. Each portfolio is held for holding periods of 1,3 6 and 12 months and the process is repeated on a 1,3,6 and 12 month rolling basis respectively. A time series of holding period returns is generated in each case. We then estimate the model recursively over the holding period returns. Each panel plots the recursive estimates of alpha and t-statistic of alpha for the formation and holding periods as indicated. Sample period 01/1990 – 10/2021.

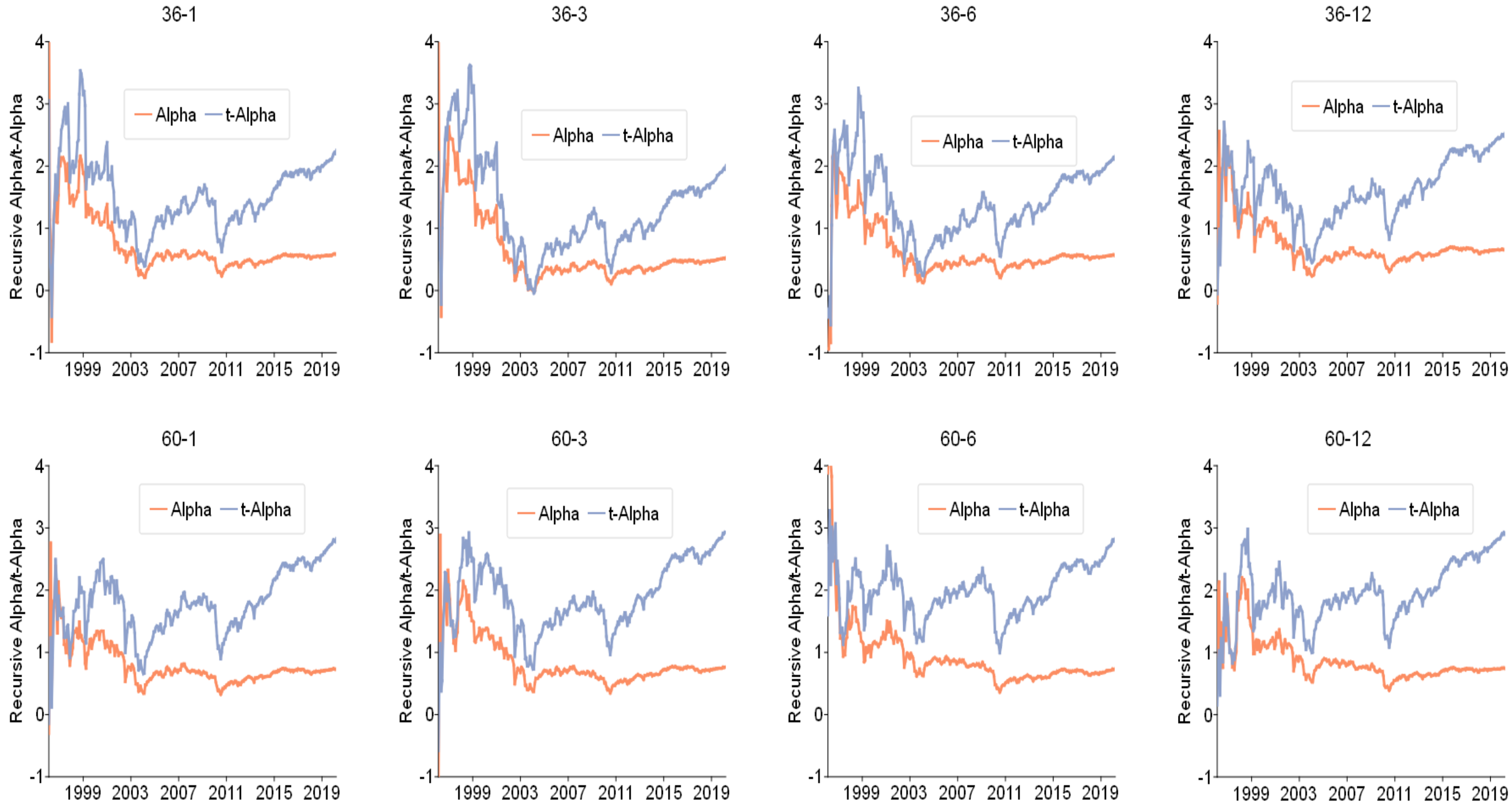
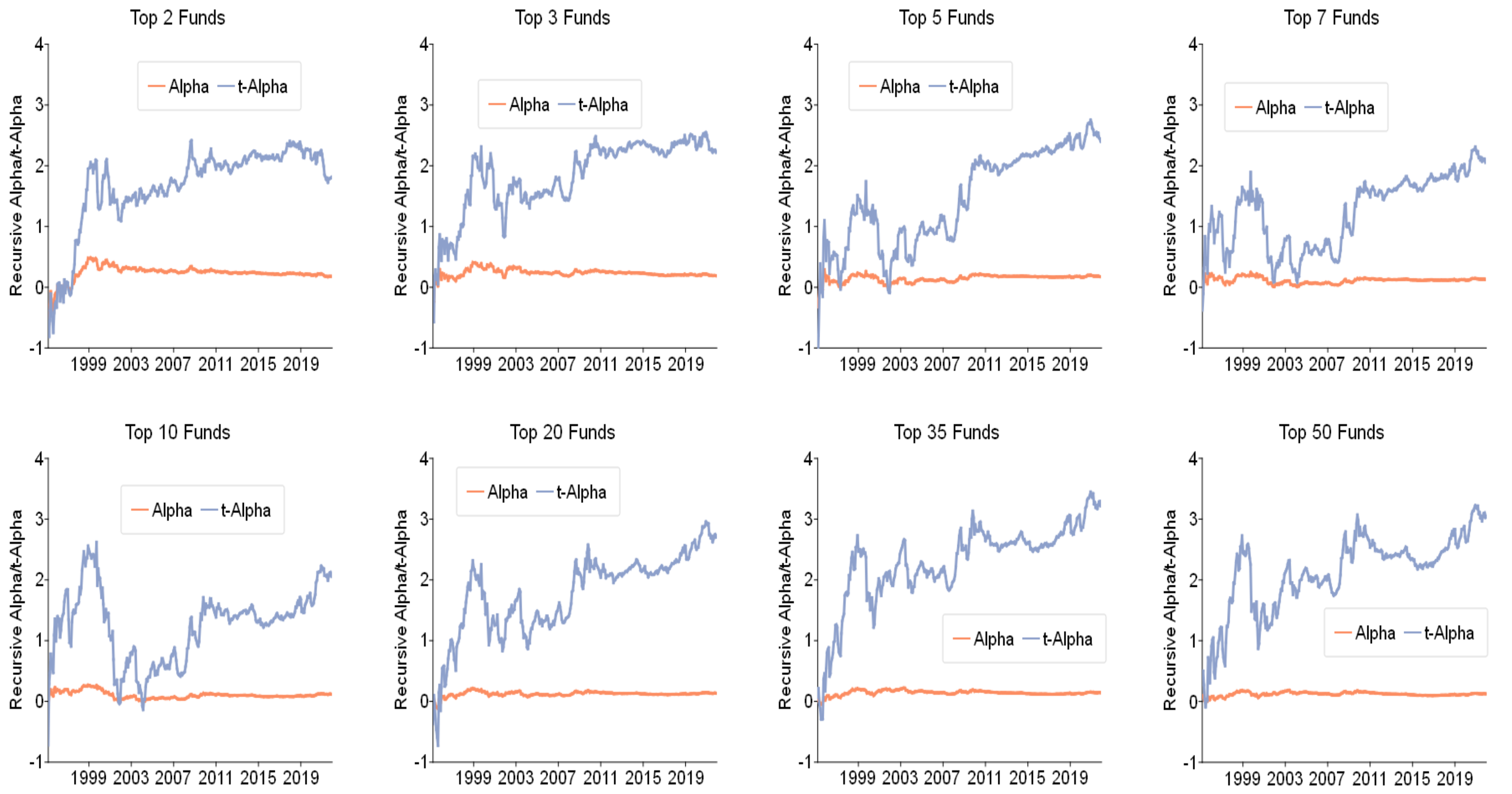


Figure 2: Recursive Estimation of Portfolios : Seven-Factor Index (IDX7) Model, (f,h = 36,1)
The figure plots the recursive estimates of alpha and t-statistic of alpha of portfolios of mutual funds sorted by various size portfolios. Each month funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from the seven-factor index (IDX7) model estimated over the previous 36 months formation period. Each size portfolio is held for a one month holding period and the process is repeated on a one month rolling basis. A time series of holding period returns is generated for each size portfolio. We then estimate the model recursively over these holding period returns. Each panel plots the recursive estimates of alpha and t-statistic of alpha for the various size portfolios as indicated. Sample period 01/1990 – 10/2021.



APPENDIX: GROSS RETURNS

Mutual Fund Performance Persistence: Factor Models and Portfolio Size.

Gross-Alphas

When using gross alphas for the FFC6 model, we find substantial persistence for the *top decile* across all formation and holding periods for both the FFC6 model and he IDX7 model (appendix Table A1).

When examining small portfolios of past winner funds for alternative combinations of (f,h), we also find strong evidence of statistically and economically significant (positive) gross-alpha funds for both models (appendix Table A2 and A3). In the case of the FFC6 model this is more evident in portfolios of size 5 or higher and is only found in smaller portfolios when using a longer formation period.

APPENDIX: GROSS RETURNS

Table A1: Performance Persistence (Gross Returns): Top Decile – alternative performance models and formation/holding periods.
This table presents the performance persistence results of mutual funds based on U.S. fund gross returns. Results relate to alternative performance models as follows: Fama-French-Carhart six-factor (FFC6) model and Cremers et al. seven-factor index (IDX7) model. At time *t*, funds are sorted into an equally weighted top decile portfolio based on the t-statistic of alpha from the performance model estimated over the previous *f* months formation period. The top decile portfolio is held for a *h* months holding period and the process is repeated on a *h* months rolling basis. A time series of holding period returns is generated for the top decile and the model is then estimated over the holding period returns. Newey-West adjusted t-statistics are calculated throughout. The table shows the alpha (%pa) over alternative values of *f-h* as indicated. Statistical significance by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. Results relate to the sample period January 1990 – October 2021.

Alpha (% p.a.)

	36-1	**36-3**	**36-6**	**36-12**	**60-1**	**60-3**	**60-6**	**60-12**
FFC6	2.328***	1.987***	2.005***	1.377***	2.038***	1.702***	1.598***	1.233***
IDX7	2.232***	2.024***	1.996***	1.564***	1.802***	1.478***	1.412***	1.405***

Table A2: Performance Persistence (Gross Returns): Small Portfolios - FFC6 factor model – alternative formation/holding periods.
This table presents the performance persistence results of portfolios of mutual funds sorted by various size portfolios based on U.S. fund gross returns. At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from the Fama-French-Carhart six-factor (FFC6) model estimated over the previous *f* months formation period. Each size portfolio is held for a *h* months holding period and the process is repeated on a *h* months rolling basis. A time series of holding period returns is generated for each size portfolio and the FFC6 model is then estimated over the holding period returns. Newey-West adjusted t-statistics are calculated throughout. The table shows the alpha (%pa) over alternative values of *f-h* as indicated. Statistical significance by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. Results relate to the sample period January 1990 – October 2021.

Alpha (% p.a.)

				-h				
Size	**36-1**	**36-3**	**36-6**	**36-12**	**60-1**	**60-3**	**60-6**	**60-12**
2	0.880	1.689	0.924	-0.507	4.086***	3.620**	3.618**	1.298
3	1.467	1.868*	1.345	-0.616	3.072***	3.055***	3.694***	1.819*
5	2.341**	2.515***	1.672*	0.673	2.580***	1.941**	2.290**	1.575**
7	2.151***	2.131***	1.905**	0.548	2.551***	2.178***	2.934***	2.368***
10	2.884***	2.544***	2.025***	1.201*	2.382***	2.198***	2.646***	1.766**
20	2.560***	2.343***	2.131***	1.124**	2.581***	2.098***	2.072***	1.540**
35	2.476***	2.157***	2.128***	1.446***	2.458***	2.218***	1.849***	1.402**
50	2.461***	2.288***	2.143***	1.449***	2.335***	2.043***	1.722***	1.212**

Table A3: Performance Persistence (Gross Returns): Small Portfolios - IDX7 index model - alternative formation/holding periods.
This table presents the performance persistence results of portfolios of mutual funds sorted by various size portfolios based on U.S. fund gross returns. At time *t*, funds are sorted into equally weighted portfolios of size 2,3,5,7,10,20,35 and 50 based on the t-statistic of alpha from the Cremers et al. seven-factor index (IDX7) model estimated over the previous *f* months formation period. Each size portfolio is held for a *h* months holding period and the process is repeated on a *h* months rolling basis. A time series of holding period returns is generated for each size portfolio and the IDX7 model is then estimated over the holding period returns. Newey-West adjusted t-statistics are calculated throughout. The table shows the alpha (%pa) over alternative values of *f-h* as indicated. Statistical significance by the bootstrap p-value at the 1%, 5%, 10% significance level is indicated by ***, **, * respectively. Results relate to the sample period January 1990 – October 2021.

Alpha (% p.a.)

	f-h							
Size	**36-1**	**36-3**	**36-6**	**36-12**	**60-1**	**60-3**	**60-6**	**60-12**
2	3.183***	3.141***	3.129***	3.062**	2.098*	1.930***	2.342*	0.560
3	3.348***	2.918***	2.728***	1.839**	1.994*	3.110***	3.922***	1.999
5	2.792***	2.355***	2.721***	1.824**	2.773***	2.850***	3.153***	2.786**
7	2.469***	2.064**	2.758***	1.292**	2.697***	2.614***	3.109***	2.895***
10	2.349***	1.575**	2.322***	1.602***	2.811***	3.213***	3.241***	3.258***
20	2.542***	2.224***	2.272***	1.904***	2.342***	2.296***	2.414***	2.112***
35	2.749***	2.274***	2.630***	1.959***	2.257***	2.108***	2.074***	1.674***
50	2.508***	2.076***	2.332***	1.774***	1.880***	1.896***	1.755***	1.519***