The Persistence In Mutual Funds:

Luck Or Skills?

By

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Abstract

This paper documents mutual fund managers do not appear to possess stock-picking skills. The persistence in mutual fund performance appears to primarily be a manifestation of momentum effect – stocks held by last year's winners outperform those held by last year's losers over the next year. Using Fama-French-Carhart model, I find that it explains much of the variation in the intercept of the model. In addition, the momentum effect is also found in five different international stock markets. Last, momentum funds do not earn higher return after the net of expenses, and this momentum cannot be lasted longer than a one-year time interval.

I. Introduction and Literature Review

The random walk hypothesis states that stock market prices evolve according to a random walk and thus cannot be predicted. Capital gains in stock markets are generally due to luck, not the superior ability of stock picking that fund managers have. The debate between luck and skills in stock returns is never faded. The conventional wisdom is that at least some mutual fund managers have stock-picking skills. Investors frequently look to past returns and historical ratings such as Morningstar for guidance on which funds will perform well in the future. Successful fund managers are glorified in the media and market their performance as outstanding stock-picking skills. In fact, asset pricing remains as a puzzle to efficient market hypothesis. If markets are fully efficient, asset prices would be fully reflected all information relevant to the firms, even including information available only to company insiders, so that investors would be able to predict the future trend by looking at past historical stock returns. But there are still many resources invested in stock picking.

The academic literature is much more mixed. Since 1960s, mutual fund performance has been a pervasive research topic. One of the earlier predecessors, Michael Jensen (1967), used the Capital Asset Pricing Model[1] (described by Sharpe, Lintner, and Treynor, 1962) to derive a risk-adjusted measurement (Jensen's Alpha). According to Jensen's (1967) measurement, the alpha from CAPM should be positive if fund managers have the ability of stock-picking skills. But Jensen (1967) discovered the fact that mutual fund performance is more likely due to luck, rather than funds picking skills from the managers. Furthermore, Fama and French (1992) used three additional

[1] Capital Asset Pricing Model is also known as CAPM.

factors such as market beta, size, and book-to-market equity to explain the cross-sectional variations in average stock. Unlike Jensen's measurement, the Fama-French model studies the portfolios of all mutual funds and concludes that the gross returns might have a slight positive alpha – but mostly in small funds (although that is insignificant). Net returns of mutual funds have negative alpha because they are swallowed by transactions costs.

It is generally agreed that there is some persistence in mutual fund performance. Jagadeesh and Titman's (1993) first discovered the momentum strategy – buying last year's winning funds and selling last year's losing funds may bring a short-term persistence in mutual fund performance. Also, Moskowitz, Asness, and Pedersen (2009)[2] find the evidence that the co-movement between value and momentum exist everywhere across diversified asset classes and markets. In addition, it is not only value and momentum are both related to momentum strategy in the U.S. market, this phenomenon is also found in the global stock markets, excluding Japan (Rouwenhorst, 1998; Chui and Titman, 2010; Fama and French, 2012). Carhart (1997) attributes almost all persistence in mutual fund performance to four-factor loadings, expenses, and transaction costs. Yet, high transaction costs and managerial fees make mutual fund performance even more opaque. Fama and French (2010) use bootstrap simulations to examine the cross-sectional data, and they conclude that few top performance managers have stock-picking skills only if it is sufficient to cover the costs not included in its expense ratio. If the market is fully efficient, then no one should pay for arbitrage fees. However, efficiently pricing an asset is still a puzzle.

[2] Moskowitz and Grinblatt (1999) has the similar findings.

On the other hand, some literatures document stock-picking skills are positively related to mutual fund performance. Wermers, Yao and Zhao (2012)[3] present a method in estimating fund managers' skills and find strong evidence that fund managers possess stock selection information even after controlling for style characteristics. Lo and Mackinlay (1988) rejected the null hypothesis that stock prices followed a random walk path, which suggests that the stock market returns should be predictable. Furthermore, a few recent studies show that fund managers are able to outperform the benchmarks by managing their portfolios that are highly active and far away from the passive indexes. This active-management allows fund managers to gain a substantial performance in mutual fund returns (Wermers, 2003; Berk and Green 2004; Avramov and Wermers, 2006; Cremers and Petajisto, 2009; Berk and van Binsergen, 2014; Cremers and Pareek, 2014; Cuthbertson, Bredin, Nitzsche, and Thomas, 2014). In addition to U.S. domestic markets, managers use active fund management skills to generate the superior performance in international mutual fund markets (Cremers, Ferreira, Matos, and Starks, 2015).

This paper documents that positive mutual fund returns are unrelated to stock-picking skills at all. In the short term, the momentum strategy suggests that buying prior year's "winners" and shorting "losers" can still outperform the benchmark before net of expenses. Managers who outperform the benchmark in short-run is due to the nature of the momentum effect that is underlying in the stocks, rather than skills of selecting the superior performing stocks. The closest research paper to mine is from Carhart (1997), in which explains that momentum in stocks accounts for momentum in funds, and it is not a

[3] Wermers (2000) has concluded the similar findings.

persistent skill. In this paper, I mainly employ the same methodology to analyze the domestic U.S. mutual funds; yet I use a newer dataset to test whether the momentum investing strategy can still be significant. I find that the persistence of good performance is explained by the momentum factors along with the other three Fama-French factors. By equally dividing ten decile portfolios of all mutual funds based on last year's ranking, I also find that monthly excess returns from the top decile portfolios (winners) are higher than the returns from the bottom decile portfolios (losers). Furthermore, the momentum factor in the Fama-French-Carhart four-factor model is strongly significantly related to monthly excess returns. Much of the variation in the intercepts can be explained by the four factors in the model. Particularly, the intercept from the spread of the top and bottom decile portfolios is approximately zero percent, which indicates the anomalies are well explained by the model.

In addition to U.S. domestic funds, I find that international stock markets have the same short-term persistence in mutual funds as in the domestic market. The momentum strategy is evidently strong in the international regions such as Europe, Asia Pacific (excluding Japan), North America, and Globe. Besides the size-effect, the difference of the average monthly excess return between "winners" and "losers", sorted on momentum, is positive. The top decile portfolios outperform the bottom ones in almost every region, which indirectly discovers that the stock-picking skills are not related to the fund performance.

The persistence in mutual funds is not pronounced in the long run, which suggests that the bottom decile portfolios (losers) can reverse the underperformance by moving up into the winning portfolios. Under three years, the top performing portfolios can move down to the bottom of the ranking. Yet, after five years later, the winning decile portfolios completely disappear in the top rank and the bottom decile portfolios have become the "winners". As a result, it is clear that fund managers do not have superior fund-picking skills that otherwise the persistent performance in mutual fund returns would be lasted forever. Most of the intercepts in the four-fact model are negative, suggesting that fund managers who are able to outperform the market in a long horizon may be due to the coincidently luck by investing a large proportion in the winning funds. Thus, the momentum exists in underlying stocks, not skills. Much of the variation in *ex-post* fund returns is due to the investments in different style of the funds such as small, large, value, growth, sector, and etc.; not because of the differences in particular stocks that managers pick. However, the momentum funds do not earn substantially good returns after the transaction costs. Expenses have negatively impact on fund performance, and the turnover also negatively impacts performance. The turnover and expense ratios together consume a large proportion of capital gains from following a momentum strategy in stocks.

The rest of the paper is organized as the following structure. Section II provides the details of model constructions and data and sample selections for both domestic and international funds. Section III presents the explanations of *ex-post* regression results on the one-year-momentum portfolios as well as in international stock markets. Section IV reports the empirical analysis of the long-term reversal momentum effect and explains why transaction costs can affect mutual fund performance. Section V concludes the findings in this research.

II. Data Selection and Models Construction

A. Data and sample selections

The sample data is from two main sources: the Centre for Research in Security Prices (CRSP) that is available on WRDS and Kenneth French's Website. All samples cover the period from January 1994 to December 2014. Further, I divide all of the domestic mutual funds into three categories: aggressive, growth, and growth and income. Aggressive funds are aiming to generate the highest possible profits. The growth funds are primarily aiming to increase the capital gains. The growth and income funds utilize the nature of the funds – dividends and interest payments to gain a stable and fixed long-term income. Using different groups of mutual funds allows me to examine the sensitivity between fund performance and the persistence. I exclude funds that are included in balanced funds, international funds, and sector funds. Also, I do not required that any fund in the sample should have at least 30 or 60 monthly returns. This may potentially eliminate the survivor-bias-ship in mutual funds.

The international mutual funds are primarily from Kenneth French's Website, at which fund portfolios are sorted based on size and momentum. The sample period is January 1994 to December 2014 and the portfolios are divided into five different regions by geography. Each region has its own factor-data for the Fama-French four-factor model. All of the mutual fund returns are in U.S. dollars and monthly excess returns are returns in excess of one-month U.S. Treasury bill rate. Due to the limitations on Kenneth French's website, the international mutual funds sample does not have detailed statistics for individual funds such as average life of the funds, average expense ratio, and/or average turnover ratio.

In order to measure the fact whether a given fund was lucky or skilful, it should be used the average performance in a group (a diversified portfolio) and thus it is better to look at some strategy that may have plausibly used for picking funds ahead of time, and then conclude what happened to all funds that were selected. All mutual funds are survivor-bias-free. Reported returns are net of all operating expenses and transaction costs, but do not include sales charges. The sample includes a total of 14,349 funds and 78,150 fund years. Table-I summarizes the characteristics and statistics of the domestic mutual funds. The growth funds account for the largest proportion in the sample. In an average year, there are approximate 3,721 funds in the sample with the total net asset (TNA) of $497 million and average expenses of 1.34 per year. In addition, funds trade 85.7 percent of the value of their assets in an average year. Since reported turnover is the minimum of purchases and sales over average TNA, I employ the same method as in Carhart (1997) to obtain Mturn by adding to reported turnover one-half of the percentage change in TNA adjusted for investment returns and mergers. Also, over the full sample, nearly 75 percent of the funds has either front-loads or rear-loads. By fund category, aggressive growth funds top the average expenses and the frequency of trades with 1.66 percent and 97.4 percent, respectively. However, the growth and income funds account for the highest TNA value, $616.6 million and the lowest Mturn, 60.9 percent. Aggressive funds also seem to be the highest fund group with loads, which yield approximately 63.3 percent. Over the full sample, the average life of a fund can last up to12 years, and the lowest life cycle that funds have falls into the Dead-funds category, suggests that fund are generally disappeared after nine calendar years. Although the actual 12B-1 fees are included in the expense ratio, I calculate the average value to show that the percentage accounts in the TNA is taken away to market the mutual funds. On average, the investors have paid 0.36 percent of the TNA of their assets, which considers close to the industry's range. By the end of the sample period (2014), more than half of the funds in the sample are still alive, and they account for an average expense of 1.25 percent, trade nearly 85 percent of their assets, and have an average life cycle close to 12 years.

B. *Models and methodologies*

There are three main regression models I employ in this paper: the Treynor-Sharpe-Lintner-Black's (1962, 1966) Capital Asset Pricing Model (CAPM), the Fama-French Three Factor Model (1993), and the Carhart Four-Factor Model (1997). In this subsection, I briefly introduce these models and explain the details of which how I apply the methodologies. As aforementioned in the introduction, CAPM was first introduced by Treynor and later developed by Sharpe and Lintener in the 1960s. Fama and French (1993) added three more factors as they found the proportion of mean return attributable to these new factors: high versus low beta stocks, large versus small market capitalization stocks, and value versus growth stocks. Fama-French model finds that small capital funds tend to have higher average excess returns over other capital-size groups. Then Carhart (1997) implemented another attribute in stocks – the momentum effect. Carhart (1997) found that the four-factor model explained the anomalies better than the Fama-French three-factor model. As a result, the Carhart Four-Factor model opened a new chapter in explaining the variations in the alphas.

I estimate performance relative to the CAPM, Three-Factor[4], and Four-Factor models as

$$r_{it} = \alpha_{iT} + \beta_{iT}\, VWRF_t + e_{it} \quad t = 1, 2, \cdots, T \tag{1}$$

$$r_{it} = \alpha_{iT} + b_{iT}\, MKTRF_t + s_{iT} SMB_t + h_{iT} HML_t + e_{it} \quad t = 1, 2, \cdots, T \tag{2}$$

$$r_{it} = \alpha_{iT} + b_{iT}\, MKTRF_t + s_{iT} SMB_t + h_{iT} HML_t + p_{iT} MOM_t + e_{it} \;\; t = 1, 2, \cdots, T \tag{3}$$

where r_{it} is the excess return on a portfolio adjusted by the one-month T-bill return; *VW* represents the CRSP Value-Weighted (VW thereafter) domestic stock returns include the distributions of dividends in each fund, and *VWRF* is the *VW* stock index minus the one-month T-bill return. *MKTRF* is the excess return of the market return minus the risk-free return. *SMB* is the difference between the returns on diversified portfolios of small stocks and big stocks, and *HML* is the difference between the returns on diversified portfolios of high book-to-market-value stocks and low book-to-market-growth stocks. *MOM* is the momentum factor described by Jegadeesh and Titman (1993) as one-year momentum strategy on stock returns. In addition, I also employ the Fama-French Three-Factor method using the data that is constructed on a 25 portfolios (5x5) based on size and momentum for both domestic and international[5] stock markets. This allows me to find any distinguishable and fundamental difference between my portfolios and Fama-French's ones. The long-term reversal effect states that the top-decile portfolios can reverse to the bottom portfolios, and vice versa, in a longer time interval. The regression model is estimated as

[4] MKTRF, SMB, HML, and MOM factors are obtained from Kenneth French's website.
[5] I only examine the momentum effect in the international stock markets by using the data from Kenneth French's website. Unfortunately, CRSP under WRDS does not provide international stock information.

$$r_{it} = \alpha_{iT} + b_{iT}\, MKTRF_t + s_{iT} SMB_t + h_{iT} HML_t + MOM_{it} + LTRev_{it} + e_{it} \quad t = 1, 2, \cdots, T \ (4)$$

where $LTRev$[6] is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. This model tests whether the momentum strategy can still capture positive returns in mutual funds in a longer horizon.

Over my sample, I form ten equal-weighted portfolios of U.S. domestic mutual funds on lagged one-year returns and estimate performance on the resulting portfolios. On January of each year, I rank the reported average monthly returns based on prior year's returns from the highest to the lowest. In addition, any mutual fund lacks of twelve monthly returns in the prior year are not valid for the pre-rank in the portfolios. Then I hold the funds for one year, and form ten equal-weighted portfolios in the following year. The decile-1 portfolios are "winners" (the highest monthly returns), and the decile-10 portfolios are "losers" (the lowest ones), according to previous (lagged) year's rankings. This yields a time series of 252 average monthly returns on each decile portfolio from 1994 to 2014. If any funds were disappeared during the course of the year are included in the equal-weighted average until they disappear, and the portfolio weights are readjusted appropriately.

The formation of portfolios on international stock returns is different from the domestic one. I employ the Fama-French (2012) method, of which portfolios are sorted into a 5x5 block based on size and momentum, which are formed monthly and the lagged momentum return takes the place of B/M. Sizes of firms are from small to big, and firms'

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[6] LTRev is constructed using six-weight portfolios formed on size and prior (13-60) returns. The portfolios are formed monthly and the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (13-60) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (13060) return breakpoints are the 30th and 70th NYSE percentiles. $LTRev = \frac{1}{2}(Small\ Low + Big\ Low) - \frac{1}{2}(Small\ High + Big\ High)$

values are from high to low. For portfolios formed at the end of month *t*, the lagged momentum return is a stock's cumulative return from *t*-11 to *t*-1.

III. Empirical Evidence and Analysis

A. U.S. domestic mutual funds analysis

This section focuses on analyzing the empirical evidence and interpreting the reason why the persistence in mutual funds is not due to the "stock-picking-skills", rather due to the "style" of the funds. First, Table-II describes a summary on the factor portfolios, in which indicates that the Carhart (1997) four-factor model still explains some variations in returns. This result is similar to the one from Carhart (1997), which can explain sizeable time-series variation because of the high variance of the *SMB*, *HML* and *MOM* and their very low correlations with each other and the market proxies – *MKTRF*. In addition, the t-test shows that the three factors, *SMB*, *HML*, and *MOM*, are not very significant. However, the high mean returns on these three factors suggest that they may account for much cross-sectional variation in the mean return on stock portfolios. The momentum effect described by Jegadeesh and Titman (1993) states that returns from last year's "winners" can still beat last year's "losers" in the following year. According to Figure-I, it clearly presents that the past "winning" portfolios keep staying in the top position and the "losing" ones are still in the bottom within a one-year short time interval. This indirectly depicts that the momentum are in the funds, not the skills of picking those funds.

The portfolios of mutual funds sorted on prior's ranking of returns demonstrate strong variation in mean return. Table-III reports the post-formation monthly excess returns decrease monotonically from the high-decile to the low-decile portfolios. The portfolio-1 (high) yields a mean of monthly excess return by 0.58 percent, and the portfolio-10 (low) has only 0.26 percent. This indicates that the top decile portfolios generate nearly 7 percent excess returns per annum, whereas the bottom ones only receive up to 3 percent return in a year. The spread of the monthly excess return between the high and low portfolios is approximate 32 basis points difference. This indicates a sizable annualized spread of nearly 4 percent. The subdivided extreme portfolios exhibit the same spread with the difference between portfolio 1 and 10. Portfolio 1A, which contains the top thirty-third of funds (34 on average), outperforms portfolio 10C, the bottom thirty-third of funds, again by 32 basis points per month. One may object this fact that good fund managers are able to select "good funds" individually and to form them into a "winning" portfolio. However, the probability for a given prior year's winning fund staying as the winner in the following year is more than 50 percent. For example, 1A-decile portfolio has the mean excess monthly return and the standard deviation that are 0.62 and 5.09 percent, respectively. Thus, the probability[7] for funds in 1A-decile staying in the top deciles is approximately 54.78 percent. Similarly, the probabilities for 1(high) staying as the "winner" and for 10(low) and 10C, remaining as "losers", are 54.78, 52.39, and 52.79 percent, respectively. Statistically, the top and bottom decile portfolios all have over a half chance to stay where they were in the previous year. In terms of risks, these probabilities are derived from portfolios of funds, which means that individual funds in the portfolio can be more volatile; so the chance of an individual winning fund staying on the top is even lower and harder. Thus, the momentum strategy

[7] This is calculated under the Normal cumulative distribution function: $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-z^2/2}\, dz$

indicates that buying previous year's "winners" and holding these funds for a year would be able to receive a positive excess return (before net of expenses). This implies that fund managers do not have skills in selecting individual funds, rather the "style" of funds.

Further, the CAPM does poorly explain the persistence and variations in the relative returns on these portfolios. The betas from CAPM are almost identical on either the top-decile portfolio or the bottom-decile portfolio, so the CAPM alphas reproduce as much dispersion as simple returns. In contrast to Carhart (1997) results, the CAPM alphas of my sample are all negative, except the top sub-divided decile, 1A. The worst CAPM alphas are from the bottom sub-divided deciles – 10A, 10B, and 10C, which range from -0.38 percent to -0.25 percent. Even the CAPM alpha on the 10 (low) is still negative 0.32 percent. According to Carhart (1997), if the CAPM measured the risk correctly, both the best and worst mutual funds would possess differential information, yet the worst funds were underperformed because of the applied wrongful information.

On the other hand, the Fama-French-Carhart four-factor model (short for FFC thereafter), explains much the variation in alphas with sensitivities to *SMB*, *HML*, and *MOM* factors. More importantly, the monthly excess returns are significantly and positively related with the momentum (*MOM*) factor among the top decile portfolios (i.e. 1A to 4). Yet, the bottom decile portfolios (losers) have a strongly negative relationship between returns and momentum factor. The momentum factor explains nearly 39 basis points of the spread in mean monthly return between decile 1 and 10. This mean return spread is even more pronounced between decile 1A and 10C, which yields 42 basis points. Further, of the 2-basis-point spread in monthly return not explained by the four-factor model, the spread between 1A and 10C deciles accounts for one basis point. This implies that the FFC model has a much better prediction and it explains the variation in the alphas very well. In addition, the high adjusted-R squares from the four-factor model suggest that the model is fitted well across the portfolios. Except for the poor performance by last year's "losers", the FFC four-factor model accounts for almost all of the cross-sectional variation in expected return on portfolios of mutual funds constructed on lagged one-year return.

In addition to the ten portfolios in my sample, I also obtain the estimates from portfolios[8] formed on momentum on Kenneth French's website. Table-IV reports the monthly excess returns with correspond standard deviations, and betas from the FFC. Surprisingly, the top decile portfolio receives a wholly 1.0 percent mean excess return per month, 12 percent annually. The bottom decile portfolio, 10 (low), is still poorly underperformed by a difference of 0.76 percent from the top one. Yet, the spread of 1 and 10 in alpha is positive that suggests the unexplained anomaly in the alpha has a larger proportion. Also, the momentum factor is strongly positively correlated with the mean excess monthly returns. Thus, the FFC four-factor model does capture much of the variation in the alphas, and this seems to account the "hot hands" effect in mutual fund performance described by Hendricks, Patel, and Zeckhauser (1993).

B. Momentum effect in international stock markets

The momentum strategy is also found in the international stock markets, which further indicates that fund-picking skills are unrelated with mutual fund performance. Table-V (Panel A) reports the average monthly excess returns with their associated

[8] The difference between Kenneth R. French's and my portfolios is that there are no details on the kinds of mutual funds (i.e. aggressive or growth) selected by Ken French.

standard deviations. The uptrend pattern in the average monthly excess returns for each size group clear indicates that last year's low (return) portfolios underperform last year's high ones. For example, the small size group for U.S. domestic stocks, the mean monthly excess return for the low decile portfolios is approximate 0.38 percent, whereas the high decile portfolios yields a much higher monthly excess return, 1.42 percent. The spread between the highest and lowest decile is more than 1 percent per month and 12 percent per annum. Also, the betas for momentum factors are negatively related to the excess returns in low decile portfolios, but strongly positively related to excess returns in top ones. This confirms the similar result with my earlier finding that the momentum effect is still valid in the stocks from 25 (5x5) portfolios. I also perform (results are not shown) the Gibbons, Ross, and Shanken (1989) test, short for GRS test, and the test statistic suggests a rejection to the null hypothesis that all the intercepts in the four-factor models are jointly zero. This means that there are still unexplained variations in the model.

There are similar size patterns in momentum returns across all of the international markets. Like Asness, Moskowitz, and Pedersen (2009), I find strong momentum returns everywhere. For instance, under the small size stocks, the last year's winners in global region outperform losers by 1.34 percent in monthly excess return, which yields approximately 16 percent per annum. This is a huge spread suggests that the global region has a stronger evidence in momentum effect than U.S. domestic. Also, the momentum factors are strongly positively related to the excess returns as the size group increases. There is no consistent relation between average return and size in the first two columns of the metrices. The small-cap funds are doing better than the big-cap ones. A typical size effect (higher average excess returns for small stocks) shows up in the fourth column of the matrices, and it is more evident in the fifth column. As a result, last year's winners show positive momentum monthly excess returns in all size groups, but small-cap stocks have a stronger persistence. In Global (excluding U.S.) matrices, small stocks are consistently doing better than big ones. Like Fama and French (1993), global investors (excluding U.S.) may invest largely in the small-cap funds because they tend to increase capital gains more than big-size stocks. Thus, international portfolios formed on momentum present strong evidence that last year's winners outperform losers in the following year in every regional market.

Asia Pacific aside, there is one exception that the average monthly excess return in last year's high (winner) deciles is smaller than the one in low (loser) under the group of big size stocks. This could be due to the sensitivity to liquidity factors in returns of big size stocks between winners and losers in the particular geographical region.

Panel B in Table-V reports the intercepts and their associated t-statistics for all of the regional markets. First, the panel suggests that the four-factor model leaves a momentum pattern in the intercepts for small-cap funds and creates a reverse momentum pattern: positive intercepts for "losers" and negative for "winners". The pattern is possible due to stronger momentum returns for small-cap funds and spreads in the intercepts between winners and losers. The rejection of GRS test (not shown) indicates that the global four-factor model may be a better choice when looking at the persistence in mutual funds due to the momentum effect, but the model performs poorly on local regional markets, especially Asia Pacific one. On average, the intercepts suggest that the small-cap groups of funds are maybe problematic. For example, the four-factor model in North American markets, leaves a momentum pattern which increase from -0.17 percent for the prior year's lowest decile portfolios to 0.55 for the highest winners. As the size of funds is increasing, the intercepts are getting decreased. However, the intercepts in small-cap for last year's losers are higher than winners within the same size group in both global (excluding U.S.) market and European market. This leads to a consistent result to Fama-French (1993) model, in which small size stocks tend to have larger intercepts. Also, the European result leaves a huge reverse momentum spread of -0.77 percent for big-size stocks. This problematic result is even bigger in the global (excluding U.S.) and Asia Pacific markets, in which yield -0.61 -1.08 percent, respectively. In short, there are common momentum patterns in mean monthly excess returns in markets from global regions, including the Global market. But with the rejection in GRS test for all of the local regions, I would suggest that the global four-factor can explain the returns on global portfolios; as the global portfolios do not have a strong tilt toward small-cap funds or toward the stocks for a particular geographical region. In short, there is no consistent and strong evidence that fund managers have superior skills in picking (winning) stocks; rather, the international stocks have the same characteristics as the domestic ones so that the momentum effect exists in stocks by default.

IV. Long-term Reversal Momentum and Mutual Funds Costs

A. Long-term reversal effect in momentum portfolios

The evidence on long-term reversal in stocks is an ongoing source of debate for the existence of skilled or unskilled fund managers. Jegadeesh and Titman (1994) empirically examined whether bid-ask spreads explained short-term reversals. Short-term contrarian profits are also due to lead-lag effects between stocks (Lo and MacKinlay (1990)). But DeBondt and Thaler (1987) pointed out those investors' tendencies to overreact to the stock market. Since differences across stocks in their past price performance tend to show up as differences in their book-to-market value of equity and in related effects (Fama and Fench 1992, Lakonishok, Shleifer, and Vishny 1994). If mutual funds managers had the superior stock-picking skills, then these managers would reproduce the winning stock-portfolios again and again in a longer horizon. Nonetheless, in this section, I will show some evidence that the fund-picking skills are not optimal as some may consider.

First, Figure-II depicts a lagged five-year average annual excess return of the funds in each decile portfolio in each of five years after the initial formation. Vividly, the momentum effect does not persist for more than one year. So these “winning” decile portfolios may revert to the bottom and the “losing” ones may escalade to the top, suggesting that the momentum strategy is not suitable for investors to replicate in a long-lived time period. If, on the other hand, were due to the skills those managers had, then the line (decile 1 or 10) would stay still or flat over time. But, it is clear shown in the figure that the persistence in mutual fund performance is a short-term effect and is mostly eliminated after the initial formation year. By the fifth year, the prior worst funds have become and surpassed the previous “winners”, suggesting that long-term reversal are existed in the four-factor model. In other words, fund managers do not continuously produce the persistence in mutual fund performance in a consecutive year. Thus, the fact that (annual) average excess returns seem to revert from the top portfolios to the bottom ones indicates the momentum effect is in stocks (which does dissipate over time), rather in skills.

Furthermore, the annual average excess returns on the top decile in the formation year perform poorly after the initial year. For instance, Figure-II shows that the decile-1 portfolios of the initial year have come down sharply by the end of the second year. On the other hand, the bottom decile-10 has reverted almost to the top by the end of the year plus the formation year. The annual average excess return in decile-1 portfolios is approximately 0.28 percent per annum; and the worst (decile 10) portfolios yield an average return by -1.43 percent per annum. In a five-year time window, the "losers" that are in the formation year have become the "winners" eventually (as shown in the figure). This simply implies that the loadings for each decile portfolios are different year after year. And more importantly, the skills for picking the best funds to form "winning" portfolios are unlikely possible to be persistent in a longer horizon.

Table-VI reports the estimates and betas for the FFC four-factor model including the additional long-term reversal factor. The ten equal-weighted portfolios are formed on the average monthly returns prior to five years. This "five-factor" model explains that the longer the period, the less pronounced momentum effect in the average excess returns. The average monthly excess returns increase as the ranking of decile portfolios is decreasing monotonically. The decile-1 (high) has an average excess monthly return of 0.78 percent five-years later. On the other hand, the five-year-ago losers (decile-10) now have an average monthly excess return of 1.13 percent. Also, the spread of decile-1 and decile-10 yields a negative 0.35 percent, which clearly implies that even a skilled mutual fund manager cannot replicate his or her model to reproduce the persistence in mutual fund performance in a longer term. Thus, if a "skilled" fund manager claimed that he or she could outperform the market index by selecting "good" funds, then it would be a false discovery as the positive average monthly excess returns would be due to the luck in the funds, not in the skills.

In addition, the long-term reversal factor is strongly positively correlated with the average excess returns in the decile-10 portfolios, but negatively related with returns in the top decile. This suggests that average returns in longer term are affected inversely by the long-term reversal factor. Moreover, across all of the decile portfolios, the long-term reversal factor in each decile is statistically significant. On the other hand, the short-term (one-year) momentum factor is indeed statistically insignificant and is rejected in the most deciles. The alphas (intercepts) in each decile regression are positive. Yet, the intercept in the decile 1-10 spread regression is negative, and close to zero. I would conclude that the FFC four-factor model with the long-term reversal factor can capture and explain the variations in the abnormal returns fairly well, but not perfect. This result draws the same conclusion with Carhart (1997), in which longer time intervals create a reversal effect or make the one-year momentum effect drop out of the analysis. These results are different from Grinblatt and Titman (1992), who find mutual fund returns are persistent in a five-year horizon. But Grinblatt and Titman fail to consider the survival-bias in the mutual funds that are selected. Also, Grinblatt and Titman do not attempt to account for differences in performance attributable to expenses or transaction costs. They construct the P-8 model to explain the variation in the excess return associated with firm size, dividend yield, three-year past returns, interest-rate sensitivity, and beta. Therefore, according to Figure II and Table VI, I conclude that the one-year momentum effect does not hold in a long-term time period.

B. Momentum funds and transaction costs

The relationship between the momentum funds and their associated transaction costs is another important aspect to discuss. Momentum funds generally perform poorly after netting the transaction costs. Yet, some fund managers claim that fees and turnover ratios do not reduce returns to investors, rather to increase the fund-picking ability in fund managers. But this cannot be true because fees loaded in mutual funds are very much paid for maintaining the funds in the active index. Figure-III series demonstrate a time-series graph that contains the average associated fees loaded in the decile portfolios. On an average year, the average annual Maximum 12B1 Fee for decile-1 portfolios is approximately 0.5 percent, and 0.3 percent for Actual 12B1 Fee. Also, the average expense ratio for decile-1 portfolios in the last two decades is nearly 1.40 percent per annum. Moreover, the decile-10 portfolios, on the other hand, yield 0.4 and 0.5 percent in Actual 12B1 and Maximum 12B1 fees. And the expense ratio, on average, for decile-10 is almost 1.5 percent. Some fund managers may argue this as fess are paid for research and basic administrative expenses so that these managers can generate good returns above the index. Nonetheless, Figure-III Series depict a bad news for "skilled" fund managers. The average annual expense ratio among the ten decile portfolios is more than 1-1 bad. This is a relative high ratio for investors to read out because they are about to pay their fund managers more than the annual earned profits that these investors receive. I have combined the graphs of decile-1 and decile-10 together on one page to show the difference between the top and bottom portfolios. As aforementioned in the previous section, the average annual excess return from the top decile (1) portfolio is approximately 7 percent, whereas the bottom decile (10) generates only 3 percent return per annum. But after deducting all of the associated costs within the mutual funds, investors may receive a very small fraction in profits if their funds are invested into the top decile portfolios. On the other hand, if the funds flow into the bottom decile portfolios, then the year-end profits can be as negative as possible after extracting the net expenses. As I calculated in the previous section, the chance for top or the bottom decile portfolios staying at the same rank in the following year is approximately 50/50, which means there is no 100-percent-guaranteed methodology to make a fund rank in the top again. One interesting finding in Figure III series graphs is that the average (time-series) management fee for all of the decile portfolios is approximately negative 0.24 percent. This is due to the sharply drop in assets' values during the 2008-2009 financial crisis; so the management fee in each decile during 2008-2009 is also negative (as the graphs show a hug downturn in the management fee).

Table-VII reports the characteristics of average annual portfolio attributes. The average life in each decile is approximately 10 years. And the average annual TNA across all of the deciles is $561 million. The average expense ratio is more than one percent per annum for each decile. This accounts for some variation in the alphas (Carhart 1997). The Mturn[9] ratio is relatively high in the bottom decile portfolios for the time period of the sample, 1994 to 2014. This is a very poor attribute. The bottom decile portfolios may have to turn over the funds at least (nearly) one time during the year, and the turnover costs may consume the profits eventually. It is also clear that the bottom decile portfolios have a higher expense ratio than the top ones. According to Carhart (1997), the momentum funds do not earn (extremely) higher returns as they are consumed by the high turnover and expense ratios in the following year. This concludes my finds in

[9] Mturn is modified turnover and represents reported turnover plus 0.5 times the percentage change in portfolio TNA adjusted for investment returns and mergers.

this literature as well because after the associated expenses, the net profits generated from the momentum funds are not superior remarkable. Figure-IV reports a time-series average annual turnover ratio for the ten-decile portfolios from January 1994 to December 2014. Evidently, the turnover ratio for bottom decile portfolios has been always higher than the top ones, suggesting that the worst funds are even worse after all of the associated costs. This is surprising me in the fact why investors are still paying (high) management fees to the fund managers. In short, momentum funds, formed on one-year prior returns, can indeed generate a higher-than-average index-fund profit; but these funds lose it (almost) all in transactions costs, especially for the bottom decile portfolios.

V. Conclusion

Mutual fund managers do not appear to possess stock-picking skills. Stocks held by last year's winners outperform those held by last year's losers over the following year, but the Fama-French-Carhart four-factor model mainly explains the persistence. In particular, much of the performance is explained by momentum. Funds that performed well over the past year are likely to hold recently appreciated stocks, which benefit from momentum over the next year. Persistence in mutual fund returns appears to primarily be a manifestation of the Jegadeesh and Titman (1993) momentum effect.

In the analysis of U.S. domestic mutual fund performance, the difference between decile-1A and decile-10C portfolios is 32 basis points. Of this spread, anomalous variations in the intercept (alpha), 1 basis point, is nearly perfectly explained by the Fama-French-Carhart four-factor model. The four factors help explain 3.6 percent (annually) in the differences of market value and momentum stocks. The most unexplained comes from the 9-10 spread, which accounts for 0.72 percent (less than one).

This suggests the “cold hands” is existed in the bottom (worse) deciles. Momentum strategy (effect) can also be found in international stock markets. But under application of Fama-French model, the small-cap funds seem to have a reversal momentum pattern: negative alphas in “winners” and positive alpha in “losers”. Furthermore, the average monthly excess return in the winning deciles has an average approximate 1 percent, which suggests a 12 percent returns per annum. There are similar size patterns in momentum returns across every regional market. The global regional market yields the highest spread in monthly excess returns, 1.34 percent, between “winners” and “losers”. Also, the small-cap funds are generally doing better than big-cap ones. A typical size effect (higher average excess returns for small-cap stocks) is found in the international market. Although, GRS test rejects the null hypothesis, the FFC four-factor model is still considerable to use for testing whether there is a momentum effect in international mutual fund performance.

The persistence in mutual fund performance does not hold in a longer time interval. Instead, a reversal momentum effect is strongly discovered. The top decile portfolios start to reverse sharply to the bottom after the initial formation year, and on the other hand, the bottom decile portfolios are escalading at a faster speed than the top of the ranking. By the end of the fifth year, the bottom decile portfolios have completely surpassed the ones that were top-ranked in the initial formation year. The long-term-reversal factor is also significantly positively correlated with portfolios that are ranked in the bottom in the formation year, yet, strongly negatively correlated with those ones that are in the top-ranking position. So this suggests that the (short-term) momentum effect insignificantly explain any variations in the model with a longer time-series fund returns.

Last but not the least, momentum funds may perform poorly due to the high industrial transaction costs. On average, the expense ratio across all of the decile portfolios is approximately 1.3 percent, and the modified turnover ratio is nearly 80 percent high. Momentum funds, sorted by the last year's winners and losers, do not earn a substantial return, compared to contrarian stocks. Expensive transaction costs and relatively high turnover ratio make the profits even harder to acquire.

Overall, the evidence is consistent with market efficiency; interpretations of the size, book-to-market, and momentum factors are still valid to explain the anomalies. The bottom decile portfolios are not only underperformed the top ones, but are also costly to invest. This suggests that the worst funds are doing worse and worse again in short term. Most momentum (winning) funds seem to earn back their transaction costs, but investors do not have much room left in profits. Buying last year's winning funds for one year to get the momentum effect without trading costs seems to be a valid wealth-increasing strategy, but investors have to buy a fund of funds to make this become executable. This strategy is difficult to implement because many funds have loads for which investors have to pay when they long or short the funds. Thus, there is still a puzzle to me: if fund managers have superior fund-picking skills, then the market's alphas are increased enough to pay for the management fees; however, why would we still not see the market is efficient and at equilibrium? This paper revisits the empirical theory that the persistence in mutual fund performance is more due to the "luck" rather than the "stock-picking-skills". Both U.S. and international equity funds exhibit short-term momentum persistence in diversified portfolios. Fund managers who claim to have superior fund-picking skills may falsely discover the momentum effect is in the stocks (funds), not in the skills. In conclusion, fund managers can have skills to choose what “style” of funds they may invest, but not the skills to find the funds that can generate prominently inverse returns again the markets.

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Appendix

Tables and Figures

Table I

Mutual Fund Summary Statistics

The table reports tome-series average of annual cross-sectional average from January 1994 to December 2014. TNA is total net assets. Average Flow is the percentage change in TNA. Expense ratio is total annual management and administrative expenses divided by average TNA. Flow is the percentage change (monthly) in TNA adjusted for investment return and mutual fund mergers. Mturn is modified turnover and represents reported turnover plus 0.5 times Flow. Actual 12B-1 fees are reported as the ratio of the total assets attributed to marketing and distribution costs and represent the actual fee paid in the most recently completed fiscal year as reported in the Annual Report Statement of Operations. Live funds are those in operation at the end of the sample, December 31, 2014. Dead funds are those of which indicate by CRSP from WRDS.

		Time-series Averages of Cross-Sectional Average Attributes, 1994-2014							
Group	**Total Number**	**Avg number**	**Avg TNA ($millions)**	**Avg Flow**	**Avg Exp Ratio (%/year)**	**Avg Mturn (%/year)**	**Percentage with Load**	**Average Actual 12B-1 Fee (%/year)**	**Avg Age (years)**
All funds	14,349	3,721.4	$496.8	1.35%	1.34%	85.7%	74.4%	0.36%	12.0
By fund category									
Aggressive growth	904	289.1	$315.6	0.89%	1.66%	97.4%	63.3%	0.41%	13.0
Growth	7,610	2,029	$434.7	1.38%	1.41%	86.3%	48.8%	0.35%	11.7
Growth & income	5,835	1,403.4	$616.6	1.38%	1.18%	60.9%	45.2%	0.36%	12.3
By current status									
Live funds	7,979	3,234.8	$275.2	3.14%	1.25%	84.9%	29.6%	0.36%	12.0
Dead funds	6,370	1,891.2	$75.3	0.45%	1.46%	90.0%	47.9%	0.44%	9.0

Table II

Performance Measurement Model Summary Statistics, January 1994 to December 2014

VWRF[10] is the Center for Research in Security Prices (CRSP) value-weight stock index minus the one-month T-bill return. MKTRF is the percent excess return on market return minus risk-free rate. SMB and HML are Fama and French's factor mimicking portfolios for size and book-to-market equity. MOM or PR1YR is a factor-mimicking portfolio for one-year return momentum.

				Cross-Correlation				
Factor Portfolio	**Monthly Excess Return (%)**	**Std Dev (%)**	***t*-stat for Mean=0**	**VWRF**	**MKTRF**	**SMB**	**HML**	**MOM**
VWRF	0.62	4.48	2.20	1.00				
MKTRF	0.63	4.45	2.27	1.00	1.00			
SMB	0.18	3.42	0.82	0.26	0.25	1.00		
HML	0.21	3.21	1.05	-0.23	-0.23	-0.35	1.00	
MOM	0.45	5.18	1.38	-0.28	-0.27	0.09	-0.15	1.00

Carhart (1997)

				Cross-Correlation				
Factor Portfolio	**Monthly Excess Return (%)**	**Std Dev (%)**	***t*-stat for Mean=0**	**VWRF**	**MKTRF**	**SMB**	**HML**	**PR1YR**
VWRF	0.44	4.39	1.93	1.00				
RMRF	0.47	4.43	2.01	1.00	1.00			
SMB	0.29	2.89	1.89	0.35	0.32	1.00		
HML	0.46	2.59	3.42	-0.36	-0.37	0.10	1.00	
PR1YR	0.82	3.49	4.46	0.01	0.01	-0.29	-0.16	1.00

[10] VW is the CRSP value-weighted stock returns include distributions.

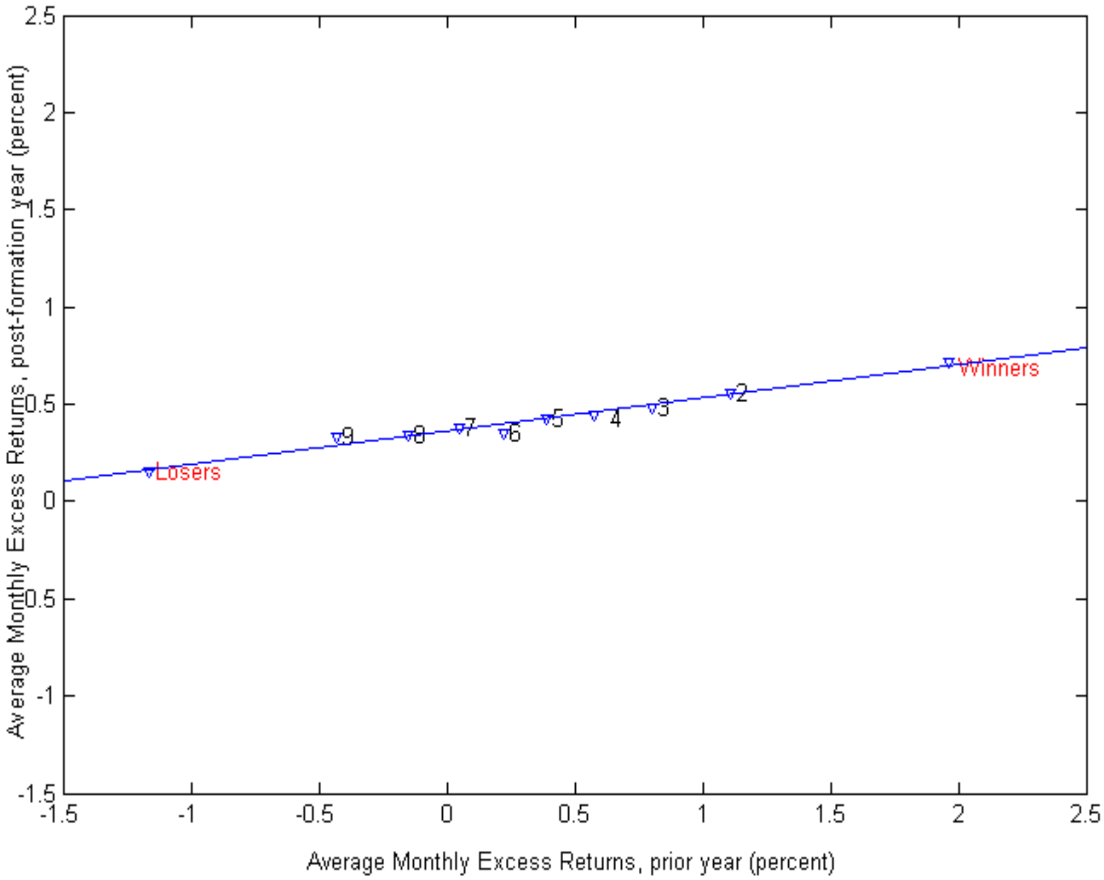


Figure I. Post-formation returns on portfolios of mutual fund sorted on momentum ranking from previous year. In each calendar year from 19994 to 2013, funds are ranked into equal-weighted decile portfolios based on prior year's monthly returns. Funds with the highest one-year return comprise decile 1, and funds with lowest comprise decile 10 (loser). The portfolios are equally weighted each month, so the weights are readjusted whenever a fund disappears from the sample.

Table III

Portfolios of Mutual Funds, January 1994 to December 2014

Mutual funds are sorted on January 1 each year from 1994 to 2014 into decile portfolios based on their previous year's return. The portfolios are equally weighted monthly so the weights are readjusted whenever a fund disappears. Funds with the highest past one-year return comprise decile 1 and funds with the lowest comprise decile 10. Decile 1 and 10 are further subdividing into thirds on the same measure. VWRF is the excess return on the CRSP value-weight market proxy. MKTRF, SMB and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. MOM is a factor-mimicking portfolio for one-year return momentum. Alpha is the intercept of the Model. The t-statistics are in parentheses.

	Monthly		CAPM			4-Factor Model					
	Excess	Std			Adj						Adj
Portfolio	**Return**	**Dev**	**Alpha**	**VWRF**	**R-Sq**	**Alpha**	**MKTRF**	**SMB**	**HML**	**MOM**	**R-Sq**
1A	0.62%	5.09%	0.02%	0.97	0.726	-0.12%	0.97	0.31	-0.08	0.22	0.829
			(0.14)	(25.80)		（-0.90）	(29.23)	(7.22)	(-1.82)	(7.88)	
1B	0.63%	4.99%	-0.003%	1.02	0.842	-0.12%	1.01	0.29	-0.11	0.18	0.931
			(-0.02)	(36.52)		(-1.38)	(49.09)	(10.95)	(-3.81)	(10.45)	
1C	0.57%	4.95%	-0.06%	1.01	0.835	-0.18%	1.01	0.23	-0.11	0.20	0.919
			(-0.46)	(35.70)		(-1.99)	(45.70)	(8.26)	(-3.47)	(10.59)	
1(high)	0.58%	5.01%	-0.05%	1.02	0.837	-0.18%	1.02	0.28	-0.10	0.19	0.930
			(-0.41)	(35.90)		(-2.10)	(48.90)	(10.64)	(-3.45)	(11.26)	
2	0.59%	4.56%	-0.03%	0.99	0.951	-0.11%	1.01	0.09	-0.01	0.10	0.967
			(-0.42)	(69.78)		(-2.14)	(77.84)	(5.60)	(-0.31)	(9.55)	
3	0.56%	4.43%	-0.05%	0.98	0.979	-0.11%	1.00	0.04	0.02	0.06	0.982
			(-1.16)	(108.93)		(-2.89)	(107.54)	(3.35)	(1.32)	(7.71)	
4	0.51%	4.33%	-0.09%	0.96	0.990	-0.12%	0.98	-0.01	0.01	0.02	0.989
			(-3.31)	(161.15)		(-4.23)	(136.74)	(-1.25)	(1.50)	(3.76)	
5	0.49%	4.32%	-0.10%	0.96	0.990	-0.11%	0.97	-0.03	0.01	-0.02	0.990
			(-3.6)	(155.42)		(-3.82)	(141.12)	(-3.26)	(1.25)	(-3.27)	
6	0.45%	4.26%	-0.13%	0.94	0.983	-0.13%	0.95	-0.04	0.04	-0.04	0.988
			(-3.79)	(121.37)		(-4.32)	(125.40)	(-4.30)	(3.54)	(-6.03)	
7	0.47%	4.26%	-0.12%	0.94	0.975	-0.10%	0.94	-0.05	0.02	-0.05	0.981
			(-2.78)	(99.63)		(-2.72)	(101.02)	(-4.49)	(1.72)	(-6.90)	
8	0.42%	4.24%	-0.15%	0.92	0.946	-0.15%	0.92	-0.06	0.06	-0.09	0.962
			(-2.36)	(66.04)		(-2.61)	(70.39)	(-3.77)	(3.36)	(-8.03)	
9	0.36%	4.33%	-0.22%	0.92	0.912	-0.16%	0.91	-0.06	0.04	-0.12	0.935
			(-2.64)	(51.06)		(-2.30)	(52.51)	(-2.67)	(1.84)	(-8.38)	
10(low)	0.26%	4.55%	-0.32%	0.93	0.840	-0.20%	0.88	-0.01	0.002	-0.20	0.886
			(-2.76)	(36.34)		(-2.04)	(36.59)	(-1.63)	(0.05)	(-9.93)	
10A	0.22%	4.72%	-0.38%	0.97	0.842	-0.27%	0.91	-0.02	0.002	-0.20	0.883
			(-3.21)	(36.56)		(-2.57)	(35.97)	(-0.51)	(0.07)	(-9.54)	
10B	0.26%	4.54%	-0.32%	0.93	0.837	-0.21%	0.88	-0.04	0.02	-0.20	0.882
			(-2.73)	(35.87)		(-2.08)	(35.91)	(-1.41)	(0.60)	(-9.59)	
10C	0.30%	4.46%	-0.25%	0.90	0.820	-0.13%	0.86	-0.09	-0.02	-0.20	0.871
			(-2.12)	(33.80)		(-1.25)	(34.07)	(-2.76)	(-0.52)	(-9.58)	
1-10	0.32%	3.56%	0.27%	0.09	0.009	0.02%	0.13	0.33	-0.10	0.39	0.511
spread			(1.18)	(1.83)		(0.15)	(3.42)	(6.66)	(-1.86)	(12.12)	
1A-10C	0.32%	4.01%	0.28%	0.07	0.002	0.01%	0.11	0.39	-0.06	0.42	0.451
spread			(1.09)	(1.18)		(0.04)	(2.35)	(6.59)	(-1.01)	(10.73)	
9-10	0.10%	0.76%	0.10%	-0.01	-0.002	0.04%	0.03	-0.01	0.04	0.08	0.241
spread			(2.12)	(-1.29)		(0.90)	(2.54)	(-0.67)	(2.94)	(9.03)	

Table IV

Portfolios of Mutual Funds, January 1994 to December 2014

Mutual funds are sorted on January 1 each year from 1994 to 2014 into decile portfolios based on their previous year's return. The portfolios constructed each month include NYSE, AMEX, and NASDAQ stocks with prior return data. To be included in a portfolio for month t (formed at the end of month t-1), a stock must have a price for the end of month t-13 and a good return for t-2. Each included stock also must have ME for the end of month t-1. Data are available from Kenneth R. French's website.

	Monthly		Ten decile portfolios formed on Momentum					
	Excess	Std.						Adj
Portfolio	**Return**	**Dev**	**Alpha**	**MKTRF**	**SMB**	**HML**	**MOM**	**R-Sq**
1(high)	1.00%	6.30%	-0.37%	1.21	0.33	-0.13	0.52	0.887
			(-0.27)	(36.43)	(7.69)	(-2.84)	(19.12)	
2	0.66%	4.46%	-0.14%	1.02	-0.12	-0.22	0.27	0.872
			(-1.36)	(41.05)	(-3.73)	(-6.36)	(12.82)	
3	0.82%	4.08%	0.10%	0.94	-0.08	0.28	0.17	0.877
			(1.10)	(41.68)	(-2.67)	(9.19)	(9.30)	
4	0.73%	4.07%	0.13%	0.87	-0.14	0.25	0.04	0.805
			(1.07)	(30.92)	(-3.94)	(6.48)	(1.76)	
5	0.63%	4.32%	0.04%	0.89	-0.09	0.29	-0.05	0.839
			(0.39)	(33.09)	(-2.49)	(7.71)	(-2.37)	
6	0.68%	4.43%	0.14%	0.88	-0.05	0.28	-0.16	0.860
			(1.30)	(33.82)	(-1.60)	(7.72)	(-7.24)	
7	0.75%	4.89%	0.27%	0.90	-0.06	0.27	-0.31	0.887
			(2.57)	(34.63)	(-1.95)	(7.60)	(-14.26)	
8	0.64%	5.71%	0.22%	0.93	-0.002	0.24	-0.50	0.903
			(1.92)	(33.36)	(-0.06)	(6.18)	(-21.37)	
9	0.51%	6.87%	0.09%	1.07	0.2	0.09	-0.67	0.939
			(0.80)	(40.19)	(3.39)	(2.54)	(-30.11)	
10(low)	0.24%	9.65%	-0.19%	1.31	0.38	-0.10	-1.00	0.882
			(-0.87)	(25.23)	(5.67)	(-1.42)	(-23.08)	
1-10 spread	0.76%	8.69%	0.15%	-0.10	-0.05	-0.03	1.53	0.859
			(0.70)	(-1.98)	(-0.77)	(-0.40)	(35.80)	

Table V

Summary statistics for the 25 size-B/M and size-momentum monthly excess returns for January 1994 – December 2014. The portfolios are constructed monthly and the intersections of 5 portfolios formed on size and 5 portfolios formed on prior (2-12) return. For international stocks, all returns are in U.S. dollars, include dividends and capital gains, and are not continuously compounded. Stocks are sorted in a region into five market cap and five lagged momentum return groups at the end of each month t. The size breakpoints for a region are the 3rd, 7th, 13th, and 25th percentiles of the regions aggregate market capitalization. For portfolios formed at the end of month t-1, the lagged momentum return is a stock's cumulative return for t-12 to t-2. The momentum breakpoints for all stocks in a region are the 20th, 40th, 60th, and 80th percentile of the lagged momentum return for big (top 90% of market cap) stocks of the region. The global portfolios use global size breaks, but the momentum breakpoints for each region are used to allocate the region's stocks to the global portfolios. Similarly, the global ex us portfolios use global ex us size breaks and regional momentum breakpoints. The 25 value-weighted size-momentum portfolios for a region are the intersections of the independent 5x5 size and momentum factors. All regressions are used equation (3).

***Panel A**: Monthly excess returns for 25 portfolios formed on size and momentum*

	Mean (percent)					Standard Deviation (percent)				
	Low	2	3	4	High	Low	2	3	4	High
U.S. Domestic										
Small	0.38	0.74	0.94	1.17	1.42	8.96	5.79	5.06	5.08	6.76
2	0.57	0.89	0.93	1.03	1.19	9.03	6.14	5.13	5.16	6.94
3	0.65	0.83	0.85	0.81	0.99	8.54	5.73	4.95	4.78	6.34
4	0.37	0.80	0.93	0.86	0.92	8.63	5.63	4.70	4.38	5.84
Big	0.32	0.67	0.60	0.76	0.80	7.77	5.24	4.23	3.99	5.03
Global										
Small	0.01	0.59	0.77	1.09	1.35	6.46	4.38	3.98	4.12	5.50
2	0.12	0.50	0.61	0.83	1.07	6.65	4.55	4.17	4.21	5.57
3	0.28	0.52	0.61	0.65	0.88	6.57	4.78	4.19	4.11	5.54
4	0.23	0.54	0.61	0.61	0.92	6.59	4.66	4.14	4.18	5.36
Big	0.16	0.43	0.47	0.62	0.63	6.30	4.60	4.05	4.17	5.33
Global Ex. US										
Small	1.09	0.49	0.69	1.02	1.32	6.23	4.59	4.14	4.22	5.49
2	-0.16	0.30	0.49	0.76	1.04	6.49	4.66	4.26	4.23	5.29
3	-0.11	0.33	0.46	0.68	0.86	6.42	4.93	4.33	4.27	5.30
4	0.06	0.39	0.49	0.47	0.85	6.15	4.92	4.49	4.36	5.12
Big	0.09	0.23	0.48	0.56	0.52	6.64	5.09	4.63	4.63	5.36
Europe										
Small	1.63	0.39	0.72	1.09	1.69	6.37	4.91	4.55	4.48	5.47
2	-0.13	0.50	0.76	0.99	1.49	7.04	5.42	4.99	4.84	5.67
3	0.13	0.52	0.77	0.85	1.19	7.19	5.52	5.04	4.91	5.76
4	0.21	0.61	0.73	0.83	1.17	7.34	5.62	5.05	5.07	5.50
Big	0.23	0.47	0.63	0.68	0.72	7.78	5.75	4.87	4.94	5.67
Asia Pacific ex. Japan										
Small	0.08	0.83	1.06	1.55	1.28	8.63	6.93	6.35	6.83	8.03
2	-0.69	0.44	0.53	0.86	0.80	9.04	7.03	6.23	6.50	7.70
3	-0.29	0.27	0.54	0.98	0.92	8.90	6.80	6.12	6.47	7.76
4	0.07	0.65	0.70	0.66	0.89	8.67	7.14	6.06	5.93	7.64
Big	0.87	0.55	0.73	0.77	0.77	8.88	7.12	6.47	6.16	6.98
North America										
Small	0.36	0.85	0.98	1.32	1.60	7.76	5.20	4.87	5.41	7.10
2	0.45	0.83	0.86	0.85	1.24	7.99	5.24	4.97	5.03	7.43
3	0.49	0.71	0.83	0.87	0.98	7.48	5.22	4.69	4.82	6.87
4	0.43	0.78	0.83	0.77	1.12	7.40	4.83	4.35	4.49	6.49
Big	0.35	0.60	0.51	0.73	0.86	6.55	4.61	3.96	4.18	6.07

Table V (continued)

***Panel B**: Estimates of regressions from the four-factor model with global and local factors to explain the excess returns on Global, North America, European, and Asia Pacific portfolios formed from independent size and momentum sorts.*
The table reports intercepts, α, and t-statistics, $t(\alpha)$.

	Intercept (α)					t-statistics (α)				
	Losers	2	3	4	Winners	Losers	2	3	4	Winners
U.S. domestic size-momentum returns regressed on U.S. factors										
Small	-0.14	0.06	0.21	0.43	0.42	-0.79	0.50	1.96	3.60	2.72
2	-0.04	0.20	0.17	0.23	0.10	-0.36	1.80	1.57	2.37	0.90
3	0.15	0.17	0.18	0.01	-0.04	0.93	1.45	1.62	0.04	-0.37
4	-0.10	0.22	0.29	0.13	-0.09	-0.56	1.94	2.70	1.20	-0.67
Big	-0.08	0.26	0.07	0.12	-0.07	-0.45	2.40	0.71	1.22	-0.65
Global size-momentum returns regressed on global factors										
Small	-0.16	0.13	0.23	0.48	0.56	-1.66	1.74	2.93	6.56	4.98
2	-0.03	0.04	0.03	0.17	0.24	-0.38	0.65	0.48	2.85	3.38
3	0.10	0.06	0.04	-0.03	-0.01	1.21	0.95	0.54	-0.48	-0.12
4	0.13	0.11	0.06	-0.10	0.04	1.43	1.95	0.89	-1.57	0.59
Big	0.12	0.08	-0.06	-0.11	-0.25	1.31	1.33	-0.87	-1.88	-2.96
Global Excluding U.S. size-momentum returns regressed on global excluding U.S. factors										
Small	1.31	0.15	0.19	0.43	0.57	3.39	1.93	2.56	6.04	4.85
2	-0.09	-0.03	-0.01	0.18	0.30	-1.13	-0.49	-0.20	2.59	3.36
3	-0.07	-0.04	-0.03	0.06	0.02	-0.82	-0.49	-0.45	0.88	0.18
4	0.06	0.12	0.01	-0.15	0.06	0.60	1.79	0.14	-1.93	0.70
Big	0.31	0.04	0.03	-0.14	-0.30	2.98	0.57	0.40	-2.16	-3.29
Europe size-momentum returns regressed on European factors										
Small	1.79	-0.01	0.20	0.38	0.77	4.31	-0.18	1.40	4.85	5.40
2	-0.18	0.03	0.13	0.21	0.48	-2.04	0.36	1.62	2.61	4.73
3	0.01	0.09	0.15	0.01	0.09	0.08	1.10	1.72	0.11	0.85
4	0.21	0.25	0.10	-0.04	0.04	1.67	2.82	1.03	-0.41	0.39
Big	0.36	0.17	0.04	-0.20	-0.41	2.98	1.64	0.48	-2.64	-3.57
Asia Pacific size-momentum returns regressed on Asian excluding Japan factors										
Small	-0.03	0.60	0.66	0.99	0.44	-0.21	4.28	5.18	5.72	2.75
2	-0.77	0.14	-0.03	0.24	-0.17	-6.61	1.10	-0.21	1.62	-1.10
3	-0.35	-0.10	0.11	0.38	0.07	-2.15	-0.64	0.79	2.77	0.41
4	-0.17	0.23	0.25	0.01	-0.01	-1.03	1.44	1.62	0.08	-0.05
Big	0.74	0.25	0.22	-0.04	-0.32	3.89	1.79	1.67	-0.29	-1.71
North America size-momentum returns regressed on North American factors										
Small	-0.17	0.19	0.27	0.51	0.55	-1.36	2.13	3.01	4.91	4.02
2	-0.09	0.18	0.12	0.02	0.08	-0.90	2.18	1.19	0.27	0.81
3	0.01	0.09	0.11	0.02	-0.09	0.07	1.00	1.16	0.23	-0.76
4	-0.05	0.19	0.15	-0.01	0.04	-0.35	2.26	1.73	-0.16	0.32
Big	0.004	0.12	-0.07	-0.04	-0.18	0.04	1.33	-0.72	-0.52	-1.66

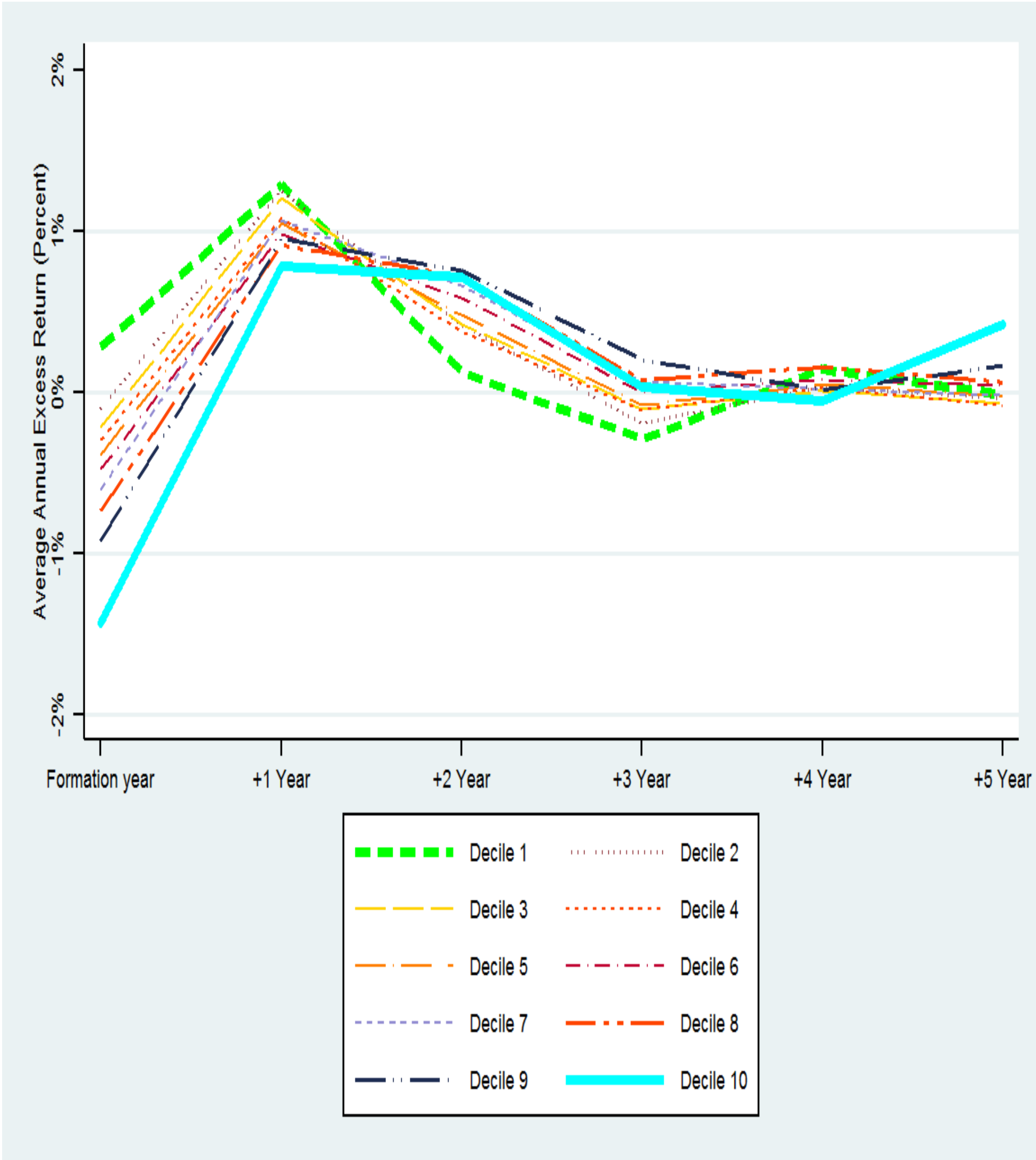


Figure II. Post-formation returns on portfolios of mutual funds sorted on lagged one-year return. In each calendar year from 1994 to 2009, funds are ranked into equal-weighted decile portfolios based on one-year return. The lines in the graph represent the excess returns on the decile portfolios in the year subsequent to initial ranking (the "formation" year) and in each of the next five years after formation. Funds with the highest one-year return comprise decile 1 and funds with the lowest comprise decile 10. The portfolios are equally weighted each month, so the weights are readjusted whenever a fund disappears from the sample.

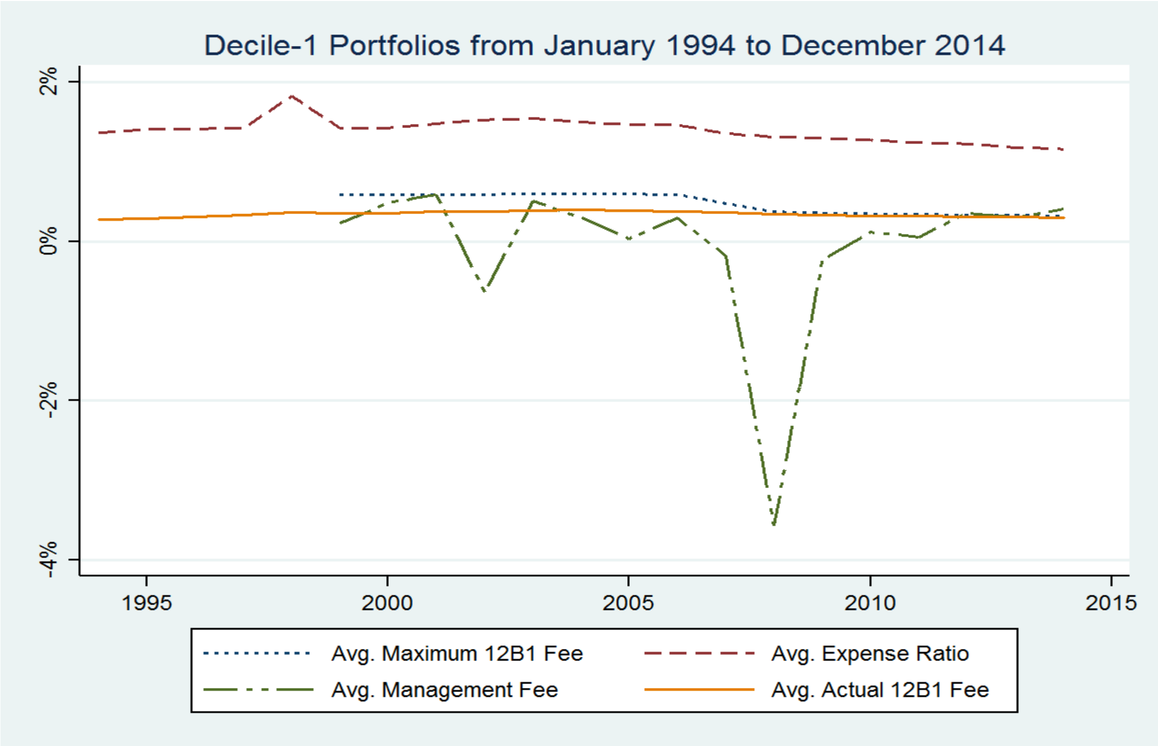
Table VI

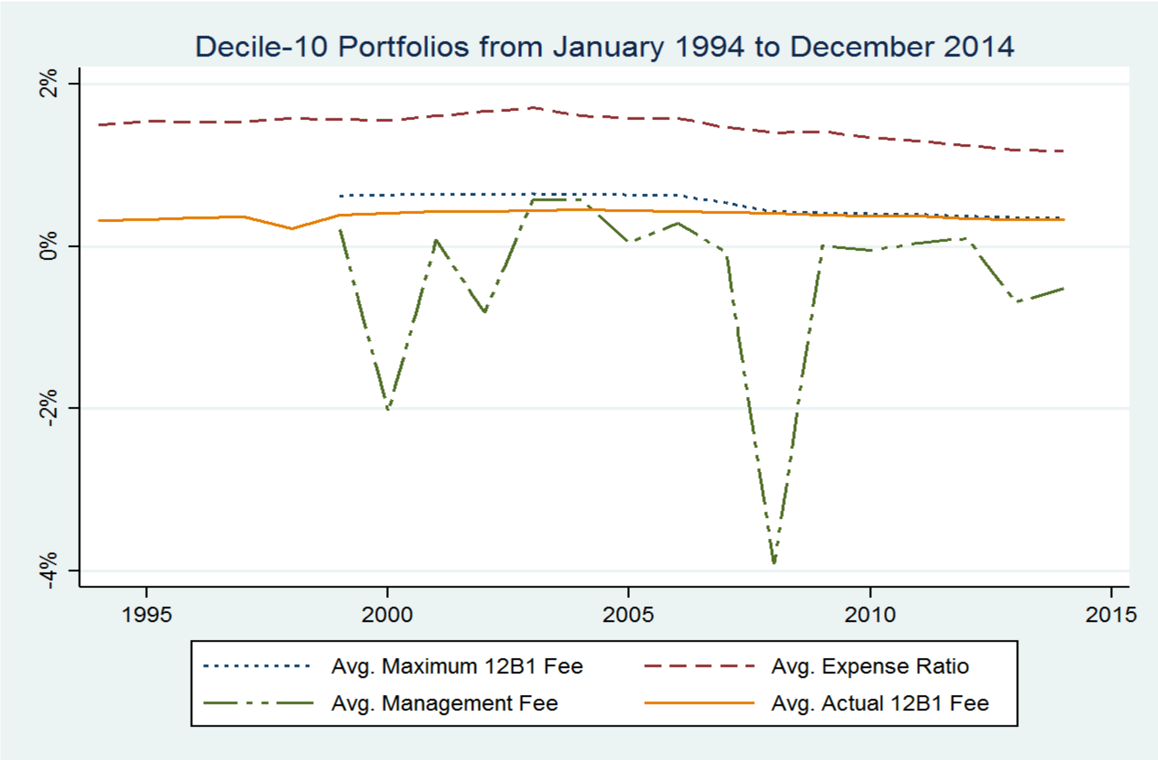
Portfolios of Mutual Funds Formed on 5-Year Lagged Returns

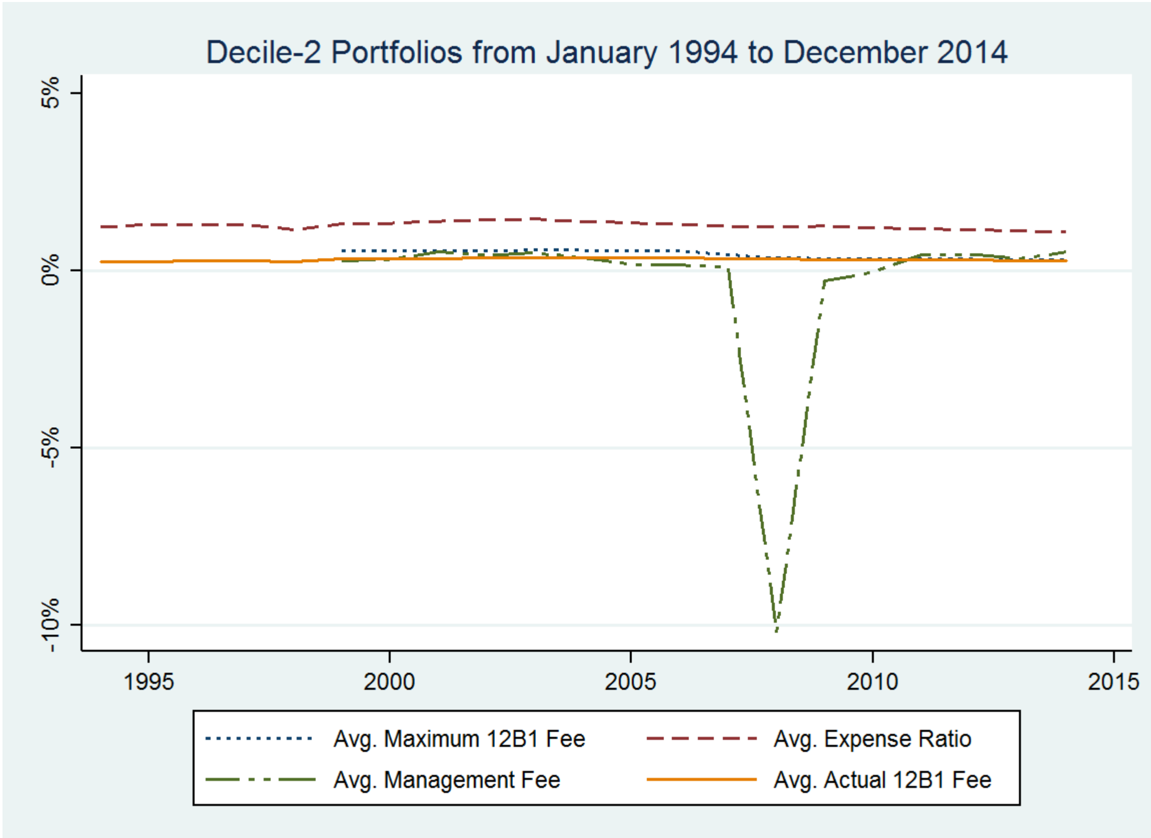
Mutual funds are constructed monthly using NYSE prior (13-60) return decile breakpoints available on WRDS. The portfolios constructed each month include NYSE, AMEX, and NASDAQ stocks with prior return data. To be included in a portfolio for month t (formed at the end of month t-1), a stock must have a price for the end of month t-61 and a good return for t-13. Regressions are from model (4). The four-factor model consists of MKTRF, SMB, HML, MOM, and LTRev. These five factors are Fama and French's (1993) market proxy and factor-mimicking portfolios for size and book-to-market equity. LT_Rv is the long-term reversal factor available on Kenneth French's website.

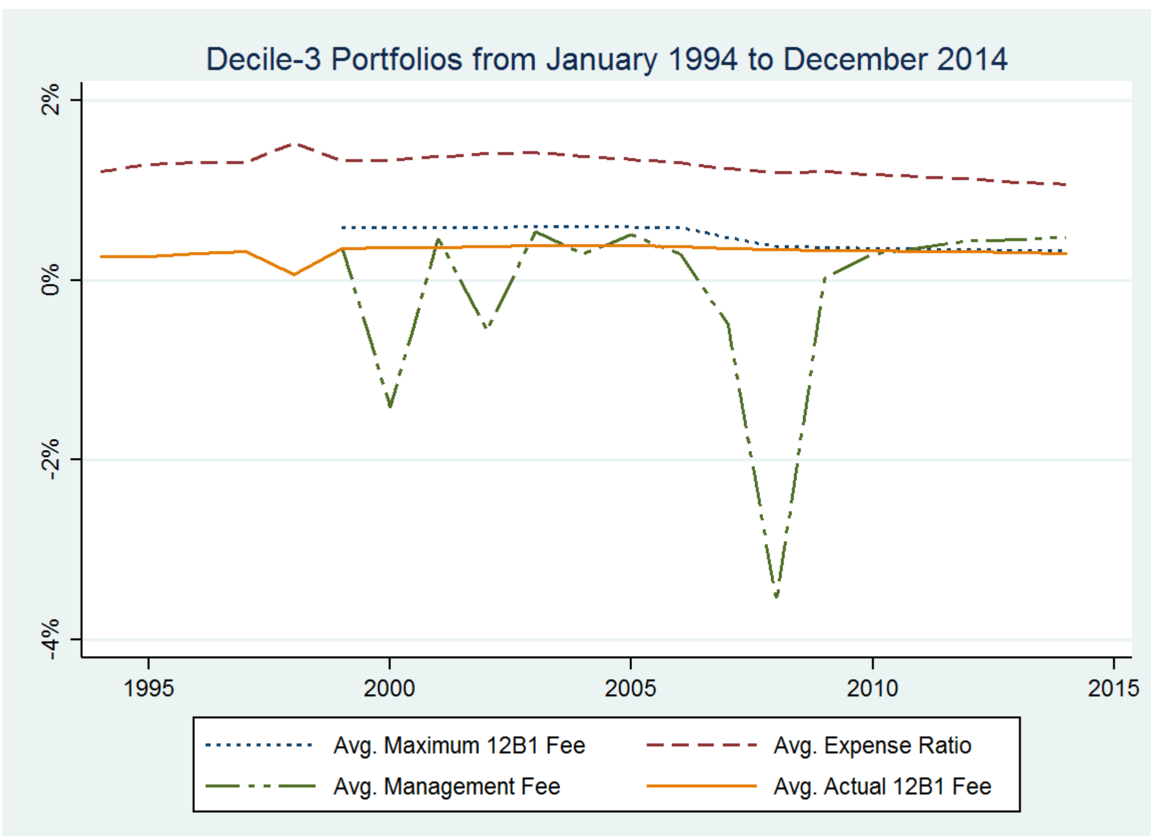
Portfolio	Monthly Excess Return	Std. Dev	Fama-French 4-Factor Model factors with Long-term Reversal Factor: Alpha	MKTRF	SMB	HML	MOM	LTRev	Adj R-Sq
1(high)	0.78%	5.94%	0.16%	1.18	0.12	-0.13	0.02	-0.57	0.889
			(1.27)	(37.85)	(2.70)	(-2.69)	(0.74)	(-9.11)	
2	0.70%	4.52%	0.08%	1.00	-0.09	0.26	0.09	-0.40	0.867
			(0.74)	(38.55)	(-2.36)	(6.25)	(4.01)	(-7.79)	
3	0.69%	4.14%	0.13%	0.90	-0.09	0.28	0.04	-0.30	0.839
			(1.21)	(34.32)	(-2.30)	(6.79)	(1.83)	-5.81	
4	0.74%	3.94%	0.15%	0.87	-0.10	0.29	0.03	-0.10	0.853
			(1.57)	(36.34)	(-2.70)	(7.59)	(1.73)	(-2.06)	
5	0.83%	4.05%	0.18%	0.87	-0.08	0.34	0.04	0.05	0.833
			(1.72)	(33.48)	(-2.04)	(8.17)	(1.97)	(0.94)	
6	0.81%	4.33%	0.14%	0.91	-0.13	0.31	0.001	0.21	0.839
			(1.21)	(33.35)	(-3.25)	(7.15)	(0.04)	(3.93)	
7	0.70%	4.36%	0.03%	0.90	0.03	0.30	-0.04	0.22	0.869
			(0.29)	(36.05)	(0.85)	(7.70)	(-2.00)	(4.53)	
8	0.91%	4.65%	0.14%	0.93	-0.02	0.15	0.01	0.61	0.883
			(1.39)	(36.88)	(-0.45)	(3.69)	(0.55)	(12.17)	
9	0.90%	5.24%	0.10%	1.00	0.07	0.12	-0.07	0.66	0.900
			(0.94)	(37.93)	(1.65)	(2.96)	(-3.17)	(12.55)	
10(low)	1.13%	6.77%	0.21%	1.12	0.43	0.03	-0.17	0.90	0.888
			(1.43)	(31.26)	(8.19)	(0.49)	(-5.48)	(12.71)	
1-10 spread	-0.35%	5.01%	-0.05%	0.07	-0.31	-0.16	0.18	-1.47	0.725
			(-0.27)	(1.60)	(-5.02)	(-2.45)	(5.29)	(-17.83)	

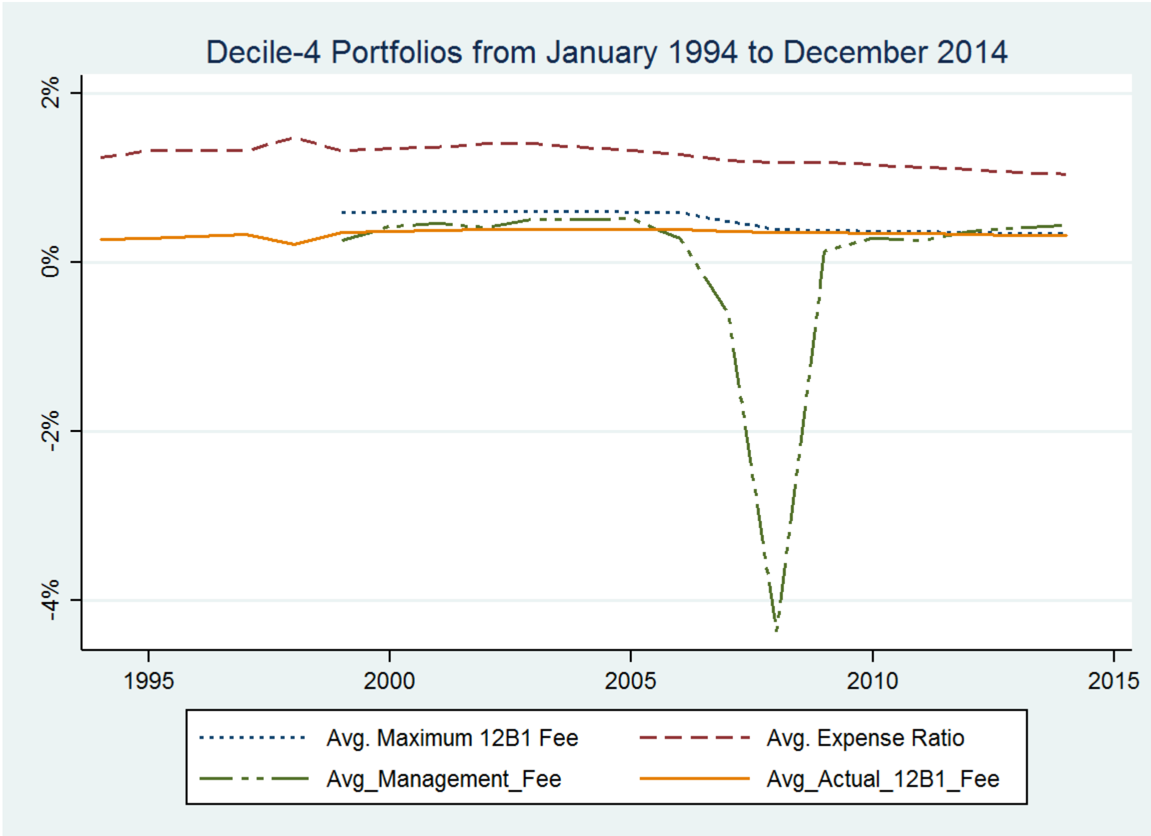
Figure III Series. Decile portfolios are sorted by the rank from 1994 to 2014. Each series includes the average annual values of maximum 12B1 fee, actual 12B1 fee, the management fee, and the expense ratio. Expense ratio is a fund's operating expenses divided by the average dollar value of its assets under management.

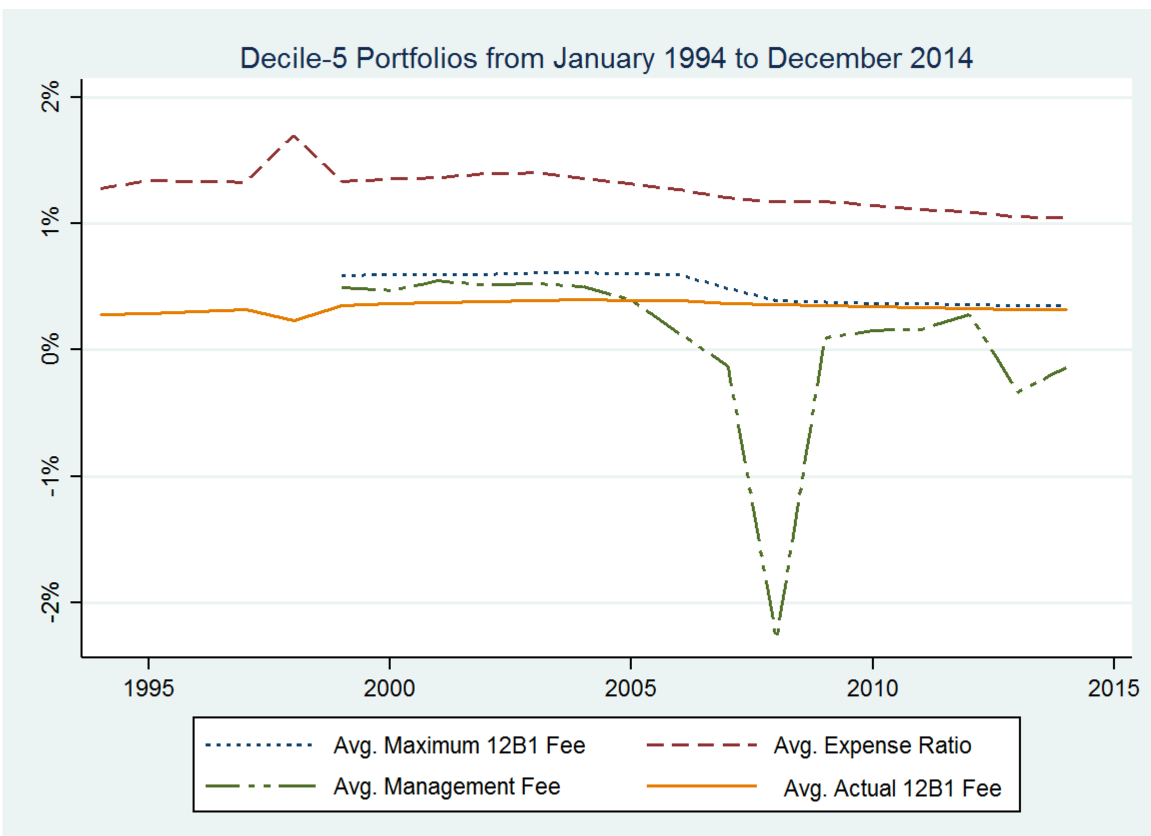


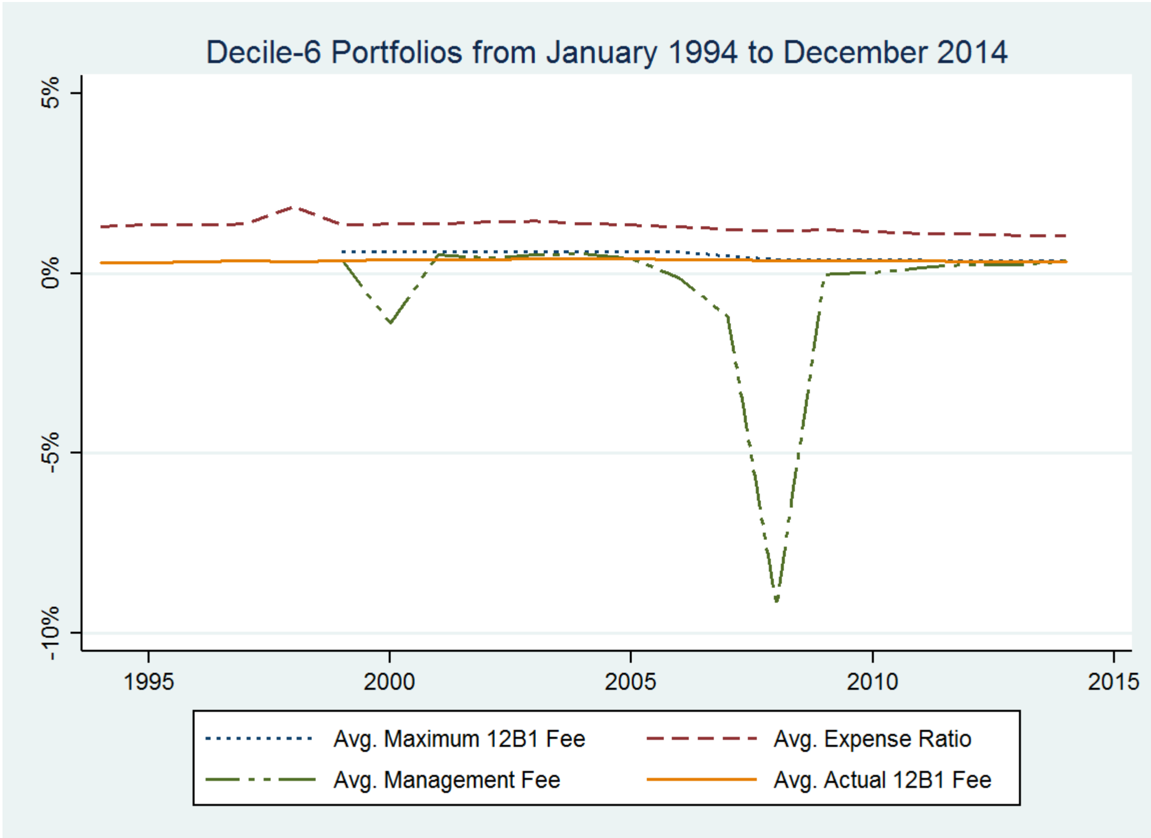


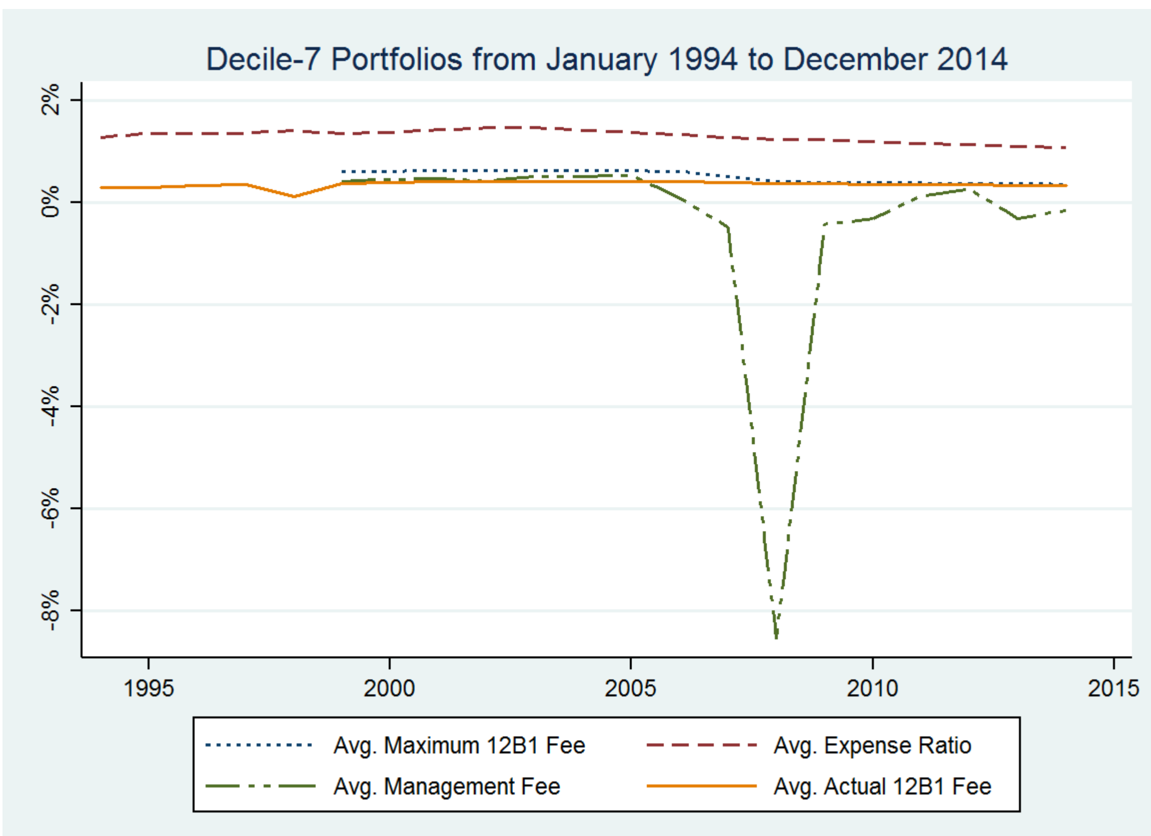

Decile-2 Portfolios from January 1994 to December 2014
5%
0%
-5%
-10%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee

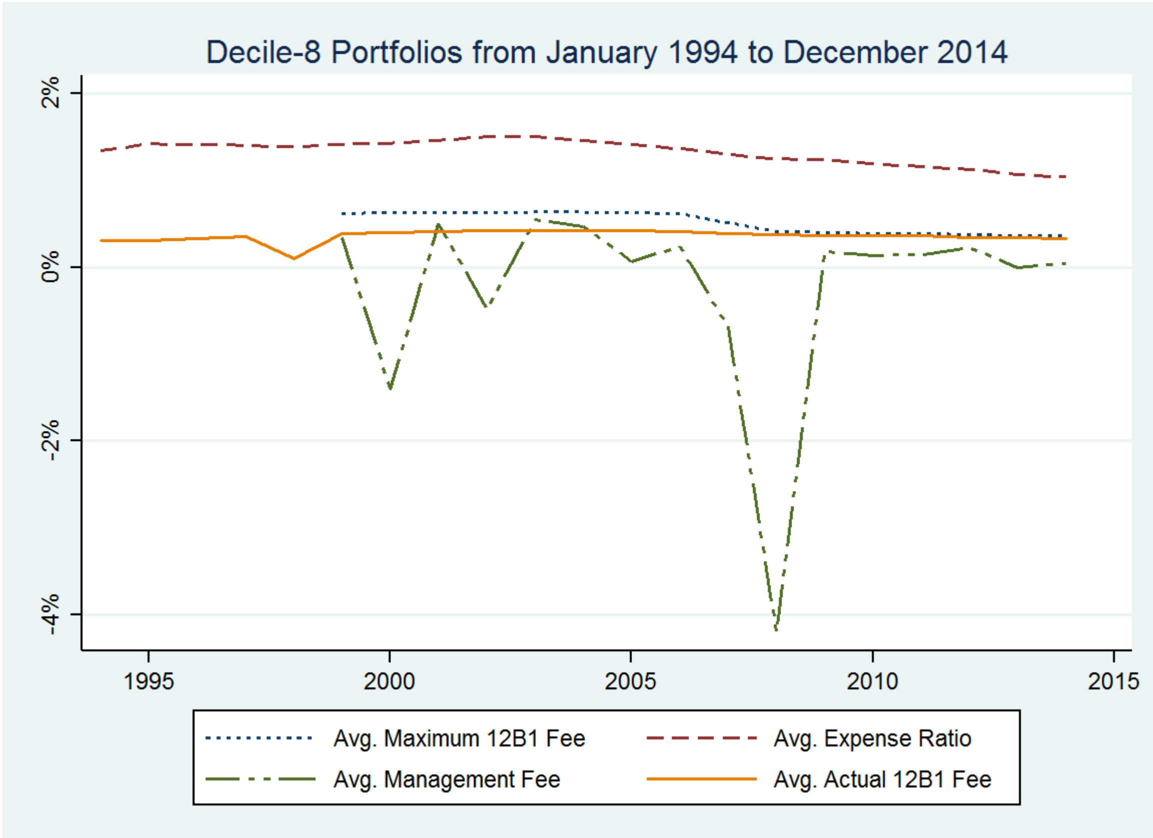

Decile-3 Portfolios from January 1994 to December 2014
2%
0%
-2%
-4%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee

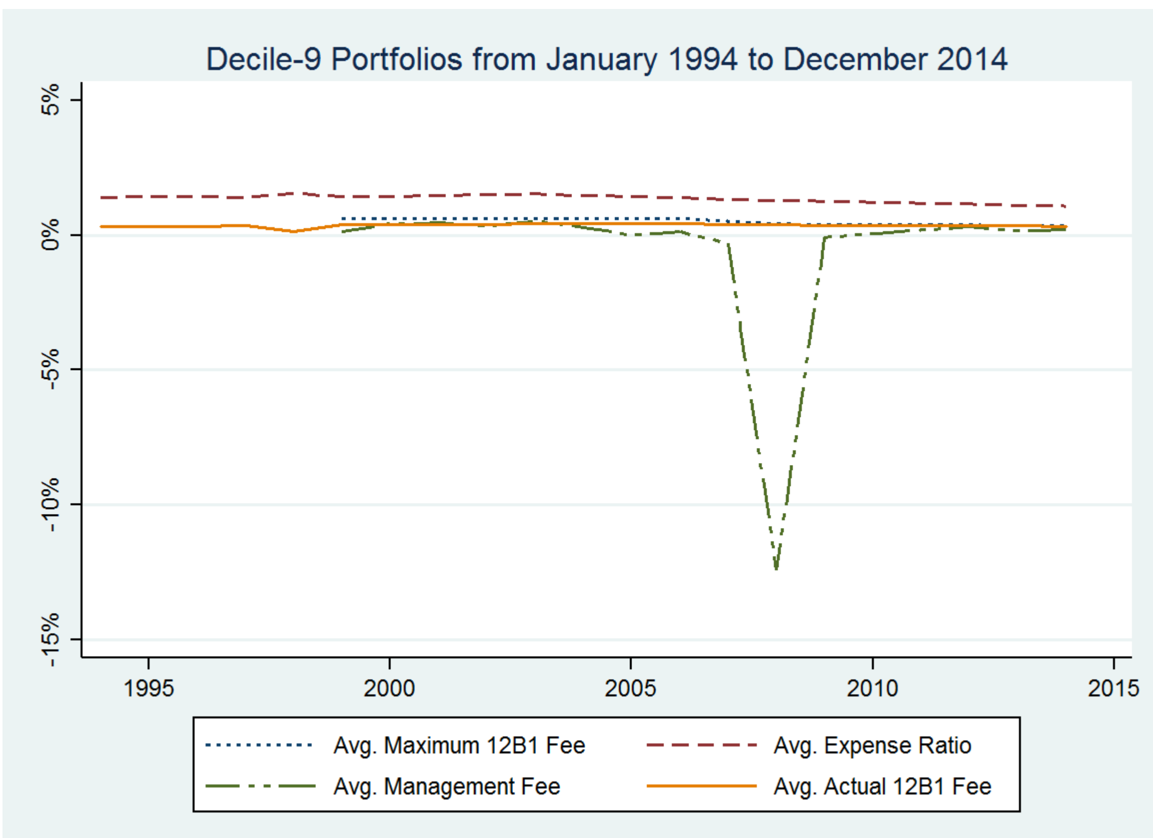

Decile-4 Portfolios from January 1994 to December 2014
2%
0%
-2%
-4%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg_Management_Fee
Avg_Actual_12B1_Fee


Decile-5 Portfolios from January 1994 to December 2014
2%
1%
0%
-1%
-2%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee


Decile-6 Portfolios from January 1994 to December 2014
5%
0%
-5%
-10%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee


Decile-7 Portfolios from January 1994 to December 2014
2%
0%
-2%
-4%
-6%
-8%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee


Decile-8 Portfolios from January 1994 to December 2014
2%
0%
-2%
-4%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee


Decile-9 Portfolios from January 1994 to December 2014
5%
0%
-5%
-10%
-15%
1995
2000
2005
2010
2015
Avg. Maximum 12B1 Fee
Avg. Expense Ratio
Avg. Management Fee
Avg. Actual 12B1 Fee

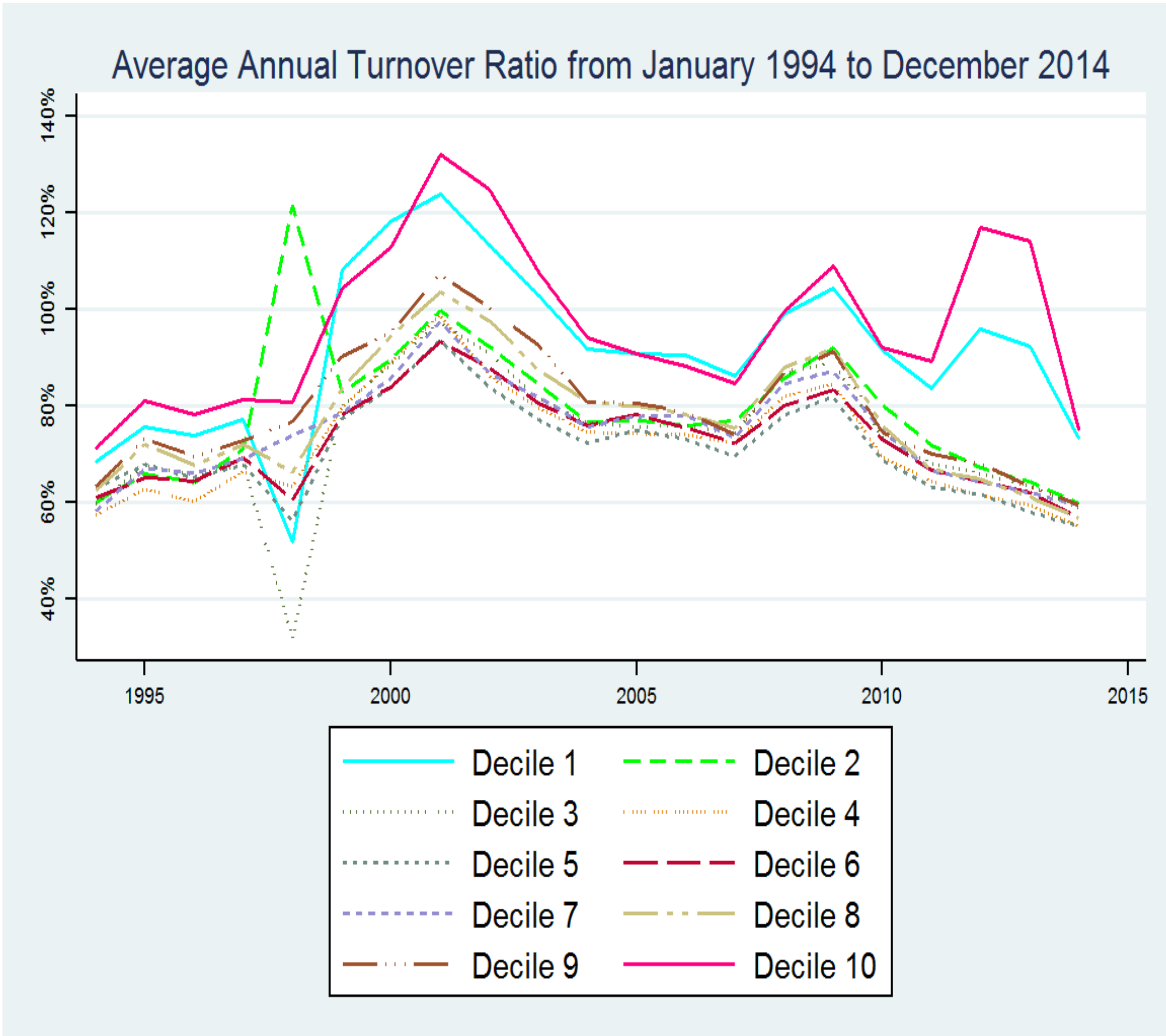


Figure IV. Time-series decile portfolios' average turnover ratio per annum. Each decile is sorted by the rank and combined into one decile from 1994 to 2014. The annual turnover is the minimum of purchases and sales divided by average TNA.

Table VII

Characteristics of the Portfolios of Mutual Funds Formed on Lagged 1-Year return

Mutual funds are sorted annually from 1994 to 2014 into equal-weighted decile portfolios based on lagged one-year return. Funds with the highest past one-year return comprise decile 1, and funds with the lowest comprise decile 10. The values in the table represent the time-series average of annual cross-sectional averages of the funds in each portfolio. TNA is total net assets. Expense ratio is the management, administrative, and 12B1 expenses divided by average TNA. Mturn is modified turnover and represents turnover plus 0.5 times Flow.

Average Annual Portfolio Attributes

Portfolio	Age (Years)	TNA ($ Millions)	Expense Ratio	Mturn (Percent)
1 (high)	10.0	631.7	1.39	90.7
2	11.0	728.0	1.29	78.6
3	10.9	691.0	1.28	72.9
4	10.9	665.9	1.27	71.7
5	10.6	658.0	1.28	70.7
6	10.5	706.1	1.31	72.6
7	10.5	644.3	1.31	74.3
8	10.1	549.0	1.33	77.1
9	9.9	543.9	1.38	79.1
10 (low)	8.9	458.4	1.48	96.3