Double Adjusted Mutual Fund Performance*

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ABSTRACT

We develop a new approach for estimating mutual fund performance that controls for both factor model betas and stock characteristics in one measure. Our double adjustment procedure shows that fund returns are significantly related to stock characteristics in the cross section after controlling for risk via factor models. Compared to standard mutual fund performance estimates, the new measure substantially affects performance rankings, with a quarter of funds experiencing a change in percentile ranking greater than ten. Double-adjusted fund performance significantly predicts four-factor alpha as far as nine years after the initial ranking period, whereas the performance attributable to characteristics shows little correspondence to future performance. Moreover, inference based on the new measure often differs, sometimes dramatically, from that based on traditional performance estimates.

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The performance evaluation of mutual fund managers is an enduring topic within financial economics. At the core of any performance analysis is the model used to determine the fund's benchmark. Among the alternative techniques utilized over the years, the factor model regression approach of Jensen (1968, 1969) and, more recently, Carhart (1997) and the characteristic-based benchmark approach of Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) stand out for their simplicity, intuitive interpretation, and widespread use. Both approaches are parsimonious, yet control for major influences identified in the empirical asset pricing literature as significantly affecting the cross section of stock returns.

For example, both the Carhart (1997) and DGTW approaches control for fund exposure to varying degrees of stock market capitalization, book-to-market ratio, and momentum, either via factor model betas, as in Carhart, or via benchmark portfolio returns, as in DGTW. Evaluating a fund by either approach provides insight into the types of stocks held by the fund through the regression factor loadings or specific characteristic benchmarks, while at the same time identifying a return hurdle for the fund commensurate with its stock portfolio.

The parsimonious structure of the models, however, has its drawbacks. For instance, factor models are imperfect, particularly vis-à-vis stocks with outlier characteristics. Fama and French (1996), for example, show that extreme small cap growth stocks show negative performance relative to their three-factor model. Consequently, a fund manager that holds small cap growth stocks might perform poorly when evaluated via a multi-factor Fama French or Carhart type of regression model, even absent poor stock selection skill (e.g., if their mandate is to invest in small cap growth stocks). Holding stocks with extreme characteristics poses similar issues for the DGTW measure because the typical DGTW implementation uses coarse quintile sorts to ensure well-populated benchmark portfolios.

Recently, the empirical asset pricing literature has examined the incremental effect stock characteristics have on the cross-section of stock returns beyond what is captured by factor model betas. That is, after controlling for risk in a Fama-French type of regression, for example, does a cross-sectional relation exist between residual returns and the stock's market capitalization? Brennan, Chordia, and Subramanyam (1998) and Chordia, Goyal, and Shanken (2013) find that characteristics such as market capitalization, book-to-market ratio, momentum, and liquidity are all statistically significantly related to average returns after controlling for factor model betas. That is, cross-sectionally, stock returns remain related to market capitalization, for example, even after controlling for market capitalization via Fama and French's (1993) SMB factor. In the context of mutual fund performance, these findings suggest that some of the abnormal performance previously identified via Fama-French or Carhart type regressions could be attributable to stock characteristics, rather than manager skill.

In this paper, we utilize in a mutual fund context the insight from the empirical asset pricing literature that both factor loadings and stock characteristics help explain the cross section of stock returns. We do so by developing a new mutual fund performance measure that controls for both types of influences. We base our measure on two variations of a two-step procedure, where we sequentially control first for exposure to factors and then for the characteristics of a mutual fund's stock holdings.

Specifically, we first compute Carhart (1997) four-factor alphas for a sample of actively managed U.S. domestic equity funds. Then, we use either a regression or portfolio sorting approach in the second pass cross-sectional adjustment. In our first approach, we regress cross sectionally the four-factor alphas on fund portfolio holding characteristics (i.e., fund portfolio holding value-weighted averages of market capitalization, book-to-market, and six-month momentum). Based on the cross-sectional regression estimates, we decompose the standard four-factor alpha into two components: (i) double-adjusted performance, which we define as the sum of the intercept and a fund's residual from the cross-sectional regression, and (ii) characteristics-driven performance, the component attributable to exposure to stock characteristics, estimated as the difference between standard four-factor alpha and double-adjusted performance.

As an alternative to the cross-sectional regression, our second approach subtracts the mean four-factor alpha of a portfolio of funds that invest in stocks with similar size, book-to-market, and momentum characteristics to produce the double-adjusted performance measure, with the mean characteristic-matched fund alpha representing the characteristic component of performance. With either approach, it is important to note that, by design, our second pass adjustment only affects fund relative performance ranking in the cross section, leaving the global mean of the double-adjusted alpha equal to the mean of the standard four-factor alpha.

Just as Brennan, Chordia, and Subramanyam (1998) and Chordia, Goyal, and Shanken (2013) find that characteristics explain the cross-section of stock returns after controlling for exposure to risk factors, we find that standard alpha measures from factor model regressions of mutual fund returns are significantly related in the cross section to the characteristics of mutual fund portfolio holdings. For instance, funds in the bottom quintile of book-to-market (i.e., those holding the smallest book-to-market stocks) have an annualized four-factor alpha that is 1.3 percent (*t*-stat.=2.5) greater than the alpha of funds in the top quintile. Funds in the top quintile of stock momentum (i.e., those holding the highest momentum stocks) have an annualized four-factor alpha that is 2.0 percent (*t*-stat.=3.6) greater than funds in the bottom quintile. Thus, funds can show higher relative performance based on standard four-factor alpha by passively loading on characteristics, even when the factor model explicitly controls for those characteristics.

To address the above issue with standard factor model performance estimates, we perform a second pass cross-sectional adjustment (or, alternatively, subtract a characteristic-matched mean fund alpha) and remove from standard alpha measures the component of performance attributable to characteristics. Our double-adjusted performance measure provides a cleaner estimate of true fund skill, to the extent that it controls for the passive effects associated with stock characteristics that are not addressed by the factor models. We find that about a quarter of a typical fund's standard four-factor alpha is attributable to stock characteristics conditional on double-adjusted and characteristics-driven components of the same sign. More importantly, we find that our second pass adjustment procedure impacts inference associated with relative fund performance, sometimes quite dramatically.

To provide some economic insight into the degree to which the second pass control impacts relative performance, we find a median percentile ranking change of about five (seven) percent with the regression (portfolio) cross-sectional adjustment. For example, a fund that ranked in the 50th percentile based on the standard Carhart four-factor alpha ranks in the 45^{th} or 55^{th} percentile after the second pass characteristics control using the regression approach. As a point of comparison, the median percentile ranking change from a Fama-French three-factor alpha to the Carhart four-factor alpha is three percent. Moreover, many funds experience extremely large percentile changes, as ten (five) percent of funds experience a change in performance percentile greater than 16 (22) percent with the regression approach and 24 (32) with the portfolio approach.

Changes in performance of this degree can obviously affect the interpretations one takes away from analysis that focuses on relative fund performance, which is central to much of the mutual fund performance literature. For example, studies of performance persistence examine consistency in relative fund rankings over time (e.g., Carhart (1997), Bollen and Busse (2005)). Ranking funds based on standard four-factor performance, we find weak evidence of long-term performance persistence, largely consistent with Carhart (1997). By contrast, after controlling for both factor exposure and characteristics, we find that double-adjusted performance predicts four-factor alpha as far as nine years following the initial ranking. Furthermore, the Appraisal ratio associated with the top-bottom portfolio of funds selected according to their double-adjusted performance measure is 0.78, whereas the corresponding Appraisal ratio for funds selected according to their standard four-factor alpha is 0.45. Thus, after removing the portion of performance attributable to the characteristics of portfolio holdings, we document new evidence that mutual fund skill persists over long periods of time. We also find strong evidence of short-term persistence (i.e., over the next month) via our new measure, where past top performing funds generate statistically significant positive performance in the future.

Beyond performance persistence, studies that emphasize relative fund performance include numerous analyses that relate performance to a particular fund feature, such as industry concentration (Kacperczyk, Sialm, and Zheng (2005)), the difference between the reported fund return and holdings-based return (i.e., return gap, Kacperczyk, Sialm, and Zheng (2008)), tendency to deviate from a benchmark (e.g., active share as in Cremers and Petajisto (2009)), or factor model regression R-squared (Amihud and Goyenko (2013)), among many others. When we use standard four-factor alpha performance measures, we confirm the major findings of these earlier mutual fund studies. However, after we adjust for the characteristics of the funds' stock holdings in the second stage of our measurement procedure, we find important changes that affect the way we interpret the results. For instance, we find no significant relation between a fund's industry concentration and our double-adjusted performance. We also find that the significant relation between a fund's standard four-factor alpha and its active share or factor model R-squared disappears after further adjusting standard performance for fund portfolio characteristics. Only the return gap is significantly related to our double-adjusted performance.

Taken together, our results suggest that it is fund exposure to particular stock characteristics that drive many of the relations documented in the literature. Furthermore, our results suggest that many prior findings are not driven by fund skill, to the extent that our double adjustment produces a cleaner measure of true fund skill. While it is debatable whether or not fund managers actively choosing to emphasize certain stock characteristics in their portfolios is a specific dimension of skill, it seems difficult to argue for an approach that only *partially* adjusts for a particular influence. Our results suggest that the most commonly used performance measures do just that. We should note that the goal of our paper is not to argue that mutual fund benchmark models should control for anomalies beyond market capitalization, book-to-market ratio, and momentum, for example, as in Carhart (1997). Our point is that, for whichever set of anomalies addressed in a model, adjusting for both the factor betas and stock characteristics more fully controls for those influences than utilizing only one type of approach.

Our paper contributes to the literature on mutual fund performance that applies innovations from the broader empirical asset pricing literature. To this point, advancements have largely proceeded either by expanding the set of factors used in the regression model, as in the move from the one-factor model of Jensen (1968, 1969) to the multi-factor models of Elton, et al. (1993) and Carhart (1997), or by the more radical move to nonparametric benchmarks that control for stock holding characteristics, as in Daniel et al. (1997).[1] Our paper is the first to incorporate both approaches in one measure to produce an estimate of performance that more

[1] Additional advancements include conditional models that allow for time-varying factor loadings (Ferson and Schadt (1996)) or time-varying alphas (Christopherson, Ferson, and Glassman (1998)) and, more recently, a model that simultaneously accommodates security selection, market timing, and volatility timing (Ferson and Mo (2015)).

comprehensively controls for influences that are not necessarily attributable to manager skill. Moreover, our analysis provides new insight into how traditional performance measures attribute performance, while at the same time raising questions regarding what constitutes genuine skill. Finally, since we base our new measure on actual fund shareholder returns, rather than returns estimated from periodic disclosures of fund portfolio holdings, we capture several effects that standard characteristic-based measures miss, including intra-quarterly fund activity, transaction costs, and trading skill (Kacperczyk, Sialm, and Zheng (2008) and Puckett and Yan (2011)).

The remainder of the paper proceeds as follows. Section I motivates the paper's methodology. Section II describes the data sample and variables. Section III presents the empirical results. Section IV concludes.

I. Methodology

A. Asset Pricing Motivation

Conventional asset pricing proposes a risk-return trade-off where greater expected returns require greater systemic risk. Within the empirical mutual fund literature, an equity fund's benchmark exposure defines the risk that drives most of the fund's return, and the convention is to interpret the remaining portion as manager skill. Jensen (1968, 1969), for example, evaluates fund manager performance as the intercept from a regression of excess fund returns on the excess returns of a stock market index.

Beginning with Ball and Brown (1968), however, numerous studies identify empirical asset pricing anomalies, where stock characteristics other than market beta help explain the cross section of stock returns. A partial list of those characteristics include market capitalization (Banz (1981)), book-to-market ratio (e.g., Fama and French (1992)), and momentum (Jegadeesh and Titman (1993)). Fama and French (1992) use these empirical regularities as motivation for multi-factor models, while Daniel and Titman (1997) advocate utilizing characteristic-based benchmarks. Both methods enjoy widespread application in the mutual fund literature via factor models like Carhart (1997) and the DGTW (1997) characteristic benchmark approach.

Rather than utilizing only one type of return control, Brennan, Chordia, and Subramanyam (1998) find that, after adjusting for risk factors, stock characteristics such as market capitalization and book-to-market ratio capture additional aspects of the cross section of stock returns. Similarly, Chordia, Goyal, and Shanken (2013) find that *both* factor loadings and stock characteristics explain cross-sectional variation of stock returns. Thus, one can express the expected excess return of a stock, j, as,

$$E(r_{j,t} - r_{f,t}) = c_0 + \sum_{k=1}^{K} \beta_{j,k}\lambda_k + \sum_{m=1}^{M} Z_{m,j,t}c_m, \tag{1}$$

where $\beta_{j,k}$ is the loading of stock j on factor k, λ_k is the risk premium associated with factor k, $Z_{m,j,t}$ represents stock j's characteristic m, c_m is the premium per unit of characteristic m, and c_0 is the zero-beta rate in excess of the risk-free rate.

In this paper, we use the insight from Brennan, Chordia, and Subramanyam's (1998) and Chordia, Goyal, and Shanken's (2013) stock analysis to examine the extent to which equity mutual fund returns relate to both factor loadings and fund portfolio holding characteristics. Controlling only for factor loadings, as in Carhart (1997), or only for characteristics, as in DGTW, may overlook the other effect, and in so doing materially impacts estimates of fund manager skill. To control for both types of return influences, we express equation (1) for mutual fund returns as

$$E(r_{i,t} - r_{f,t}) = a + \sum_{k=1}^{4} \beta_{i,k}E\left(F_{k,t}\right) + \sum_{m=1}^{M} Z_{m,i}c_m + \mu_i, \tag{2}$$

where $r_{i,t}$ is the return of fund i, $r_{f,t}$ is the risk-free rate, $\beta_{i,k}$ is the loading of fund i on factor k, $F_{k,t}$ is the return of factor k, $Z_{m,i}$ is fund i's portfolio value-weighted average stock characteristic *m*, a measures the average skill across all mutual funds in the industry, and μ_i measures the skill of fund *i* over the industry average. By construction, the cross-sectional average of μ_i equals zero. We note that, as in Brennan, Chordia, and Subramanyam (1998), we assume $c_0 = 0$, and set the risk premia of factor loadings equal to the expected excess return of their respective risk factors ($\lambda_k = E(F_{k,t})$).

B. Empirical Specification

Multi-factor models (e.g., Carhart (1997)) specify mutual fund returns as

$$r_{i,t} - r_{f,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \varepsilon_{i,t}. \tag{3}$$

We can rewrite equation (3) as

$$E(r_{i,t} - r_{f,t}) = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} E\left(F_{k,t}\right). \tag{4}$$

Combining equations (2) and (4) yields

$$\alpha_i = a + \sum_{m=1}^{M} Z_{m,i} c_m + \mu_i. \tag{5}$$

Equation (5) shows that the standard performance measure, α_i, from a multi-factor model such as Carhart (1997) captures performance attributable to both fund exposure to stock characteristics and true fund skill. To control for the effects of stock characteristics, we define mutual fund double-adjusted performance as

$$\alpha_i^* = \alpha_i - \sum_{m=1}^{M} Z_{m,i} c_m = a + \mu_i. \tag{6}$$

We define characteristic-driven performance as

$$\alpha_i^{char} = \alpha_i - a - \mu_i = \sum_{m=1}^{M} Z_{m,i} c_m. \tag{7}$$

Empirically, we estimate the cross-sectional regression of equation (5) with ordinary least squares (OLS) and use $\hat{\alpha}_i - \sum_{m=1}^{M} Z_{m,i} \hat{c}_m$ to calculate the double-adjusted performance measure.

Under regularity assumptions, the estimated coefficient $\hat{c}_m$ in equation (5) is unbiased, even though $\hat{\alpha}_i$ is estimated from equation (3) (see Brennan, Chordia, and Subramanyam (1998)). To preview our later findings, using mutual fund data from 1980 to 2012, we find that the c_m significantly differ from zero (which indicates the importance of the second stage adjustment), and, consequently, α_i^* often differs from α_i.

We utilize two alternative approaches to calculate our double-adjusted performance measure, both based on a two-step procedure. In both alternatives, we first compute alphas via the Carhart (1997) four-factor model over a 24-month estimation period, rolling this window a month at a time.[2] In our first approach, for each month in our sample period, we regress cross-sectionally the four-factor alphas on fund portfolio holding characteristics averaged over the past 24 months, lagged one month, using all sample funds in that month. We standardize each of the holding characteristics by subtracting its monthly cross-sectional mean before including them in the regressions. The demeaning procedure ensures that the intercept of each monthly regression equals the cross-sectional mean four factor alpha, so that our second stage adjustment only affects relative performance ranking. In this approach, we define double-adjusted performance as the sum of the intercept and the residual of a fund from the cross-sectional regression. Characteristics-driven performance, the component attributable to exposure to stock characteristics, is the difference between the standard four-factor alpha and double-adjusted performance.

In our second alternative approach, for each month in our sample period, we assign each fund to a cell based on either a three-way sequential tercile or quartile sort (i.e., 3×3×3 or 4×4×4) on fund portfolio stock holding characteristics (size, book-to-market, and momentum, in that

[2] Our results are qualitatively similar if we use a 36-month estimation period.

order) averaged over the past 24 months, lagged one month.[3] We calculate the mean alpha in each cell and subtract from it the global mean alpha of all sample funds. In this approach, the characteristic-matched demeaned alpha represents the fund's characteristics-driven performance. The difference between the fund's standard four-factor alpha and its characteristic-matched demeaned alpha is the fund's double-adjusted alpha. Note that subtracting the global mean alpha from the mean characteristic alphas again ensures that our procedure only affects relative performance rankings, leaving the global mean double-adjusted alpha equal to the mean standard four-factor alpha. For both alternative approaches, the sum of the two performance components, the double-adjusted performance and the characteristics-driven performance, always equals the standard four-factor alpha, as in equations (6) and (7).

II. Data and Variables

A. Data Description

We obtain our data from several sources. We take fund names, returns, total net assets (TNA), expense ratios, investment objectives, and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database. The CRSP mutual fund database lists multiple share classes separately. We obtain mutual fund portfolio holdings from the Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12) database. The database contains quarterly or semi-annual portfolio holdings for all U.S. equity mutual funds. We merge the CRSP Mutual Fund database and the Thomson Reuters Mutual Fund Holdings (also known as Thomson S12) database using the MFLINKS tables available via WRDS (see Wermers (2000)).

[3] To ensure well-populated cells, we utilize tercile sorts during the first portion of our sample period (1980-1994) when fewer funds exist. We sort funds into quartiles beginning in 1995 when the number of mutual funds in the CRSP database increases dramatically (i.e., above 640 funds with at least 10 funds in each cell).

We examine actively-managed U.S. equity mutual funds from April 1980 to December 2012.[4] We exclude balanced, bond, sector, index, and international funds. Similar to prior studies (e.g., Kacperczyk, Sialm, and Zheng (2008)), we base our selection criteria on objective codes and on disclosed asset compositions. First, we select funds with the following Lipper classification codes: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If a fund does not have a Lipper Classification code, we select funds with Strategic Insight objectives AGG, GMC, GRI, GRO, ING, or SCG. If neither the Strategic Insight nor the Lipper objective is available, we use the Wiesenberger Fund Type Code and select funds with objectives G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, or SCG. If none of these objectives is available, we keep a fund if it has a CS policy (i.e., the fund holds mainly common stocks). Further, we exclude funds that have the following Investment Objective Codes in the Thomson Reuters Mutual Fund Holdings database: International, Municipal Bonds, Bond and Preferred, Balanced, and Metals. We identify and exclude index funds using their names and CRSP index fund identifier.[5] To be included in the sample, a fund's average percentage of stocks in the portfolio as reported by CRSP must be at least 70 percent. We exclude funds with fewer than 10 stocks to focus on diversified funds. Following Elton et al. (2001), Chen et al. (2004), Yan (2008), and Pástor et al. (2015), we exclude funds with less than $15 million in TNA. We further follow Evans (2010) and use the date the fund ticker was created to address incubation

[4] Our sample period begins in April 1980 because portfolio holdings data from Thomson Reuters begin at the end of the first quarter in 1980.

[5] Similar to Busse and Tong (2012) and Ferson and Lin (2014), we exclude from our sample funds whose names contain any of the following text strings: *Index, Ind, Idx, Indx, Mkt,Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000*. We also remove funds with CRSP index fund flag equal to "D" (pure index fund) or "E" (enhanced index fund).

bias.[6] Our final sample consists of 2,927 unique actively-managed U.S. equity mutual funds and 370,587 fund-month observations.

B. Variable Construction

B.1. Fund Characteristics

To measure performance, we compute alphas using the Carhart (1997) four-factor model with fund net returns over a 24-month estimation period. We require a minimum of 12 monthly observations in our estimation. The four-factor model includes the CRSP value-weighted excess market return (Mktrf), size (SMB), book-to-market (HML), and momentum (UMD) factors from Ken French's website.[7] We also compute the Daniel et al. (DGTW, 1997) characteristic selectivity (CS) benchmark-adjusted return. We form 125 portfolios in June of each year based on a three-way quintile sort along the size (using the NYSE size quintile), book-to-market ratio, and momentum dimensions. The abnormal performance of a stock position is its return in excess of its DGTW benchmark portfolio, and the DGTW-adjusted return for each fund aggregates over all the component stocks using the most recent portfolio dollar value weighting.

Fund TNA is the sum of portfolio assets across all share classes of a fund. The variable Fund Age is the age of the oldest share class in the fund. Family TNA is the aggregate total assets under management of each fund in a fund family (excluding the fund itself). Expense Ratio is the average expense ratio value-weighted across all fund share classes. We define fund

[6] We address incubation bias as follows. As in Evans (2010), we use the fund ticker creation date to identify funds that are incubated (i.e., when the difference between the earliest ticker creation date and the date of the first reported monthly return is greater than 12 months). If a fund is classified as incubated, we eliminate all data before the ticker creation date. The ticker creation date data cover all funds in existence at any point in time between January 1999 and January 2008. For a small set of funds that are not covered in the ticker creation date data (i.e., those terminated before January 1999 or those that first appear after January 2008), we remove the first 3 years of return history as suggested by Evans (2010). We thank Richard Evans for sharing the ticker creation date data.

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

cash flow as the average monthly net growth in fund assets beyond capital gains and dividends (e.g., Sirri and Tufano (1998)).

B.2. Portfolio Holding Characteristics

For each stock in a fund's portfolio, we obtain stock-level characteristics from CRSP and COMPUSTAT, including market capitalization, book-to-market ratio, past six-month cumulative return, and the Amihud (2002) measure of illiquidity. We only keep stocks with CRSP share codes 10 or 11 (i.e., common stock) and NYSE, AMEX, or NASDAQ listings. For each fund in our sample, we use individual stock holdings to calculate the monthly fund-level market capitalization, book-to-market ratio, momentum, and Amihud measure. To calculate the fund-level statistic, we weight each firm-level stock characteristic according to its dollar weight in the most recent fund portfolio. Since fund holdings are usually available at a quarterly frequency, we obtain monthly measures by keeping the fund holdings constant between quarters.

We calculate the book-to-market ratio of a firm as the book value of equity (assumed to be available six months after the fiscal year end) divided by previous month-end market capitalization. We take book value from COMPUSTAT supplemented by the book values from Ken French's website. We winsorize the book-to-market ratios at the 0.5% and 99.5% levels to eliminate outliers, although our results are not sensitive to this winsorization. We define momentum as the six-month cumulative stock return over the period from month $t-7$ to $t-2$. For a given stock, we calculate the Amihud (2002) illiquidity measure as the average ratio of the daily absolute return to its dollar trading volume over all trading dates in a month, adjusting for NASDAQ trading volume as in Gao and Ritter (2010).

III. Empirical Analysis

A. Relation between Characteristics and Performance

To provide initial evidence that standard factor models imperfectly control for passive characteristics of the stocks held in fund portfolios, we examine the contemporaneous four-factor alpha of funds sorted into quintiles by their holding value-weighted average market capitalization, book-to-market ratio, six-month price momentum, or Amihud illiquidity measure. Table 1, Panel A reports sample summary statistics for these characteristics. Of these characteristics, all except the Amihud illiquidity measure are addressed in the four-factor model. Here, we include illiquidity in our analysis because the empirical asset pricing literature (e.g., Amihud and Mendelson (1986) and Acharya and Pedersen (2005)) finds a statistically significant cross-sectional relation between stock liquidity and returns (i.e., less liquid stocks show greater returns, on average).

[Insert Table 1 about here]

Each month beginning with the 24th month during our 1980-2012 sample period, we sort by average portfolio holding characteristics during a 24-month time period and examine the standard four-factor alpha estimated over that same 24-month period. To the extent that the four-factor model controls for influences related to market capitalization, book-to-market ratio, and price momentum via the Fama-French SMB, HML, and UMD factor loadings, we would not expect any significant relation between fund four-factor alpha and the characteristic quintile for market capitalization, book-to-market ratio, and six-month price momentum. Since there is a 23-month overlap in the estimation periods of two consecutive monthly alpha measures, we compute *t*-statistics of the differences between the top and bottom quintiles with Newey-West (1987) correction for time-series correlation with 12 lags.[8]

Table 1, Panel B reports the average four-factor alpha (each computed from 24 monthly returns) for each quintile. The results indicate that for sorts associated with all four

[8] Our results are qualitatively similar if we use 23 lags in the Newey-West (1987) correction.

characteristics, the difference between the top quintile (which includes funds that hold stocks of the greatest market capitalization, book-to-market ratio, six-month price momentum, or illiquidity) and the bottom quintile (which includes funds that hold stocks with the smallest market capitalization, book-to-market ratio, six-month price momentum, or illiquidity) is statistically significant at the ten percent level or lower.[9] The magnitude of these differences is economically large. For instance, funds in the bottom quintile of stock holding book-to-market have an annualized four-factor alpha that is 1.3 percent (*t*-stat.=2.55) higher than funds in the top quintile. Funds in the top quintile of stock holding momentum have an annualized four-factor alpha that is 2.0 percent (*t*-stat.=3.62) higher than funds in the top quintile. That is, funds show higher four-factor performance by passively loading on characteristics, even when those characteristics are explicitly addressed in the four-factor model.

Since funds holding smaller cap and higher six-month price momentum stocks show higher four-factor alphas than funds holding larger cap or lower six-month price momentum stocks, the four-factor model appears to under-adjust for influences related to market capitalization and momentum. That is, funds with small cap stock (high six-month price momentum) holdings outperform despite the SMB (UMD) control factor, which sets a higher than average hurdle for funds that hold small cap (high momentum) stocks. By contrast, the book-to-market results indicate that funds that hold stocks with high book-to-market ratios underperform funds that hold stocks with low book-to-market ratios, which suggests that the four-factor model over adjusts for influences related to book-to-market. Since the four-factor model does not include a liquidity factor, it is not surprising that the liquidity results in the last column of Panel B indicate that the four-factor model does not adjust well for illiquidity (i.e.,

[9] In column 1 of Table 1, Panel B, if we compare portfolio Q2 (funds that hold stocks of the second smallest market capitalization) and portfolio Q5 (funds that hold stocks of the greatest market capitalization), the difference is -1.18 percent with a t-stat. of -2.96.

funds holding less liquid stocks show greater performance than funds holding more liquid stocks).

To more formally examine the relation between standard factor model alphas and the characteristics of the funds' stock holdings, we regress cross sectionally the fund alphas used in Table 1 on the 24-month average of fund holding characteristics. That is,

$$\alpha_{i,t} = a + \sum_{m=1}^{M} Z_{m,i,t-1} c_m + \eta_{i,t}, \tag{8}$$

where $Z_{m,i,t-1}$ represents lagged fund holding characteristics, including portfolio value-weighted measures of market capitalization, book-to-market ratio, six-month price momentum, or illiquidity. For α_i, we examine four- and five-factor model performance, where the five-factor specification adds the Pástor and Stambaugh (2003) liquidity factor to the Carhart (1997) four-factor model.

Table 2 shows the results, where we compute the mean regression coefficients across all sample months. Again, to address time series correlation due to the overlap in estimation windows, we calculate Fama and MacBeth (1973) *t*-statistics with Newey-West (1987) correction for time-series correlation with 12 lags. Panel A reports results associated with the four-factor model, and Panel B reports the results associated with the five-factor model.[10] The alternative specifications control for each characteristic by itself as shown in the first four columns of Table 2 and all characteristics jointly as in the last column of Table 2.

[Insert Table 2 about here]

Similar to the inference associated with the results in Table 1, the results in Table 2 again show that standard fund performance measures are sensitive to the characteristics of the stocks held in the fund portfolios. Three of the four univariate regression results show a statistically

[10] Before including the Amihud measure in the regression, following Acharya and Pedersen (2005), we normalize it to adjust for inflation and truncate it at 30 to reduce the effect of outliers.

significant relation at the five percent level or higher between the fund factor model alpha estimate and the value-weighted mean stock characteristic. In untabulated results, we find that 303, 279, and 311 of the 393 individual monthly size, book-to-market, and momentum regression coefficients in the first three columns of Panel A in Table 2 are statistically significant at the five percent level, compared to an expectation of 20 under the null hypothesis, providing further evidence that standard measures of risk-adjusted performance via factor models are sensitive to stock holding characteristics.

B. Double-Adjusted Performance Effects

The results in the prior section demonstrate an important shortcoming in standard multi-factor abnormal performance estimates, insofar as they attribute skill to passive exposure to common characteristics. Our double adjustment procedure helps to alleviate this issue by removing performance attributable to characteristics from the factor model performance estimate.

In this section, we examine the extent to which the second adjustment in our two-stage procedure affects performance. We begin by estimating the fraction of standard alphas that is driven by exposure to characteristics. Later, we estimate the difference in fund percentile performance rankings before and after the second adjustment. That is, we examine the economic difference between standard performance measures (i.e., the first stage in our double-adjustment procedure) and our new performance measure.

In Section I, we show that standard factor model abnormal performance estimates can be decomposed into the sum of our new double-adjusted performance estimate and the portion of performance attributable to exposure to characteristics. Consequently, for a given fund, we can estimate the fraction of its standard performance measure that is attributable to characteristics, i.e., the ratio of the characteristic-driven component to the standard estimate,

$$frac^{char} = \alpha_i^{char} / \alpha_i, \tag{9}$$

with the remaining fraction, $1 - frac^{char}$, attributable to double-adjusted performance. This ratio is difficult to interpret, however, when the two components of skill are of different sign. As an extreme example, when the two components are equal in magnitude but of opposite sign, the ratio in equation (9) is undefined. Consequently, we focus on the subset of fund observations where the two components have the same sign, and we report statistics for this subset of funds in Table 3, Panel A. We find that the median ratio defined by equation (9) across our sample is 0.23 and 0.32 for the regression and portfolio approaches respectively. That is, characteristics account for between one quarter and one third of traditional four-factor abnormal performance estimates for a typical fund, conditional on the two components being the same sign.

[Insert Table 3 about here]

Naturally, given that as much as a third of a fund's performance is attributable to the stock characteristics of its portfolio holdings, one might anticipate that removing the characteristics component could materially impact fund performance rankings. When we compare percentile performance rankings of standard four-factor performance estimates to our double-adjusted performance estimate, the median change in percentile performance estimate is 4.8 (7.2) percent, based on the regression (portfolio) double-adjustment approach. That is, a typical fund originally ranked in the 50th percentile would be ranked at the 45th or 55th (43th or 57th) percentile after the second pass adjustment with the regression (portfolio) approach. As a point of comparison, the median change in performance from a Fama-French three-factor performance estimate to the Carhart four-factor performance estimate is three percent.

Furthermore, some funds experience dramatic changes in performance, with ten (five) percent of funds experiencing a mean change in percentile ranking of at least 16.4 (21.6) with the regression approach and 24.4 (31.6) with the portfolio approach.

C. Performance Persistence

The fraction of standard alpha attributable to characteristics and the degree to which the new double-adjusted measure impacts fund performance together suggest that the new performance measure could impact the inference of studies that analyze relative performance rankings. Central to the empirical mutual fund literature, studies that focus on relative performance rankings include analyses of performance persistence (e.g., Carhart (1997)) as well as studies that examine the relation between a specific fund feature and performance. Some recent studies in the latter category include Kacperczyk, Sialm, and Zheng's (2005, 2008) analysis of industry concentration and return gap, Cremers and Petajisto's (2009) analysis of active share, and Amihud and Goyenko's (2013) analysis of fund factor model R-squared. We explore how the double-adjusted skill measure affects inference in these mutual fund analyses.

Analyses of performance persistence include those that examine long- and short-term persistence. Long-term persistence studies, such as Carhart (1997), analyze the tendency for relative performance rankings to persist for at least one year beyond the ranking period. Short-term persistence studies, such as Bollen and Busse (2005), analyze persistence in relative performance rankings over shorter time periods, up to one quarter, for example.[11] Here, we examine persistence over both long and short post-ranking periods. We examine persistence in standard alpha performance measures as well as the two components of performance defined in

[11] Additional persistence studies include Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Malkiel (1995), Elton, Gruber, and Blake (1996), Busse and Irvine (2006), Busse and Tong (2012), and Berk and van Binsbergen (2015).

equations (6) and (7), i.e., our double-adjusted measure and the component attributable to characteristics. To the extent that our double-adjusted measure of performance represents a cleaner estimate of genuine skill, analyzing both components of performance will indicate whether evidence of persistence is attributable to fund manager skill or to passive effects attributable to characteristics.

C.1. Short Term Persistence

We begin with short-term persistence, where we examine whether fund performance during a ranking period persists to the following month (i.e., the one month post-ranking period). Each month, we sort funds into deciles based on performance measures estimated over the 24-month time period ending that month. We sort based on four different performance measures: standard four-factor alpha, the two components of standard performance, and, for comparison purposes, the average DGTW CS measure. For performance during the post-ranking month, we use standard four-factor performance, which we estimate by taking the difference between the realized fund return and the sum of the product of the standard four-factor betas estimated during the 24-month sorting period and the factor returns during the post-ranking month. As an example, we use performance estimates over the period from January 2000 through December 2001 to rank at the end of December 2001. We tie this December 2001 ranking to the January 2002 post-ranking month. We then move forward one month to analyze end of January 2002 rankings and the February 2002 post-ranking month performance. We examine post-ranking four-factor performance, rather than the characteristic-based DGTW measure, because four-factor performance utilizes actual shareholder returns, rather than a proxy for returns gleaned from fund portfolio holdings. We compute *t*-statistics of the differences between the top and bottom post-ranking quintiles with Newey-West (1987) correction for time-series correlation with three lags.

Table 4 shows the short-term persistence results. The table reports the one-month post-ranking performance estimates, averaged across all post-ranking periods. The results show strong evidence of persistence in the standard four-factor alpha. The 6.06 percent annualized difference in post-ranking top-bottom performance is both statistically and economically significant. We also find strong evidence that the double-adjusted performance measure predicts future four-factor performance, with a statistically significant 5.85 (5.80) percent annualized top-bottom post ranking abnormal return difference based on the regression (portfolio) double-adjustment approach. Thus, the double-adjusted portion of performance predicts almost all of the post-ranking abnormal return difference associated with standard four-factor alpha sorts. By contrast, the returns associated with characteristics show much weaker correspondence to future four-factor performance, with statistical significance only via the portfolio adjustment approach. For the characteristics sort, the difference between the top and bottom post-ranking four-factor returns represents a small fraction (approximately one fifth) of that associated with the double-adjusted performance sorts. To the extent that a fund's stock holding characteristics are an artifact of their investment style, rather than an active choice of the fund manager, our results suggest that short-term persistence is attributable to persistence in genuine fund manager skill.[12]

[Insert Table 4 about here]

We also find statistically significant positive four-factor performance in the top post-ranking decile sorted by standard alpha or double-adjusted measure. That is, funds that performed well in the past produce statistically significant positive abnormal performance of approximately 2.2-2.3 percent annualized (with *t*-statistics (not shown) greater than 3.5) over the

[12] We find qualitatively similar results if we examine short-term performance persistence with a one quarter post-ranking period.

subsequent month. This result suggests that the evidence of short-term persistence is not solely attributable to persistence in the poorly performing funds.

Lastly, we find that the DGTW CS performance measure predicts future four-factor fund performance, with a statistically significant 1.82 percent difference between the top and bottom post-ranking deciles. Note, however, that this difference represents less than one third the post-ranking difference associated with double-adjusted performance ranks. Together with the other persistence results, this evidence suggests that controlling for both risk factors and characteristics provides a cleaner picture of fund manager skill, insofar as such controls produce a performance measure that more closely aligns with future performance.

As a robustness test, we examine short-term persistence by regressing cross-sectionally the post-ranking monthly standard four-factor alpha on the ranking period performance, $perf$,

$$\alpha_{i,t} = a + bperf_{i,t-1} + \gamma \mathrm{X}_{i,t-1} + \eta_{i,t}, \tag{10}$$

where $perf$ is the four-factor alpha or 24-month average DGTW CS measure, or on both the ranking period double-adjusted alpha and characteristic-related alpha,

$$\alpha_{i,t} = a + b\alpha^{*}_{i,t-1} + c\alpha^{char}_{i,t-1} + \gamma \mathrm{X}_{i,t-1} + \eta_{i,t}. \tag{11}$$

In some specifications, we include X_i as regressors, which represent fund-level control variables (e.g., fund TNA, age, expense ratio, fund flow, and family TNA). We calculate Fama and MacBeth (1973) *t*-statistics with Newey-West (1987) correction for time-series correlation with three lags.

Table 5 shows the results. Panel A provides summary statistics of the fund-level control variables. In Panel B, the cross-sectional regression results show a strong association between the post-ranking alpha and the ranking-period alpha, which is driven predominantly by the double-adjusted component of alpha (*t*-stat.=7.88 (8.28) for the regression (portfolio) double adjustment approach) rather than the characteristic-related component (t-stat.=0.57 (2.90) for the regression (portfolio) approach). The regression results closely coincide with the decile analysis of short term persistence. The DGTW CS measure also strongly predicts future post-ranking alpha (t-stat.=2.88), although the relation appears to be weaker than the relation between double-adjusted performance and post-ranking alpha, also consistent with the decile results in Table 4. The last four columns of the table show that this result is not sensitive to the inclusion of several control variables. Our interpretation is that the double-adjusted performance measure captures genuine fund skill, which persists over time, and persistence in this component of alpha leads to persistence in standard four-factor alpha. The characteristics-related component weakly persists, at best, probably because the characteristic premia of size, value, and momentum time vary.

[Insert Table 5 about here]

C.2. Long Term Persistence

We turn next to long-term persistence. We use the same set of performance estimates that we use in the short-term persistence analysis. We aggregate the ranking period alphas in each calendar year (i.e., we average monthly alphas over the twelve months in a calendar year, with each monthly alpha estimated over a 24-month window ending that month) and move the ranking period forward one year at a time. We keep the decile assignment constant for post-ranking periods ranging from one to ten years and compute mean returns each month for each decile. We then estimate four-factor alphas for each decile over each post ranking year using concatenated time series of post-ranking returns (similar to Carhart (1997)). For example, we base one-year post ranking period performance on 32 annual ranking periods (each year from 1980 to 2011) and a concatenated set of one-year post-ranking periods (each year from 1981 to 2012), where each post-ranking period immediately follows its ranking period. We base the tenth-year post-ranking performance on the concatenated set of 23 post-ranking periods (from 1990 to 2012) that begin the tenth year after the ranking period.

Table 6 shows the long-term persistence results. The alternative panels reflect decile sorting based on the same four alternative performance measures used in Table 4. The panels reflect results based on net fund returns unless indicated otherwise. Panel A sorts based on standard four-factor alpha; Panels B, C, D, and E sort based on double-adjusted alpha; Panels F and G sort based on characteristic-driven alpha; and Panel H sorts based on 36-month average DGTW CS performance measure. We utilize both the regression-based approach for computing the double-adjusted performance (Panels B, C, and F) and the portfolio approach (Panels D, E, and G). Panels C and E are similar to Panels B and D, except we compute alphas for each decile using gross fund returns (i.e., where we add one-twelfth of the annual expense ratio back to the shareholder return). The results for each post-ranking year reflect non-cumulative post-ranking periods, so that the year ten results reflect standard four-factor performance only during the tenth year after the initial ranking, rather than the performance across all ten post-ranking years.

[Insert Table 6 about here]

Compared to the short-term persistence results, we see weaker persistence in the long term, as one might expect given results previously documented in the literature. The results in Panel A show mixed evidence of long-term persistence in standard four-factor alpha, largely consistent with Carhart (1997). Although three post-ranking years (years 2, 3, and 6) are statistically significantly consistent with past top performers outperforming past bottom performers, the remaining seven post-ranking years show a statistically insignificant difference (at the five percent significance level) between past top and bottom performers.

By contrast to the standard alpha results in Panel A, each of the four iterations of the double-adjusted results in Panels B, C, D, and E (varying by double-adjusted approach and net vs. gross returns) show a statistically significant four-factor performance difference between past top and bottom double-adjusted performers for at least seven out of the ten post-ranking years. The evidence of significant differences when utilizing gross fund returns in Panels C and E suggests that the double-adjusted performance measure is not simply isolating differences in expense ratios. Thus, sorting on performance that excludes the portion attributable to the characteristics of portfolio holdings predicts future four-factor performance better than sorting on total four-factor performance. To the extent that the double-adjusted measure provides a more precise estimate of genuine fund skill, we document new evidence that mutual fund skill persists over long periods of time. Using a four-factor model, Carhart (1997) found little evidence of persistence in mutual fund performance in the five years after ranking by four-factor alpha.[13] By contrast, our new measure shows evidence of skill predictability even in the ninth post-ranking year. Note, however, that, in contrast to the short-term persistence results, the evidence of predictability in net returns is largely driven by poor performance in the bottom-ranked funds, as the top decile in Panels B and D fail to produce statistically significant positive four-factor abnormal returns during any post-ranking year (*t*-statistics not shown).

Regardless of the post-ranking year, the results in Panels F and G show no evidence that the portion of standard alpha attributable to characteristics predicts future four-factor performance. These results help to explain why we see stronger evidence of predictability based on the double-adjusted measure than on the standard four-factor alpha. In particular, the standard alpha includes performance attributable to characteristics, which does not predict future

[13] When ranking by lagged one-year fund net returns, Carhart (1997) finds no evidence of persistence in fund performance even during the first post-ranking year.

performance. The combination of genuine skill that does help forecast future performance (as in Panels B and D) plus characteristic-driven performance that does not (as in Panels F and G) produces the weaker evidence of persistence that we see in Panel A.

The interplay between the standard four-factor performance measure and the double-adjusted performance measure becomes clear when we cumulate the post-ranking four-factor performance across the post-ranking years, rather than examining the performance of each post-ranking year in isolation as in Table 6. In Figure 1, we show the cumulative abnormal post-ranking four-factor performance difference between top and bottom decile funds, where the three plot lines represent alternative sorts based on the standard four-factor performance, the double-adjusted performance, and the characteristics component of performance. Panel A reflects the regression approach for determining double-adjusted performance, and Panel B reflects the portfolio approach. In both panels, the upward trending plots associated with the standard and double-adjusted sorts reflect the evidence of long-run persistence in relative performance shown in Table 6. That is, funds originally ranked in the top decile (based on standard four-factor alpha or double-adjusted performance) outperform funds originally ranked in the bottom decile, and the outperformance persists over many years. By contrast, the cumulative four-factor performance for funds sorted by their characteristic-driven component of performance indicates that the characteristic component of performance does not forecast subsequent four-factor performance over any post-ranking time frame. The plots suggest that whatever evidence exists that standard four-factor performance or fund manager skill persists is largely driven by the double-adjusted component of performance. By contrast, the plots also suggest that the characteristic-driven portion of performance is not associated with an enduring component of four-factor performance.

[Insert Figure 1 about here]

This last point could justify, perhaps to a great extent, the second-stage adjustment that is central to our double-adjusted measure. In examining the relations evident in Table 2, Panel B, one could argue that skillful fund managers are especially adept at uncovering profitable investment opportunities among certain types of stocks. For example, it seems reasonable to expect the stock market to be less efficient among smaller cap stocks, perhaps because some large funds are reluctant to trade less liquid, smaller cap stocks. If that were the case, then the second stage adjustment would unfairly punish those managers, by removing premia that extends beyond that which is passively associated with the characteristic. However, the results in Tables 4, 5, and 6, as well as the evidence in Figure 1, all indicate that the component of performance that we remove in the second stage of our procedure, i.e., the characteristics driven component, does not forecast future performance. To the extent that we unfairly remove true skill in our second stage, then we would expect to see some evidence that the extracted component relates to future performance.

One potential implication of the persistence results is that we may be able to identify funds with similar four-factor alpha but lower levels of idiosyncratic risk. That is, it seems likely that selecting funds based on the double-adjusted measure of performance, rather than standard four-factor alpha, would result in a portfolio of funds less influenced by the characteristic component of performance, which, going forward, would be expected to increase a fund's risk but not its abnormal return. To examine this possibility, we compute the Appraisal ratio (i.e., the ratio of the mean to the standard deviation of the 120 post ranking monthly abnormal returns) for the top-bottom portfolio of funds associated with the double-adjusted performance sorts in

Panels B and D (i.e., based on net fund returns) and the standard four-factor alpha sorts in Panel A.

As expected, selecting funds based on double-adjusted performance produces a greater average Appraisal ratio compared to selecting funds based on the standard four-factor alpha. The Appraisal ratio associated with the top-bottom portfolio of funds selected according to their double-adjusted performance measure is 0.784 (0.781) based on the regression (portfolio) approach to compute double adjusted performance, whereas the corresponding Appraisal ratio for funds selected according to their standard four-factor alpha is 0.448. To put it differently, although the plot lines corresponding to standard four-factor and double-adjusted performance sorts in Panels A and B of Figure 1 are close to each other, the confidence intervals of the former are substantially larger than the latter.

Finally, in Panel H, we see no relation between the DGTW CS performance measure and future long-term four-factor performance, as none of the post-ranking years show a statistically significant difference in four-factor performance between the top and bottom deciles. Our long-term CS persistence results are consistent with Daniel et al. (1997), who also find no relation between the CS measure and future fund performance. Similar to the short-term persistence results, these long-term persistence results highlight the importance of controlling for both risk factors and characteristics when trying to extract a signal for future performance.

D. Impact on Prior Studies on Industry Concentration, Return Gap, Active Share, and R-squared

Beyond studies of performance persistence, many other analyses examined in the recent mutual fund literature emphasize relative performance, especially relating it to a specific fund feature (rather than stock characteristic). In this section, we examine whether the inference one takes away from these analyses can be sensitive to more fully controlling for fund holding characteristics. Given the prevalence of this type of analysis in the mutual fund literature, numerous suitable candidates for examination exist. We focus on the following four recent studies: Kacperczyk, Sialm, and Zheng (2005, 2008) on industry concentration and return gap, Cremers and Petajisto (2009) on active share, and Amihud and Goyenko (2013) on factor model R-squared.

We begin by examining the performance implications of these four studies and replicate some of the main analyses. In particular, we examine the relation between each of the measures and fund performance using four-factor alpha as our baseline measure of performance. By utilizing the four-factor alpha for baseline performance, we can also relate the various fund measures to the two components of performance, our double-adjusted measure and the portion of performance attributable to characteristics. Relating the fund measures to the two components of performance will help disentangle which of the two components drives the main findings. To examine the relation between the various measures and fund performance, we sort funds into quintiles based on each measure each month and then examine the subsequent performance of the quintiles. For performance during the post-ranking month, we use four-factor alpha calculated as the difference between the realized fund return and the sum of the product of the factor betas estimated over the previous 24-month and the factor returns during the month.

D.1. Industry Concentration

We begin with the industry concentration index of Kacperczyk, Sialm, and Zheng (2005). We compute this index as the sum of the squared deviations of the value weights for each of ten different industries held by the mutual fund, relative to the industry weights of the total stock market. Panel A of Table 7 reports summary statistics for this index and the other fund measures that we examine. We impose a three-month lag between the industry concentration measure and subsequent performance, consistent with the original study. For example, we relate industry concentration as of the end of March to performance during July.

Table 7, Panel B1 shows the industry concentration quintile results. First, we find slightly weaker evidence of a correspondence between industry concentration and standard four-factor alpha compared to the original study, probably due to differences in sample period. However, our results show a statistically strong relation between industry concentration and the subsequent performance associated with fund stockholding characteristics. That is, funds with the highest industry concentration show the greatest characteristic-based performance. By contrast, we see no significant relation between industry concentration and double-adjusted performance. These results suggest that, rather than proxying for fund skill, industry concentration proxies for stockholding characteristics that produce higher standard four-factor alphas.

[Insert Table 7 about here]

D.2. Return Gap

The return gap measure (Kacperczyk, Sialm, and Zheng (2008)) is the difference between fund gross returns and holdings-based returns. We compute gross fund returns by adding one-twelfth of the year-end expense ratio to the monthly net fund returns during the year. We calculate the holdings-based gross portfolio return each month as the return of the disclosed portfolio by assuming constant fund portfolio holdings from the fund's most recent disclosure. For our analysis of the return gap, we sort based on the average return gap over the prior 12 months, consistent with the original study, and then examine performance over the following month.

The results in Table 7, Panel B2 indicate that the return gap is positively related to subsequent double-adjusted fund performance, with a statistically significant difference between the top and bottom post-ranking performance deciles. The results also indicate that the return gap is not related to the characteristic-driven component of fund performance. These results are consistent with the interpretation that the return gap proxies for an unobserved action of the fund manager that affects performance not attributable to exposure to stock characteristics. That performance could relate to transaction costs and interim trading activity (e.g., stock picking, timing the entry or exit of positions, or unusual trading ability), but cannot be attributed to the size, book-to-market, or price momentum of fund holdings. Our findings, therefore, are consistent with the authors' original interpretations of their results.

D.3. Active Share

We next examine the relation between fund active share (Cremers and Petajisto (2009)) and performance. Active share captures the percentage of a manager's portfolio that differs from its benchmark index. It is calculated by aggregating the absolute differences between the weight of a portfolio's actual holdings and the weight of its closest matching index. Here we sort into active share quintiles each month and examine performance of the quintiles during the following month. The results in Panel B3 of Table 7 indicate a statistically significant relation between active share and the performance driven by the characteristics of the fund stock holding, with the results significant at the ten percent level when using the regression double-adjustment approach and at the five percent level when using the portfolio approach. By contrast, we find no statistically significant correspondence between active share and double-adjusted fund performance for either double adjustment approach. Thus, the significant relation between active share and standard four-factor alpha is driven by the characteristic-related component of performance, rather than fund skill (i.e., performance unrelated to characteristics). Greater deviations from one's benchmark produces performance that our results tie back to stock characteristics, but that is not necessarily associated with stock-picking skill.

D.4. R-squared

Finally, we examine the relation between R-squared (Amihud and Goyenko (2013)) and performance. We obtain a fund's R-squared by regressing its excess returns on the Carhart four-factor model over a 24-month estimation period. Each month, we sort our sample funds into R-squared quintiles and examine performance of the quintiles over the following month. Panel B4 of Table 7 shows the results. Similar to the industry concentration and active share results, the R-squared results show a significant relation (here the relation is an inverse one) between R-squared and the characteristic component of performance, rather than double-adjusted performance. A low R-squared indicates fund returns are not well explained by the four factors of the regression model, which the original study interprets as high fund selectivity. One could hypothesize that characteristics help explain stock returns in instances where factors do not well explain fund returns, and that could lead to the strong inverse relation we find between R-squared and the characteristic component of performance.

D.5. Prior Studies Robustness Test

As a robustness test, we use cross-sectional regressions to examine the same relations between the various fund features and performance that we examined via quintiles in Table 7. We regress future monthly performance on each of the four fund measures,

$$perf_{i,t} = a + bfundchar_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}, \tag{12}$$

where $perf_{i,t}$ refers to fund i's standard four-factor alpha, double-adjusted performance measure from equation (6), or characteristic component of performance from equation (7) for month t, and $fundchar_{i,t-1}$ represents fund i's lagged industry concentration index, return gap, active share, or log transformed R-squared.[14] We examine alternative specifications that exclude and include fund-level control variables, denoted by X_i in equation (12).

Table 8 reports the cross-sectional regression coefficients averaged across time along with Fama-Macbeth *t*-statistics with Newey-West (1987) correction for time-series correlation with three lags. To a large extent, the inference that we take away from the cross-sectional results match the quintile analysis interpretations associated with Table 7. With and without fund-level controls, active share and R-squared are statistically significantly related to the characteristic component of performance, but not to double-adjusted performance. Any significant relation between these measures and standard performance, therefore, appears to be driven by the portion of standard performance attributable to stock holding characteristics. By contrast, the return gap significantly relates to double-adjusted performance. Finally, none of the key variables in the industry concentration cross-sectional analysis attain statistical significance.

[Insert Table 8 about here]

E. Investor Cash Flows

Lastly, we examine which component of fund performance investors respond to, similar in spirit to the analysis of Busse and Irvine (2006), Berk and van Binsbergen (2016), and Barber, Huang, and Odean (2014). To do so, we examine the cross-sectional relation between fund cash flows and the alternative performance estimates at the annual level. Following Sirri and Tufano (1998), we define fund cash flow as the average monthly net percentage growth in fund assets beyond capital gains and dividends. It reflects the percentage growth of a fund in excess of the

[14] Following Amihud and Goyenko (2013), we use the logistic transformation of R-squared in our regressions since the distribution of R-squared is skewed towards 1.0. Results using non-transformed R-squared are qualitatively similar.

growth that would have occurred with no new inflow and had all dividends been reinvested. We then regress cross sectionally annual cash flow estimates on prior annual return or four-factor alpha,

$$CF_{i,t} = a + bperf_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}, \tag{13}$$

or on both the prior annual double-adjusted alpha and characteristic-related alpha,

$$CF_{i,t} = a + b\alpha^{*}_{i,t-1} + c\alpha^{char}_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}, \tag{14}$$

where $perf_i$ represents fund i's return or four-factor alpha, and CF_i represent fund i's annual net flow estimate. Similar to our earlier regressions, we include the fund-level control variables, X_i, as regressors in some specifications.

The results in Table 9 suggest strong relations between all of the alternative performance measures and subsequent cash flows. Fund investors do not show a strong preference for a particular type of performance and invest in funds that show relatively higher net returns, regardless of the source of those returns.

[Insert Table 9 about here]

IV. Conclusion

Many mutual fund studies incorporate both factor model regressions and characteristic benchmarks in their performance analyses. But by estimating the alternative measures separately, rather than in a unified framework, each performance estimate only *partially* controls for passive influences on fund returns. Motivated by recent developments in the empirical asset pricing literature, we advocate adjusting for both factor exposure and stock characteristics simultaneously in one measure.

We find that stock characteristics drive up to a third of a fund's four-factor alpha, an amount that, when taken away, can dramatically impact the inference drawn from a sample of performance estimates. When we re-examine several recent mutual fund analyses that emphasize relations between specific fund features and relative performance, we find that, quite often, the feature correlates with performance attributable to stock characteristics of the fund's portfolio holdings, rather than the skill that remains after controlling for those effects. At the very least, more fully controlling for the impact of characteristics can alter how one interprets the results of studies that emphasize relative performance.

By more fully controlling for passive effects associated with stockholding characteristics and by utilizing actual fund shareholder returns rather than proxies based on periodic disclosures of fund portfolio holdings, we argue that our double-adjusted performance measures provide a cleaner estimate of genuine fund manager skill. We find that this new proxy for mutual fund skill forecasts future fund performance much longer than standard measures do, up to nine years in our analysis, and thereby provides a clearer signal of future performance that may be beneficial to investors.

References

Acharya, Viral, and Lasse Pedersen, 2005, "Asset pricing with liquidity risk," *Journal of Financial Economics* 77, 375–410.

Amihud, Yakov, 2002, "Illiquidity and stock returns: Cross section and time series effects," *Journal of Financial Markets* 5, 31–56.

Amihud, Yakov, and Ruslan Goyenko, 2013, "Mutual fund's R^2 as predictor of performance," *Review of Financial Studies* 26, 667–694.

Amihud, Yakov, and Mendelson, Haim, 1986, "Asset pricing and the bid-ask spread," *Journal of Financial Economics* 17, 223-249.

Ball, Ray, and Phillip Brown, 1968, "An empirical evaluation of accounting income numbers," *Journal of Accounting Research* 6, 159–178.

Banz, R.W., 1981. "The relationship between return and market value of common stocks," *Journal of Financial Economics* 9, 3-18.

Barber, Brad, Xing Huang, and Terrance Odean, 2014, "What risk factors matter to investors? Evidence from mutual fund flows," Working Paper, University of California, Davis.

Berk, Jonathan, and Jules van Binsbergen, 2015, "Measuring skill in the mutual fund industry," *Journal of Financial Economics* 118, 1–20.

Berk, Jonathan, and Jules van Binsbergen, 2016, "Assessing asset pricing models using revealed preference," forthcoming, *Journal of Financial Economics*.

Bollen, Nicolas, and Jeffrey Busse, 2005, "Short-term persistence in mutual fund performance," *Review of Financial Studies* 18, 569–597.

Brennan, Michael, Tarun Chordia, and Avanidhar Subrahmanyam, 1998, "Alternative factor specifications, security characteristics and the cross-section of expected stock returns," *Journal of Financial Economics* 49, 345–373.

Brown, Stephen, and William Goetzmann, 1995, "Performance persistence," *Journal of Finance* 50, 679-698.

Busse, Jeffrey, and Paul Irvine, 2006, "Bayesian alphas and mutual fund persistence," *Journal of Finance* 61, 2251-2288.

Busse, Jeffrey, and Qing Tong, 2012, "Mutual fund industry selection and persistence," *Review of Asset Pricing Studies* 2, 245-274.

Carhart, Mark, 1997, “On persistence in mutual fund performance,” *Journal of Finance* 52, 57–82.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey Kubik, 2004, “Does fund size erode mutual fund performance? The role of liquidity and organization,” *American Economic Review* 94, 1276–1302.

Chordia, Tarun, Amit Goyal, and Jay Shanken, 2013, “Cross-sectional asset pricing with individual stocks: betas versus characteristics,” Working Paper, Emory University.

Chrisopherson, Jon, Wayne Ferson, and Debra Glassman, 1998, “Conditioning manager alphas on economic information: Another look at the persistence of performance,” *Review of Financial Studies* 11, 111-142.

Cremers, Martijn, and Antti Petajisto, 2009, “How active is your fund manager?” *Review of Financial Studies* 22, 3329–3365.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, “Measuring mutual fund performance with characteristic-based benchmarks,” *Journal of Finance* 52, 1035–58.

Daniel Kent, and Sheridan Titman, 1997, “Evidence on the characteristics of cross sectional variation in stock returns,” *Journal of Finance* 52, 1–33.

Elton, Edwin, Martin Gruber, and Christopher Blake, 1996, “The persistence of risk-adjusted mutual fund performance,” *Journal of Business* 69, 133-157.

Elton, Edwin, Martin Gruber, and Christopher Blake, 2001, “A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases,” *Journal of Finance* 56, 2415–2430.

Elton, Edwin, Martin Gruber, Sanjiv Das, and Matthew Hlavka, 1993, “Efficiency with costly information: A reinterpretation of the evidence for managed portfolios,” *Review of Financial Studies* 6, 1–22.

Evans, Richard B., 2010, “Mutual fund incubation,” *Journal of Finance* 65, 1581–1611.

Fama, Eugene, and Kenneth French, 1992, “The cross-section of expected stock returns,” *Journal of Finance* 47, 427–465.

Fama, Eugene, and Kenneth French, 1993, “Common risk factors in the returns on stocks and bonds,” *Journal of Financial Economics* 33, 3–56.

Fama, Eugene, and Kenneth French, 1996, “Multifactor explanations of asset pricing anomalies,” *Journal of Finance* 51, 55-84.

Fama, Eugene, and James MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy* 81, 607-636.

Ferson, Wayne, and Jerchern Lin, 2014, "Alpha and performance measurement: The effects of investor disagreement and heterogeneity," *Journal of Finance* 69, 1565-1596.

Ferson, Wayne, and Haitao Mo, 2015, "Performance measurement with market and volatility timing and selectivity," forthcoming, *Journal of Financial Economics*.

Ferson, Wayne, and Rudi Schadt, 1996, "Measuring fund strategy and performance in changing economic conditions," *Journal of Finance* 51, 425-461.

Gao, Xiaohui, and Jay R Ritter, 2010, "The marketing of seasoned equity offerings," *Journal of Financial Economics* 97, 33-52.

Goetzmann, William, and Roger Ibbotson, 1994, "Do winners repeat? Patterns in mutual fund performance," *Journal of Portfolio Management* 20, 9-18.

Grinblatt, Mark, and Sheridan Titman, 1992, "The persistence of mutual fund performance," *Journal of Finance* 47, 1977-1984.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, "Hot hands in mutual funds: Short-run persistence of performance, 1974-1988," *Journal of Finance* 48, 93-130.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency," *Journal of Finance* 48, 65–92.

Jensen, Michael, 1968, "The performance of mutual funds in the period 1945-1964," *Journal of Finance* 23, 389-416.

Jensen, Michael, 1969, "Risk, the pricing of capital assets, and the evaluation of investment portfolios," *Journal of Business* 42, 167-247.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, "On the industry concentration of actively managed mutual funds," *Journal of Finance* 60, 1983-2011.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, "Unobserved actions of mutual funds," *Review of Financial Studies* 21, 2379-2416.

Malkiel, Burton, 1995, "Returns from investing in equity mutual funds 1971 to 1991," *Journal of Finance* 50, 549-572.

Newey, Whitney and Kenneth West, 1987, "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica* 55, 703–708.

Pástor, Luboš, and Robert F. Stambaugh, 2003, "Liquidity risk and expected stock returns," *Journal of Political Economy* 111, 642–685.

Pástor, Luboš, Robert F. Stambaugh, and Luke A. Taylor, 2015, "Scale and skill in active management," *Journal of Financial Economics* 116, 23-45.

Puckett, Andy, and Xuemin Sterling Yan, 2011, "The interim trading skills of institutional investors," *Journal of Finance* 66, 601-633.

Sirri, Erik, and Peter Tufano, 1998, "Costly search and mutual fund flows," *Journal of Finance* 53, 1589-1622.

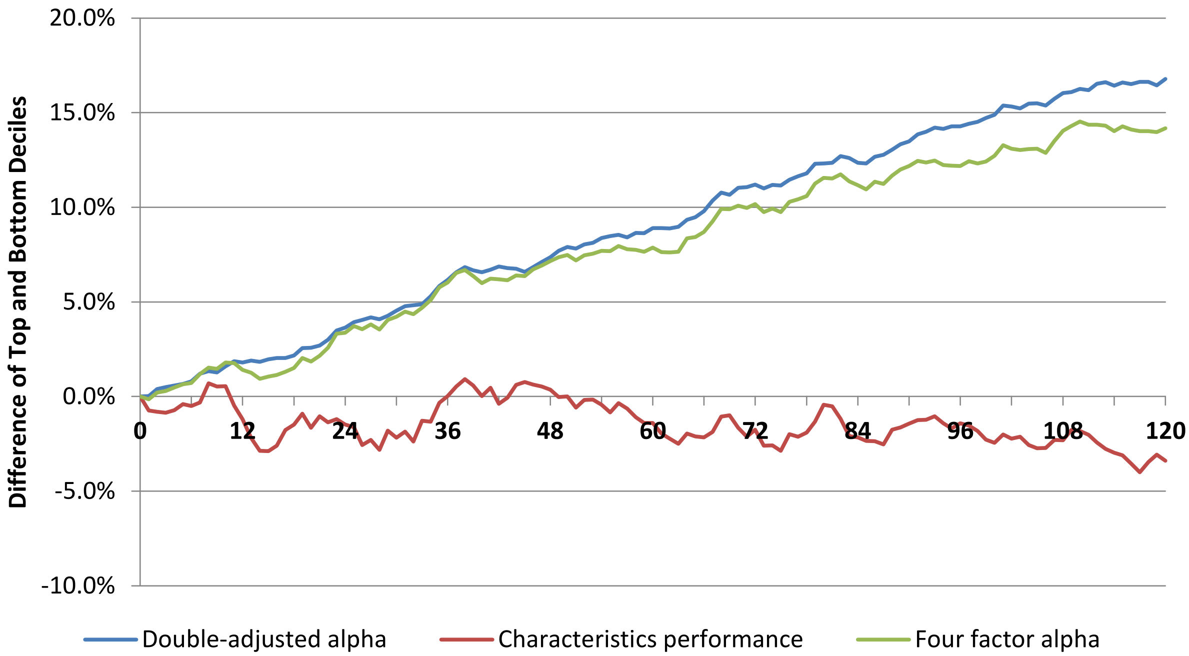
Wermers, Russ, 2000, "Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses," *Journal of Finance* 55, 1655–95.

Yan, Xuemin, 2008, "Liquidity, investment style, and the relation between fund size and fund performance," *Journal of Financial and Quantitative Analysis* 43, 741–767.

Figure 1. Long-term persistence

The figure shows cumulative post-ranking four-factor alpha for top-bottom portfolios of funds sorted by four-factor alpha, double-adjusted performance, or the characteristic component of performance during the initial ranking period. The horizontal axes show the post-ranking month number.

Panel A. Regression approach



Panel B. Portfolio approach

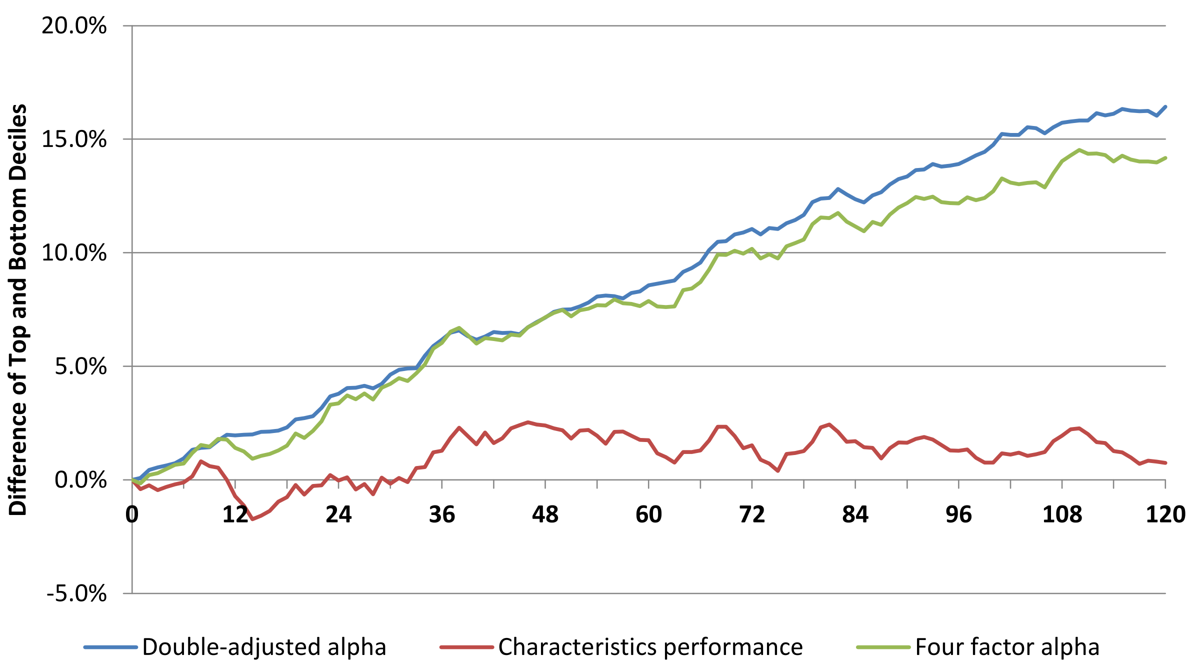


Table 1. Fund Stockholding Characteristics

Panel A reports statistics for fund portfolio holding stock characteristics. Panel B reports mean post-ranking period Carhart (1997) four-factor alphas for funds sorted into deciles based on average portfolio characteristics during a 24-month ranking period. We compute *t*-statistics of the differences between the top and bottom quintiles with Newey-West (1987) correction for time-series correlation with 12 lags. ** and *** indicate statistical significance at the five and one percent level respectively. The results reflect 393 individual monthly observations over a 1980m4-2012m12 sample period.

Panel A. Stock characteristic statistics

Characteristic	Mean	Std.	1st percentile	Median	99th percentile
Market cap ($ million)	34,034	36,892	309	16,273	139,224
Book-to-market	0.44	0.21	0.11	0.41	1.12
Six-month return (%)	12.50	20.26	-31.40	10.74	80.13
Illiquidity	0.0502	0.4734	0.0000	0.0012	0.9408

Panel B. Performance of stock characteristic sorts

Quintile	Market cap	Book-to-market	Six-month return	Illiquidity
Bottom	-0.02	0.76	-1.26	-0.87
2	0.44	-0.53	-0.58	-0.77
3	-0.48	-0.69	-0.30	-0.31
4	-0.67	-0.47	-0.10	0.30
Top	-0.74	-0.54	0.76	0.17
Top-bottom	-0.72*	-1.31**	2.02***	1.04***
t-statistic	(-1.77)	(-2.55)	(3.62)	(2.99)

Table 2. Fund Stock Holding Characteristic Regressions

The table reports average coefficients from monthly cross-sectional regressions,

$$\alpha_{i,t} = a + \sum_{m=1}^{M} Z_{m,i,t-1} c_m + \eta_{i,t}, \quad (8)$$

where $Z_{m,i,t-1}$ represents lagged fund holding characteristics, including portfolio value-weighted measures of market capitalization, book-to-market ratio, six-month price momentum, or illiquidity. Panel A reports Carhart (1997) four-factor alpha results, and Panel B reports five-factor alpha results, with Carhart (1997) model augmented with the Pástor and Stambaugh (2003) liquidity factor. We estimate the *t*-statistics in parenthesis as in Fama and MacBeth (1973) with Newey-West (1987) correction for time-series correlation with 12 lags. *** indicates statistical significance at the one percent level. The results reflect 393 individual monthly regressions over a 1980m4-2012m12 sample period.

		Panel A. Four-factor Alpha			
Market cap	-0.262**				-0.083
	(-2.29)				(-0.73)
Book-to-market		-1.196***			-0.078
		(-3.07)			(-0.19)
Six-month return			0.090***		0.070***
			(5.15)		(3.85)
Constant	-0.312	-0.312	-0.312		-0.312
	(-1.13)	(-1.13)	(-1.13)		(-1.13)
R-squared	0.024	0.035	0.046		0.081
No. of months	393	393	393		393
		Panel B. Five-factor Alpha			
Market cap	-0.282**				-0.038
	(-2.24)				(-0.25)
Book-to-market		-1.336***			-0.369
		(-3.71)			(-1.10)
Six-month return			0.090***		0.066***
			(5.41)		(3.76)
Illiquidity				0.491	0.407
				(1.62)	(1.63)
Constant	-0.223	-0.223	-0.223	-0.223	-0.223
	(-0.78)	(-0.78)	(-0.78)	(-0.78)	(-0.78)
R-squared	0.027	0.034	0.045	0.009	0.086
No. of months	393	393	393	393	393

Table 3. Double-Adjusted Performance Effects

Panel A reports statistics associated with the fraction of standard four-factor alpha attributable to characteristics,

$$frac^{char} = \alpha_i^{char} / \alpha_i, \tag{9}$$

and the fraction of double-adjusted performance, $1 - frac^{char}$. Panel B reports statistics that describe the change in performance percentile from standard four-factor alpha to the double-adjusted measure using the regression or portfolio approach. The results reflect 370,587 fund observations over a 1980m4-2012m12 sample period.

	Percentile						
	5	10	25	50	75	90	95
			Panel A. Performance attribution				
Double-adjusted							
Regression	0.20	0.33	0.57	0.77	0.89	0.96	0.98
Portfolio	0.14	0.24	0.46	0.68	0.85	0.94	0.97
Characteristics							
Regression	0.02	0.04	0.11	0.23	0.43	0.67	0.80
Portfolio	0.03	0.06	0.15	0.32	0.54	0.76	0.86
			Panel B. Change in performance rank				
Rank (%)							
Regression	-17.27	-11.71	-4.38	0.29	5.10	11.35	15.73
Portfolio	-25.44	-17.52	-6.77	0.19	7.58	16.95	23.45
Abs. Rank (%)							
Regression	0.23	0.54	1.78	4.78	9.90	16.44	21.62
Portfolio	0.38	0.85	2.71	7.19	14.81	24.41	31.57

Table 4. Short-term Persistence Sorts

The table reports mean annualized post-ranking percentage four-factor alphas for funds sorted into deciles based on performance during a 24-month ranking period. The four-factor alpha in the post-ranking month is calculated as the difference between the realized fund return and the sum of the product of the factor betas estimated over the previous 24-month and the factor returns during the month. We compute *t*-statistics of the differences between the top and bottom deciles with Newey-West (1987) correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 392 individual monthly observations over a 1980m5-2012m12 sample period.

	Model					
		Double-adjusted		Characteristics		
Decile	Four-factor	Regression	Portfolio	Regression	Portfolio	DGTW CS
Bottom	-3.92	-3.58	-3.59	-0.93	-1.38	-1.54
2	-2.17	-2.68	-2.49	-0.71	-1.22	-1.06
3	-1.57	-1.64	-1.67	-0.85	-1.35	-1.09
4	-1.36	-1.45	-1.13	-1.06	-0.99	-0.99
5	-1.04	-1.05	-1.18	-0.80	-0.46	-0.71
6	-0.71	-0.43	-0.60	-1.00	-1.12	-0.77
7	-0.25	-0.19	-0.43	-0.95	-0.86	-0.82
8	-0.05	-0.01	0.20	-1.48	-0.74	-0.78
9	0.57	0.39	0.33	-0.39	-0.32	-0.38
Top	2.14	2.27	2.21	-0.16	0.13	0.28
Top-bottom	6.06***	5.85***	5.80***	0.77	1.51**	1.82***
t-statistic	(7.34)	(8.09)	(7.97)	(0.94)	(2.18)	(3.07)

Table 5. Short-term Persistence

Panel A reports sample fund statistics. Panel B reports mean coefficients from monthly cross-sectional regressions of four-factor alpha on past four-factor alpha

$$\alpha_{i,t} = a + b\alpha_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}, \tag{10}$$

or on both past double-adjusted alpha and past characteristic related alpha,

$$\alpha_{i,t} = a + b\alpha^{*}_{i,t-1} + c\alpha^{char}_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}. \tag{11}$$

The last three columns include fund-level control variables. We estimate the *t*-statistics in parenthesis as in Fama and MacBeth (1973) with Newey-West (1987) correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 389 or 392 individual monthly regressions over a 1980-2012 sample period.

Panel A. Fund Statistics

Characteristic	Mean	Std.	1st percentile	Median	99th percentile
TNA ($ million)	1,262	4,733	18	259	18,268
Age (months)	187	171	18	133	833
Expense ratio (%)	1.23	0.42	0.17	1.20	2.41
Cash flow (%)	0.12	4.13	-13.08	-0.37	20.09
Family TNA ($ million)	100,192	255,448	0	12,493	1,413,278

Panel B. Cross sectional regressions

Four fact alpha	0.310***				0.315***			
	(7.33)				(7.11)			
DA regression		0.323***				0.326***		
		(7.88)				(7.58)		
Char regression		0.110				0.130		
		(0.57)				(0.65)		
DA portfolio			0.334***				0.338***	
			(8.28)				(7.95)	
Char portfolio			0.223***				0.226***	
			(2.90)				(2.93)	
DGTW CS				0.112***				0.103***
				(2.88)				(2.63)
log TNA					-0.377***	-0.371***	-0.380***	-0.339***
					(-4.36)	(-4.35)	(-4.36)	(-3.98)
log Age					0.106	0.073	0.115	-0.066
					(0.99)	(0.69)	(1.08)	(-0.59)
Expense ratio					-0.857***	-0.751***	-0.865***	-1.083***
					(-3.01)	(-2.82)	(-3.02)	(-4.04)
Cash flow					-0.030	-0.029	-0.025	0.042*
					(-1.12)	(-1.06)	(-0.85)	(1.77)
log fam TNA					0.124***	0.131***	0.123***	0.146***
					(3.59)	(3.76)	(3.58)	(4.24)
Constant	-0.669**	-0.720**	-0.687**	-0.778**	0.788	0.722	0.732	1.420*
	(-2.05)	(-2.18)	(-2.08)	(-2.45)	(1.04)	(0.94)	(0.96)	(1.84)
R-squared	0.041	0.070	0.058	0.025	0.067	0.094	0.082	0.049
No. of months	392	392	392	389	392	392	392	389

Table 6. Long-term Persistence Sorts

The table reports mean annualized post-ranking percentage four-factor alphas from net fund returns for funds sorted into deciles based on four-factor alpha (Panel A), double-adjusted performance (Panel B), characteristics performance (Panel D), or DGTW CS measure (Panel E). Panel C reports annualized post-ranking percentage four-factor alphas from gross fund returns for funds sorted based on double-adjusted performance. The post-ranking performance measure, four-factor alpha, for each decile over each post ranking year is the intercept of the regression of the concatenated time series over the entire sample period of post-ranking monthly fund returns on Mktrf, SMB, HML, and UMD factor returns. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results comprise 384 individual post-ranking monthly observations over a 1981-2012 sample period.

	Post-ranking year									
Decile	1	2	3	4	5	6	7	8	9	10
					Panel A. Four-factor alpha					
Bottom	-1.19	-2.16	-2.28	-0.97	-0.78	-1.51	-0.95	-1.04	-1.17	-0.89
2	-1.12	-0.86	-1.61	-1.18	-0.81	-1.03	-0.62	-1.49	-1.14	-0.72
3	-1.32	-1.22	-1.12	-1.49	-0.76	-0.80	-0.69	-1.05	-0.91	-0.20
4	-1.17	-1.26	-1.42	-1.42	-0.88	-0.50	-1.06	-1.37	-0.63	-1.32
5	-0.73	-0.87	-1.22	-1.06	-0.87	-0.83	-0.73	-1.43	-0.86	0.16
6	-0.72	-0.58	-0.70	-0.85	-0.46	-0.79	-1.13	-0.70	-0.77	-0.48
7	-1.32	-0.59	-0.73	-0.76	-1.29	-0.78	-0.45	-0.66	-0.49	-0.71
8	-0.81	-0.60	-0.76	-0.65	-0.69	-0.73	-0.52	-0.10	-0.46	-0.78
9	-0.64	-0.50	-0.48	-0.49	-0.58	-0.31	-0.20	-0.91	-0.20	-0.75
Top	0.21	-0.24	0.27	0.09	-0.11	0.61	-0.05	-0.13	0.48	-0.77
Top-bottom	1.40	1.93**	2.55***	1.06	0.67	2.12***	0.90	0.91	1.65*	0.12
t-statistic	(1.41)	(2.15)	(2.79)	(1.45)	(0.86)	(2.60)	(1.06)	(1.12)	(1.91)	(0.14)
					Panel B. Double-adjusted alpha, regression approach, net return results					
Bottom	-1.57	-1.84	-2.35	-1.10	-1.06	-1.90	-1.24	-1.40	-1.43	-1.17
2	-1.13	-0.91	-1.08	-1.25	-0.99	-0.93	-0.84	-1.21	-0.79	-0.57
3	-0.92	-1.12	-1.32	-1.36	-0.88	-1.08	-0.58	-1.15	-0.54	-0.70
4	-1.42	-0.96	-1.35	-1.35	-1.25	-0.66	-0.87	-1.32	-1.20	0.08
5	-1.06	-1.18	-1.14	-1.10	-1.05	-0.78	-0.73	-1.05	-0.75	-0.96
6	-0.81	-1.03	-0.83	-0.94	-0.60	-0.72	-0.98	-0.78	-0.92	-0.75
7	-1.09	-0.71	-0.83	-0.71	-0.69	-0.55	-0.44	-0.68	-0.49	-0.25
8	-0.48	-0.31	-0.45	-0.67	-0.77	-0.44	-0.26	-0.62	-0.41	-1.26
9	-0.55	-0.73	-0.69	-0.35	-0.33	0.14	-0.22	-0.97	0.30	-0.29
Top	0.21	-0.05	0.06	0.01	0.37	0.20	-0.22	0.29	0.10	-0.53
Top-bottom	1.78***	1.79***	2.41***	1.12**	1.43**	2.10***	1.03	1.69***	1.54**	0.64
t-statistic	(2.73)	(3.19)	(4.00)	(2.05)	(2.41)	(3.63)	(1.49)	(2.58)	(2.23)	(1.03)

Table 6 continued.

	Panel C. Double-adjusted alpha, regression approach, gross return results									
Bottom	-0.26	-0.54	-1.05	0.17	0.19	-0.66	0.00	-0.17	-0.19	0.08
2	0.06	0.28	0.10	-0.08	0.19	0.24	0.33	-0.04	0.36	0.55
3	0.21	0.01	-0.19	-0.23	0.24	0.04	0.52	-0.02	0.58	0.41
4	-0.32	0.14	-0.26	-0.24	-0.16	0.42	0.22	-0.23	-0.11	1.19
5	0.02	-0.11	-0.06	-0.02	0.03	0.30	0.35	0.03	0.34	0.13
6	0.23	0.02	0.21	0.09	0.43	0.31	0.05	0.25	0.12	0.28
7	-0.05	0.33	0.20	0.32	0.34	0.47	0.58	0.35	0.53	0.75
8	0.60	0.76	0.62	0.39	0.28	0.62	0.80	0.44	0.65	-0.20
9	0.56	0.37	0.39	0.73	0.76	1.21	0.85	0.10	1.36	0.78
Top	1.39	1.12	1.21	1.15	1.50	1.32	0.90	1.42	1.22	0.57
Top-bottom	1.65**	1.66***	2.27***	0.98*	1.31**	1.98***	0.90	1.58**	1.40**	0.49
t-statistic	(2.54)	(2.95)	(3.76)	(1.80)	(2.19)	(3.43)	(1.30)	(2.42)	(2.03)	(0.79)
	Panel D. Double-adjusted alpha, portfolio approach, net return results									
Bottom	-1.49	-1.79	-2.40	-0.94	-1.05	-1.93	-1.20	-1.28	-1.30	-1.24
2	-1.28	-1.09	-1.53	-1.40	-1.08	-1.01	-1.46	-0.98	-0.71	-0.47
3	-1.05	-1.27	-1.03	-1.42	-0.84	-0.73	-0.61	-1.45	-0.66	-0.39
4	-1.17	-0.97	-1.23	-1.12	-1.05	-1.06	-1.15	-1.34	-1.00	-0.65
5	-1.01	-0.99	-0.75	-1.05	-0.47	-0.71	-0.69	-1.21	-0.66	-0.61
6	-0.98	-0.88	-1.37	-0.70	-1.14	-0.40	-0.19	-0.83	-1.02	-0.45
7	-0.96	-0.41	-0.57	-0.87	-0.83	-0.70	-0.59	-0.73	-0.73	-0.49
8	-0.57	-0.56	-0.67	-0.67	-0.55	-0.37	-0.29	-0.51	-0.06	-0.60
9	-0.77	-0.85	-0.35	-0.61	-0.50	-0.16	-0.14	-0.61	-0.27	-0.89
Top	0.45	-0.01	-0.13	-0.02	0.27	0.33	-0.03	0.09	0.28	-0.62
Top-bottom	1.94***	1.78***	2.27***	0.92*	1.32**	2.26***	1.17*	1.37**	1.59**	0.62
t-statistic	(3.24)	(3.36)	(4.25)	(1.80)	(2.32)	(4.00)	(1.76)	(2.23)	(2.46)	(1.00)

Table 6 continued.

Panel E. Double-adjusted alpha, portfolio approach, gross return results										
Bottom	-0.18	-0.48	-1.10	0.34	0.20	-0.68	0.05	-0.03	-0.05	0.01
2	-0.09	0.10	-0.35	-0.24	0.10	0.16	-0.30	0.17	0.45	0.68
3	0.11	-0.12	0.12	-0.27	0.30	0.38	0.51	-0.33	0.47	0.71
4	-0.09	0.11	-0.16	-0.04	0.03	0.01	-0.09	-0.27	0.05	0.41
5	0.07	0.10	0.33	0.03	0.60	0.36	0.38	-0.14	0.41	0.47
6	0.06	0.16	-0.33	0.35	-0.10	0.65	0.86	0.23	0.04	0.61
7	0.09	0.64	0.48	0.18	0.21	0.34	0.45	0.31	0.32	0.54
8	0.50	0.50	0.38	0.37	0.50	0.68	0.75	0.53	0.98	0.44
9	0.34	0.25	0.75	0.46	0.57	0.90	0.92	0.46	0.78	0.17
Top	1.64	1.17	1.02	1.12	1.41	1.46	1.10	1.22	1.41	0.50
Top-bottom	1.82***	1.65***	2.12***	0.78	1.21**	2.14***	1.05	1.25**	1.46**	0.49
t-statistic	(3.04)	(3.11)	(3.97)	(1.53)	(2.12)	(3.78)	(1.57)	(2.04)	(2.26)	(0.80)
Panel F. Characteristics performance, regression approach										
Bottom	-0.53	-0.43	-1.44	-0.76	-0.15	-0.50	-0.22	-1.65	-0.38	0.21
2	-0.14	-0.83	-0.94	-0.85	-0.28	-0.16	-0.78	-1.65	-1.06	-0.06
3	-0.82	-0.52	-1.61	-1.09	-0.78	-0.18	-0.69	-0.61	-1.15	0.02
4	-0.71	-1.28	-1.46	-0.99	-0.25	-0.42	-0.64	-1.22	-0.48	-1.55
5	-0.96	-0.70	-1.35	-0.99	-0.86	-0.76	-0.42	-0.88	-0.52	-0.98
6	-0.69	-1.10	-1.17	-0.71	-0.90	-0.99	-1.14	-0.32	-0.37	-0.67
7	-0.95	-1.03	-1.16	-1.19	-0.46	-0.95	-1.03	-0.74	-0.59	-1.16
8	-1.11	-0.98	-0.77	-0.45	-0.44	-0.78	-0.53	-0.51	-0.07	-0.70
9	-1.17	-1.24	-0.15	-1.35	-1.17	-1.11	-0.32	-0.43	-0.25	-0.63
Top	-1.72	-0.70	0.11	-0.41	-1.91	-0.86	-0.61	-0.88	-1.29	-0.89
Top-bottom	-1.19	-0.27	1.55	0.35	-1.76	-0.36	-0.39	0.78	-0.91	-1.11
t-statistic	(-0.64)	(-0.13)	(0.68)	(0.21)	(-1.15)	(-0.24)	(-0.27)	(0.57)	(-0.70)	(-0.73)

Table 6 continued.

					Panel G. Characteristics performance, portfolio approach					
Bottom	-0.24	-1.57	-1.63	-1.26	-0.68	-0.89	-1.01	-0.96	-0.65	-0.31
2	-0.70	-0.41	-1.32	-0.70	-0.70	-0.43	-0.56	-0.35	-1.40	0.03
3	-1.17	-1.13	-1.16	-1.11	-0.30	-0.56	0.39	-1.80	-0.90	-0.82
4	-1.06	-0.98	-1.21	-0.82	-0.48	-0.61	-0.81	-1.10	-0.60	-0.77
5	-0.97	-0.58	-1.22	-0.88	-0.61	-0.45	-0.09	-1.37	-0.94	-1.12
6	-0.65	-0.60	-0.48	-0.90	0.04	-0.75	-1.10	-0.68	-0.83	-0.55
7	-0.83	-0.91	-0.34	-0.93	-1.27	-0.44	-1.21	-1.10	-0.17	-1.31
8	-1.43	-0.73	-1.22	-1.77	-0.59	-1.36	-0.38	0.03	-0.38	-0.06
9	-0.73	-1.09	-1.05	-0.30	-1.31	-0.14	-0.68	-0.16	-0.24	0.03
Top	-0.96	-0.87	-0.33	-0.15	-1.31	-1.11	-0.82	-1.37	0.01	-1.49
Top-bottom	-0.71	0.71	1.30	1.11	-0.63	-0.21	0.19	-0.41	0.66	-1.18
t-statistic	(-0.46)	(0.44)	(0.88)	(0.97)	(-0.56)	(-0.19)	(0.17)	(-0.38)	(0.63)	(-0.94)
					Panel H. DGTW CS					
Bottom	-0.72	-1.12	-1.00	-1.05	-0.34	-1.09	-0.78	-0.90	-0.48	-0.36
2	-0.36	-0.99	-0.66	-0.66	-0.39	-0.64	-0.55	-1.16	-0.34	-0.37
3	-0.74	-0.99	-1.13	-0.54	-0.51	-0.83	-0.29	-1.65	-1.07	-0.73
4	-0.90	-1.02	-1.12	-1.28	-0.67	0.09	-1.17	-0.67	-0.49	-0.84
5	-1.02	-0.74	-1.09	-0.89	-0.91	-0.94	-1.06	-1.47	-1.28	-0.64
6	-0.77	-1.29	-1.43	-1.22	-0.83	-1.12	-0.32	-0.99	0.07	-0.84
7	-1.15	-0.86	-0.74	-0.99	-1.05	-0.40	-1.20	-0.75	-0.48	-0.54
8	-1.18	-0.58	-1.25	-0.81	-0.71	-0.79	-0.62	-0.76	-1.16	-0.53
9	-1.04	-0.56	-1.26	-1.05	-1.14	-0.56	-0.27	-0.66	-0.32	-0.51
Top	-0.91	-0.62	-0.21	-0.29	-0.70	-0.46	-0.23	0.08	-0.69	-1.13
Top-bottom	-0.18	0.50	0.78	0.76	-0.36	0.63	0.55	0.97	-0.21	-0.77
t-statistic	(-0.16)	(0.46)	(0.78)	(0.88)	(-0.45)	(0.76)	(0.64)	(1.03)	(-0.21)	(-0.81)

Table 7. Fund Characteristic Sorts

Panel A reports fund characteristic summary statistics. Panel B reports mean annualized post-ranking percentage four-factor alphas for funds sorted into quintiles based on industry concentration index (Panel B1), return gap (Panel B2), active share (Panel B3), or R-squared (Panel B4). Post-ranking four-factor alpha is defined in Table 4. We compute *t*-statistics of the differences between the top and bottom quintiles with Newey-West (1987) correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results in reflect between 381 and 393 individual monthly observations over a 1980-2012 sample period.

Panel A. Fund characteristic statistics

			Percentile		
Characteristic	Mean	Std.	1	50	99
ICI	0.091	0.150	0.002	0.042	0.755
Return gap	-0.014	0.400	-1.145	-0.018	1.182
Active share	0.82	0.16	0.33	0.87	0.99
R-squared	0.90	0.10	0.47	0.93	0.99

Table 7 continued.

Panel B. Performance of fund characteristic sorts

	Model				
		Double-adjusted		Characteristics	
Quintile	Four-factor	Regression	Portfolio	Regression	Portfolio
B1. Industry concentration					
Bottom	-1.21	-0.89	-0.79	-0.31	-0.42
2	-1.00	-0.86	-0.81	-0.14	-0.18
3	-0.78	-0.82	-0.83	0.04	0.04
4	-0.51	-0.67	-0.77	0.16	0.26
Top	-0.46	-0.71	-0.79	0.26	0.33
Top-bottom	0.75*	0.18	0.01	0.57**	0.75**
t-statistic	(1.66)	(0.54)	(0.04)	(2.50)	(2.17)
B2. Return gap					
Bottom	-1.43	-1.56	-1.42	0.13	0.00
2	-0.83	-0.81	-0.71	-0.03	-0.12
3	-0.72	-0.68	-0.69	-0.04	-0.03
4	-0.55	-0.48	-0.58	-0.06	0.02
Top	-0.03	-0.02	-0.18	0.01	0.17
Top-bottom	1.40***	1.53***	1.24***	-0.13	0.17
t-statistic	(4.67)	(5.91)	(5.38)	(-0.84)	(0.97)
B3. Active share					
Bottom	-1.15	-0.76	-0.60	-0.39	-0.55
2	-1.05	-0.82	-0.72	-0.23	-0.32
3	-0.64	-0.59	-0.69	-0.05	0.04
4	-0.32	-0.59	-0.70	0.27	0.42
Top	-0.27	-0.64	-0.68	0.39	0.41
Top-bottom	0.89*	0.12	-0.08	0.78*	0.96**
t-statistic	(1.69)	(0.58)	(-0.55)	(1.79)	(2.03)
B4. R-squared					
Bottom	-0.11	-0.38	-0.52	0.28	0.42
2	-0.62	-0.86	-0.91	0.24	0.29
3	-0.96	-0.98	-0.98	0.02	0.02
4	-1.21	-1.03	-0.95	-0.18	-0.27
Top	-1.22	-0.85	-0.75	-0.37	-0.46
Top-bottom	-1.11**	-0.47	-0.23	-0.65***	-0.89***
t-statistic	(-2.45)	(-1.31)	(-0.81)	(-2.86)	(-3.09)

Table 8. Fund Characteristic Regressions

The table reports mean coefficients from monthly cross-sectional regressions of fund performance on past fund characteristics,

$$perf_{i,t} = a + b fundchar_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}, \tag{12}$$

where $perf_i$ represents fund i's four-factor alpha, double-adjusted alpha, or characteristic-related alpha, and $fundchar_i$ represents fund i's industry concentration index (ICI, Panel A), return gap (Panel B), active share (Panel C), or log transformed R-squared (log TR-sq, Panel D). We estimate the regressions with and without fund level control variables. We estimate the *t*-statistics in parenthesis as in Fama and MacBeth (1973) with Newey-West (1987) correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect between 381 and 393 individual monthly regressions over a 1980-2012 sample period.

			Double-adjusted				Characteristics			
	Four-factor alpha		Regression		Portfolio		Regression		Portfolio	
					Panel A. Industry concentration					
ICI	0.679	0.663	0.210	0.348	0.067	0.267	0.412	0.263	0.402	0.195
	(0.55)	(0.54)	(0.19)	(0.30)	(0.07)	(0.29)	(1.15)	(0.77)	(0.70)	(0.36)
log TNA		-0.300***		-0.223***		-0.171***		-0.081**		-0.133***
		(-3.54)		(-3.02)		(-2.62)		(-2.50)		(-3.37)
log Age		-0.118		-0.173**		-0.140*		0.053		0.019
		(-1.16)		(-1.98)		(-1.82)		(0.86)		(0.27)
Expense ratio		-1.192***		-1.298***		-1.182***		0.087		-0.047
		(-4.29)		(-5.64)		(-5.76)		(0.62)		(-0.29)
Cash flow		0.083***		0.072***		0.073***		0.011		0.012
		(3.45)		(3.43)		(3.83)		(0.94)		(0.88)
log family TNA		0.118***		0.108***		0.083***		0.011		0.032***
		(3.67)		(3.56)		(2.95)		(1.29)		(3.00)
Constant	-0.896***	1.708**	-0.845**	1.828**	-0.822**	1.478**	-0.041	-0.075	-0.063	0.328
	(-2.74)	(2.16)	(-2.55)	(2.54)	(-2.42)	(2.26)	(-1.21)	(-0.22)	(-1.06)	(0.75)
R-squared	0.016	0.041	0.015	0.037	0.010	0.031	0.012	0.077	0.017	0.050
No. of months	387	387	387	387	387	387	387	387	387	387

Table 8 continued.

Panel B. Return gap

Return gap	0.143***	0.130***	0.150***	0.137***	0.126***	0.115***	-0.007	-0.008	0.016	0.013
	(5.75)	(5.27)	(6.53)	(5.96)	(6.07)	(5.64)	(-0.63)	(-0.73)	(1.25)	(1.07)
log TNA		-0.337***		-0.244***		-0.173**		-0.093**		-0.162***
		(-3.86)		(-3.10)		(-2.49)		(-2.50)		(-3.82)
log Age		-0.054		-0.097		-0.091		0.042		0.030
		(-0.56)		(-1.10)		(-1.24)		(0.65)		(0.46)
Expense ratio		-1.205***		-1.318***		-1.190***		0.091		-0.045
		(-4.33)		(-5.91)		(-6.05)		(0.71)		(-0.27)
Cash flow		0.077***		0.067***		0.068***		0.010		0.009
		(3.22)		(3.09)		(3.45)		(0.79)		(0.67)
log family TNA		0.140***		0.121***		0.094***		0.018**		0.043***
		(3.94)		(3.58)		(3.15)		(2.41)		(3.90)
Constant	0.143***	0.130***	0.150***	0.137***	0.126***	0.115***	-0.007	-0.008	0.016	0.013
	(5.75)	(5.27)	(6.53)	(5.96)	(6.07)	(5.64)	(-0.63)	(-0.73)	(1.25)	(1.07)
R-squared	0.008	0.034	0.007	0.030	0.007	0.027	0.015	0.075	0.009	0.043
No. of months	381	381	381	381	381	381	381	381	381	381

Panel C. Active share

Active share	2.118	2.771**	0.233	0.913	-0.333	0.363	1.831*	1.827*	2.522**	2.483**
	(1.61)	(2.01)	(0.36)	(1.24)	(-0.91)	(0.81)	(1.71)	(1.75)	(2.00)	(1.97)
log TNA		-0.271***		-0.218***		-0.163**		-0.054*		-0.109**
		(-3.20)		(-2.80)		(-2.37)		(-1.67)		(-2.56)
log Age		-0.025		-0.088		-0.088		0.062		0.056
		(-0.30)		(-1.08)		(-1.23)		(1.50)		(1.27)
Expense ratio		-1.230***		-1.259***		-1.131***		0.015		-0.099
		(-5.08)		(-5.91)		(-5.73)		(0.15)		(-0.74)
Cash flow		0.091***		0.078***		0.077***		0.012		0.017
		(3.73)		(3.57)		(3.82)		(1.05)		(1.23)
log family TNA		0.143***		0.123***		0.094***		0.020**		0.049***
		(4.11)		(3.77)		(3.30)		(2.56)		(3.90)
Constant	-2.447**	-1.210	-0.879*	0.571	-0.399	0.862	-1.522*	-1.729*	-2.094*	-2.085*
	(-2.49)	(-0.90)	(-1.86)	(0.63)	(-1.03)	(1.25)	(-1.65)	(-1.89)	(-1.95)	(-1.74)
R-squared	0.021	0.045	0.004	0.027	0.001	0.022	0.142	0.174	0.077	0.100
No. of months	382	382	382	382	382	382	382	382	382	382

Table 8 continued.

Panel D. R-squared

log TR-sq	-0.671**	-0.752**	-0.341	-0.486*	-0.188	-0.340	-0.312**	-0.250**	-0.455***	-0.384***
	(-2.25)	(-2.46)	(-1.33)	(-1.84)	(-0.90)	(-1.59)	(-2.55)	(-2.11)	(-2.95)	(-2.59)
log TNA		-0.253***		-0.193***		-0.149**		-0.064**		-0.110***
		(-3.17)		(-2.65)		(-2.37)		(-2.00)		(-2.73)
log Age		-0.090		-0.157*		-0.147*		0.066		0.053
		(-0.87)		(-1.65)		(-1.78)		(1.02)		(0.86)
Expense ratio		-1.240***		-1.351***		-1.243***		0.090		-0.042
		(-4.68)		(-6.17)		(-6.34)		(0.68)		(-0.27)
Cash flow		0.070***		0.063***		0.067***		0.006		0.004
		(2.85)		(2.79)		(3.28)		(0.55)		(0.30)
log family TNA		0.132***		0.117***		0.090***		0.015**		0.040***
		(4.00)		(3.75)		(3.23)		(2.13)		(3.64)
Constant	0.988	3.338***	0.100	2.928***	-0.348	2.315***	0.840***	0.402	1.249***	1.047*
	(1.01)	(2.89)	(0.12)	(2.79)	(-0.49)	(2.59)	(2.59)	(0.75)	(2.96)	(1.67)
R-squared	0.017	0.043	0.014	0.036	0.010	0.031	0.026	0.087	0.022	0.055
No. of months	393	393	393	393	393	393	393	393	393	393

Table 9. Cash Flow Regressions

The table reports mean coefficients from annual cross-sectional regressions of fund cash flow on past four-factor alpha,

$$CF_{i,t} = a + b\alpha_{i,t-1} + \gamma X_{i,t-1} + \eta_{i,t}, \tag{13}$$

or on both past double-adjusted alpha and past characteristic-related alpha,

$$CF_{i,t} = a + b\alpha^{*}_{i,t-1} + c\alpha^{char}_{i,t-1} + \gamma \mathrm{X}_{i,t-1} + \eta_{i,t}. \tag{14}$$

The last three columns show results where the regressions include fund-level control variables. We estimate the *t*-statistics in parenthesis as in Fama and MacBeth (1973) with Newey-West (1987) correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 32 individual annual regressions over a 1981-2012 sample period.

Return	0.063***				0.048***			
	(7.93)				(8.15)			
Four-factor alpha		0.131***				0.071***		
		(13.12)				(8.31)		
DA regression			0.124***				0.069***	
			(9.96)				(6.91)	
Char regression			0.183***				0.087***	
			(3.09)				(2.78)	
DA portfolio				0.122***				0.068***
				(9.11)				(6.47)
Char portfolio				0.159***				0.083***
				(5.12)				(4.87)
Cash flow					0.342***	0.336***	0.332***	0.335***
					(17.39)	(17.96)	(18.85)	(17.72)
log TNA					-0.221***	-0.233***	-0.228***	-0.231***
					(-7.57)	(-8.56)	(-8.43)	(-8.58)
log Age					-0.156***	-0.107**	-0.103***	-0.109**
					(-3.22)	(-2.26)	(-2.75)	(-2.42)
Expense ratio					0.007	0.010	0.005	0.015
					(0.06)	(0.08)	(0.04)	(0.13)
log family TNA					0.076***	0.078***	0.077***	0.078***
					(5.73)	(5.89)	(5.83)	(5.97)
Constant	-0.112	0.284**	0.277**	0.278**	1.215***	1.351***	1.302***	1.333***
	(-0.72)	(2.18)	(2.11)	(2.13)	(5.74)	(6.06)	(6.05)	(6.06)
R-squared	0.059	0.062	0.089	0.073	0.247	0.233	0.247	0.240
No. groups	32	32	32	32	32	32	32	32