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Double Adjusted Mutual Fund Performance*

Jeffrey A. Busse† Lei Jiang‡ Yuehua Tang§

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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 persists a full nine years after the initial ranking period, much longer than standard 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 et al. (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 stocks, 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.

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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 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 compute Carhart (1997) four-factor alphas for a sample of funds and then regress cross sectionally the four-factor alphas on fund portfolio holding characteristics (i.e., fund portfolio 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

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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.

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 stock size (i.e., those holding the smallest market capitalization stocks) have an annualized four-factor alpha that is 1.1 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 2.9 percent (*t*-stat.=5.4) 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 those characteristics are explicitly addressed in the factor model.

To address the above issue with standard factor model performance estimates, we perform a second pass cross-sectional adjustment and remove the component of performance attributable to characteristics from standard alpha measures. 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 is 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 percent. 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. 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 17 (22) percent.

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 persists a full nine years after the initial ranking period. 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 their 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.

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, Grinblatt, Titman, and Wermers (1997).[1] Our paper is the first to incorporate both approaches in one measure to produce an estimate of performance that more 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

[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 a model that simultaneously accommodates security selection, market timing, and volatility timing (Ferson and Mo (2013)).

Conventional asset pricing proposes a risk-return trade-off where greater expected returns require greater systemic risk. Within the empirical mutual fund literature, a 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 (1977)), 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 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 premium 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

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

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) method 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.

In particular, we calculate our double-adjusted performance measure based on the following two-step procedure. First, we compute alphas via the Carhart (1997) four-factor model over a 24-month estimation period, rolling this window a month at a time.[2] Second, for each month in our sample period, we regress cross-sectionally the four-factor alphas on fund portfolio

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

holding characteristics 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 insures that the intercept of each monthly regression equals the cross-sectional mean of the four factor alphas, so that our second stage adjustment only affects relative performance ranking. Based on the cross-sectional regression estimates, we decompose the standard four factor alpha into two components: (i) double-adjusted performance, defined as the sum of the intercept and the residual of a fund from the cross-sectional regression, and (ii) characteristics-driven performance, the component attributable to exposure to stock characteristics. As in equations (6) and (7), the sum of these two components always equals the standard four-factor alpha.

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 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 table available on WRDS (see Wermers (2000)).

We examine actively-managed U.S. equity mutual funds from January 1980 to December 2012. We exclude balanced, bond, sector, index, and international funds. Similar to priors 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.[3] 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 or missing. We exclude funds with fewer than 10 stocks to focus on diversified funds. Following Elton et al. (2001), Chen et al. (2004), and Yan (2008), we exclude funds with less than \$15 million in TNA. We further eliminate observations before the fund's starting date reported by CRSP to address the incubation bias (Evans (2010)). Our final sample consists of 3,126 unique actively-managed U.S. equity mutual funds and 400,914 fund-month observations.

B. Variable Construction

B.1. Fund Characteristics

[3] 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).

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.[4] 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 portfolio 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 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-

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

level statistic, we weight each firm-level stock characteristic according to its dollar weight in the most recent fund portfolio. Since the fund holdings are usually available at a quarterly frequency, we obtain the monthly measures by keeping the fund holdings constant between quarters.

We calculate 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 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 the trading dates in a month, adjusting for NASDAQ trading volume as in Gao and Ritter (2010). Following Acharya and Pedersen (2005), we normalize the Amihud ratio to adjust for inflation and truncate it at 30 to eliminate the effect of outliers.

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), 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 correction for time-series correlation with 12 lags.[5]

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 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 five percent level or lower. The magnitude of these differences is economically large. For instance, funds in the bottom quintile of holding stock size have an annualized four-factor alpha that is 1.1 percent (*t*-stat.=2.53) higher than funds in the top quintile.

[5] Our results are qualitatively the same if we use 23 lags in the Newey-West correction.

Funds in the top quintile of holding stock momentum have an annualized four-factor alpha that is 2.9 percent (t-statistic=5.41) 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.

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. These results suggest that the four-factor model under-adjusts 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., 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,

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

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. 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 the series-correlation due to the overlap in estimation windows, we calculate Fama and MacBeth (1973) *t*-statistics with Newey-West 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. 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. All four univariate regression results show a statistically significant relation at the one percent level between fund factor model alpha measure and the value-weighted mean market capitalization, book-to-market ratio, six-month price momentum, or illiquidity of the fund stock portfolio. In untabulated results, we find that 307, 293, and 324 of the 396 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 from the factor model performance attributable to characteristics.

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

0.24. That is, characteristics account for roughly a quarter 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 roughly a quarter of a fund's performance is attributable to the stock characteristics of its portfolio holdings, one might anticipate that removing the characteristics component could 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 five percent. That is, a fund originally ranked in the 50th percentile would be ranked at the 45th or 55th percentile via the new measure. 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 17 (22).

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.[6] 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 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 is 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 performance during a ranking period persists to the next month after (i.e., the one month post-ranking period). Each month, we sort 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

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[6] 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 (2014).

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 quintiles with Newey-West 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 6.23 percent annualized difference in post-ranking top-bottom performance is both statistically and economically significant. We also find strong persistence in the double-adjusted performance measure, with a statistically significant 6.19 percent annualized top-bottom post ranking return difference that accounts for almost all of the return difference in the standard four-factor alpha. By contrast, the returns associated with characteristics do not persist. The difference between the top and bottom post-ranking returns is small in magnitude and is not significantly different from zero. 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.[7]

[Insert Table 4 about here]

We also find statistically significant positive 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 2.3-2.5 percent annualized over the 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 2.34 percent difference between the top and bottom post-ranking deciles. Note, however, that this difference represents less than half 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,

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

[7] We find qualitatively similar results if we examine performance persistence over a quarter.

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 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 by the double-adjusted component of alpha (*t*-stat.=8.53) rather than the characteristic-related component (*t*-stat.=1.26). The regression results very much coincide with the decile analysis of short term persistence. The DGTW CS measure also strongly predicts future post-ranking alpha (*t*-statistic = 3.44), 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 three 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 does not persist over time, 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 over the twelve months in a calendar year monthly alphas, each estimated over a 24-month window ending that month) and move forward the ranking period by 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 of the 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 the post-ranking periods immediately follow the 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, and we compute four-factor alphas for each decile using net fund returns unless mentioned otherwise. Panel A sorts based on standard four-factor alpha; Panel B sorts based on double-adjusted alpha; Panel D sorts based on characteristic-driven alpha; and Panel E sorts based on 36-month average DGTW CS performance measure. In Panel C, we report results for sorts based on double-adjusted alpha similar to Panel B, but 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 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 are statistically significantly consistent with past top performers outperforming past bottom performers (years 2, 3, and 6), 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, the double-adjusted results in Panels B and C show a statistically significant difference between past top and bottom performers for almost all of the ten post-ranking years. For net returns in Panel B, years 1-3 and 5-9 all show evidence of statistically significantly greater performance (at the one or five percent significance level) in past winning funds compared to past losing funds. We find similar evidence on gross fund returns in Panel C, which suggests that such performance persistence is not due to the difference in fund expense ratios. Thus, after removing the portion of performance attributable to the characteristics of portfolio holdings, we find stronger evidence of performance persistence. 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.[8] By contrast, our new measure shows evidence of persistence through the ninth post-ranking year. Note, however, that, in contrast to the short-term persistence results, the evidence of persistence is solely driven by the poorly-performing funds, as the top decile in Panel B fails to produce statistically significant positive abnormal returns during any post-ranking year.

[8] 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.

Regardless of the post-ranking year, the results in Panel D show no evidence of persistence in the portion of standard alpha attributable to characteristics. These results help to explain why we see stronger evidence of persistence in the double-adjusted measure than in the standard four-factor alpha. In particular, the standard alpha includes performance attributable to characteristics, which does not persist. The combination of genuine skill that does persist (as in Panels B and C) plus characteristic-driven performance that does not persist (as in Panel D) produces the weaker evidence of persistence that we see in Panel A.

In Panel E, 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, Grinblatt, Titman, and Wermers (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.

Figure 1 shows cumulative post-ranking performance for funds sorted into deciles based on the double-adjusted measure. The figure illustrates the consistency in relative performance across the performance deciles over time. Panel A reports results for net fund returns, and Panel B reports results for gross fund returns. Both panels show an increasing cumulative performance gap between top, middle, and bottom decile funds over the first nine years of the ten-year post ranking period. These two panels show that, although past winning funds outperform benchmarks gross of expenses, the past winning fund companies extract all of the positive performance via the expense ratio, such that, going forward, fund investors of past winners receive no additional net abnormal returns. Panel C shows a gradual increase in performance difference between top and bottom decile funds from the first post-ranking year to the ninth. In all of the panels, we finally see a leveling off of performance differences in the tenth year. The strong evidence of continuation in double-adjusted performance through year nine contrasts with Carhart's (1997) analysis of standard four-factor performance (e.g., see Carhart's (1997) Figure 4).

[Insert Figure 1 about here]

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 measure 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. 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, statistically, the strongest results indicate a 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 end of the previous quarter. For our analysis of the return gap, we sort based on the average return gap over the prior year, 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 holdings. By contrast, we see little correspondence between active share and double-adjusted fund performance. Thus, the significant relation between active share and standard four-factor alpha is driven by the characteristic-related component, 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 from regressing its excess returns on the returns of 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,

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

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.[9] We examine alternative specifications that exclude and include the 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 correction for time-series correlation with three lags. The inference that we take away from the cross-sectional results closely match the quintile analysis interpretations associated with Table 7. Without fund-level controls, industry concentration, 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. Our results are

[9] 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 untransformed R-squared are qualitatively similar.

qualitatively similar if we examine the relation between the various measures and future performance with a standard set of control variables as additional regressors.

[Insert Table 8 about here]

E. Investor Cash Flows

Lastly, we examine which component of fund performance investors respond to. 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 growth in fund assets beyond capital gains and dividends. It reflects the percentage growth of a fund in excess of the 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,

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

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

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

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 roughly a quarter 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 persists much longer than standard measures, up to nine years in our analysis, and thereby provides a clearer signal of future performance that may be beneficial to investors.

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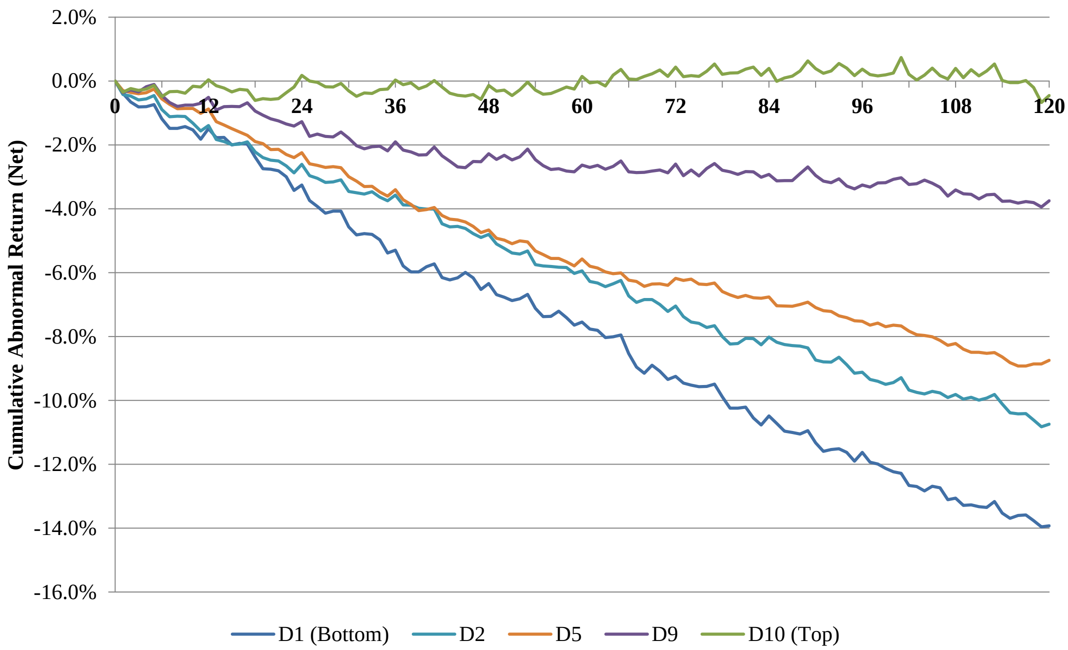
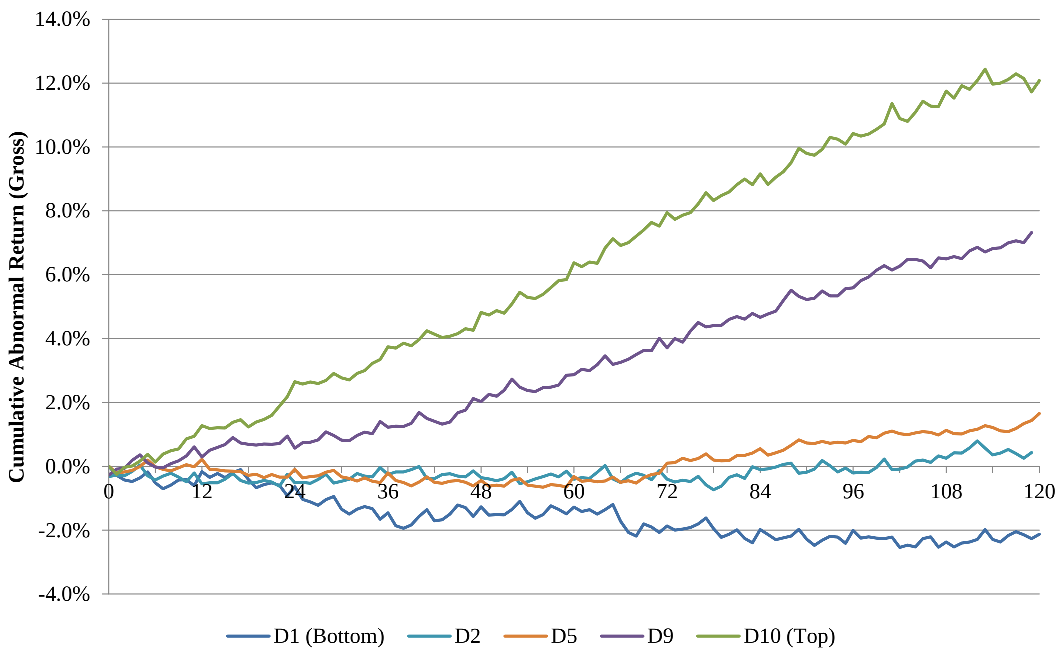
Figure 1. Long-term persistence

The figure shows cumulative post-ranking performance of select deciles during a ten-year post-ranking period for funds sorted by double-adjusted performance during the initial ranking period. The horizontal axes show the post-ranking month number.

Panel A. Net performance by decile



Panel B. Gross performance by decile



Panel C. Performance difference between top and bottom deciles

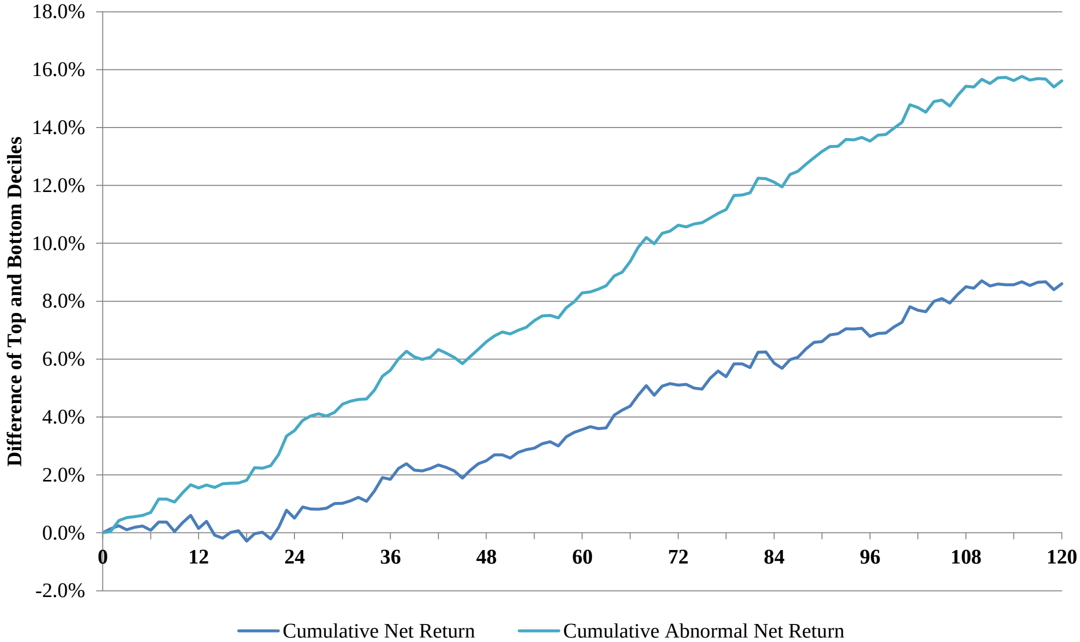


Table 1. Fund Stockholding Characteristics

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 correction for time-series correlation with 12 lags. ** and *** indicate statistical significance at the five and one percent level respectively. The results reflect 396 individual monthly observations over a 1980-2012 sample period.

Panel A. Stock characteristic statistics

Characteristic	Mean	Std.	1st percentile	Median	99th percentile
Size ($ million)	33,376	36,846	295	15,176	139,635
Book-to-market	0.43	0.20	0.11	0.40	1.08
Six-month return (%)	12.94	20.49	-30.37	11.02	81.80
Illiquidity	0.72	1.35	0.25	0.30	7.19

Panel B. Performance of stock characteristic sorts

Quintile	Market cap	Book-to-market	Six-month return	Illiquidity
Bottom	0.33	1.19	-1.52	-0.85
2	0.66	-0.46	-0.75	-0.77
3	-0.28	-0.59	-0.19	-0.25
4	-0.71	-0.37	0.28	0.63
Top	-0.78	-0.56	1.39	0.46
Top-bottom	-1.11**	-1.75***	2.91***	1.31***
t-statistic	(-2.53)	(-3.49)	(5.41)	(3.71)

Table 2. Fund Stock Holding Characteristic Regressions

The table reports regression coefficients averaged monthly cross-sectional regressions,

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

where $Z_{m,i,t-1}$ represents lagged fund holding characteristics, including portfolio value-weighted measures of market capitalization, book-to-market value, 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 correction for time-series correlation with 12 lags. *** indicates statistical significance at the one percent level. The results reflect 396 individual monthly regressions over a 1980-2012 sample period.

			Panel A. Four-factor Alpha		
Market cap	-0.385***				-0.169
	(-3.35)				(-1.49)
Book-to-market		-1.315***			-0.103
		(-3.32)			(-0.25)
Six-month return			0.098***		0.076***
			(5.45)		(4.03)
Constant	-0.183	-0.183	-0.183		-0.183
	(-0.67)	(-0.67)	(-0.67)		(-0.67)
R-squared	0.027	0.036	0.051		0.086
			Panel B. Five-factor Alpha		
Market cap	-0.395***				0.031
	(-3.25)				(0.17)
Book-to-market		-1.439***			-0.431
		(-4.04)			(-1.28)
Six-month return			0.097***		0.073***
			(5.70)		(3.87)
Illiquidity				0.307***	0.398***
				(3.44)	(3.02)
Constant	-0.106	-0.106	-0.106	-0.106	-0.106
	(-0.37)	(-0.37)	(-0.37)	(-0.37)	(-0.37)
R-squared	0.029	0.034	0.049	0.011	0.095

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. The results reflect 397,590 fund observations over a 1980-2012 sample period.

	Percentile						
	5	10	25	50	75	90	95
				Panel A. Performance attribution			
Double-adjusted	0.186	0.315	0.555	0.761	0.888	0.955	0.977
Characteristics	0.023	0.045	0.112	0.239	0.445	0.685	0.814
				Panel B. Change in performance			
Rank (%)	-18.182	-12.195	-4.477	0.374	5.536	11.787	15.900
Abs. Rank (%)	0.236	0.564	1.869	5.061	10.338	16.900	22.147

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 correction for time-series correlation with three lags. *** indicates statistical significance at the one percent level. The results reflect 396 individual monthly observations over a 1980-2012 sample period.

	Model			
Decile	Four-factor	Double-adjusted	Characteristics	DGTW CS
Bottom	-3.92	-3.71	-0.87	-1.85
2	-2.39	-2.44	-0.86	-1.05
3	-1.54	-1.91	-0.85	-0.96
4	-1.40	-1.40	-1.20	-0.96
5	-1.11	-1.03	-0.96	-0.74
6	-0.79	-0.61	-1.00	-0.75
7	-0.19	-0.05	-0.99	-0.84
8	-0.27	-0.24	-1.44	-0.64
9	0.76	0.51	-0.20	-0.39
Top	2.31	2.48	0.07	0.48
Top-bottom	6.23***	6.19***	0.93	2.34***
t-statistic	(7.80)	(8.67)	(-1.18)	(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 correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 396 individual monthly regressions over a 1980-2012 sample period.

Panel A. Fund statistics

Characteristic	Mean	Std.	1st percentile	Median	99th percentile
TNA ($ million)	1,180	4,566	16	229	17,440
Age (months)	178.1	169.0	16.0	124.0	824.0
Expense ratio (%)	1.24	0.44	0.02	1.20	2.49
Cash flow (%)	0.43	4.97	-13.23	-0.30	25.40
Family TNA ($ million)	94,988	247,617	0	11,541	1,390,823

Panel B. Cross sectional regressions

Four-factor alpha	0.313***			0.314***		
	(7.82)			(7.54)		
Double-adjusted alpha		0.328***			0.325***	
		(8.53)			(8.16)	
Characteristics		0.202			0.224	
		(1.26)			(1.36)	
DGTW CS			0.115***			0.103***
			(3.44)			(3.08)
log TNA				-0.367***	-0.344***	-0.323***
				(-4.27)	(-4.04)	(-3.94)
log Age				0.182*	0.185*	0.047
				(1.76)	(1.82)	(0.49)
Expense ratio				-0.692***	-0.553**	-0.890***
				(-2.66)	(-2.30)	(-3.69)
Cash flow				-0.004	-0.006	0.046**
				(-0.14)	(-0.22)	(1.99)
log family TNA				0.127***	0.131***	0.144***
				(3.88)	(3.94)	(4.62)
Constant	-0.702**	-0.742**	-0.788**	0.158	-0.180	0.533
	(-2.16)	(-2.26)	(-2.50)	(0.23)	(-0.26)	(0.78)
R-squared	0.040	0.069	0.022	0.066	0.092	0.045

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 1980-2012 sample period.

	Post-ranking year									
Decile	1	2	3	4	5	6	7	8	9	10
					Panel A. Four-factor alpha					
Bottom	-1.30	-2.07	-2.17	-1.10	-1.12	-1.72	-1.20	-0.87	-1.37	-0.71
2	-1.00	-1.14	-1.35	-1.33	-1.00	-0.92	-0.75	-1.70	-1.18	-0.69
3	-1.38	-1.08	-1.25	-1.33	-0.75	-0.83	-0.70	-0.88	-0.97	-0.55
4	-1.33	-1.10	-1.36	-1.58	-1.04	-0.84	-0.71	-1.21	-0.96	-1.47
5	-0.66	-1.01	-1.31	-0.99	-0.90	-0.47	-0.94	-1.42	-0.78	-0.11
6	-0.92	-0.61	-0.80	-0.73	-0.47	-0.81	-1.12	-0.75	-0.95	-0.68
7	-1.09	-0.69	-0.86	-0.73	-1.02	-0.79	-0.51	-0.89	-0.52	-0.61
8	-0.89	-0.54	-0.66	-0.70	-0.94	-0.70	-0.49	-0.42	-0.47	-0.77
9	-0.44	-0.60	-0.63	-0.59	-0.57	-0.22	-0.12	-0.43	-0.56	-0.63
Top	-0.18	-0.06	0.18	0.06	0.20	0.53	0.21	-0.23	0.32	-0.81
Top-bottom	1.12	2.01**	2.35***	1.16	1.32*	2.25***	1.41*	0.64	1.69*	-0.09
t-statistic	(1.12)	(2.19)	(2.74)	(1.65)	(1.74)	(2.87)	(1.75)	(0.79)	(1.95)	(-0.10)
					Panel B. Double-adjusted Alpha, net return results					
Bottom	-1.50	-1.80	-2.13	-1.10	-1.29	-1.85	-1.37	-1.28	-1.63	-1.00
2	-1.40	-1.23	-0.99	-1.29	-1.20	-1.17	-1.05	-1.20	-0.77	-1.04
3	-0.93	-0.73	-1.26	-1.20	-1.09	-0.91	-0.37	-1.19	-1.39	-0.46
4	-1.23	-0.93	-1.44	-1.31	-1.13	-0.66	-0.80	-1.17	-1.02	-0.34
5	-0.87	-1.39	-1.19	-1.31	-0.96	-0.64	-0.62	-0.82	-0.75	-0.57
6	-1.11	-1.02	-0.95	-0.79	-0.80	-0.64	-0.62	-0.89	-0.87	-0.99
7	-0.89	-0.89	-0.70	-0.81	-0.58	-0.65	-0.69	-0.76	-0.55	-0.57
8	-0.79	-0.27	-0.72	-0.67	-0.51	-0.58	-0.44	-1.08	-0.38	-0.93
9	-0.51	-0.77	-0.64	-0.38	-0.37	0.03	-0.33	-0.34	-0.16	-0.35
Top	0.04	0.14	-0.14	-0.17	0.29	0.29	-0.04	-0.02	0.03	-0.84
Top-bottom	1.54**	1.94***	1.99***	0.93*	1.58***	2.14***	1.34**	1.26**	1.66**	0.16
t-statistic	(2.40)	(3.43)	(3.45)	(1.77)	(2.73)	(3.95)	(2.09)	(2.01)	(2.40)	(0.25)

Table 6 continued.

Panel C. Double-adjusted Alpha, gross return results										
Bottom	-0.16	-0.47	-0.82	0.19	-0.01	-0.59	-0.12	-0.02	-0.37	0.25
2	-0.21	-0.03	0.21	-0.10	-0.01	0.01	0.13	-0.04	0.38	0.11
3	0.22	0.41	-0.12	-0.06	0.04	0.21	0.74	-0.07	-0.25	0.66
4	-0.12	0.18	-0.34	-0.20	-0.02	0.44	0.31	-0.04	0.11	0.80
5	0.22	-0.31	-0.12	-0.23	0.12	0.42	0.45	0.26	0.32	0.52
6	-0.04	0.05	0.12	0.27	0.25	0.41	0.44	0.15	0.18	0.06
7	0.15	0.15	0.36	0.24	0.47	0.40	0.36	0.29	0.50	0.47
8	0.30	0.82	0.36	0.40	0.56	0.49	0.62	-0.02	0.68	0.12
9	0.61	0.34	0.45	0.71	0.72	1.12	0.75	0.74	0.91	0.74
Top	1.27	1.35	1.06	1.03	1.48	1.47	1.13	1.15	1.20	0.30
Top-bottom	1.43**	1.83***	1.88***	0.84	1.49***	2.06***	1.24*	1.17*	1.57**	0.05
t-statistic	(2.23)	(3.23)	(3.26)	(1.59)	(2.58)	(3.80)	(1.95)	(1.87)	(2.26)	(0.08)
Panel D. Characteristics										
Bottom	-0.57	-0.58	-1.23	-1.18	-0.15	-0.40	-0.49	-1.63	-0.55	0.07
2	-0.18	-1.34	-1.14	-1.03	-0.53	-0.37	-0.73	-1.37	-0.75	-0.04
3	-0.86	-1.45	-1.14	-1.42	-0.70	-0.65	-0.67	-1.19	-0.98	-0.69
4	-0.76	-0.90	-1.39	-0.96	-0.58	-0.43	-0.65	-0.77	-0.53	-1.68
5	-0.76	-1.01	-1.10	-1.19	-0.66	-0.55	-0.95	-0.64	-0.85	-0.98
6	-1.06	-0.72	-1.24	-0.72	-0.67	-0.90	-0.81	-0.54	-0.64	-0.75
7	-1.07	-0.57	-0.95	-1.06	-0.63	-0.85	-0.88	-0.81	-0.64	-0.64
8	-0.77	-0.88	-1.25	-0.67	-0.87	-1.15	-0.29	-0.28	-0.51	-0.52
9	-1.34	-0.61	-0.61	-0.84	-1.22	-0.72	-0.32	-0.05	-0.41	-0.74
Top	-1.79	-0.84	-0.09	0.00	-1.61	-0.77	-0.59	-1.51	-1.62	-1.06
Top-bottom	-1.22	-0.27	1.14	1.18	-1.46	-0.36	-0.11	0.12	-1.07	-1.13
t-statistic	(-0.68)	(-0.14)	(0.64)	(0.81)	(-1.02)	(-0.25)	(-0.08)	(0.09)	(-0.90)	(-0.76)

Table 6 continued.

Panel E. DGTW CS

Bottom	-0.73	-0.92	-0.78	-1.15	-0.14	-1.05	-1.03	-0.65	-1.03	-0.54
2	-0.43	-1.01	-0.68	-0.55	-0.37	-0.66	-0.53	-1.04	-0.42	-0.84
3	-0.67	-0.94	-1.09	-0.68	-0.82	-0.78	-0.40	-1.70	-1.14	-0.94
4	-1.09	-1.14	-0.97	-1.25	-0.63	-0.24	-1.41	-0.67	-0.44	-1.18
5	-0.67	-0.84	-1.12	-0.83	-1.02	-0.89	-1.27	-1.39	-1.43	-0.94
6	-0.87	-1.40	-1.40	-1.17	-0.72	-1.02	-0.84	-0.68	-0.03	-1.01
7	-1.11	-0.95	-0.80	-0.82	-1.22	-0.35	-1.20	-0.67	-0.74	-0.94
8	-1.28	-0.72	-1.11	-0.74	-0.52	-1.05	-0.77	-0.43	-1.19	-0.92
9	-1.07	-0.57	-1.09	-0.81	-0.88	-0.49	-0.82	-0.28	-0.53	-0.64
Top	-0.86	-0.94	-0.23	0.15	-0.50	-0.26	-0.17	0.30	-0.81	-1.10
Top-bottom	-0.13	-0.01	0.55	1.30	-0.35	0.79	0.86	0.95	0.22	-0.57
t-statistic	(-0.10)	(-0.01)	(0.54)	(1.51)	(-0.43)	(0.95)	(1.00)	(1.01)	(0.22)	(-0.57)

Table 7. Fund Characteristic Sorts

The table reports mean annualized post-ranking percentage four-factor alphas for funds sorted into quintiles based on industry concentration index (Panel A), return gap (Panel B), active share (Panel C), or R-squared (Panel D). Post-ranking four-factor alphas is defined in Table 4. We compute *t*-statistics of the differences between the top and bottom quintiles with Newey-West correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 396 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

Panel B. Performance of fund characteristic sorts

	Model		
Decile	Four-factor	Double-adjusted	Characteristics
B1. Industry concentration			
Bottom	-1.25	-0.89	-0.36
2	-0.95	-0.78	-0.17
3	-0.66	-0.68	0.02
4	-0.49	-0.68	0.20
Top	-0.46	-0.73	0.27
Top-bottom	0.79*	0.16	0.63***
t-statistic	(1.70)	(0.49)	(2.68)
B2. Return gap			
Bottom	-1.38	-1.53	0.14
2	-0.85	-0.80	-0.05
3	-0.67	-0.61	-0.06
4	-0.61	-0.49	-0.11
Top	0.03	-0.02	0.05
Top-bottom	1.41***	1.51***	-0.09
t-statistic	(4.67)	(5.82)	(-0.61)
B3. Active share			
Bottom	-1.17	-0.70	-0.47
2	-1.06	-0.76	-0.30
3	-0.65	-0.56	-0.08
4	-0.19	-0.54	0.35
Top	-0.23	-0.69	0.48
Top-bottom	0.95*	0.01	0.95**
t-statistic	(1.79)	(0.06)	(2.12)
B4. R-squared			
Bottom	`-0.08	-0.38	0.33
2	-0.52	-0.77	0.26
3	-0.94	-0.93	0.00
4	-1.24	-1.03	-0.20
Top	-1.20	-0.80	-0.40
Top-bottom	-1.12**	-0.42	-0.73***
t-statistic	(-2.42)	(-1.16)	(-3.14)

Table 8. Fund Characteristic Regressions

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

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

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 correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 396 individual monthly regressions over a 1980-2012 sample period.

	Four-factor alpha		Double-adjusted		Characteristics	
			Panel A. Industry concentration			
ICI	0.883	0.687	0.107	0.107	0.623**	0.434
	(0.77)	(0.60)	(0.10)	(0.10)	(2.12)	(1.55)
log TNA		-0.281***		-0.206***		-0.075**
		(-3.41)		(-2.86)		(-2.48)
log Age		-0.002		-0.045		0.036
		(-0.02)		(-0.57)		(0.71)
Expense ratio		-0.842***		-0.992***		0.126
		(-3.48)		(-5.06)		(0.93)
Cash flow		0.088***		0.069***		0.020**
		(4.10)		(3.69)		(2.02)
log family TNA		0.115***		0.104***		0.011
		(3.57)		(3.36)		(1.43)
Constant	-0.879***	0.651	-0.797**	0.805	-0.071**	-0.093
	(-2.69)	(1.02)	(-2.40)	(1.38)	(-2.24)	(-0.36)
R-squared	0.015	0.039	0.014	0.035	0.012	0.073
			Panel B. Return gap			
Return gap	0.138***	0.122***	0.142***	0.129***	-0.004	-0.006
	(5.61)	(5.07)	(6.36)	(5.73)	(-0.38)	(-0.59)
log TNA		-0.333***		-0.245***		-0.087**
		(-3.71)		(-2.99)		(-2.55)
log Age		0.048		0.016		0.024
		(0.50)		(0.20)		(0.45)
Expense ratio		-0.949***		-1.131***		0.145
		(-3.69)		(-5.51)		(1.18)
Cash flow		0.077***		0.061***		0.016
		(3.58)		(3.07)		(1.64)
log family TNA		0.132***		0.114***		0.017**
		(3.91)		(3.49)		(2.27)
Constant	-0.677**	0.827	-0.645**	0.920	-0.036*	-0.026
	(-2.19)	(1.13)	(-2.07)	(1.46)	(-1.89)	(-0.08)
R-squared	0.008	0.033	0.007	0.029	0.015	0.073

Table 8 continued.

			Panel C. Active share			
Active share	2.195*	2.594**	-0.051	0.490	2.141**	2.019**
	(1.76)	(1.97)	(-0.08)	(0.64)	(2.06)	(1.99)
log TNA		-0.257***		-0.208***		-0.049
		(-3.02)		(-2.63)		(-1.62)
log Age		0.070		0.034		0.026
		(0.77)		(0.42)		(0.65)
Expense ratio		-0.909***		-0.955***		0.024
		(-3.98)		(-5.14)		(0.27)
Cash flow		0.086***		0.067***		0.019**
		(4.03)		(3.53)		(2.12)
log family TNA		0.137***		0.117***		0.020***
		(4.18)		(3.64)		(2.60)
Constant	-2.485***	-1.895	-0.607	-0.003	-1.795**	-1.753**
	(-2.76)	(-1.62)	(-1.29)	(-0.00)	(-2.00)	(-2.00)
R-squared	0.020	0.044	0.004	0.026	0.141	0.172
			Panel D. R-squared			
log TR-sq	-0.659**	-0.739**	-0.247	-0.391	-0.379***	-0.319***
	(-2.21)	(-2.50)	(-0.93)	(-1.49)	(-3.25)	(-2.78)
log TNA		-0.258***		-0.209***		-0.051*
		(-3.24)		(-2.79)		(-1.68)
log Age		0.009		0.001		-0.001
		(0.09)		(0.01)		(-0.02)
Expense ratio		-0.902***		-1.059***		0.132
		(-4.00)		(-5.80)		(1.03)
Cash flow		0.087***		0.069***		0.018**
		(3.79)		(3.36)		(2.06)
log family TNA		0.137***		0.124***		0.014*
		(4.29)		(3.96)		(1.73)
Constant	0.935	2.415**	-0.178	1.553	1.018***	0.854*
	(0.96)	(2.31)	(-0.20)	(1.63)	(3.31)	(1.78)
R-squared	0.017	0.042	0.014	0.035	0.027	0.085

Table 9. Cash Flow Regressions

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

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

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

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

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 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 1980-2012 sample period.

Return	0.082***			0.063***		
	(9.48)			(8.58)		
Four-factor alpha		0.139***			0.077***	
		(11.23)			(6.58)	
Double-adjusted alpha			0.130***			0.074***
			(9.41)			(5.81)
Characteristics			0.207***			0.109***
			(3.08)			(2.77)
log TNA				0.293***	0.292***	0.286***
				(12.92)	(13.76)	(15.45)
log Age				-0.227***	-0.238***	-0.235***
				(-8.86)	(-8.69)	(-8.27)
Expense ratio				-0.105***	-0.071*	-0.067**
				(-2.86)	(-1.82)	(-2.07)
Cash flow				0.028	0.011	0.005
				(0.21)	(0.08)	(0.05)
log family TNA				0.069***	0.074***	0.072***
				(6.14)	(6.15)	(5.93)
Constant	-0.365*	0.337**	0.333**	0.811**	1.237***	1.204***
	(-1.72)	(2.59)	(2.53)	(2.12)	(4.39)	(4.32)
R-squared	0.081	0.062	0.088	0.242	0.213	0.226