Mutual Fund Industry Selection and Persistence

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Abstract

We analyze mutual fund industry selectivity—the performance of a fund's industry allocation relative to the market. We find that industry selection accounts for a full third of fund performance based on two-digit standard industrial classification (SIC) codes, with the remaining attributable to the performance of individual stocks relative to their own industries. More importantly, we find that industry-selection skill drives persistence in relative performance. Unlike stock-selection ability, industry selectivity is not eroded by increasing fund assets. Our results suggest that accounting for a manager's ability to pick outperforming industries provides information beyond standard performance measures that can enhance a fund investor's future performance.

Mutual fund studies typically analyze fund performance either at the fund level or at the individual security level. At the fund level, shareholder returns are usually compared with one or more benchmarks, such as the S&P 500. At the security level, individual stock returns are evaluated relative to stock-specific benchmarks, such as DGTW characteristic benchmarks. Examples of the former range from the earliest mutual fund studies, including Jensen (1968), up to the present. Examples of the latter include Grinblatt and Titman (1989), Daniel, Grinblatt, Titman, and Wermers (1997), and Wermers (2000), among many others.

The interpretation of these performance studies invariably emphasizes the fund manager's stock-picking ability. For instance, a positive alpha suggests that the manager has stock-picking skill. However, the specific reason why a fund manager holds a top-performing stock can go far beyond his ability to pick individual stocks. For example, a manager may have skill in interpreting changes in the economy and shifting his portfolio toward the types of stocks that do well during certain macroeconomic environments. When interest rates begin to decrease, for instance, banks tend to outperform as their margins improve.

The stock-picker label seems most appropriate for those that employ a bottom-up investment technique. In this type of approach, the manager focuses on the analysis of individual companies and de-emphasizes economic cycles and industry trends. The alternative to the bottom-up investment style is the top-down approach. In this approach, managers first make decisions regarding broad industry allocations before moving on to the finer details and eventually selecting individual stocks.

In this article, we explore manager skill in making decisions regarding broader allocations. Specifically, we examine the relative importance of industry selection compared with stock selection in the performance of a manager's portfolio. That is, we examine the extent to which a manager's industry allocations drive his performance versus his specific stock choices within the industries held in his portfolio. Top-performing managers may do well because they choose stocks in top-performing industries, where average stocks in those same top industries would have performed just as well as the stocks chosen by the managers. Alternatively, top-performing managers may choose the best stocks in average or even underperforming industries.

We show that industry selection contributes substantially to fund performance, accounting for roughly one-third of a fund's abnormal performance based on two-digit standard industrial classification (SIC) codes. Our analysis indicates that the importance of industry selection is remarkably stable across time, with little variation over time in the mean contribution across funds. As a point of comparison, we find that a fund's style, defined by the market capitalization, book-to-market, and momentum characteristics of its individual stock holdings, accounts for between one-quarter and one-half of fund abnormal performance, depending on the factors in the regression model.

The skill sets associated with industry- and stock-selection ability could differ considerably, with industry-selection ability relying on understanding macroeconomic relationships, and stock-selection skill relying on the ability to size up firm-specific drivers, such as innovative products or managerial competence. We analyze the extent to which each component of skill persists. Numerous articles examine the extent to which overall skill persists, including Grinblatt and Titman (1992), Hendricks, Patel, and

Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Malkiel (1995), Elton, Gruber, and Blake (1996), among others. The general consensus is that good performance persists, if at all, only a quarter or two after controlling for momentum (Carhart 1997 and Bollen and Busse 2005), whereas poor performance persists more strongly, typically because of high expenses. We find that the industry-selection component of performance persists, while the stock-selection component of performance does not. Whereas past industry selectivity predicts future industry selectivity for investment horizons up to two quarters, stock selectivity does not predict future stock selectivity even one quarter away. Our results suggest that industry selection, rather than stock selection, drives the evidence of overall performance persistence documented in the literature.

Our results can also be interpreted in the context of market timing. The standard market timing literature (for example, Treynor and Mazuy 1966 or Henriksson and Merton 1981) examines whether funds skillfully shift their portfolios between stocks and cash as market conditions change. It has been difficult, however, to clearly distinguish between timing and selectivity. For example, a strong negative relation exists between contemporaneously estimated measures of alpha and timing ability (Jagannathan and Korajczyk 1986), such that selection ability could be mistaken for timing. Furthermore, drivers unrelated to market timing, such as exogenous investor cash flows (Ferson and Schadt 1996; Ferson and Warther 1996; and Edelen 1999) option holdings, interim trading, public information, and systematic stale pricing (Chen, Ferson, and Peters 2010), can affect fund beta, possibly leading to erroneous interpretations. At a more practical level, many mutual funds, with balanced and asset allocation funds being the exception (see Becker, Ferson, Myers, and Schill 1999), operate under a mandate to fully invest in the stock market. Consequently, with their emphasis on market betas and movements between stocks and cash, standard timing tests may be ill suited for identifying more subtle forms of timing that likely typify the equity mutual fund industry.

Industry-selection ability arises when a mutual fund invests in outperforming industries. As an extreme example, a fund that invests in pro-cyclical industries during a bull market and/or utilities during a bear market would likely show positive industry-selection ability, depending on controls for risk. Because rotating across industries as market conditions change characterizes the type of timing that many funds utilize, our estimates of industry selectivity may provide a more realistic way to infer timing ability. Our estimates of industry-selection ability also overcome many of the issues that hamper standard tests of market timing. For instance, industry selectivity is not sensitive to cash holdings nor obscured by mutual fund fees or trading costs because we base them on fund equity holdings rather than net shareholder returns.

Berk and Green (2004) hypothesize that the large flows of capital into successful funds eventually lead to the successful funds losing their performance edge. Successful funds face increasing transaction costs (due to greater-size trades) and/or the addition of less-attractive stocks to their portfolio. Using net shareholder returns, Chen, Hong, Huang, and Kubik (2004) find a negative relation between fund portfolio size and overall performance. Elton, Gruber, and Blake (forthcoming) use different size breakpoints for each investment objective and find no evidence of a negative relation between fund size and net shareholder performance. Using Elton, Gruber, and Blake’s methodology with different size breakpoints for each investment objective, we find weak evidence of a negative relation between fund size and before cost total fund performance, where the strength of the negative relation depends on the number of factors in the regression model. However, we find a strong negative relation between fund portfolio size and stock-selection skill. In contrast, we find no evidence of a negative relation between fund size and industry-selection skill. Our results suggest that although funds are unable to maintain their stock selectivity when their assets increase, they do maintain their industry-selection ability. Thus, flows into successful funds do not appear to erode industry skill. Apparently, unlike individual stocks, industries provide ample opportunities for further investments.

Examining the industry features of fund portfolios has received little attention among mutual fund studies. Rather than controlling for industry exposure, most mutual fund studies control for exposure to size, value, and momentum factors in their performance measures, consistent with trends in the empirical asset pricing literature. Recent articles that examine industry allocations include Kacperczyk, Sialm, and Zheng (2005) and Avramov and Wermers (2006). Kacperczyk, Sialm, and Zheng (2005) find that funds that concentrate their holdings in fewer industries tend to outperform funds that diversify more across industries. Avramov and Wermers (2006) examine the industry allocations of funds predicted to outperform based on manager skill, risk loadings, and benchmark returns. They find that optimally chosen funds show ability to time industry allocations across the business cycle and have larger exposure to the energy, utilities, and metals industries. Cremers and Petajisto (2009) examine the extent to which fund portfolios differ from their benchmarks on a stock-by-stock basis, and Amihud and Goyenko (2011) examine the relation between a fund's factor model regression R^2 and future fund performance. Over- or under-allocating to various industries would be one reason a portfolio differs from its benchmark or has relatively low R^2.

Kacperczyk, Sialm, and Zheng (2005), Cremers and Petajisto (2009), and Amihud and Goyenko (2011) find that fund manager skill manifests itself in portfolios that differ from passive indices, and they find a positive relation between these differences and fund performance. A key difference between our study and these articles is that our emphasis is not on the extent to which portfolios differ from passive indices, but on the performance of the industries of the stocks in the portfolio. That is, in our view, a fund whose portfolio differs substantially from a passive index could either outperform or underperform, with the outcome critically depending on the performance of its constituent industries.

In an article widely referenced by practitioners, Brinson, Hood, and Beebower (1986) explore the importance of allocations one step higher in the investment process for portfolios managed by institutional money managers. They analyze allocations among stocks, bonds, and cash, and find that these allocation decisions explain more than 90% of the variation in a portfolio's total return. By construction, our sample of mutual funds already holds primarily equities. Consequently, we begin at the industry, rather than asset-class, level. Furthermore, we focus on determining the extent to which industry allocations explain risk-adjusted performance, rather than variation in total return.

The article proceeds as follows. Section 1 describes the data. Section 2 defines our measures of industry and stock selection. Section 3 presents our empirical analysis, including performance persistence and issues related to scale. Section 4 concludes.

1. Data

We obtain mutual fund holdings from Thomson Financial's CDA/Spectrum Mutual Fund Holdings database. The database consists of portfolio stockholdings data for virtually all U.S. mutual funds between January 1980 and September 2009 (inclusive), with no minimum survival requirement for a fund to be included. For each stock holding of each fund, the data include CUSIP, ticker symbol, company name, and number of shares held. Thomson Financial collects these data both from reports filed by mutual funds with the Securities and Exchange Commission (SEC), as required by amendments to Section 30 of the Investment Company Act of 1940, and from voluntary fund reports. Mutual funds have been required to file portfolio holdings reports with the SEC semiannually since 1985 and quarterly since 2004. Quarterly holdings exist for 86% of our sample. Thomson Financial's holdings database has no known survivorship bias (see Cici, Gibson, and Moussawi 2010).

We focus on domestic equity funds and include those with the following investment objective codes as indicated by Thomson Financial: Aggressive Growth, Growth, and Growth & Income. Because we are interested in analyzing the skill associated with actively managed funds, we remove funds that are likely to be passively managed.[1] We also remove sector funds because their industry allocation decisions are substantially constrained.[2]

We obtain individual stock returns, prices, shares outstanding, and SIC codes from the Center in the Research of Security Prices (CRSP) Daily and Monthly Stock files. We collect the data from CRSP for the thirty-year sample period from 1980 to 2009.

We match the stock holdings from Thomson Financial with the daily stock returns from CRSP. Although we are unable to match all stock holdings to companies listed in CRSP, the missing data constitute less than 1% of the stock holdings, which is consistent with the match rate of Kacperczyk, Sialm, and Zheng (2005). Because CRSP focuses on U.S. listed stocks, which are required to meet minimum market capitalization requirements, unmatched holdings likely consist mainly of micro-cap and foreign stocks not listed on the NYSE, Amex, or NASDAQ. In untabulated results, we find that our main findings are not sensitive to the degree of match.[3]

We compute gross daily hypothetical fund returns using portfolio weights derived from the most recent portfolio holdings snapshot. For example, we compute returns for 1990Q3 using portfolio holdings from the end of June 1990. We determine each portfolio holding's initial weight by taking the product of stock price and shares held and then dividing this dollar investment by the sum of the dollar investments across all stocks in the portfolio. The weights evolve during the quarter as they would in a buy-and-hold portfolio, where weights change daily as a function of the total returns (with dividends reflected on the ex-div date) of all portfolio holdings. When additional holdings data become available during a calendar quarter, we reset the individual holding initial weights beginning the day after the date of the new holdings data using the new share holdings and stock prices. In instances where holdings are not reported quarterly (e.g., semi-annual holdings) or do not align with calendar quarters, we use the most recently reported share holdings. The calendar time between a daily return estimate and the fund holdings it is derived from is at most six months (and typically less than three months).

The procedure that we use to compute returns is similar to that used by others, such as Grinblatt and Titman (1989) and Wermers (2000). The return series differ from actual shareholder returns because they ignore expenses, transaction costs, non-U.S. equity holdings, and intra-quarter portfolio adjustments. Consequently, we estimate ability on a before-cost basis. We subsequently compare our performance measures to estimates of transaction costs, expenses, and other nonequity effects that impact net shareholder returns.

Table 1 provides portfolio statistics of our fund sample for select years during our sample period. The number of funds increases dramatically from 1980 through 2009, consistent with the explosive growth in the mutual fund industry over the past thirty years. The number of stocks per portfolio also increases considerably during the sample period, coinciding with an increase in average assets under management per fund. Increasing the number of stocks in a portfolio can help to mitigate the increase in transaction costs that would normally accompany an increase in assets.

The table also reports the number of industries per portfolio, where we use the historically accurate two-digit SIC code to define industries, taken from CRSP. SIC codes are typically used at the two- or four-digit level. We use the coarser two-digit level in our analysis for two main reasons. First, fine industry groupings (such as those associated with four-digit SIC codes) often lead to sparsely populated industries, making it difficult to disentangle the industry effect from the individual stock effect. For example, Microsoft Corp. (ticker MSFT) accounts for 38% of the total market capitalization associated with the 7370 SIC code during the 1986–2009 time period. During periods of time when MSFT stock outperforms the market, the entire four-digit software industry typically does well also (due to MSFT's direct weighting in the industry's returns), and MSFT's performance beyond the industry is muted. Coarser industry groupings lead to more heavily populated industries and smaller individual stock influences. A second and less quantifiable reason is that most diversified fund managers are unlikely to categorize their holdings into groups much beyond the equivalent of two-digit SIC codes. Fund managers, for instance, often incorporate information from third-party data providers as one input into their analysis, and many of these data are organized into industry groupings of similar granularity to that of two-digit SIC codes.[4]

Alternatives to the SIC classification system include North American Industry Classification System (NAICS) codes and Global Industry Classification System (GICS) codes. We choose the SIC system because of its widespread use in the academic literature. However, as a robustness test, we repeat our main analyses with three-digit NAICS codes, which we take from Compustat, and find very similar results. GICS codes are not available until the mid-1990s, and are therefore unavailable for roughly half of our sample period.

A total of ninety-five unique two-digit SIC codes exist, ranging from 01 (Agricultural Production—Crops) to 99 (Nonclassifiable Establishments).[5] At any point in time, our sample funds in aggregate hold stocks in about 95% of these two-digit SIC codes. With roughly 8,000 stocks in operation and available on CRSP at any given point in time during our sample period, an average of about eighty CRSP stocks exist per specific two-digit SIC code. As indicated in Table 1, each fund in our sample holds a median of fifty-four stocks in a median of twenty-three unique two-digit SIC industries.

Thus, on average, funds hold roughly 3% of the stocks within the industries included in their portfolio.[6]

2. Performance Decomposition

Here and elsewhere in the article, we evaluate the performance of the daily hypothetical fund returns using three different standard base models: a one-factor model, based on the capital asset pricing model, that uses the excess returns on a proxy for the overall stock market as the factor; the four-factor model that uses size (SMB), value (HML), and momentum (UMD) factors together with the market factor (see Fama and French 1993 and Carhart 1997); and a five-factor model that adds an industry momentum factor to the four-factor model (see Moskowitz and Grinblatt 1999):

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k} \left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1} \right) + \varepsilon_{p,t}\,, \tag{1}$$

where $r_{p,t}$ is the excess return of a fund portfolio at time *t*, and $r_{j,t}$ are the returns of the $k = 1$ to five factors.

We use the value-weighted CRSP return series for our market proxy, and take the SMB, HML, and UMD factors and the risk-free return (to compute excess portfolio returns) from Ken French’s website. We construct the industry momentum factor similar to Moskowitz and Grinblatt (1999). We take the difference between the returns of industries with high past twelve-month returns and industries with low past twelve-month returns. We value-weight both the individual industry returns that compose the high and low momentum industries and the returns within each individual industry. We use the seventieth and thirtieth percentiles as cutoffs to define high and low industry returns, and use two-digit SIC codes to define industries. The lag factors in regression equation (1) control for nonsynchronous trading in individual portfolio holdings (see Scholes and Williams 1977 and Dimson 1979). The intercept, α_p, is a standard estimate of mutual fund skill, and it captures the ability of funds to outperform the market on a risk-adjusted basis, with adjustments for size, value, stock momentum, and industry momentum anomalies in the four- and five-factor models.

With daily fund returns, we estimate regression equation (1) over short quarterly intervals. Although our approach differs from that of Ferson and Schadt (1996), who use macroeconomic conditioning variables in conjunction with monthly frequency data and longer estimation intervals, we interpret our regression coefficients as conditional estimates because we capture coefficient changes across quarters (see Braun, Nelson, and Sunier 1995).[7] As an alternative to our base estimates to further control for time-varying factor exposures, we divide our quarterly measurement intervals into two equal halves, and estimate regression equation (1) twice per quarter, taking the average of the two sets of estimates as the full quarter estimate. In doing so, we capture some of the intra-quarterly changes in factor exposures, resulting in a cleaner estimate of selectivity.

We interpret the standard estimate of mutual fund skill, alpha, as the sum of two distinct components of skill: industry-selection skill and stock-selection skill. Industry-selection skill is the ability to allocate assets to industries that subsequently outperform other industries. For many fund managers, industry-selection skill captures expertise in one of the early steps in the investment process—the ability to choose the broad areas of the market that will outperform. Stock-selection skill is the ability to pick the best stocks within the industries in which a fund invests.

We decompose standard alpha into industry-selection skill and stock-selection skill as follows. First, for each fund, we construct a corresponding time series of industry returns, $R_{pi,t}$, consistent with the fund's industry exposures. To do so, we replace each stock in the fund's portfolio with its value-weighted industry return.[8] Thus, we replace Microsoft, for example, by the value-weighted return associated with two-digit SIC industry 73, which is Microsoft's two-digit SIC industry assignment. Each industry return receives the same initial weight as the stock it represents in the fund portfolio. The weight subsequently evolves over time as a function of the returns of all of the industries included in the portfolio. Thus, this new time series of returns strips out the dynamics of individual stocks, leaving only that which is attributable to the fund's industry exposures. The procedure we use to construct industry returns is similar to DGTW's (Daniel et al. 1997) procedure for characteristic benchmark returns. Instead of using 125 size/book-to-market/momentum bins as in DGTW, we use 95 two-digit SIC industry bins.[9]

We use the excess returns of this fund-specific industry time series as a regressand in a regression similar to equation (1),

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k} \left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1} \right) + \varepsilon_{p,t}, \tag{2}$$

where $r_{pi,t} = R_{pi,t} - r_{f,t}$. We interpret the intercept in these models, α_{pi}, as fund industry-selection skill, the ability to allocate assets to industries that outperform other industries. Our procedure differs from DGTW because our industry bins do not control for size, book-to-market, and momentum. Regression equation (2) removes these style-related effects from the industry returns to produce our estimate of industry-selection skill.

Funds with industry-selection ability hold industries that outperform the market on a risk-adjusted basis. Because different industries outperform as market conditions change, industry selectivity captures a form of market timing. But whereas standard market timing tests, such as Treynor and Mazuy (1966) or Henriksson and Merton (1981), emphasize fund movements between stocks and cash, industry selection emphasizes movements across industries. By focusing on movements across different areas of the equity universe, industry-selection skill captures in a more realistic way the manner in which mutual funds, often mandated to be fully invested, time the market.

We define stock-selection skill, α_{ps}, as the difference between total fund alpha (α_p in equation (1)) and industry-selection skill (α_{pi} in equation (2)). We interpret stock-selection skill as the ability of funds to pick stocks that outperform other stocks in the same industries held by the fund.

We estimate regression equations (1) and (2) for each fund each quarter (or twice per quarter in the alternative specification), and take the mean of the skill estimates each quarter and then across quarters. Table 2, Panel A, shows the mean α_p, α_{pi}, and α_{ps} and *t*-statistics (based on the Newey-West corrected standard error of the mean of the time series of mean quarterly alphas) for the base one-, four-, and five-factor regression models and the five-factor biquarterly model.

Note first that the mean estimates of overall skill are positive. On an individual fund basis, most of these skill measures are not statistically significantly different from zero, which is not surprising given the short quarterly time series of returns associated with their estimation. However, across funds, the mean alpha is statistically significantly different from zero. Recall that our returns are gross of expenses and transaction costs, so it is perhaps not surprising that these results are not directionally consistent with the results of studies that examine shareholder returns (net of expenses and transaction costs). Examining shareholder returns typically leads to evidence of negative risk-adjusted performance (see, for example, Gruber (1996), who finds average net four-factor abnormal shareholder returns of –0.65% per year). Expense ratios average approximately 1.1% in Gruber's (1996) sample, and Wermers (2000) estimates transaction costs of about 0.75% per year in his mutual fund sample. Netting out similar expenses and transaction costs from the performance estimates in Table 2 would produce estimates of mean performance consistent with the prior literature. Our evidence of a positive mean gross skill estimate is also similar to Wermers (2000), who finds evidence of positive mean gross performance net of DGTW benchmarks and estimates a 2.3% difference between gross and net returns.

The table also shows positive mean estimates for the industry-selection and stock-selection components of alpha for all four regression models. However, these are not statistically significant on a fund-by-fund basis, and the means across funds are also not statistically significant. Our main goal in examining these skill estimates is to provide an initial indication of the relative importance of the industry-selection component of alpha. Based on the sample means, industry-selection skill appears to drive about a third of the fund's overall performance. For example, for the five-factor model, industry-selection skill is 33% of total skill (0.38% per year out of 1.16%).[10,11] However, the lack of statistical significance in the estimates of industry- and stock-selection skill suggests that this initial estimate should be interpreted with caution, perhaps pointing in the direction of the importance of industry-selection skill, but not representing a precise estimate.

We next examine the relative importance of industry-selection skill versus stock-selection skill across time. For each fund each quarter, we again compute industry-selection skill and total alpha. Table 3, Panel A, reports the ratio of the mean industry-selection alpha to the mean total alpha for various subsample periods. Across all fund quarters, the ratio is 0.32, 0.31, and 0.32 for the single-, four-, and five-factor base models, respectively, and 0.32 for the five-factor biquarterly model.[12] Note also the stability of the estimated industry contribution over time. Across all four models and all five five-year subsample periods, the portion of performance attributable to industry selection is between 30.1% and 33.5%. These results provide additional evidence that a meaningful fraction of the skill managers bring to the table is the skill associated with their industry selections. The ratios suggest that if funds invested in passive industry indices, rather than individual stocks, with weights identical to those in their actual portfolios, they would earn about a third of the abnormal performance that they realize with their actual stock selections. The consistency of the results across time suggests that about a third of mutual fund performance is attributable to industry selection irrespective of market environment.

As a point of comparison to the industry selection contribution to total alpha, we also compute the fraction of total performance attributable to fund style selection, where we define fund style along the market capitalization, book-to-market, and momentum dimensions. Our approach parallels the procedure we use with industries, except that we use characteristic benchmark returns instead of two-digit SIC industry returns to compute fund style returns. Specifically, we replace each stock return in a fund's portfolio with its DGTW characteristic benchmark return.[13] Each stock's characteristic benchmark return receives the same initial weight as the stock itself, and the weight subsequently evolves over time as a function of all of the other characteristic benchmark returns included in the portfolio. This time series of returns, $R_{p,style,t}$, thus captures fund style returns while removing idiosyncratic stock effects unrelated to the DGTW characterization of fund style.

Similar to regression equation (2), we use the excess returns of fund style as a regressand in our single-, four-, five-, and biquarterly five-factor models,

$$r_{p,style,t} = \alpha_{p,style} + \sum_{j=1}^{k} \left(\beta_{p,style,j} r_{j,t} + \beta_{lp,style,j} r_{j,t-1} \right) + \varepsilon_{p,t} \,, \tag{3}$$

where $r_{p,style,t} = R_{p,style,t} - r_{f,t}$. Finally, we estimate the fraction of total performance attributable to fund style as the ratio of the intercept, $\alpha_{p,style}$, in regression equation (3) to the intercept, α_p , in regression equation (1). Table 3, Panel B, shows the results.

Overall, the results in Panel B show that style drives a substantial fraction of performance, consistent with Chan, Chen, and Lakonishok (2002). Fund style drives between a quarter and a half of fund performance, depending on the number of factors in the regression model. As expected, style competes with the factor model: when factors in the model subsume more of the abnormal performance, as in the four- or five-factor model, style explains a smaller fraction of performance. Thus, style explains the greatest fraction of performance with the single-factor model, because the model does not control for the size, book-to-market, and momentum characteristics that define style. However, after controlling for size, book-to-market, and momentum in the factor model, style explains less of the remaining portion of abnormal performance than industry.

In a result not shown in the table, the mean cross-sectional correlation between five-factor estimates of the industry-selection and stock-selection components of alpha is 0.05.[14] Because the components of alpha reflect estimation error, however, the true correlation could differ somewhat from 0.05. Nevertheless, the correlation suggests that, among fund managers, skillful industry selection often does not coincide with skillful stock selection. In fact, 50% of our sample funds have industry-selection skill and stock-selection skill point estimates of opposite sign. The small correlation suggests that two distinct components of skill drive total alpha. The industry-selection and stock-selection components of alpha are not closely related perhaps because the skill sets that drive each differ considerably.

Table 3, Panel C, reports cross-sectional correlations between individual fund estimates of five-factor industry-selection skill and several fund characteristics, including expense ratio, turnover, size (i.e., total fund assets), active share (Cremers and Petajisto 2009), industry concentration (Kacperczyk, Sialm, and Zheng 2005), and return gap (Kacperczyk, Sialm, and Zheng 2008).[15] We compute the correlations each quarter and then average the correlations across quarters. Bearing in mind the caveat that our correlations could lack the power to detect a connection between the variables that we analyze in Panel C, the overall very low correlations provide prima facie evidence that little relation exists between industry-selection ability and any of the other fund characteristics that we examine. In particular, the correlations suggest little relation between industry-selection skill and intrinsic fund characteristics such as expense ratio, turnover, or size. Thus, no evidence of extra costs exists for funds that skillfully choose industries. Furthermore, focusing on industries does not lead to greater portfolio turnover, on average, such that industry selectivity need not require frequent rotations into fresh industries. The size results indicate no correspondence between industry selectivity and the size of the fund, which suggests that diseconomies of scale do not exist in industry-selection ability, an issue we address in detail later. The correlations also show that no relation exists between industry-selection skill and active share, industry concentration, or return gap. The low correlation with industry concentration suggests that industry-selection skill is not relegated to funds that disproportionately invest in certain industries. Thus, funds with industry-selection ability are no more likely to be diversified across industries than they are to be concentrated in certain industries. Furthermore, the low correlations with active share and industry concentration provide evidence that our industry-selection skill estimates capture a different dynamic than these other measures.

3. Empirical Analysis

3.1 Persistence

We next examine performance persistence, the ability of funds to maintain their relative performance over time. Numerous papers have examined persistence in overall skill, finding evidence of persistence in risk-adjusted returns including single- and three-factor alphas over one-year intervals (see, for example, Grinblatt and Titman 1992; Hendricks, Patel, and Zeckhauser 1993; Brown and Goetzmann 1995; Malkiel 1995; Elton, Gruber, and Blake 1996; and Carhart 1997) and in four-factor alphas over shorter, quarterly horizons (Bollen and Busse 2005). We explore whether the prior findings are associated with industry-selection skill, stock-selection skill, or both. Most studies also find evidence of persistence specifically in poor performance regardless of the performance measure or measurement interval, which is typically attributed to high expenses. Since we analyze returns gross of expenses, we are unable to shed light on that form of poor performance persistence.

Although previous studies analyze one-year post-ranking horizons most often (e.g., Carhart 1997), evidence of persistence beyond that attributable to momentum is associated with shorter post-ranking horizons (see Bollen and Busse 2005). Other studies examine longer, three-year post-ranking horizons (e.g., Gruber 1996). We examine persistence across several post-ranking horizons ranging from one quarter to three years.

Each quarter we regress total fund performance on past total fund performance:

$$\alpha_{p,t} = a + b\alpha_{p,t-l} + \varepsilon_{p,t}, \tag{4}$$

where α_p is from regression equation (1) and l ranges from one to twelve quarters. Regardless of the post-ranking horizon, we use one-quarter performance measures for both the regressand and regressor. For example, for our estimate of persistence at three years, we regress the quarterly alpha at time t on the quarterly alpha at time t – 12 (rather than using the cumulative performance from time t – 11 through time t as the regressand). With this approach, we can estimate how far into the future performance persists. Early persistence could obscure evidence of longer-run persistence in an approach based on cumulative performance. We estimate the regressions as a panel, including time fixed effects, and use panel-corrected standard errors (Beck and Katz 1995) to determine significance. The panel-corrected standard errors adjust for contemporaneous correlation and heteroscedasticity among fund alphas as well as for autocorrelation within each fund's alpha. A significant positive b coefficient would be consistent with predictability.

We repeat the panel regressions in equation (4) except replacing total fund performance, α_p, first with industry-selection skill, α_{pi},

$$\alpha_{pi,t} = a + b\alpha_{pi,t-l} + \varepsilon_{p,t}, \tag{5}$$

and then with stock-selection skill, α_{ps},

$$\alpha_{ps,t} = a + b\alpha_{ps,t-l} + \varepsilon_{p,t}. \tag{6}$$

We repeat our analysis for fund alphas based on all three sets of factors (i.e., one, four, and five) using our base model and on the five-factor biquarterly model. As before, we base our performance estimates on the gross returns imputed from portfolio holdings. Our total alpha analysis (equation (4)) merely repeats the persistence tests of earlier papers using our specific sample.

Table 4 shows the persistence results. Panel A reports the results for total fund alpha, and panels B and C report the results for the two components of total alpha, industry-selection skill (Panel B), and stock-selection skill (Panel C). Each panel reports the results using one, four, and five factors in the base regression model as well as five factors in the biquarterly model. The table reports persistence results for select future quarters ranging from the first subsequent quarter to the twelfth. The table reports *b* coefficients and *t*-statistics for regression equations (4), (5), and (6).

The total alpha results in Panel A are consistent with results documented elsewhere in the literature. For the shorter post-ranking horizons, the results suggest that performance persists. The *b* coefficients are statistically significant at the 5% level or better for horizons up to two quarters for the single- and five-factor models and up to three quarters for the four-factor model. These results are consistent with the persistence results of Bollen and Busse (2005), who also find evidence of short-term persistence after controlling for momentum.

Table 4, Panel B, reports persistence results for industry-selection skill. The results in Panel B suggest that industry-selection skill persists to about the same extent as total alpha in Panel A. The *b* coefficients are statistically significant at standard levels through one quarter for the single-factor model and through two quarters for the four- and five-factor models. These results indicate that managers who allocate their assets to the better industries during one quarter continue to do so for the next several months.

Panel C of Table 4 reports results that assess persistence in stock-selection skill. By contrast to the persistence results in Panels A and B, the results in this panel show no evidence of a relation between past stock-selection skill and future stock-selection skill. The *b* coefficients are not significant at the 5% significance level at any horizon. Together with the industry-selection skill results in Panel B, these results suggest that the evidence of persistence in relative performance documented in Panel A is driven by industry selection.[16] More generally, our results suggest that evidence of performance persistence documented repeatedly in the literature over the years stems from industry-selection skill rather than stock-selection skill. Thus, the ability to skillfully allocate assets to industries that subsequently outperform appears to be more enduring than the ability to pick stocks that outperform other stocks within the same industries.

As noted earlier, industry selection can be interpreted as a type of timing, where the emphasis is on moving across different parts of the equity universe, rather than shifting between stocks and cash. The persistence results in Table 4 provide further evidence to support this interpretation. In particular, to the extent that industry-selection skill persists over time, it suggests that funds with industry-selection skill rotate into better-performing industries as market conditions change (i.e., time the market).

Note that regressions such as equations (4), (5), and (6) pick up persistence in biases in the estimated alphas (see, for example, Christopherson, Ferson, and Glassman 1998). It is unclear whether these biases are stronger or weaker at the industry level. Although no perfect solution exists to this issue, we partially address it by mixing up alpha estimates from different factor models for the left- and right-hand sides of equations (4), (5), and (6), similar to Elton, Gruber, and Blake (2012). Specifically, we combine right-hand-side ranking periods based on the five-factor model with left-hand-side post-ranking periods based on single-, four-, and biquarterly five-factor models. In untabulated results, we find no material differences between the results based on this alternative approach and the original approach reported in Table 5.

Because we construct fund industry returns from individual stock holdings, we base our performance estimates on gross mutual fund returns. By itself, this approach leaves open the possibility that expenses, transaction costs, or other drags on performance disproportionately impact top-performing funds in our analysis, such that net relative fund performance would not persist. Recall, however, in Table 3, Panel B, that industry-selection skill shows no correlation with several metrics that together likely constitute much of the difference between gross fund returns and net shareholder returns. The return gap (Kacperczyk, Sialm, and Zheng 2008) itself captures the difference between gross portfolio returns (net of expenses) and net shareholder returns. The return gap thus accounts for transaction costs and trading activity (e.g., round-trip transactions) that take place between portfolio holding snapshots. The expense ratio directly factors into the difference between gross and net returns, while turnover and size impact transaction costs via commissions and price pressure associated with fund trades. Since Table 3, Panel B, shows no correlation between industry-selection skill and any of these cost-related measures, persistence results based on net shareholder returns are likely to be similar to the persistence results reported in Table 4 for gross portfolio returns.

Nonetheless, to further explore the possibility that using gross rather than net fund returns materially impacts our inference, we repeat our persistence analysis using estimated net fund returns. For each fund, we compute the difference between gross and net monthly fund returns (similar to the return gap, but without netting out the expense ratio from gross returns), where we take net fund returns from the CRSP Survivor-Bias-Free U.S. Mutual Fund database. We use MFLINKS from WRDS to connect the data to Thomson Financial's portfolio holdings and the gross fund returns. The gross-net difference represents a combination of expense ratio, transaction costs, the return effects of cash and other nondomestic equity holdings, and performance associated with intra-period trading. To examine persistence in net fund performance, we take each fund's gross-net estimate each month, divide it by the number of daily returns in the month to yield a daily gross-net estimate, and then subtract the daily gross-net estimate from each fund's total and industry daily return series. We then re-run regression equations (4), (5), and (6) using performance estimates based on the net return time series.

In non-tabulated results, we find that the persistence results based on net fund returns are very similar to the persistence results shown in Table 4 for gross fund returns. Thus, industry-selection skill (and total alpha as well) net of estimates of expenses, transaction costs, etc. persists for horizons up to three quarters, depending on the model. Stock-selection skill, however, once again does not persist.[17]

Here and in subsequent analysis, we explore whether the results are sensitive to controls related to intrinsic fund characteristics, including expense ratio, turnover, ln(size), and age. Including these controls does not impact our inference. Since we have no strong ex ante reason to believe these variables are related to industry-selection skill, we opt for reporting results from streamlined regressions that do not include these controls.

Given that investors' main priority is maximizing total performance, rather than either of the two components of alpha, we next examine the extent to which industry-selection skill and stock-selection skill predict future total alpha.[18] We proceed similarly to our prior analysis. Each quarter, we regress future performance on past industry-selection skill,

$$\alpha_{p,t} = a + b\alpha_{pi,t-1} + \varepsilon_{p,t}, \tag{7}$$

past stock-selection skill,

$$\alpha_{p,t} = a + b\alpha_{ps,t-1} + \varepsilon_{p,t}, \tag{8}$$

and both past industry- and stock-selection skill simultaneously,

$$\alpha_{p,t} = a + b\alpha_{pi,t-1} + c\alpha_{ps,t-1} + \varepsilon_{p,t}, \tag{9}$$

where α_p and α_{pi} are from equations (1) and (2), respectively, and α_{ps} is the difference between α_p and α_{pi}. As before, we estimate the regressions as a panel, including time fixed effects, and use panel-corrected standard errors to determine significance. Significant positive *b* and *c* coefficients would be consistent with predictability. In these regressions, the total alpha estimate lags the industry- and stock-selection skill estimates by one quarter. We repeat our analysis for alphas based on all three sets of factors in our base model and based on the five-factor biquarterly model.

Table 5 reports the panel regression results. The table reports the *b* and *c* coefficients, *t*-statistics, and adjusted *R*-squares. The first three sets of columns in the table report the results associated with the single-, four-, and five-factor base models respectively, and the last set of columns reports results for the five-factor biquarterly model.

For all models, a statistically significant relation exists between past industry-selection skill and future total alpha (regression equation (7)). By contrast, no significant relation exists between past stock-selection skill and future total alpha (regression equation (8)) for any factor model. This result is consistent with the lack of evidence of persistence in stock-selection skill in Table 4. That is, if past stock-selection skill does not predict future stock-selection skill, then we would not expect it to be strongly related to future total alpha.

The third column of results under each model heading in Table 5 jointly examines the relation between future total alpha and past industry- and stock-selection skill, as in regression equation (9). The results confirm that persistence in total alpha is driven by the industry-selection component of alpha, rather than the stock-selection component. For all models, future total alpha is positively and statistically significantly related to past industry-selection skill, but insignificantly related to past stock-selection skill.[19]

Having established the significant relation between past industry-selection skill and future total alpha, we next examine whether the relation is robust to including in the regression other characteristics previously shown to be related to the cross-section of future fund performance. We focus on active share (Cremers and Petajisto 2009), industry concentration (Kacperczyk, Sialm, and Zheng 2005), and the performance attributable to fund style (Chan, Chen, and Lakonishok 2002), where we use the style estimates from Section 2.

We regress as a panel future fund performance simultaneously on past estimates of industry-selection skill, stock-selection skill, active share, industry concentration, and style alpha,

$$\alpha_{p,t} = a + b\alpha_{pi,t-1} + c\alpha_{ps,t-1} + dAS_{t-1} + eIC_{t-1} + f\alpha_{p,style,t-1} + \varepsilon_{p,t}. \tag{10}$$

We include time fixed effects in regression equation (10) and again use panel-corrected standard errors to determine significance.

The final column under each regression model heading in Table 5 shows the results. The results confirm in our sample that past active share and industry concentration are statistically significantly related to future fund performance. Though positively related to future performance, style alpha is not statistically significantly related to future performance after controlling for all of the other characteristics. By contrast, industry-selection skill maintains its statistical significance after controlling for all of the other variables. This last result is not surprising, perhaps, given the near-zero correlations between industry-selection skill and the other measures documented in Table 3.

To determine whether the advantages associated with industry-selection skill are economically important, we repeat analysis similar to Table 5 except that we sort into deciles based on industry-selection skill or stock-selection skill, and then examine the mean post-ranking total alphas of each decile. Table 6, Panel A, shows the five-factor results. The table shows that the post-ranking total alpha of the top industry-selection skill decile is greater than the top stock-selection skill decile during all post-ranking quarters. Similarly, post-ranking total alpha differences between the top and bottom deciles are always greater for the industry-selection skill sorts than for the stock-selection skill sorts during all post-ranking quarters and are approximately twice as large. For example, during the fourth post-ranking quarter, the total alpha difference between funds in the top and bottom industry-selection skill sort deciles (3.38% per year) is almost twice the total alpha difference between funds in the top and bottom stock-selection skill sort deciles (1.71% per year). Although the top decile post-ranking total alpha for the industry-selection skill sort does not statistically significantly differ from that for the stock-selection skill sort, the 10–1 differences of the industry-selection skill sort are statistically significantly greater than those of the stock-selection skill sort at the 10% level for post-ranking quarters 1–3. This result provides further evidence that industry allocations play an important role in the persistence of relative performance.

To determine whether industry-selection skill provides incremental information beyond total alpha beneficial to an investor's investment decision, we examine total alpha for funds double-sorted, first based on total alpha and subsequently on industry-selection skill. That is, conditional on a given level of past total alpha, we examine whether future fund performance varies with past industry-selection skill. To the extent that funds with high industry-selection skill outperform funds with low industry-selection skill (controlling for total alpha), investors could benefit from the information inherent in industry-selection skill.

Table 6, Panel B, reports the difference in total alpha between funds with high industry-selection skill and funds with low industry-selection skill (i.e., decile 10 minus decile 1) for deciles of funds initially sorted according to total alpha. The panel reports results associated with initial total alpha deciles 10, 5, and 1. The results clearly indicate that the secondary industry-selection skill sort provides additional information beyond total alpha related to future fund performance. Among funds in the same total alpha decile, the total alpha of funds with high industry-selection skill is statistically significantly greater than the total alpha of funds with low industry-selection skill up to three quarters following the sort. For example, among top-decile total alpha funds, funds further classified in the top industry-selection skill decile outperform funds in the bottom decile by 1.76% annually during the first post-ranking quarter. The incremental information provided by industry-selection skill is apparent regardless of the level of total alpha, as the table shows similar performance differences for total alpha deciles 5 and 1.

Overall, the results in Tables 4, 5, and 6 suggest that the enduring component of raw fund manager selection ability lies more within their choice of industries than within their choice of individual stocks.

3.2 Stock and Industry Selectivity Versus Fund Size

Ippolito (1992), Gruber (1996), and Sirri and Tufano (1998) show that investors chase winners, since cash flows correlate positively with past performance. As their asset bases swell, top-performing funds find it increasingly difficult to maintain stellar performance. Popular funds experience diseconomies of scale, as indicated in Berk and Green (2004), Chen, Hong, Huang, and Kubik (2004), and Edelen, Evans, and Kadlec

(2007). One key implication from Berk and Green's (2004) theoretical model is that top performance should not persist indefinitely, as increasing transaction costs associated with larger transactions (e.g., price pressure), the exhausting of one's preferred stock list, or greater fees charged by the managers work to eliminate excess performance. Similarly, poor performance could reverse. For instance, if their asset bases shrink, lagging funds may find it easier to manage their remaining assets, perhaps because they can focus on their best ideas.

In this section, we examine the effects of fund size on the industry-selection and stock-selection components of mutual fund performance. Ex ante, reasons exist to believe that the size of a fund's asset base could differentially affect the two components of performance. As mentioned above, one of the main contributors to diseconomies of scale is the increase in transaction costs associated with large stock trades. That is, if a 100-stock fund grows its asset base ten-fold, but continues holding the same 100 stocks, the fund will need to trade ten times as many shares per stock. What previously could be accomplished with a 1,000-share trade would now require a 10,000-share trade. For all but the most liquid stocks, transacting substantially larger quantities is considerably more difficult, as market impact tends to move prices in the wrong direction. To avoid larger per-share transaction costs, funds may eliminate from consideration stocks that lack sufficient liquidity. Alternatively, funds may choose to increase the number of stocks to hold in their portfolios, an effect consistent with the portfolio data in Table 1. However, since their favorite stocks are typically already in their portfolio, the new additions could hurt fund performance. That is, they almost certainly are less optimistic about the new additions, or they would have already had them in their portfolio. Alexander, Cici, and

Gibson (2007), for example, find that the stocks that funds purchase in order to absorb excess cash underperform their valuation-motivated purchases. So, unless a fund can continue to generate additional stock picks that they like as much as their core holdings, getting larger would be expected to hurt their stock selectivity.

Consider, however, a fund that focuses on maintaining a particular industry allocation. A given industry consists of numerous individual issues, often consisting of an assortment of market capitalizations, share prices, and trading volumes. A manager that finds it too costly to transact too much in one stock could add another stock in the same industry. The fund manager would, thus, have numerous opportunities to maintain a specific industry exposure without having to exert undue pressure on any one particular stock. Alternatively, the fund manager could begin investing in a closely related industry. Consequently, we might anticipate industry-selection ability to suffer less from a larger base of assets than stock-selection ability.

To examine the relation between fund size and performance, we sort funds into deciles based on the size of their stock portfolios at the beginning of the quarter, and then examine the performance of the portfolios over the course of the quarter. Following Elton, Gruber, and Blake (forthcoming), we first divide funds into deciles by investment objective (Aggressive Growth, Growth, and Growth & Income from Thomson Financial's CDA/Spectrum Mutual Fund Holdings database) and then aggregate the size deciles across investment objectives. Similar to Chen, Hong, Huang, and Kubik (2004), we examine total alpha, but we also examine the two distinct components of total alpha, industry-selection skill and stock-selection skill. We assess the relation between fund size and performance with the Spearman rank correlation coefficient, measured between the beginning-of-quarter size decile and the subsequent performance decile, and with the difference in mean post-ranking performance for the largest and smallest size deciles.

Table 7 shows the results. Panel A reports the results for total alpha, Panel B reports the results for industry-selection skill, and Panel C reports the results for stock-selection skill. The total alpha results in Panel A show a weak to modest negative correspondence between fund size and future total alpha, with the strength of the relation depending on the factor model. Four-factor results provide the greatest evidence of a negative relation, where the Spearman rank correlation between size decile and subsequent four-factor alpha is statistically significant at the 5% level, and the difference between the total alpha of the largest and the smallest size deciles is significant at the 10% level. Results associated with the single-, five-, and biquarterly five-factor models indicate an insignificantly negative relation between fund size and future performance. On net, these results suggest a somewhat weaker relation between fund size and future performance compared with Chen, Hong, Huang, and Kubik (2004), perhaps more in line with Elton, Gruber, and Blake (forthcoming), who find no evidence of a negative relation. One caveat, however, is the gross fund returns that we use in our analysis do not account for most of the transaction costs that funds incur when they trade, and price impact should disproportionately impact larger funds.[20]

The results in Panel B provide no evidence of diseconomies of scale in mutual fund industry-selection skill. If anything, the results suggest the opposite, with statistically significantly positive Spearman correlations between size and future industry-selection skill for the four-, five-, and biquarterly five-factor models. The difference in industry-selection skill between the largest and smallest size deciles is positive for all four models but not statistically significantly different from zero. A conservative interpretation of these results is that no evidence of diseconomies of scale in industry-selection ability exists, as an increasing asset base does not coincide with deteriorating industry-selection skill. It appears that fund managers find ample opportunities either in their current industries or possibly in others to maintain their industry performance even as their asset bases grow. The lack of a relation between size and industry-selection skill helps to explain why the industry component of alpha persists, as indicated in Table 4, Panel B.

The stock-selection skill results in Panel C provide strong evidence of diseconomies of scale. The Spearman rank correlation coefficients are statistically significant at the 1% level for the single-, five-, and biquarterly five-factor models, and at the 10% level for the four-factor model. Differences in stock-selection skill for the largest and smallest size deciles are significant at the 5% level for the single- and five-factor models and at the 10% level for the four-factor model. The weak evidence of diseconomies of scale in total alpha thus appears to be driven entirely by the stock-selection component of alpha, which economies of scale in industry-selection skill partially offset. Although funds appear to maintain an equally attractive industry allocation as their size increases, they apparently have a difficult time adding stocks that do as well as their original choices.[21]

4. Conclusion

Some funds excel at picking individual stocks; others stand out with their industry allocations. We find that both types of skill play an important role in ultimately determining a fund's concurrent risk-adjusted performance, and thereby shed light on the mechanism by which mutual funds deliver alpha.

We also find that the industry-selection component of total alpha persists while the stock-selection component does not. These results suggest that industry-selection ability drives the evidence of performance persistence documented often elsewhere in the literature. By suggesting that funds with industry-selection ability successfully rotate into different industries as market conditions change, our analysis provides a new way to infer timing ability. Our results further suggest that investors can achieve greater future performance by focusing on industry-selection skill rather than stock-selection skill, and that industry-selection skill provides incremental information beyond total alpha that can be beneficial to investors.

Investors chase performance, leading to inflows at the top-performing funds. We find that larger fund sizes do not erode the industry-selection component of performance, possibly because fund managers have ample room to add further to their current industries, or because they are able to find other industries that are equally attractive. In contrast, we find that stock selectivity suffers as fund size increases, consistent with the total performance results of Chen, Hong, Huang, and Kubik (2004). This result suggests that diseconomies of scale in mutual funds are specifically attributable to the stock-selection component of performance.

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Table 1
Summary Sample Statistics

The table shows fund portfolio statistics over select years during the 1980–2009 sample period. We define industry using two-digit SIC codes.

Year	Number of funds	Median assets ($M)	Median stocks	Median industries
1980	382	38	33	17
1985	464	84	39	18
1990	590	87	41	21
1995	1,981	98	49	22
2000	2,054	245	58	21
2005	1,541	361	69	27
2009	1,450	301	68	25
1980–2009	3,678	159	54	23

Table 2
Factor Model Estimates Using Daily Data

The table reports statistics from single- and multifactor model regressions estimated over quarterly horizons:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k} \left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1} \right) + \varepsilon_{p,t} \, , \tag{1}$$

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k} \left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1} \right) + \varepsilon_{p,t} \, , \tag{2}$$

and $\alpha_{ps} = \alpha_p - \alpha_{pi}$. r_p represents fund gross excess returns, r_{pi} represents fund-specific industry excess returns, and r_j represents market, size, value, stock momentum, or industry momentum factors. We base the *t*-statistics for the skill estimates (shown in parentheses) on Newey-West corrected standard errors. Alphas represent annualized figures. The sample consists of 3,678 funds over a 1980–2009 sample period.

Skill type	α	β_m	β_{smb}	β_{hml}	β_{umd}	β_{indumd}	R^2
				Panel A. Single-factor			
α_p	0.0105 (2.37)	1.002					0.729
α_{pi}	0.0035 (1.50)	1.007					0.839
α_{ps}	0.0071 (1.74)						
				Panel B. Four-factor			
α_p	0.0121 (2.32)	1.003	0.230	–0.009			0.805
α_{pi}	0.0038 (1.50)	1.011	0.109	–0.003			0.870
α_{ps}	0.0086 (1.71)						
				Panel C. Five-factor			
α_p	0.0116 (2.21)	1.005	0.211	–0.011	0.021	0.002	0.816
α_{pi}	0.0038 (1.54)	1.013	0.100	–0.008	0.009	0.003	0.882
α_{ps}	0.0078 (1.75)						
				Panel D. Biquarterly five-factor			
α_p	0.0111 (2.06)	1.004	0.205	–0.010	0.020	0.003	0.804
α_{pi}	0.0038 (1.50)	1.015	0.099	–0.008	0.008	0.003	0.871
α_{ps}	0.0073 (1.72)						

Table 3
Industry Selection Statistics

Panels A and B report the ratio of mean industry-selection skill, α_{pi}, (Panel A):

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k} \left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1} \right) + \varepsilon_{p,t}\ , \tag{2}$$

or mean style alpha, (Panel B):

$$r_{p,style,t} = \alpha_{p,style} + \sum_{j=1}^{k} \left(\beta_{p,style,j} r_{j,t} + \beta_{lp,style,j} r_{j,t-1} \right) + \varepsilon_{p,t}\ , \tag{3}$$

to mean total alpha, α_p:

$$r_{p,t} = \alpha_{p} + \sum_{j=1}^{k} \left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1} \right) + \varepsilon_{p,t}\ , \tag{1}$$

estimated over quarterly horizons, where r_p represents fund gross excess returns, r_{pi} represents fund-specific industry excess returns, and r_j represents market, size, value, stock momentum, or industry momentum factors. Panel C reports the mean cross-sectional correlation between the five-factor industry-selection skill estimate and several fund characteristics. The sample consists of 3,678 funds over a 1980–2009 sample period.

Time period	Single-factor	Four-factor	Five-factor	Biquarterly five-factor
Panel A. Fraction of alpha attributable to industry selection				
1980–1985	0.320	0.313	0.321	0.326
1986–1990	0.329	0.322	0.306	0.304
1991–1995	0.304	0.301	0.320	0.319
1996–2000	0.319	0.307	0.332	0.335
2001–2005	0.312	0.305	0.318	0.315
2006–2009	0.332	0.309	0.309	0.311
1980–2009	0.320	0.312	0.317	0.318
Panel B. Fraction of alpha attributable to style selection				
1980–1985	0.424	0.253	0.245	0.248
1986–1990	0.570	0.305	0.300	0.310
1991–1995	0.550	0.298	0.281	0.292
1996–2000	0.429	0.238	0.224	0.220
2001–2005	0.522	0.310	0.308	0.302
2006–2009	0.453	0.220	0.214	0.224
1980–2009	0.490	0.272	0.263	0.267

Panel C. Correlation with five-factor industry-selection skill estimate

	Industry-selection skill
Expense ratio	–0.04
Turnover	–0.03
ln(Size)	–0.02
Active Share	0.03
Industry Concentration	0.03
Return Gap	0.02

Table 4
Performance Persistence

The table shows results from panel regressions of performance on past performance:

$$\alpha_{p,t} = a + b\alpha_{p,t-1} + \varepsilon_{p,t} , \tag{4}$$

$$\alpha_{pi,t} = a + b\alpha_{pi,t-1} + \varepsilon_{p,t} , \tag{5}$$

and

$$\alpha_{ps,t} = a + b\alpha_{ps,t-1} + \varepsilon_{p,t} . \tag{6}$$

α_p , α_{pi}, and α_{ps} refer to total alpha (Panel A), industry-selection skill (Panel B), and stock-selection skill (Panel C), respectively, estimated over quarterly horizons:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k} \left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1} \right) + \varepsilon_{p,t} , \tag{1}$$

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k} \left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1} \right) + \varepsilon_{p,t} , \tag{2}$$

and $\alpha_{ps} = \alpha_p - \alpha_{pi}$. r_p represents fund gross excess returns, r_{pi} represents fund-specific industry excess returns, and r_j represents market, size, value, stock momentum, or industry momentum factors. The table reports coefficient estimates and *t*-statistics (in parentheses) based on panel-corrected standard errors. The sample consists of 3,678 funds over a 1980–2009 sample period.

	Post-ranking quarter					
Model	1	2	3	4	8	12
			Panel A. Total alpha			
Single-factor	0.052	0.042	0.020	0.015	0.011	0.006
	(2.36)	(2.13)	(1.82)	(1.40)	(1.14)	(0.87)
Four-factor	0.046	0.039	0.035	0.024	0.014	0.007
	(2.24)	(3.01)	(2.42)	(1.94)	(1.20)	(0.94)
Five-factor	0.040	0.033	0.025	0.020	0.012	0.005
	(2.32)	(2.10)	(1.78)	(1.53)	(0.85)	(0.34)
Biqtr five-factor	0.045	0.043	0.031	0.022	0.018	0.004
	(2.20)	(2.03)	(1.65)	(1.50)	(0.99)	(0.09)
			Panel B. Industry-selection skill			
Single-factor	0.036	0.032	0.028	0.017	0.015	0.003
	(2.19)	(1.91)	(1.83)	(1.40)	(1.24)	(0.34)
Four-factor	0.042	0.036	0.025	0.015	0.008	0.006
	(2.42)	(2.20)	(1.91)	(1.54)	(1.06)	(0.53)
Five-factor	0.040	0.035	0.030	0.027	0.009	0.004
	(2.22)	(2.18)	(1.79)	(1.53)	(0.77)	(0.35)
Biqtr five-factor	0.039	0.036	0.027	0.017	0.011	0.002
	(2.15)	(2.01)	(1.53)	(1.31)	(0.55)	(0.22)
			Panel C. Stock-selection skill			
Single-factor	0.015	0.018	0.013	0.010	0.008	0.002
	(1.02)	(1.24)	(0.79)	(0.35)	(0.78)	(0.01)
Four-factor	0.013	0.012	0.014	0.009	0.007	0.003
	(1.32)	(0.78)	(1.21)	(0.98)	(0.65)	(0.15)
Five-factor	0.010	0.011	0.007	0.003	0.006	0.004
	(1.12)	(0.43)	(0.36)	(0.22)	(0.60)	(0.29)
Biqtr five-factor	0.011	0.012	0.005	0.004	0.004	0.005
	(1.06)	(1.08)	(0.67)	(0.54)	(0.24)	(0.10)

Table 5
Predicting Total Alpha with Past Total Alpha, Industry-Selection Skill, or Stock-Selection Skill

The table shows results from panel regressions of total alpha versus past performance:

$$\alpha_{p,t} = a + b\alpha_{pi,t-1} + \varepsilon_{p,t}\,, \tag{7}$$

$$\alpha_{p,t} = a + b\alpha_{ps,t-1} + \varepsilon_{p,t}\,, \tag{8}$$

$$\alpha_{p,t} = a + b\alpha_{pi,t-1} + c\alpha_{ps,t-1} + \varepsilon_{p,t}\,, \tag{9}$$

and

$$\alpha_{p,t} = a + b\alpha_{pi,t-1} + c\alpha_{ps,t-1} + dAS_{t-1} + eIC_{t-1} + fStyle_{t-1} + \varepsilon_{p,t}\,. \tag{10}$$

α_p, α_{pi}, and α_{ps} refer to total alpha, industry-selection skill, and stock-selection skill, respectively, estimated over quarterly horizons:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k}\left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1}\right) + \varepsilon_{p,t}\,, \tag{1}$$

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k}\left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1}\right) + \varepsilon_{p,t}\,, \tag{2}$$

and $\alpha_{ps} = \alpha_p - \alpha_{pi}$. r_p represents fund gross excess returns, r_{pi} represents fund-specific industry excess returns, and r_j represents market, size, value, stock momentum, or industry momentum factors. AS represents active share, IC represents industry concentration, and style represents fund style. The table reports coefficient estimates, *t*-statistics (in parentheses) based on panel-corrected standard errors, and adjusted *R*-squares. The sample consists of 3,678 funds over a 1980–2009 sample period.

	Single-factor				Four-factor				Five-factor				Biquarterly five-factor			
intercept	0.004	0.005	0.006	0.003	0.004	0.004	0.005	0.004	0.005	0.005	0.005	0.004	0.006	0.006	0.005	0.004
	(1.76)	(1.94)	(1.89)	(1.32)	(3.21)	(3.24)	(4.25)	(2.60)	(2.34)	(2.64)	(2.19)	(2.20)	(2.43)	(2.95)	(2.54)	(2.42)
α_{pi}	0.096		0.089	0.075	0.070		0.064	0.058	0.065		0.058	0.052	0.068		0.059	0.050
	(2.63)		(2.49)	(2.10)	(2.12)		(2.20)	(2.20)	(2.65)		(2.32)	(2.18)	(2.89)		(2.32)	(2.30)
α_{ps}		0.038	0.031	0.022		0.023	0.021	0.018		0.019	0.015	0.013		0.019	0.016	0.015
		(1.29)	(1.30)	(1.06)		(1.19)	(1.23)	(1.03)		(1.28)	(1.00)	(1.20)		(1.20)	(1.04)	(1.02)
ICI				0.025				0.030				0.036				0.047
				(2.15)				(2.06)				(2.21)				(2.45)
AS				0.035				0.042				0.036				0.043
				(2.07)				(2.20)				(2.11)				(2.27)
Style				0.037				0.027				0.026				0.024
				(1.88)				(1.50)				(1.43)				(1.32)
Adj. R^2	0.051	0.035	0.056	0.064	0.033	0.025	0.036	0.045	0.039	0.028	0.042	0.043	0.039	0.031	0.042	0.045

Table 6
Future Total Alpha of Deciles Sorted on Past Performance

The table shows average annualized percentage total alpha estimates during various quarters of a three-year post-ranking horizon for deciles of funds based on univariate sorts according to industry-selection skill (Panel A) or stock-selection skill (Panel B), or double-sorted first on total alpha and then on industry-selection skill (Panel C). Total alpha is the intercept, α_p, in a standard regression model:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k}\left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1}\right) + \varepsilon_{p,t}\ , \tag{1}$$

where r_p represents fund gross excess returns, and r_j represents market, size, value, stock momentum, or industry momentum factors. Industry-selection skill is the intercept, α_{pi}, in the regression model:

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k}\left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1}\right) + \varepsilon_{p,t}\ , \tag{2}$$

where we use fund-specific industry excess returns, $r_{pi,t}$, as the regressand. Stock-selection skill, α_{ps}, is the difference between α_p and α_{pi}. The table reports average annualized percentage returns associated with each post-ranking quarter, rather than the cumulative returns through each quarter. All results are based on the five-factor model. "10" refers to the best past performance decile, and "1" refers to the worst past performance decile. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample consists of 3,678 funds over a 1980–2009 sample period.

Sort	Post-ranking quarter					
Decile	1	2	3	4	8	12
	Panel A. Total alpha based on industry-selection skill sort					
10	0.0383	0.0353	0.0348	0.0323	0.0242	0.0227
9	0.0330	0.0318	0.0227	0.0229	0.0234	0.0181
2	−0.0005	0.0008	0.0010	0.0081	0.0076	0.0106
1	−0.0040	−0.0005	0.0010	0.0030	0.0060	0.0123
10–1	0.0423***	0.0358***	0.0338***	0.0292***	0.0181**	0.0103
	Panel B. Total alpha based on stock-selection skill sort					
10	0.0267	0.0262	0.0260	0.0232	0.0204	0.0181
9	0.0202	0.0159	0.0176	0.0174	0.0136	0.0197
2	0.0013	0.0043	0.0028	0.0063	0.0118	0.0103
1	0.0025	0.0045	0.0088	0.0091	0.0116	0.0118
10–1	0.0242***	0.0217***	0.0171**	0.0141*	0.0088	0.0063

Panel C. Difference between total alpha in industry selection skill decile 10 and industry selection skill decile 1 based on double sort of total alpha first and then industry-selection skill

Alpha decile		Post-ranking quarter					
Total	Industry	1	2	3	4	8	12
10	10–1	0.0176**	0.0164**	0.0151*	0.0113	0.0071	0.0063
5	10–1	0.0199**	0.0156**	0.0139*	0.0121	0.0055	0.0038
1	10–1	0.0189**	0.0166**	0.0159**	0.0126	0.0060	0.0053

Table 7
Performance and Fund Portfolio Size

The table shows average annualized percentage performance estimates over a quarterly horizon for deciles of funds sorted according to fund portfolio size at the end of the previous quarter. Total alpha (Panel A) is the intercept, α_p, in a standard regression model:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k} \left(\beta_{pj} r_{j,t} + \beta_{lpj} r_{j,t-1} \right) + \varepsilon_{p,t}\ , \tag{1}$$

where r_p represents fund gross excess returns, and r_j represents market, size, value, stock momentum, or industry momentum factors. Industry-selection skill (Panel B) is the intercept, α_{pi}, in the regression model:

$$r_{pi,t} = \alpha_{pi} + \sum_{j=1}^{k} \left(\beta_{pij} r_{j,t} + \beta_{lpij} r_{j,t-1} \right) + \varepsilon_{p,t}\ , \tag{2}$$

where we use fund-specific industry excess returns, $r_{pi,t}$, as the regressand. Stock-selection skill, α_{ps}, (Panel C) is the difference between α_p and α_{pi}. "10" refers to the largest size decile, and "1" refers to the smallest size decile. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample consists of 3,678 funds over a 1980–2009 sample period.

Size decile	Single-factor	Four-factor	Five-factor	Biqtr five-factor
		Panel A. Total alpha		
10	0.0038	0.0076	0.0091	0.0086
9	0.0068	0.0134	0.0081	0.0123
2	0.0159	0.0121	0.0101	0.0091
1	0.0126	0.0171	0.0161	0.0136
10–1	–0.0088	–0.0096*	–0.0071	–0.0050
Spearman	–0.588*	–0.750**	–0.407	–0.321
		Panel B. Industry-selection skill		
10	0.0015	0.0033	0.0050	0.0040
9	0.0040	0.0025	0.0045	0.0025
2	0.0035	0.0015	0.0015	0.0043
1	0.0010	0.0013	0.0018	0.0023
10–1	0.0005	0.0020	0.0033	0.0018
Spearman	0.219	0.857***	0.848***	0.750**
		Panel C. Stock-selection skill		
10	0.0000	0.0015	-0.0015	0.0025
9	0.0050	0.0050	0.0058	0.0055
2	0.0113	0.0091	0.0103	0.0108
1	0.0149	0.0116	0.0108	0.0121
10–1	–0.0149**	–0.0101*	–0.0123**	–0.0096
Spearman	–0.855***	–0.608*	–0.827***	–0.888***

[1] The standard research databases do not identify passively managed funds over our entire sample period. During sample periods that overlap with Cremers and Petajisto (2009) and Petajisto (2010), we use their active share data available at http://www.petajisto.net/data.html to remove funds whose holdings closely mimic the holdings of their benchmarks. We remove funds with active share less than 0.2. For the remainder of our sample period (2007–2009), we use the CRSP identifier for index funds. Because this identifier is incomplete, we also remove from the 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*, *StreetTRACKS*, *100*, *400*, *500*, *600*, *1000*, *1500*, *2000*, *3000*, *5000*. These procedures eliminate roughly 5% of the sample.

[2] The standard research databases also do not identify sector funds. We remove funds whose names contain text strings typically associated with a sector fund, such as *bank*, *mining*, and *tech*, among many others. This procedure removes approximately 6% of the sample.

[3] To determine whether the unmatched stocks likely affect our inference, we divide our sample into quintiles based on the degree of match. We then repeat our main analyses (Tables 3, 4, and 7) on each quintile, and examine whether the results differ across the quintiles. The quintile results provide no indication that unmatched stocks impact our findings.

[4] For example, Ned Davis Research, one of the most widely subscribed to investment research services for institutional money managers, divides stocks into 115 “subindustry” groups, while Standard & Poor’s uses a total of 145 industry groups.

[5] There are ninety-nine unique three-digit NAICS codes.

[6] 54/23 stocks held per industry out of 80 stocks total per industry.

[7] An advantage of our approach compared with that of Ferson and Schadt (1996) or Ferson and Warther (1996) is it controls for changes in factor exposures unrelated to a limited set of macroeconomic conditioning variables (see Ferson and Qian 2004). A disadvantage is it removes factor exposure changes associated with intentional timing—e.g., timing unrelated to macroeconomic conditioning variables.

[8] An alternative approach is to remove the specific stock from the industry return that replaces it. The results associated with this alternative do not materially differ from the results we report (based on including the stock).

[9] We also construct alternative fund industry returns that strip out industry momentum. For each industry, we identify its industry momentum decile based on its past twelve months of returns relative to other industry returns. We then remove the industry from its industry momentum decile and regress the industry's returns against its industry momentum decile returns (excluding the industry). We take the sum of the alpha and the residuals from this regression to represent the industry's returns excluding industry momentum. We use this new industry return series (ex-industry momentum) to compute alternative fund industry returns (ex-industry momentum). Four-factor results based on this alternative approach are very similar to the five-factor results reported in the article, where the factor model controls for industry momentum.

[10] No material differences exist in the performance estimates in Table 2 when we first compute time-series means for each fund and then compute the cross-sectional average of the time-series means.

[11] When we use three-digit NAICS codes to define industries rather than two-digit SIC codes, the corresponding four-factor industry-selection skill fraction is 31%.

[12] In untabulated results, the corresponding ratios associated with three-digit NAICS industry groupings are 0.32, 0.33, 0.31, and 0.30.

[13] The DGTW benchmarks are available via Russ Wermers's website at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm. See Daniel et al. (1997) and Wermers (2004).

[14] The mean cross-sectional correlation between the stock (industry) component of alpha and total alpha is 0.60 (0.45).

[15] We take turnover from the CRSP Survivor-Bias-Free U.S. Mutual Fund database. We use MFLINKS from WRDS to connect the CRSP data to the Thomson Financial portfolio holdings data. We compute each fund's Industry Concentration as in Kacperczyk, Sialm, and Zheng (2005), except that we use two-digit SIC codes to define industries rather than the ten-industry classification used by Kacperczyk, Sialm, and Zheng.

[16] When we use three-digit NAICS codes to define industries, the persistence results are very similar to the results in Table 4 based on two-digit SIC codes.

[17] We repeat the gross-net robustness test in all of our analyses and find no materially differences compared with the net return results reported in the tables.

[18] Note that mutual funds typically report portfolio holdings to the SEC with a lag of forty-five to fifty-five days after the portfolio holdings date, with a maximum allowed lag of sixty days (Frank, Poterba, Shackelford, and Shoven 2004). Consequently, an investor interested in buying funds with industry-selection skill would base their estimate of skill on holdings that are up to sixty days stale. Some lag is necessary, however, to estimate industry-selection skill via multifactor regressions using post-holdings snapshot return data.

[19] Although not shown in Table 5, the persistence results are very similar when we use three-digit NAICS codes rather than two-digit SIC codes to define industries, with significant positive relations between future total alpha and past industry-selection skill, and insignificant relations between future total alpha and past stock-selection skill.

[20] Stock prices on the date of the portfolio holdings snapshot incorporate some price pressure effects for recent purchases.

[21] NAICS-based results are very similar to the SIC-based results shown in Table 7, with weak evidence of a negative relation between size and total alpha, strong evidence of a negative relation between size and stock-selection skill, and no evidence of a negative relation between size and industry-selection skill.