Dynamic Factor Timing and the Predictability of Actively Managed Mutual Fund Returns

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Using data on large U.S. mutual funds, we find that mutual fund managers primarily generate alpha relative to their stated benchmarks by picking stocks. By contrast, active managers underperform their benchmarks when it comes to allocating to market factors (based on size, style, and industry groupings). Further, we find that managers who have successfully timed market factors in the past generate higher benchmark-adjusted returns in the future. We argue that the successful timing of market factors is more likely to result from manager skill, and our results suggest that this skill is persistent.

Key words: Mutual fund, mutual fund return predictability, mutual fund investment, active management

1. Introduction

Mutual fund investors turn to actively managed funds in the hopes of receiving higher returns relative to passively managed, index-based alternatives. Key problems facing these investors include determining whether actively managed mutual funds produce alpha and whether this can be predicted *ex ante*. While these problems are straightforward, few topics in finance have proven to be as contentious as the value of active management and the predictability of mutual fund returns. A large body research, starting with Sharpe (1966) and Jensen (1968), has found that active managers are unable to consistently beat the market return, particularly net of fees and expenses and especially after being adjusted for risk. This body of research has meaningfully improved the popularity of low-cost equity index funds. Nevertheless, as of 2013 only 18% of equity mutual fund assets were in index funds.[1]

[1] See Investment Company Institute, 2014 Investment Company Fact Book (Washington, DC: Investment Company Institute, 2014).

Research interest in active mutual fund management has centered on whether active mutual fund managers are able to generate returns in excess of the systematic risks to which their portfolios are exposed and, if so, whether this ability is persistent. To answer these questions, the literature has frequently used pricing models to evaluate manager performance. Developed to explain the cross-section of stock returns, common pricing models include market-models and multifactor models (such as the three-factor Fama-French and four-factor Fama-French-Carhart models, see Fama and French (1993) and Carhart (1997)). However, while these models are consistent with measuring a kind of performance of interest to researchers, they are rarely employed by market participants to measure the performance of mutual fund managers.[2] Industry participants (including investors and asset managers) most commonly measure mutual fund performance relative to a stated, SEC-required benchmark index. While there are well understood problems with measuring performance in this way - namely that fund managers can pick a benchmark index whose risk profile differs substantially from the risk profile of the fund - the fact that this practice represents industry convention complicates the interpretation of many of the results in the academic literature in that, by using performance measures that are relatively unused in industry, they may fail to characterize the kind of performance in which investors are interested and which managers seek to deliver.

In this paper we use a model that allows us to measure manager performance against a fund's stated benchmark - which most closely resembles industry practice - while disentangling the portion of alpha that arises from activities associated with manager skill and simple exposure to risk premia. In particular, we use the holdings-based attribution model of Hsu et al. (2010). This model represents a multi-period derivation of the so-called "Brinson" attribution model (see Brinson and Fachler (1985) and Brinson et al. (1986)), which is widely used and understood by industry participants. The attribution model decomposes a fund's average alpha (measured relative to a benchmark portfolio) into three components: static factor allocation, dynamic factor allocation, and stock selection. Each of these components have an intuitive interpretation reflecting distinct investing practices which allows a better understanding of the ways managers seek to outperform their benchmark.

The static factor allocation component measures the portion of fund alpha that results from a constant allocation to a "factor" (such as industry classification, size, or value/growth) relative to the benchmark exposure. For example, if a fund benchmarks against the S&P 500 Growth index, then a manager may consistently tilt the portfolio towards value stocks in an

[2] Multi-factor alphas are rarely used by investors to evaluate fund performance when making investment decisions; they are not regularly featured in investment research reports, neither are they commonly featured in the software-based analytical tools created by various vendors to assist mutual fund investors (e.g., Morningstar research reports, Bloomberg terminals, Lipper analytical software, Google finance, analytical software provided by brokers, etc.). Further, multi-factor alphas are rarely used by asset managers, either in the promotional material for their funds (e.g., factsheets) or to determine the compensation of mutual fund managers.

attempt to capture the historical value premium. The attribution model will attribute any alpha that results from this strategy to the static factor allocation component of the fund's historical alpha. If this value is non-zero then the fund's risk profile has consistently differed from that of the benchmark portfolio against which it is being measured and, on this basis, one might reasonably conclude that the benchmark is inappropriate for the fund (e.g., a value fund whose performance is measured relative to a growth index). In spirit, a fund whose historical benchmark-adjusted alpha owes entirely to static factor allocation is similar to a fund with a zero alpha as measured by a factor model. Attempting to deliver a benchmark-adjusted alpha by increasing the risk of the fund in a consistent way is not commonly associated with manager skill.

The dynamic factor allocation component is the covariance between a fund's excess factor weights (relative to the benchmark) and factor returns and measures the extent to which a fund manager has timed the market with respect to factor risk. For example, a manager may seek to outperform the benchmark index by timing industry returns. If the manager succeeds in, say, increasing portfolio weights to the manufacturing industry before in outperforms, or decreasing portfolio weights to the energy sector before it under-performs, then the portion of the funds alpha that results from this successful market timing will be attributed to the dynamic factor allocation component of the attribution model. The successful market timing of factor returns is commonly considered to reflect a kind of manager skill.

Finally, the stock selection component represents the portion of a fund's alpha that results from the manager's ability to pick individual securities relative to the benchmark index. For example, a small-cap fund manager may attempt to beat his benchmark index by selecting individual securities that he feels is undervalued. To the extent that the manager is successful in this strategy, it will be reflected in the stock selection component of the fund's historical benchmark-adjusted alpha. Like factor timing, the timing of idiosyncratic risk is also commonly viewed as reflecting a kind of manager skill.

We use this model to examine several basic questions. First, how do active managers attempt to beat their benchmark? Do they attempt to increase portfolio weights towards factors with historical risk premiums? For example, do they persistently increase portfolio weights towards small and value stocks relative to their benchmark? Or do they, say, attempt to time industry returns? Or pick stocks? Also, do fund strategies differ between different types of funds? For example, industry perception is that there are more market inefficiencies in the pricing of small-cap stocks, making stock selection an attractive strategy for active managers - do managers of small-cap funds exhibit superior stock selection skill. Second, is the benchmark-adjusted return of actively managed funds predictable? In particular, do the different strategies for generating alpha, as measured by the attribution model, differ in their ability to predict future returns?

To examine how mutual funds generate alpha, we run the attribution model on holdings and return data for all of the mutual funds in our sample, and define factor groupings along size, style, and industry dimensions. We find that, between 1993 and 2012, and for funds with at least 36 months of return data, the average gross alpha (defined as a fund's gross returns minus the return of it's stated benchmark) is 0.398% per quarter. Of this 0.398%, 0.773% is the result of stock selection, while −0.312% results from static factor allocation (i.e., persistent style tilts away from the benchmark index) and −0.063% results from factor timing. That the average static allocation of a fund's average quarterly alpha is negative is somewhat surprising and much of it is explained that neutral funds are more than twice as likely to over-allocate portfolio weights to growth stocks than they are to value stocks.

We find that, overall, large-cap funds are more likely to have positive factor allocation components (both static and dynamic) relative to small-cap funds; i.e., active managers of large-cap funds are more likely to successfully time factor risk. By contrast, small-cap fund managers are less likely to time factor risk; this is consistent with small-cap stocks being less correlated with factor risk. By contrast, Small-cap funds are more likely to generate a positive alpha from stock selection relative to large-cap funds. This is consistent with the industry perception that market inefficiencies are more prevalent in the market for small-cap stocks making stock selection a viable strategy for active managers. Further, higher expenses are correlated with lower factor allocation components, but a higher stock selection component of a fund's average alpha.

We also examine whether the way a fund produces it's alpha predicts future returns. Each quarter we sort funds into quintiles based on the components of the attribution model run over the prior 36-month period. In general, and similar to prior research, we do not find that a funds historical alpha predicts future returns. However, we find that funds with a high dynamic factor timing component experience higher future returns. In particular, fund's in the high quintile have benchmark-adjusted gross and net returns that are 0.55% and 0.46% higher than those in the low quintile, respectively. We find that this effect is particularly strong for large-cap funds as well as neutral funds. This result holds when we adjust future returns using a Fama-French-Carhart four-factor model.

Examining the portfolio characteristics of funds in each of the dynamic factor timing quintiles, we find that funds in the high quintile have greater total net assets and longer manager tenure than those in the bottom quintile. Further, we find that fund's belonging to the high and low quintile have higher Active Share measures, higher tracking error, higher turnover, and lower number of stocks than those funds in the middle.

Previous research has shown that a fund's Active Share measure predicts future returns (see Cremers and Petajisto (2009)). This result suggests that, among funds with a high Active Share measure, higher future returns are restricted to those funds that have also successfully timed market factors in the past. To test this we perform two-way sorts each quarter based on the dynamic allocation component of each fund's historical alpha and the fund's Active Share measure, and then examine future benchmark-adjusted returns. We find that, for both gross and net returns, fund's with a high dynamic component and a high Active Share measure deliver the highest alpha over subsequent period. Funds with a low dynamic timing component and a low Active Share measure do the worst.

We further examine these results in panel regressions. We find that the basic result holds: future alphas are higher for fund's that successfully timed factor risk in the past. We further find that, in this multivariate setting, the interaction between dynamic factor timing and Active Share is a statistically significant predictor of future fund alpha. Lastly, we find that the dynamic timing component predicts the future returns of large cap and neutral funds. It does not appear to predict the future returns of small-cap or value or growth funds.

2. Measuring Manager Performance

Much of the research interest into active mutual fund management has centered on two related questions: can mutual fund managers successfully generate returns in excess of the systematic risks to which their portfolios are exposed, and whether or not mutual fund performance is predictable. To answer these questions, pricing models, originally developed to explain the cross-section of stock returns (e.g., Fama and French (1993)), have frequently been employed by researchers. Multifactor models, including those that include momentum, have also been developed to explain the cross-section of mutual fund returns (for example, Carhart (1997)). However, while popular in the literature, these models are rarely used by market participants to evaluate fund performance, and this complicates the interpretation of many of the results of that literature in a number of ways.

Benchmark models, the object of which is to provide an "accurate estimate of a portfolio managers added value relative to a passive strategy," provide an alternative to factor models to measure manager performance and are more commonly used by industry (Cremers et al. (2012)). A good benchmark model includes a pricing model in that the benchmark portfolio is typically designed or selected to mirror the risk profile of the fund so as to preclude the manager from appearing to offer superior performance by bearing more systematic risk. Benchmark models typically define a fund "alpha" as being the simple difference between the return of the fund and the benchmark portfolio.

In contrast to much of the literature, market participants almost always benchmark the performance of actively managed mutual funds against the SEC-required benchmark index as listed on the funds prospectus. From the perspective of a market participant, there are several advantages to using a benchmark model based on a funds stated benchmark index to evaluate fund performance rather than a factor model. First, it is easier to implement than a factor model and the "alpha" is easier to communicate to, and be understood by, investors, asset managers, and other stakeholders.

Second, market indexes represent a realistic passive alternative to actively managed funds, something that is not always true for the factor-mimicking portfolios commonly used in factor models. For example, while they represent very different levels of market capitalization, Fama-French methodology equal weights the long and short positions of the size and book-to-market positions in creating the small-minus-big (SMB) and high-minus-low (HML) factor-mimicking portfolios. In addition, mutual funds are prohibited from short-selling stocks and, even if this were not the case, short positions are not costless to construct. Further, the CRSP market return is frequently defined to include non-U.S. firms, closed-end funds, and REITS, and other securities not typically included in U.S. equity mutual funds. Thus the factor portfolios used in popular multifactor models do not always represent either desirable or achievable alternative passive strategies to equity fund investors. By contrast, the widespread availability of cheap, index-based mutual funds means that the benchmark indexes specified by mutual funds represent viable passive alternatives to actively managed funds.[3]

And third, many benchmark indexes have statistically significant non-zero alphas as measured by commonly used multifactor pricing models.[4] This complicates the interpretation of alpha as measured by a given multifactor pricing model when applied to an actively managed mutual fund. For example, from 1980 through 2005, the S&P 500 had a statistically significant alpha of 0.82% per year as measured by a Fama-French-Carhart four-factor model (Cremers et al. (2012)). If an actively managed mutual fund that benchmarks to the S&P 500 were to produce a similarly statistically significant alpha over the same time period, does it mean this manager is skilled in the sense that his or her performance was superior to the cheaper, passive alternative available to investors? The positive risk-adjusted alpha notwithstanding, the answer to this question is not an obvious "yes" given that a passive alternative was available to investors that produced a similarly measured alpha.

While using the stated benchmark of a fund to measure the performance of actively managed funds has some advantages over factor models, it is, of course, a practice that is not without problems. Most egregious, there are no formal restrictions that prohibit a manager from creating a fund whose risk profile differs substantially from the fund's stated benchmark (see Sensoy (2009)). For example, a manager may choose a large-cap growth index as a benchmark while

[3] Index providers take a number of market frictions into account when determining index constituents and portfolio weights in an effort to make sure that the resulting index portfolio is investable. For example, and among other things, index providers typically "float adjust" the market capitalization of constituents to exclude shares that are ostensibly unavailable to investors (e.g., those that are held by governments, other companies, controlling shareholders, or management).

[4] We are quick to point out that this does not necessarily mean that there is something wrong with the factor models as it is possible, if *prima facie* counterintuitive, that index providers have "skill" in determining and weighting index constituents (see Crane and Crotty (2015))

creating a portfolio that more heavily weights small-cap and value stocks in an attempt to capture the historical size and value premia. If such a fund were to outperform its benchmark, it would not be immediately clear whether this outperformance was a consequence of managerial "skill" or merely the result of performance being measured relative to an inappropriate benchmark. Thus, since practitioners most commonly measure fund performance relative to the fund's stated benchmark, managers have strategic incentive to select an inappropriate benchmark. Market participants, particularly institutional investors, are generally not naive to these kinds of problems. However, they account for them in ways that differ from the literature. For example, a common practice among pension funds that contract with actively managed mutual funds is to limit the tracking error of the actively managed fund with respect to its benchmark index. Widely available and commonly used investor tools, such as Moody style-boxes, also enable investors to determine whether or not the fund reflects the risk profile of it's stated benchmark along size and value/growth dimensions.

In response to some of the shortcomings of using stated benchmarks to measure manager performance, researchers have developed alternative benchmark models. These typically have the advantage of benchmarking mutual funds against portfolios that more closely resemble the risk profile of the fund (see, for example, Daniel et al. (1997)) However, by measuring manager performance relative to a benchmark created *ex post* ny the researcher, these models may mischaracterize manager and investor behavior for the simple fact that market participants did not use their benchmark portfolios to measure fund performance.

In this paper we use a methodology that allows us to measure performance relative to a fund's stated benchmark (which most closely resembles industry practice) while disentangling the components of any benchmark-adjusted alpha in a way that is of interest to researchers (i.e., the portion that results from the selection of an inappropriate benchmark and the portion that results from manager skill). We argue that this allows us to better understand the investment processes of active managers. THIS NEEDS CLARIFICATION/MORE WORK.

3. Literature Review

TODO: Add section on how managers generate alpha (e.g., Sensoy (2009)).

The literature on mutual fund performance predictability is extremely diverse (see Jones and Wermers (2011) for a survey). Our results are consistent with recent work that finds that alpha, if properly adjusted, predicts future performance. These studies include Kosowski et al. (2014) who find that adjusting alphas for non-normality improves the odds of identifying funds whose alpha is the result of skilled management and whose performance is persistent. Similarly, Harlow and Brown (2006) find that conditioning on past style-adjusted returns improves the odds of identifying a superior fund. Fama and French (2010) find that some managers have sufficient skill to cover costs, but conclude that there are few of them. Barras et al. (2010)

develop a method that distinguishes between funds that produce significant alphas by luck alone and those that result from skill, and find that while some fund managers are skilled, distinguishing them from those who are merely lucky is difficult. To this literature we add the finding that alpha, properly adjusted (in our case by disaggregating a fund's historical alpha into separate components), allows the identification of funds whose performance is persistent.

Our study also contributes to the literature which uses holdings data to identify skilled managers. This literature includes Chen et al. (2000) who find that the stocks that managers buy outperform those they sell. Kacperczyk et al. (2008) compare the actual performance of funds to the return to their holdings at the beginning of a quarter and conclude that funds, on average, outperform gross of fees. Wei et al. (Forthcoming) find that contrarian managers are more likely to consistently outperform. Cremers and Petajisto (2009) find that funds whose holdings deviate sharply from their benchmark tend to outperform in future periods. To this literature we add the observation that managers whose holdings are correlated with factor group returns (i.e., funds whose alpha includes a larger dynamic allocation component) are more likely to beat their benchmark in future periods than those that do not. Further, our analysis can improve the Active Share approach of Cremers and Petajisto (2009). Specifically, we find that high Active Share managers, whose historical alpha includes a large dynamic allocation component, outperform high Active Share managers whose historical alpha does not. That is, it is not simply the funds with a high Active Share that outperform; it is funds with a high Active Share and a record of timing factor groups that outperform in future periods.

Finally, our study is related to the literature that examines the sources and types of manager skill. This literature includes Coval and Moskowitz (2001), who find that funds that invest in local assets do better than those that do not. Cohen et al. (2008) find that portfolio managers that place more portfolio weight on firms to which they are social connected predict future performance. Baker et al. (2010) find that the stocks active managers purchase around earnings announcement dates outperform those they sell. Kacperczyk et al. (2014) find that managers successfully time markets in periods where the market performs poorly and successfully select stocks in times when the market performs well. Berk et al. (2014) find that manager skill is persistent in terms of the dollar value they produce, but not necessarily in terms of their return alpha. To this literature we add the observation that managers that successfully time market factor groups are more likely to outperform their benchmark in the future relative to those that do not.

4. Attribution Methodology

In order to decompose the benchmark-adjusted alpha of equity mutual funds relative to their stated benchmark into portions that result from excess factor exposure and manager skill, we use the dynamic attribution model of Hsu et al. (2010). The HKM model is derived from a multi-period version of the attribution models proposed by Brinson and Fachler (1985) and Brinson et al. (1986). The key innovation of the HKM model is that it further decomposes the factor allocation component of the standard Brinson model into static and dynamic components. The use of this model requires fund holdings data, the definition of a factor grouping, and holdings data for the fund's benchmark. With this data, the historical average alpha of a fund with N factor groupings over T periods can be calculated by:

$$\begin{aligned}\text{Average Alpha} &= \frac{1}{T}\sum_{t-1}^{T}\left(R_t^p - R_t^b\right)\\ &= \frac{1}{T}\sum_{t-1}^{T}\sum_{i=1}^{N}\left(w_{i,t-1}^p R_{i,t}^p - w_{i,t-1}^b R_{i,t}^b\right), \qquad (1)\end{aligned}$$

where R_t^p and R_t^b are the returns to the portfolio and benchmark at time t, $w_{i,t-1}^p$ and $w_{i,t-1}^b$ are the weights for factor group i at time $t-1$, and $R_{i,t}^p$ and $R_{i,t}^p$ are the returns for factor group i over time t for the manager portfolio and the benchmark. Factor groups represent factor-mimicking portfolios that characterize the kinds of systematic risks to which the fund is exposed, though the researcher has a great deal of flexibility in defining them. For example, factor groupings can be based upon the ten S&P industry classifications, NYSE book-to-market breakpoints, dividend yields, measures of profitability, past returns, leverage, market betas, etc. It is also important to note that the characterization of factor groups in the attribution need not be defined along a single dimension. For instance, stocks can be categorized as large or small, and as value or growth. These two characteristics can be combined into four separate factor groups: large-value, small-value, large-growth, and small-growth, corresponding to $i = 1, 2, 3, 4$, respectively. In this paper, we define factor groupings based on size, style, and industry, as these are the most common "factors" along which equity investors characterize risk and returns.

The HKM methodology modifies the standard Brinson methodology to decompose the average alpha into static allocation, dynamic allocation, and stock selection components such that

$$\text{Average Alpha} = \text{Static Allocation} + \text{Dynamic Allocation} + \text{Stock Selection}.$$

These components are calculated by:

$$\text{Static Allocation} = \sum_{i=1}^{N}\left[\frac{1}{T}\sum_{t=1}^{T}\left(w_{i,t-1}^p - w_{i,t-1}^b\right)\right]\left[\frac{1}{T}\sum_{t=1}^{T}\left(R_{i,t}^b - R_t^b\right)\right], \qquad (2)$$

$$\begin{aligned}\text{Dynamic Allocation} = \sum_{i=1}^{N}\Bigg\{\frac{1}{T}\sum_{t=1}^{T}&\left[\left(w_{i,t-1}^p - w_{i,t-1}^b\right) - \frac{1}{T}\sum_{j=1}^{T}\left(w_{i,j-1}^p - w_{i,j-1}^b\right)\right]\\ &\left[\left(R_{i,t}^b - R_t^b\right) - \frac{1}{T}\sum_{j}^{T}\left(R_{i,j}^b - R_j^b\right)\right]\Bigg\}, \qquad (3)\end{aligned}$$

$$\text{Stock Selection} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} w_{i,t-1}^p\left(R_{i,t}^p - R_{i,t}^b\right). \qquad (4)$$

While the holdings-based approach to disaggregating a fund's alpha in this way is computationally complex relative to many other forms of alpha analysis, the interpretation of each component is straightforward. Intuitively, static factor allocation is the portion of a fund's alpha that results from a static over- or under-allocation to a factor group relative to the benchmark allocation. For example, noting that small and value stocks have historically outperformed large and growth stocks, a fund manager may wish to generate alpha by consistently over-weighting small and value stocks relative to a benchmark. If the manager does not change his or her allocation to these factor groups in a way that is correlated with returns, then any portion of a fund's historical alpha that is generated by this kind strategy will be attributed by the model to static allocation. We argue that any apparent "alpha" that is generated in this way is more likely to result from an inappropriately selected benchmark rather than what is commonly thought of as manager skill.

The dynamic allocation is the portion of a fund's alpha that can be attributed to the timing of factor returns. It is defined as the covariance of excess portfolio factor weights and factor returns. To the extent that a manager generates alpha by successfully timing, say, industry returns (e.g., the manager places greater weight in manufacturing before it outperforms and less when it under-performs) then the portion of a fund's overall alpha that is generated by this timing will be attributed to dynamic allocation.

The stock selection component is the remaining historical alpha that is not explained by either static or dynamic allocation. If the user successfully identifies all the risk factors affecting stock returns and defines a set of factor groups accordingly, then this component reflects a manager's security selection ability and an interaction between security selection and factor allocation (for details see Brinson et al. (1986)). Of course, as a practical matter, any set of factor groups is unlikely to perfectly characterize systemic risk if only because the precise identification of every systematic risk factor affecting stock returns has eluded researchers in financial economics. While the industry convention is to refer to this component as "stock selection" or "security selection," it is more accurately characterized as "residual allocation," or the portion of a fund's alpha that is not attributable to the combination of static and dynamic allocation as specified.

In some respects, the HKM model is similar to the attribution model proposed by Daniel et al. (1997) (DGTW) which also measures characteristic timing ability. However, there are key differences between the DGTW model and the HKM model. The DGTW model examines a fund's performance relative to a characteristic-based benchmark that is specific to the fund and which is updated every year to reflect the previous year's risk profile (and thus the methodology precludes an analysis relative to a fund's stated benchmark). By contrast, the HKM model does not require updating the benchmark every period (or at all), and allows the analysis to be performed against any benchmark portfolio (including both the characteristic based benchmark of DGTW and a fund's stated benchmark). Further, the DGTW model characterizes manager timing of factor risk as the value added from trades that deviate from the previous period. This makes DGTW model sensitive to the definition of periodicity and, if the researcher does not know the investment horizon of a manager's trades, can produce flawed estimates of a manager's timing abilities. The HKM model characterizes factor group timing as the portion of a fund's alpha that results portfolio weights being correlated with returns, and is less sensitive to specifying a period of analysis that is different from a manager's investment horizon.

5. Data

Our analysis requires multiple data sources. Below we discuss the data used to perform the attribution analysis as discussed in the preceding section. Then we discuss the data used to conduct the ex ante performance analysis.

5.1. Data Required for Attribution Analysis

The attribution analysis requires holdings data for mutual funds and benchmarks, as well as the definition of factor groups. Our source for mutual fund holdings is the Thompson Reuters s12 database, which provides common stock holdings data on a quarterly basis for all registered mutual funds that report their holdings to the U.S. Securities and Exchange Commission (SEC). We evaluate each fund's performance relative to their stated benchmark as this is the measure by which the fund is most often evaluated by investors and against which managerial incentive pay is most likely to be based. Benchmarks are obtained from the fund's prospectus benchmark as reported by Morningstar. The Morningstar prospectus data is matched to our mutual fund holdings data using CUSIP identifiers.

The benchmark indexes we use in this study are the S&P 500, S&P 400, S&P 600, Russell 1000, Russell 2000, Russell 2500, Russell 3000, and Russell Midcap indexes, as well as their value and growth versions. These 24 indexes are the most commonly used benchmark indexes for U.S. equity market mutual funds. Benchmark holdings data are from Standard & Poors and Russell.

We match the individual equity holdings in the mutual fund and benchmark databases to individual stock returns in the Center for Research in Security Prices (CRSP) database using CUSIP identifiers and, when necessary, by ticker symbols.

The attribution analysis requires the definition of factor groupings. In this paper, we define factor groupings based on size, style, and industry. This is accomplished by assigning each stock in CRSP to a size decile based on monthly NYSE breakpoints, a book-to-market decile based on annual NYSE breakpoints (where the book-to-market ratio is defined for each stock as in Fama and French (1993) using COMPUSTAT financial statement data), and a Fama-French 12-industry group based on the SIC classification in CRSP.[5]

[5] NYSE breakpoint and industry classification data is from Kenneth French's website at: http://mba.tuck.dartmouth.edu/pages//faculty//ken.french/data_library.html.

Each resulting factor group is defined as the intersection of each of these dimensions. For example, a stock in the 9th size decile, the 2nd book-to-market decile, and with an industry classification of manufacturing, would be assigned to the same factor group as every other stock similarly classified. Thus the potential number of factor groupings is equal to $10 \times 10 \times 12 = 1200$. However, the three factor dimensions are correlated such that only 26 factor groupings account for approximately 50% of the market capitalization in CRSP each month (and 112 and 320 factor groupings account for 75% and 90% of CRSP market capitalization, respectively), thus the effective number of factor groups is somewhat smaller.

We use this factor definition for the bulk of our analysis. However, we note that the analyst has a great deal of flexibility in defining a factor and we repeat the analysis using a number of different factor definitions (e.g., market capitalization deciles, book-to-market deciles, the combination of market capitalization and book-to-market deciles, Fama-French 49 industry definitions, etc.). In general, we find that our results are robust to a number of alternative definitions of factor groupings.

Finally, using holdings data and the factor groupings assigned to each stock, we calculate factor weights and three-month returns for every fund and benchmark in our sample by

$$w_{i,t-1} = \sum_{s=1}^{S} w^{s}_{i,t-1}, \tag{5}$$

$$R_{i,t} = \frac{1}{w_{i,t-1}} \sum_{s=1}^{S} w_{i,t-1} R^{s}_{i,t}, \tag{6}$$

where S is the number of stocks in factor group i, $w^{s}_{i,t-1}$ is the portfolio weight in stock s belonging to factor group i at the beginning of each quarter, and $R^{s}_{i,t}$ is the subsequent three-month return for stock s in factor group i.

5.2. Mutual Fund Characteristic and Return Data

Much of our focus centers on using the output from the attribution analysis to predict future performance. We use mutual fund monthly return data net of fees from CRSP and match it to our holdings and attribution data using MFLINKS. We also use CRSP mutual fund summary data as a source of fund characteristics. Some of our analysis uses gross returns, which we estimate as the hypothetical returns based on holdings data (similar to Cremers and Petajisto (2009)). Monthly return data for benchmark indexes are from Bloomberg

Mutual fund data in CRSP includes funds with multiple share classes. For these funds, we compute the total net assets for each share class to arrive at the total net assets managed by the fund. For portfolio characteristics such as fees, turnover ratio, etc., we weight each share class by its net assets to arrive at a weighted average for each fund.

Our focus is on actively managed equity mutual funds. Similar to Cremers and Petajisto (2009), we classify a fund as being an equity fund if its average percentage invested in common stock is greater than 80%. As this value is missing for many funds, we also look at the value of the stock holdings from the holdings database that we have matched to CRSP and if this exceeds 67% of the fund's assets then we classify the fund as an equity fund. We exclude equity mutual funds which are classified as an index fund using and indicator variable in the CRSP mutual fund summary data, and we also exclude "closet indexers" whose Active Share measure is less than 0.05 relative to the fund's stated benchmark (see Cremers and Petajisto (2009) for details on the calculation of Active Share).

6. Analysis

6.1. How Often do Funds Deviate from their Benchmark?

It is well known that active equity mutual fund managers often deviate from their stated benchmarks. For example, Sensoy (2009) finds that the stated benchmark-adjusted returns exhibit non-zero factor loadings as measured by common factor models. To further quantify this result, each quarter we calculate the Active Share for each mutual fund in our sample relative to each benchmark index. We pick the index against which the fund's Active Share measure is the smallest (i.e., the index to which the fund most closely resembles) and assign each fund a minimum Active Share benchmark each quarter. We then determine the most frequent minimum Active Share benchmark index for each fund (i.e., the time series mode). Finally, we tablulate the size and style of the stated benchmark relative to the size and style of the most frequent Active Share benchmark and report the results in Table 1.

Each row of Table 1 reports the size and style of the stated benchmarks for each fund in our sample, and the columns report the overall number of funds in each category as well as the percentage of the size and style of the most frequent minimum Active Share benchmarks. It can be seen that the size of each fund's stated benchmark almost always resembles the size of the most frequent minimum Active Share benchmark. Further, for value and growth funds, the minimum Active Share benchmark most often reflects the size and style of the stated benchmark. That is, funds whose stated benchmark is a value and growth index most often resemble value and growth indexes. For example, for funds whose stated benchmark is a large-cap growth index, 93.5% of the most frequent minimum Active Share benchmark is also a large growth index. Similarly, the holdings of a fund whose stated benchmark is a mid-cap value index reflects a mid-cap value index 78.1% of the time.

However, this is not true for the neutral indexes (i.e., those funds that do not have a growth or value mandate). For example, the actual holdings of funds that benchmark to large-cap neutral indexes (e.g., the S&P 500) most often reflect a large-cap neutral index only 38.4% of the time. By contrast, 32.4% of the time the holdings more closely resemble a large-cap growth index, and 14.7% of the time fund holdings most closely resemble a large-cap value index. Results are more dramatic for mid-cap and small-cap funds. In the case of small-cap neutral funds, fund holdings reflect a small-cap neutral index (e.g., the Russell 2000) only 15.8% of the time. 39.6% and 23.8% of the time fund holdings better reflect a small-cap growth or a small-cap value index.

Overall, the results of Table 1 demonstrate that managers deviate from the style of their stated benchmark for long periods of time. However, with regards to style, they do not appear to do so in the way one might expect: managers of neutral funds are almost twice as likely to tilt their portfolio weights towards growth stocks than they do value stocks.

6.2. Summary Statistics of Attribution Components

We run the HKM attribution model for each fund in our sample with the requirement that each fund have at least 12 quarters of holdings data and relative to the stated benchmark of each fund. We report summary statistics of this analysis in Table 2. Panel A reports the mean, standard deviation, and percentile ranks for this analysis. It can be seen that, on average, the quarterly alpha for each fund relative to its stated benchmark is 0.398%, and with a median of 0.299%. At first glance, this seems to run counter to the findings of previous research that actively managed funds do not outperform their benchmarks on average. This number is positive for two reasons. First, the attribution analysis is performed using holdings data and is gross of fees. Second, the requirement that each fund has at least three-years of holdings data introduces a survivorship bias in these numbers; funds with fewer than three years of holdings data are excluded, and funds that are excluded contain a larger portion of poorly-performing funds.[6]

The average stock selection component of this historical alpha is 0.773% per quarter (the median is 0.556%). Thus, on average, fund managers appear to do relatively will when it comes to picking individual securities. By contrast, the average factor allocation is −0.375% each quarter. Of this −0.375%, −0.312% results from static factor allocation and −0.063% results from dynamic factor allocation. Thus it appears to be the case that managers, on average, over-weight their portfolios to factors that have a lower premium relative to their benchmark. This result is somewhat puzzling, though likely to result from the fact that active managers are more likely to tilt their portfolios towards growth stocks (see Table 1).

In Panel B of Table 2 we report the correlation between the the average alpha of each fund and its different components. Overall the static, dynamic, and security selection components are relatively uncorrelated with each other, consistent with their resulting from different investment processes. In unreported results, we also run a principle component analysis on the three components of the HKM model and find that, on average, the resulting three factors explain 43%, 35%, and 22% of the variance of HMK model outputs, consistent with three separate

[6] Note that our empirical examination of the predictability of fund returns is focused on testing manager outperformance over future periods using past three years of fund performance data and the predictability examination is not biased by this or any other survivorship problem.

factors. Overall, these findings are consistent with the components of the attribution model reflecting distinct sources of alpha.

6.3. The Determinants of HKM Attribution Components

What fund characteristics are correlated with different sources of alpha? In panel regressions, we examine the determinants of attribution components calculated on a rolling 36-month basis each quarter. Independent variables are measured at t and include a fund's Active Share measure, a dummy if the fund is either a small-cap or a large-cap fund (as determined by the fund's stated benchmark), the fund's 12-month tracking error relative to it's stated benchmark, turnover ratio, expense ratio, the log of the fund's total net assets, the number of stocks, the age of the fund in the CRSP database (in months) and the manager tenure (in months). The dependent variable includes the attribution components (i.e., static allocation, dynamic allocation, and stock selection) are time $t + 36$. All specifications include quarterly fixed-effects and standard errors are clustered at the fund level and by time to account for autocorrelation in the panel

Results are reported in Table 3. In Panel A we examine the correlation between the size or style of the fund and the different sources of alpha by including dummy variables which are equal to one if the fund is either a large-cap or a small cap fund (specifications (1), (3), and (5)), or if they are either a value or growth fund (specifications (2), (4), and (6)). In Panel B we repeat the analysis but include the aforementioned control variables. It can be seen that, on average, large-cap funds are more likely to obtain alpha by timing market factors relative to mid-cap funds, and less likely to do so by picking stocks. The reverse is true for small-cap funds. This is consistent with the industry perception that market inefficiencies are more pronounced among small-cap stocks making stock selection a more fruitful exercise. It is also consistent with their being more idiosyncratic risk among small-cap stocks making factor timing a more difficult strategy to implement. Results are similar when control variables are included in Panel B of Table 3.

It can be seen in Panel B that Active Share is associated with higher dynamic and stock selection components of a fund's historical or future alpha, but is negatively correlated with the static allocation component. A fund's exense ratio is negatively correlated with both static and dynamic factor components of a fund's alpha. However, a fund's expense ratio is positively correlated with the stock selection component. Also, funds with fewer stocks generally have higher alpha overall.

NEED MORE COMMENTS ON THIS TABLE.

6.4. Do Attribution Components Predict Future Benchmark-Adjusted Returns?

We are interested in examining whether the various components of the HKM attribution model predict future performance. Each component represents a distinct investment strategy and whether any of them predicts future performance is an empirical question. Each quarter we perform a portfolio attribution analysis and separate funds into quintiles based on their overall historical alpha (representing the sum of the output of the attribution model), the factor allocation component (from the standard Brinson model), the static and dynamic allocation components (unique to the HKM model), and the stock component. We then examine each of these quintiles separately to determine whether or not they predict future excess returns over the benchmark for the subsequent quarter. Results of this analysis are reported in Table 4.

Panel A reports the results for future gross returns, while Panel B reports results for net returns. In the first row, funds are sorted into quintiles based on their historical alpha relative to their benchmark. The average alphas for each quintile over the subsequent three-month period are reported in columns, as well as the difference between the top and bottom quintile. Not surprisingly, and consistent with past research, the historical overall alpha of a fund does not predict future performance. In the case of gross returns (Panel A), funds in the high quintile (i.e. those with the largest historical alpha) outperform their benchmark by an average of 0.57% over the subsequent three-month period while in the low quintile outperform by an average 0.33%. Neither of these results are statistically significant. The difference between the high and low quintile is neither economically or statistically significant. Results are similar when net returns are considered (Panel B of Table 4).

Subsequent rows repeat the analysis using the components of a fund's overall historical alpha as the basis for sorts into quintiles. It can be seen that similar to the results for a fund's overall alpha, the components of a fund's historical alpha do not generally predict future alpha over the subsequent three-month period.

The exception involves sorts based on the dynamic allocation component of a fund's historical alpha. In the case of gross returns (Panel A), fund's that have successfully timed factors in the past deliver greater future benchmark-adjusted returns on average. Funds in the high quintile outperform their benchmark by 0.72% over the subsequent three-month period, and this results is statistically significant (with a t-statistic of 2.27). Funds in the low quintile outperform their benchmark by a statistically insignificant 0.17% over the next three months. The difference between the high and low quintiles is 0.55% and statistically significant (with a t-statistic of 2.65). Finally, future performance is monotonically increasing by quintile. These results are consistent with the hypothesis that dynamic timing more directly measures manager skill and that this skill is persistent.

In the case of net returns (Panel B), the results are similar. In general, attribution components fail to predict future benchmark-adjusted returns. However, as with gross returns, future benchmark adjusted returns are monotonically increasing by dynamic allocation quintile. Funds in the high quintile outperform their benchmark by 0.10% over the next three-month period (though this result is not statistically significant) while funds in the low quintile underperform their benchmark by a statistically significant 0.36% (with a t-statistic of -2.18). The difference between the high and low quintiles is 0.46% (with a t-statistic of 2.47).

Overall, these results are consistent with dynamic factor timing skill being more persistent that skill associated with stock selection or creating persistent tilts toward factors with a risk premium.

In Table 3 we found that different fund types were associated with different sources of alpha. We examine whether this is true for performance persistance by repeating the analysis in Table 4 by fund size and style. Overall we find that, as with Table 4, average alpha, static factor allocation, and stock selection components of a fund's alpha do not predict future performance. However, we find that dynamic factor allocation does predict future performance of some types of funds. We report the results of the analysis by fund type in Table 5. It can be seen in Panel A that dynamic factor allocation does not typically predict future returns for small-cap funds, but it does predict the future returns of mid-cap and large-cap funds. For mid-cap funds, the high quintile outperforms the low quintile by 0.50% and 0.41% over the subsequent quarter for gross and net returns, respectively, and these results are statistically significant. The results for large-cap funds are more pronounced: the high quintile outperforms the low quintile by 0.76% and 0.66% for gross and net returns, respectively, over the subsequent quarter, and these results are also statistically significant. In Panel B we find that dynamic allocation predicts future returns for neutral funds and growth funds, but not value funds.

6.5. Do Attribution Components Predict Future Benchmark-Adjusted Returns?

To further adjust for risk, we repeat the analysis in Table 5 but regress the average excess returns of each quintile on the Fama-French-Carhart four-factor model (see Fama and French (1993) and Carhart (1997)). Results are reported in Table 6. We report the results for all funds in Panel A, the results for funds sorted by fund size in Panel B, and results sorted by fund style in Panel C.

Overall, the results in Table 6 are similar to those reported in Table 5. As before, and for growth and net returns, dynamic factor allocation is positively associated with subsequent 3-month risk-adjusted returns, particularly for large-cap and neutral funds. Finally, in unreported results, we repeat the analysis using a single-factor market model and a three-factor Fama-French model. Results are qualitatively similar to those reported in Table 6.

6.6. Fund Characteristics of Dynamic Allocation Quintiles

What are the characteristics of funds in dynamic allocation quintiles? We report summary statistics for key fund characteristics in Table 7. Average, median (in square brackets), and standard deviations (in parenthesis) of each characteristics are reported. We find that, relative to funds in the low quintile, those in high quintile have more assets under management on average ($1.438 versus $0.881 billion). They also have more experienced managers, though the difference isn't large (90.3 vs 81.6 months). Relative the the middle quintile, funds in the high or low quintile have higher Active Share measures, higher tracking error, higher turnover, and lower number of stocks.

Active Share has been shown to predict future fund performance (Cremers and Petajisto (2009)). These statistics suggest that it is not just those funds that have a higher Active Share that have higher performance, it is those that also have a record of successful factor timing (as measured by the dynamic allocation component of their historical alpha) that have higher future performance, and not those high Active Share funds in the low dynamic timing quintile.

To examine this possibility, each quarter we perform a two-way sort for each fund based on their dynamic allocation component over the preceeding 36-month period and the Active Share measure of the fund with respect to its stated benchmark. We then examine the subsequent benchmark-adjusted 3-month return for each portfolio and report the results in Table 8. Panel A reports results for gross returns and Panel B reports results for net returns. It can be seen that, consistent with Table 7, funds with both higher dynamic factor allocation components of their historical alpha and higher Active Share measures have higher returns than funds with low dynamic factor allocation components and Active Share measures. Funds in the highest dynamic allocation and Active Share quintiles outperform their stated benchmark by 1.50% and 0.69% gross and net of fees, respectively. These results are consistent with the idea that fund managers that have timed the market successfully in the past and are confident in their future views (as evidenced by the high Active Share of their fund) are more likely to outperform in the future.

6.7. Panel Regressions

To more directly examine the effects of past dynamic factor group timing on future returns and to control for other fund characteristics, we run panel regressions on 3-month benchmark adjusted returns, where fund characteristics are measured at the end of the prior quarter. The results are reported in Table 9.

Panel A contains results with a limited set of control variables. The dependent variable in each regression is the 3-month benchmark-adjusted gross or net return, from time t through time $t + 3$. The independent variables of interest, measured at time t, include the attribution components. Each model contains time fixed effects. The time fixed effects absorb any omitted variable that has a constant impact on each fund in each period and the fund fixed effect absorbs any omitted variable that has a fund-specific (but time-invariant) effect. Finally, standard error estimates are clustered by time.

Models (1) and (4) present results for gross and net returns, respectively, where the attribution components are the only independent variables. It can be seen that the dynamic allocation component is significantly correlated with future benchmark-adjusted returns. Models (2) and

(5) includes Active Share in addition to the attribution components. It can be seen that the dynamic allocation component and Active Share are both correlated with higher future returns. Finally, Models (3) and (6) includes an interaction between a fund's dynamic allocation component. In each case the interaction term is positive and significant. However, the coefficient on the dynamic allocation component is negative (but statistically insignificant). Because of the interaction term, the marginal effect of an increase in the dynamic allocation component is equal to the coefficient on that variable plus the coefficient on the interaction term multiplied by the fund's Active Share. Thus, in the case of Model (3), it can be seen that this effect is positive when the Active Share is greater than $0.550/1.116 = 0.493$. Approximately 90% of the funds in our sample have an Active Share greater than 0.493, and thus, according to the coefficient estimates in model (3), a higher dynamic attribution component is positively related to higher future returns for 90% of the funds in our sample.

Panel B repeats the analysis in Panel A but includes fund characteristics from the empirical model used in Cremers and Petajisto (2009), with one exception: we exclude the independent variables that measure a funds historical alpha as, in our application, this information is contained in the various components of the attribution model (dynamic, static, and security selection). Overall, the results are similar to those in Panel A.

Finally, we include an interaction between dummy variables representing a fund's size (small-, mid-, or large-cap) and style (growth, neutral, or value) and repeat the analysis. Results are reported in Table 10. It can be seen that the dynamic allocation component is strongest for large-cap and neutral funds. This is consistent with these funds being less restricted by their mandate to allocate to factor risk: large-cap funds can allocate to constituents that make up over 90% of the market capitalization of the overall market and neither are they restricted to value or growth stocks.

7. Conclusion

In this paper we find that mutual fund managers generate alpha primarily by selecting stocks. Managers under-perform their benchmark indexes when it comes to allocating to factor risk. This results primarily from funds with a neutral style mandate tilting their portfolio weights to growth stocks.

We also find that managers that have dynamically timed market factors in the past are more likely to generate higher alpha in the future. We argue that skilled equity managers produce risk-adjusted alpha through some form of factor timing, and that skill in factor timing can be measured with a holdings-based attribution analysis that parses factor allocation into two piecesa static factor allocation and a dynamic factor allocation. Our empirical results show that the dynamic factor allocation is predictive of future benchmark-adjusted returns.

Our results are consistent with a growing body of literature that claims it is possible to predict alpha based on properly adjusted past alpha. While there is considerably more work to do to better understand skill and factor timing, we believe that continued research in this area will lead to considerable benefits for investors as we learn more about the sources of alpha and skill.

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Table 1 Stated Benchmark Styles vs. Minimum Active Share Benchmark (1993 - 2012)

This table shows the size and style of each fund's stated benchmark index and the size and style of the benchmark index that the fund most closely resembles. This is accomplished by calculating the Active Share for each mutual fund in our sample relative to each benchmark index each quarter. The benchmark index with the minimum Active Share for that quarter is assigned as the minimum Active Share benchmark index for that period. In the first column, we present the size and style of the fund's stated benchmark index. In subsequent columns, we present the percent of cases where the fund's stated benchmark matches the size and style of available benchmark indexes.

Stated Benchmark Size / Style		Count	Style of Most Frequent Minimum Active Share Benchmark: Large-Cap Growth	Large-Cap Neutral	Large-Cap Value	Mid-Cap Growth	Mid-Cap Neutral	Mid-Cap Value	Small-Cap Growth	Small-Cap Neutral	Small-Cap Value
Large-cap	Value	150	6.1	7.2	85.0	0.0	0.0	1.1	0.0	0.0	0.6
	Neutral	1155	32.4	38.4	14.7	6.2	0.6	4.1	1.9	0.3	1.3
	Growth	190	93.5	4.3	0.0	1.7	0.0	0.4	0.0	0.0	0.0
Mid-cap	Value	81	0.0	0.0	6.8	9.6	1.4	78.1	0.0	0.0	4.1
	Neutral	142	3.9	0.0	2.3	50.8	20.3	18.8	2.3	0.8	0.8
	Growth	180	4.3	0.0	0.0	85.3	0.0	0.0	10.4	0.0	0.0
Small-cap	Value	98	0.0	0.0	0.9	0.0	0.0	6.5	9.3	0.0	83.3
	Neutral	239	1.9	1.1	0.8	9.4	0.0	7.5	39.6	15.8	23.8
	Growth	139	0.6	0.0	0.0	17.5	0.0	0.6	81.2	0.0	0.0

Table 2 Summary Statistics of Attribution Analysis (1993 - 2012)

This table contains summary statistics for components of the Hsu, Kalesnik, and Myers (2010) attribution model which decomposes a fund's average historical alpha into static allocation and dynamic allocation components (which sum to an overall factor allocation component of the standard Brinson model) as well as a stock selection component. The analysis was performed quarterly for each fund relative to its stated benchmark index using three-years of holdings data. Numbers are reported in percentages. Panel A reports the time-series average of cross-sectional values measured each quarter. Included are the quarterly mean, standard deviation, and 0.05, 0.50, and 0.95 percentiles for each of the attribution components. Panel B reports the time-series average of the cross-sectional correlation matrix between each of the attribution model components.

Panel A: Attribution Summary Statistics

			Percentile		
	Mean	Std Dev	0.05	0.50	0.95
Attribution alpha	0.398	0.900	−0.746	0.299	1.850
Factor allocation	−0.375	0.720	−1.612	−0.271	0.575
Static allocation	−0.312	0.511	−1.202	−0.217	0.268
Dynamic allocation	−0.063	0.451	−0.746	−0.063	0.655
Stock selection	0.773	0.931	−0.187	0.556	2.429

Panel B: Correlation Matrix

	Alpha	Factor Allocation	Static Allocation	Dynamic Allocation	Stock Selection
Attribution alpha	1.000	0.355	0.088	0.467	0.691
Factor allocation	0.355	1.000	0.783	0.709	−0.430
Dynamic allocation	0.088	0.783	1.000	0.116	−0.520
Dynamic allocation	0.467	0.709	0.116	1.000	−0.097
Stock selection	0.691	−0.430	−0.520	−0.097	1.000

Table 3 Determinants of Alpha (1993 - 2012)

This table contains the results of panel regressions on the static factor allocation, dynamic factor allocation, and stock selection components from the attribution analysis (measured as a percentage) run on a rolling 36-month basis, and is measured at either t or $t+36$. Independent variables are measured at time t and include Active Share, a dummy variable if the fund's stated benchmark is either a small cap or a large cap index, 12-month tracking error relative to the stated benchmark, turnover ratio, expense ratio, the log of total net assets, the number of stocks, the age of the fund (in months), and manager tenure (in months). All models include time fixed effects. Standard errors are adjusted for clustering by fund, and t-statistics are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Panel A: Determinants of Alpha - Fund Type

Control Variables (Measured at t)	Static Allocation (From t to $t+36$)		Dynamic Allocation (From t to $t+36$)		Stock Selection (From t to $t+36$)	
	(1)	(2)	(3)	(4)	(5)	(6)
Large-cap fund	0.244**		0.166**		−0.217**	
	(6.29)		(4.89)		(−3.67)	
Small-cap fund	−0.066		−0.013		0.406**	
	(−1.46)		(−0.34)		(4.78)	
Value fund		0.145**		0.104**		−0.148**
		(3.02)		(3.57)		(−2.32)
Growth fund		−0.024		0.049**		−0.019
		(−0.54)		(2.08)		(−0.28)
Observations	52,788	52,788	52,788	52,788	52,788	52,788
R-squared	0.266	0.255	0.120	0.107	0.171	0.149

Panel B: Determinants of Alpha - Fund Type (w/ Control Variables)

Control Variables (Measured at t)	Static Allocation (From t to $t+36$)		Dynamic Allocation (From t to $t+36$)		Stock Selection (From t to $t+36$)	
	(1)	(2)	(3)	(4)	(5)	(6)
Large cap fund	0.224**		0.218**		−0.017	
	(4.22)		(5.71)		(−0.30)	
Small cap fund	−0.081*		−0.042		0.320**	
	(−1.65)		(−1.06)		(4.04)	
Value fund		0.107**		0.097**		−0.078
		(2.26)		(3.60)		(−1.46)
Growth fund		−0.036		0.052**		0.000
		(−0.79)		(2.10)		(0.01)
Active Share	−0.104	−0.431**	0.375**	0.071	1.324**	1.553**
	(−0.57)	(−3.18)	(4.89)	(0.96)	(6.31)	(7.00)
Tracking error	−0.196	0.042	0.144	0.433*	1.857*	1.732
	(−0.46)	(0.10)	(0.62)	(1.83)	(1.72)	(1.62)
Turnover ratio	0.009	0.011	−0.008	−0.015	−0.032	−0.037
	(0.51)	(0.59)	(−0.67)	(−1.22)	(−0.99)	(−1.15)
Expense ratio	−6.765**	−6.316*	−3.796*	−4.030*	12.637**	13.334**
	(−2.11)	(−1.90)	(−1.65)	(−1.67)	(2.39)	(2.47)
log$_10$(TNA)	−0.066**	−0.053**	−0.031**	−0.021	−0.043	−0.057*
	(−3.35)	(−2.87)	(−1.99)	(−1.38)	(−1.36)	(−1.85)
Number of stocks / 100	0.023	−0.020*	0.036**	0.000	0.095**	0.133**
	(1.34)	(−1.88)	(4.03)	(0.07)	(4.86)	(5.65)
Fund age / 100	0.027**	0.034**	−0.006	0.001	−0.018	−0.023*
	(3.18)	(4.03)	(−0.76)	(0.12)	(−1.33)	(−1.68)
Manager tenure / 100	0.011	0.009	0.018	0.020*	0.032	0.034
	(0.77)	(0.67)	(1.57)	(1.65)	(1.49)	(1.55)
Observations	52,788	52,788	52,788	52,788	52,788	52,788
R-squared	0.273	0.265	0.131	0.111	0.219	0.214

Table 4 Attribution Components and the Predictability of Benchmark-Adjusted Mutual Fund Returns (1993 - 2012)

Each quarter, funds are sorted into quintiles based on their average quarterly alpha and on each of the components of the attribution model (factor allocation, static and dynamic allocation, and the stock selection component) as measured at time t. Average benchmark-adjusted returns for each quintile are then reported over the subsequent quarter (from time t to $t+3$). Benchmark-adjusted returns are defined as the fund return minus the return of the fund's stated benchmark. Panel A reports benchmark-adjusted gross returns, while Panel B reports benchmark-adjusted net returns. Average quarterly benchmark-adjusted returns are presented as percentages and t-statistics based on White's standard errors are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Panel A: Benchmark-Adjusted Gross Returns (From t to $t+3$)

Sort Variable (Measured at t)	Quintile Low	2	3	4	High	High Minus Low
Attribution alpha	0.33	0.16	0.28	0.35	0.57	0.23
	(1.19)	(0.89)	(1.42)	(1.61)	(1.19)	(0.47)
Factor allocation	0.18	0.30	0.27	0.33	0.60*	0.42
	(0.64)	(1.29)	(1.32)	(1.40)	(1.78)	(1.16)
Static allocation	0.30	0.28	0.34	0.38	0.39	0.09
	(0.97)	(1.27)	(1.30)	(1.57)	(1.10)	(0.20)
Dynamic allocation	0.17	0.18	0.21	0.39**	0.72**	0.55**
	(0.56)	(0.82)	(1.36)	(2.02)	(2.27)	(2.65)
Stock selection	0.51**	0.34**	0.26	0.33	0.24	−0.27
	(2.03)	(2.01)	(1.39)	(1.46)	(0.54)	(−0.71)

Panel B: Benchmark-Adjusted Net Returns (From t to $t+3$)

Sort Variable (Measured at t)	Quintile Low	2	3	4	High	High Minus Low
Attribution alpha	−0.17	−0.30**	−0.23**	−0.19	−0.03	0.14
	(−0.70)	(−2.10)	(−2.25)	(−1.46)	(−0.10)	(0.35)
Factor allocation	−0.30	−0.19	−0.23**	−0.20*	0.00	0.29
	(−1.16)	(−1.29)	(−2.12)	(−1.67)	(−0.01)	(0.89)
Static allocation	−0.19	−0.19	−0.22*	−0.19	−0.13	0.06
	(−0.64)	(−1.20)	(−1.84)	(−1.60)	(−0.54)	(0.15)
Dynamic allocation	−0.36**	−0.31**	−0.23**	−0.13	0.10	0.46**
	(−2.18)	(−2.40)	(−2.05)	(−0.92)	(0.49)	(2.47)
Stock selection	−0.05	−0.15	−0.23*	−0.17	−0.32	−0.27
	(−0.27)	(−1.18)	(−1.80)	(−1.22)	(−1.17)	(−0.86)

Table 5 Attribution Components and the Predictability of Benchmark-Adjusted Mutual Fund Returns by Fund Size and Style (1993 - 2012)

Each quarter, funds are sorted into quintiles based on the dynamic allocation component of their historical alpha as measured at time t. Average benchmark-adjusted returns for each quintile are then reported over the subsequent quarter (from time t to $t+3$). Benchmark-adjusted returns are defined as the fund return minus the return of the fund's stated benchmark. Panel A reports results sorted by the size of the fund and Panel B reports results sorted by the style of the fund. Average quarterly benchmark-adjusted returns are presented as percentages and t-statistics based on White's standard errors are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Panel A: Benchmark-Adjusted Returns by Fund Size (From t to $t+3$)

Benchmark Size	Return Type	Dynamic Allocation Quintile (Measured at t) Low	2	3	4	High	High Minus Low
Small-cap	Gross	0.22	0.50	0.37	0.50	0.90	0.68
(476 funds)		(0.71)	(1.14)	(1.19)	(1.47)	(1.30)	(1.49)
	Net	−0.18	−0.09	−0.07	−0.05	0.03	0.21
		(−0.85)	(−0.53)	(−0.45)	(−0.25)	(0.11)	(0.87)
Mid-cap	Gross	−0.03	0.42	0.14	0.40*	0.47	0.50**
(403 funds)		(−0.10)	(1.18)	(0.51)	(1.72)	(1.27)	(2.48)
	Net	−0.50**	−0.16	−0.38**	−0.11	−0.09	0.41**
		(−2.92)	(−1.09)	(−2.97)	(−0.88)	(−0.57)	(2.10)
Large-cap	Gross	0.09	0.12	0.21	0.43**	0.85**	0.76**
(1,495 funds)		(0.34)	(0.64)	(1.40)	(2.28)	(2.80)	(2.69)
	Net	−0.38*	−0.34**	−0.23*	−0.08	0.28	0.66**
		(−1.64)	(−2.53)	(−1.93)	(−0.46)	(1.06)	(2.56)

Panel B: Benchmark-Adjusted Returns by Fund Style (From t to $t+3$)

Benchmark Style	Return Type	Dynamic Allocation Quintile (Measured at t) Low	2	3	4	High	High Minus Low
Growth	Gross	0.10	0.32	0.38	0.37	0.58	0.48**
(692 funds)		(0.27)	(0.92)	(1.36)	(1.51)	(1.27)	(2.41)
	Net	−0.38**	−0.23*	−0.11	−0.12	−0.09	0.29*
		(−2.35)	(−1.66)	(−0.68)	(−0.69)	(−0.39)	(1.64)
Neutral	Gross	0.14	0.07	0.18	0.48**	0.92**	0.78**
(1,235 funds)		(0.47)	(0.33)	(1.10)	(2.42)	(3.02)	(2.61)
	Net	−0.37	−0.35**	−0.25*	−0.05	0.35	0.72**
		(−1.51)	(−2.34)	(−1.91)	(−0.30)	(1.34)	(2.70)
Value	Gross	0.40*	0.10	0.13	0.32*	0.53	0.13
(447 funds)		(1.85)	(0.65)	(0.82)	(1.84)	(1.59)	(0.70)
	Net	−0.17	−0.37**	−0.35**	−0.18	−0.20	−0.03
		(−1.17)	(−2.88)	(−2.54)	(−1.26)	(−1.15)	(−0.24)

Table 6 Attribution Components and the Predictability of Risk-Adjusted Mutual Fund Returns (1993 - 2012)

Each quarter, funds are sorted into quintiles based on the dynamic allocation component of their historical alpha as measured at time t. Average benchmark-adjusted returns for each quintile are then reported over the subsequent quarter (from time t to $t+3$). The Fama-French-Carhart four-factor alpha for the average excess returns for each quintile are reported. Panel A reports results for all funds, Panel B reports results sorted by the size of the fund, and Panel C reports results sorted by the style of the fund. The quarterly risk-adjusted alphas are presented as percentages and t-statistics based on White's standard errors are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Panel A: Four-Factor Alphas for All Funds (From t to $t+3$)

	Return Type	Dynamic Allocation Quintile (Measured at t)					High Minus Low
		Low	2	3	4	High	
All funds	Gross	−0.08	−0.04	0.14	0.23	0.34	0.41*
(2,374 funds)		(−0.24)	(−0.17)	(1.07)	(1.36)	(1.19)	(1.94)
	Net	−0.36*	−0.32**	−0.15	−0.09	−0.04	0.33*
		(−1.64)	(−2.24)	(−1.18)	(−0.62)	(−0.17)	(1.71)

Panel B: Four-Factor Alphas by Fund Size (From t to $t+3$)

Benchmark Size	Return Type	Dynamic Allocation Quintile (Measured at t)					High Minus Low
		Low	2	3	4	High	
Small-cap	Gross	−0.51	−0.02	0.00	−0.09	−0.42	0.09
(476 funds)		(−1.39)	(−0.05)	(−0.01)	(−0.30)	(−0.74)	(0.21)
	Net	−0.63*	−0.23	−0.21	−0.36	−0.76**	−0.14
		(−1.87)	(−0.82)	(−0.98)	(−1.47)	(−3.12)	(−0.47)
Mid-cap	Gross	−0.21	0.16	−0.09	0.13	0.08	0.29
(403 funds)		(−0.48)	(0.34)	(−0.24)	(0.43)	(0.18)	(1.28)
	Net	−0.37	−0.14	−0.30	−0.15	−0.14	0.23
		(−1.25)	(−0.48)	(−1.15)	(−0.54)	(−0.46)	(1.08)
Large-cap	Gross	−0.08	0.04	0.12	0.24	0.46*	0.53**
(1,495 funds)		(−0.35)	(0.27)	(0.99)	(1.52)	(1.86)	(2.17)
	Net	−0.39*	−0.24**	−0.21*	−0.10	0.06	0.45**
		(−1.95)	(−2.13)	(−1.94)	(−0.69)	(0.28)	(2.05)

Panel C: Four-Factor Alphas by Fund Style (From t to $t+3$)

Benchmark Style	Return Type	Dynamic Allocation Quintile (Measured at t)					High Minus Low
		Low	2	3	4	High	
Growth	Gross	−0.25	−0.11	0.09	0.08	0.00	0.25
(692 funds)		(−0.54)	(−0.24)	(0.30)	(0.32)	(0.00)	(0.93)
	Net	−0.44	−0.37	−0.18	−0.24	−0.35	0.08
		(−1.49)	(−1.38)	(−0.83)	(−0.97)	(−1.27)	(0.35)
Neutral	Gross	−0.03	−0.05	0.12	0.31*	0.58**	0.61**
(1,235 funds)		(−0.11)	(−0.39)	(1.00)	(1.72)	(2.13)	(2.14)
	Net	−0.35	−0.30**	−0.19	−0.06	0.21	0.57**
		(−1.45)	(−2.29)	(−1.61)	(−0.40)	(0.91)	(2.15)
Value	Gross	0.20	0.08	0.12	0.26	0.36	0.16
(447 funds)		(0.76)	(0.46)	(0.59)	(1.25)	(1.20)	(0.63)
	Net	−0.16	−0.21	−0.18	−0.08	0.02	0.18
		(−0.66)	(−1.22)	(−0.88)	(−0.36)	(0.08)	(0.85)

Table 7 Portfolio Characteristics of Dynamic Allocation Quintiles (1993 - 2012)

This table presents the time-series average of cross-sectional means, medians (reported in square brackets), and standard deviations (reported in parenthesis) of portfolio characteristics for funds in each of the dynamic allocation quintiles. Statistics are reported for Active Share, tracking error, turnover ration, expense ratio, total net assets, the number of stocks in the portfolio, the age of the fund in months, manager tenure in months, and the 3-month fund flow.

	Dynamic Factor Allocation Quintile					
	Low	2	3	4	High	All
Active share	0.868	0.788	0.749	0.761	0.856	0.804
	[0.906]	[0.817]	[0.782]	[0.801]	[0.889]	[0.852]
	(0.119)	(0.159)	(0.192)	(0.191)	(0.122)	(0.173)
Tracking error	0.084	0.067	0.062	0.066	0.087	0.073
	[0.070]	[0.055]	[0.051]	[0.054]	[0.071]	[0.060]
	(0.056)	(0.047)	(0.046)	(0.050)	(0.058)	(0.054)
Turnover ratio	0.965	0.860	0.796	0.819	0.946	0.877
	[0.742]	[0.637]	[0.582]	[0.593]	[0.639]	[0.637]
	(1.001)	(0.966)	(0.867)	(0.969)	(1.167)	(1.026)
Expense ratio	0.014	0.012	0.012	0.012	0.013	0.013
	[0.013]	[0.012]	[0.011]	[0.012]	[0.013]	[0.012]
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Total net assets	881	1390	1607	1772	1537	1438
	[224]	[306]	[355]	[396]	[356]	[315]
	(2738)	(4253)	(5028)	(5474)	(4362)	(4841)
Number of stocks	97.1	126.7	150.8	139.5	95.8	122.0
	[69.7]	[75.4]	[81.7]	[78.3]	[64.2]	[73.3]
	(113.6)	(199.9)	(250.7)	(215.2)	(147.0)	(206.1)
Fund age (months)	160	177	175	178	173	173
	[121]	[132]	[130]	[135]	[129]	[128]
	(111)	(124)	(124)	(125)	(120)	(121)
Manager tenure (months)	81.6	82.4	84.1	84.5	90.3	84.6
	[67.6]	[66.6]	[67.3]	[67.5]	[71.0]	[67.4]
	(66.6)	(67.8)	(69.2)	(70.2)	(75.4)	(70.4)
Fund flow (3-month)	-0.004	-0.003	-0.002	-0.001	0.000	-0.002
	[-0.019]	[-0.014]	[-0.010]	[-0.006]	[0.002]	[-0.010]
	(0.283)	(0.201)	(0.187)	(0.217)	(0.262)	(0.282)

Table 8 Dynamic Factor Allocation, Active Share, and the Predictability of Benchmark-Adjusted Mutual Fund Returns (1993 - 2012)

Each quarter, funds are sorted into quintiles based on the dynamic factor allocation component as measured at time t. Within each quintile, funds are further sorted into quintiles based on the fund's Active Share with respect to the fund's stated benchmark, also measured at time t. Average benchmark-adjusted returns for each quintile are then reported over the subsequent quarter (from time t to $t+3$). Benchmark-adjusted returns are defined as the fund return minus the return of the fund's stated benchmark. Panel A reports benchmark-adjusted gross returns, while Panel B reports benchmark-adjusted net returns. Average quarterly benchmark-adjusted returns are presented as percentages and t-statistics based on White's standard errors are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Panel A: Benchmark-Adjusted Gross Returns (From t to $t+3$)

Active Share Quintile	Dynamic Allocation Quintile						High Minus Low
	Low	2	3	4	High	All	
Low	0.14	0.19	0.14**	0.18*	0.35**	0.20*	0.21
	(0.68)	(1.62)	(1.97)	(1.65)	(2.04)	(1.67)	(1.23)
2	0.21	0.08	0.15	0.27	0.49*	0.24	0.28
	(0.67)	(0.40)	(1.02)	(1.62)	(1.78)	(1.18)	(1.21)
3	0.15	0.07	0.13	0.43**	0.56	0.27	0.41
	(0.35)	(0.35)	(0.70)	(2.12)	(1.59)	(1.09)	(1.32)
4	0.21	−0.01	0.22	0.28	0.69*	0.28	0.48
	(0.50)	(−0.03)	(1.00)	(1.28)	(1.82)	(0.97)	(1.61)
High	0.14	0.61	0.43	0.79**	1.50**	0.69*	1.36**
	(0.30)	(1.50)	(1.58)	(2.08)	(2.92)	(1.96)	(2.74)
All	0.17	0.18	0.21	0.39**	0.72**	0.34	0.55**
	(0.56)	(0.82)	(1.36)	(2.02)	(2.27)	(1.48)	(2.65)
High minus low	0.00	0.42	0.29	0.61*	1.15**	0.49*	
	(0.00)	(1.18)	(1.12)	(1.83)	(2.79)	(1.68)	

Panel B: Benchmark-Adjusted Net Returns (From t to $t+3$)

Active Share Quintile	Dynamic Allocation Quintile						High Minus Low
	Low	2	3	4	High	All	
Low	−0.37**	−0.17**	−0.25**	−0.21**	−0.17	−0.23**	0.20
	(−3.26)	(−2.35)	(−4.74)	(−2.99)	(−1.10)	(−3.55)	(1.21)
2	−0.26	−0.46**	−0.29**	−0.20	−0.14	−0.27**	0.11
	(−1.50)	(−3.92)	(−2.93)	(−1.62)	(−0.73)	(−2.38)	(0.53)
3	−0.39*	−0.44**	−0.34**	−0.12	−0.06	−0.27**	0.33
	(−1.83)	(−3.69)	(−2.56)	(−0.78)	(−0.28)	(−2.00)	(1.31)
4	−0.36*	−0.46**	−0.24	−0.24	0.20	−0.22	0.56**
	(−1.96)	(−2.24)	(−1.64)	(−1.21)	(0.77)	(−1.42)	(2.19)
High	−0.41	−0.01	0.00	0.13	0.69*	0.08	1.10**
	(−0.90)	(−0.05)	(0.00)	(0.44)	(1.88)	(0.29)	(2.57)
All	−0.36**	−0.31**	−0.23**	−0.13	0.10	−0.18	0.46**
	(−2.18)	(−2.40)	(−2.05)	(−0.92)	(0.49)	(−1.38)	(2.47)
High minus low	−0.03	0.15	0.25	0.33	0.86**	0.31	
	(−0.08)	(0.57)	(1.03)	(1.20)	(2.73)	(1.26)	

Table 9 Predictive Panel Regressions Benchmark-Adjusted Returns (1993 - 2012)

This table presents the results of panel regressions where the independent variable is the quarterly benchmark-adjusted return to mutual funds (from t to $t+3$). Independent variables include the components of the attribution model and Active Share as measured at time t. Panel A reports results without control variables, while Panel B reports results with control variables. All models include time fixed effects. Standard errors are adjusted for clustering by time, and t-statistics are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Panel A: Panel Regressions Without Control Variables

Control Variables (Measured at t)	Gross Returns (From t to $t+3$) (1)	(2)	(3)	Net Returns (From t to $t+3$) (4)	(5)	(6)
Dynamic allocation	0.443**	0.423**	−0.550	0.379**	0.367**	−0.704
	(2.41)	(2.32)	(−1.06)	(2.27)	(2.22)	(−1.47)
Static allocation	−0.067	−0.028	−0.036	−0.084	−0.059	−0.069
	(−0.22)	(−0.09)	(−0.12)	(−0.32)	(−0.22)	(−0.26)
Stock selection	−0.124	−0.164	−0.162	−0.105	−0.129	−0.128
	(−0.79)	(−1.04)	(−1.03)	(−0.81)	(−0.99)	(−0.97)
Active Share		0.011**	0.011**		0.007**	0.007**
		(3.32)	(3.27)		(2.76)	(2.71)
Dynamic × Active Share			1.116**			1.228**
			(2.19)			(2.58)
Observations	77,258	77,258	77,258	77,258	77,258	77,258
R-squared	0.100	0.102	0.102	0.052	0.053	0.053

Panel B: Panel Regressions With Control Variables

Control Variables (Measured at t)	Gross Returns (From t to $t+3$) (1)	(2)	(3)	Net Returns (From t to $t+3$) (4)	(5)	(6)
Dynamic allocation	0.438**	0.421**	−0.593	0.368**	0.356**	−0.736*
	(2.32)	(2.30)	(−1.27)	(2.15)	(2.13)	(−1.68)
Static allocation	−0.052	−0.019	−0.028	−0.077	−0.053	−0.062
	(−0.17)	(−0.06)	(−0.09)	(−0.28)	(−0.20)	(−0.24)
Stock selection	−0.158	−0.183	−0.182	−0.130	−0.149	−0.147
	(−1.14)	(−1.29)	(−1.27)	(−1.11)	(−1.23)	(−1.22)
Active Share		0.016**	0.016**		0.011**	0.011**
		(2.60)	(2.62)		(2.43)	(2.46)
Dynamic × Active Share			1.162**			1.253**
			(2.43)			(2.78)
Tracking error	0.016	0.001	0.000	0.020	0.009	0.009
	(0.48)	(0.03)	(0.01)	(0.67)	(0.28)	(0.26)
Turnover ratio	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.12)	(−0.22)	(−0.25)	(−0.19)	(−0.27)	(−0.31)
Expense ratio (bp)	0.226	0.064	0.065	−0.079	−0.197**	−0.196**
	(1.61)	(0.64)	(0.65)	(−0.73)	(−2.35)	(−2.34)
$\log_{10}$(TNA)	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.17)	(−1.32)	(−1.30)	(−1.34)	(−1.44)	(−1.43)
Number of stocks / 100	0.000	0.001**	0.001**	0.000	0.001**	0.001**
	(0.64)	(2.43)	(2.49)	(0.36)	(2.58)	(2.66)
Fund age / 100	0.000	0.000	0.000	0.000	0.000	0.000
	(0.95)	(1.12)	(1.08)	(1.16)	(1.30)	(1.25)
Manager tenure / 100	0.001	0.001	0.001	0.000	0.000	0.000
	(1.46)	(1.10)	(1.11)	(−0.06)	(−0.44)	(−0.44)
Inflow ($t-1$ to t)	0.010	0.010	0.011	0.013	0.013	0.013
	(0.94)	(1.01)	(1.04)	(1.31)	(1.36)	(1.40)
Inflow ($t-4$ to $t-1$)	0.003	0.004	0.004	0.003	0.003	0.003
	(1.10)	(1.18)	(1.20)	(0.89)	(0.95)	(0.96)
Bench return ($t-1$ to t)	0.068	0.054	0.052	0.049	0.039	0.037
	(1.14)	(0.88)	(0.84)	(0.92)	(0.69)	(0.65)
Bench return ($t-4$ to $t-1$)	0.026	0.013	0.011	0.015	0.006	0.004
	(0.75)	(0.35)	(0.30)	(0.41)	(0.15)	(0.09)
Observations	77,258	77,258	77,258	77,258	77,258	77,258
R-squared	0.101	0.103	0.103	0.053	0.054	0.054

Table 10 Predictive Panel Regressions Benchmark-Adjusted Returns: Fund Size and Style Effects (1993 - 2012)

This table presents the results of panel regressions where the independent variable is the quarterly benchmark-adjusted return to mutual funds (from t to $t+3$). Independent variables include the components of the attribution model and Active Share as measured at time t. Panel A reports results without control variables, while Panel B reports results with control variables. All models include time fixed effects. Standard errors are adjusted for clustering by time, and t-statistics are reported in parentheses, with * and ** representing statistical significance at the 0.10 and 0.05 levels, respectively.

Control Variables	Gross Returns (From t to $t+3$)		Net Returns (From t to $t+3$)	
(Measured at t)	(1)	(2)	(3)	(4)
Large-cap × dynamic allocation	0.782**		0.642**	
	(2.80)		(2.58)	
Mid-cap × dynamic allocation	0.043		0.047	
	(0.28)		(0.35)	
Small-cap × dynamic allocation	0.122		0.092	
	(1.40)		(1.05)	
Value × dynamic allocation		0.175		0.135
		(1.33)		(1.09)
Neutral × dynamic allocation		0.774**		0.686**
		(3.00)		(2.93)
Growth × dynamic allocation		0.127		0.047
		(1.03)		(0.39)
Control variables	X	X	X	X
Observations	77,258	77,258	77,258	77,258
R-squared	0.101	0.101	0.053	0.053