Academic Knowledge Dissemination in the Mutual Fund Industry: *Can Mutual Funds Successfully Adopt Factor Investing Strategies?*

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While the investment management industry is generally considered to be a knowledge-based industry, surprisingly little has been documented about the effectiveness and the added value of incorporating academic insights by investment managers into investment strategies. To the best of our knowledge, no study has been conducted on the added value of innovative investment strategies that incorporate academic insights. Consequently, we have no clear understanding of how many investment managers have incorporated academic insights into their investment strategies; the added value of incorporating these insights into investment strategies; in which cases application of these insights is successful; or what criteria might be helpful to determine the successful application of these insights.

At the same time, the relevance of an in-depth study on the differential performance of adaptors of academic knowledge in the investment management industry seems to be high, and its implications are expected to be significant. Numerous investment managers claim to have incorporated insights from academic studies. For example, after the publication of the results of the study of Fama and French [1993], who documented that strategies that invest in small capitalization stocks and value stocks earn positive excess returns, many investment managers claim that they have adopted investment styles based on the Fama–French small cap and value factors. Interestingly, there is currently no solid empirical evidence indicating that investment managers who have adopted investment styles based on factors that originate from academic research show sustainable better performance. There are a few studies that evaluate the performance of specific investment vehicles such as value funds, but there is no all-encompassing study that investigates the more general research question of whether the adopters of academic knowledge gain excess returns, or under which circumstances application of this knowledge is successful. The aim of this study is to fill this gap in the literature.

When we consider the application of academic insights into investment strategies, we restrict ourselves to strategies that incorporate factors that have been documented in academic studies to have predictive power for stock returns above and beyond market betas. Such strategies are often referred to as factor investing strategies. We do not consider the application of academic knowledge in a broad context, such as the application of insights from option pricing theory in the context of risk management. The underlying reason for us to focus specifically on factor investing strategies is that the application of such strategies can reliably be measured through regression-based techniques like return-based style analysis in line with Sharpe, and our aim is to perform a large-scale empirical study.

In the first part of the article, we evaluate the monthly performance for a large sample of U.S. equity mutual funds over the period 1990 to 2010, and use a regression-based method to indicate whether the funds follow factor investing strategies based on the low-beta, small cap, value, momentum, short-term reversal, and long-term reversal anomalies. We find that a significant number of funds (i.e., roughly 20% to 30%) have adapted small cap and value investment strategies. Only a small number of funds (1% to 6%) follow low-beta, momentum, and short-term and long-term reversal strategies.

Subsequently, we investigate whether the funds that have adopted the factor investing strategies exhibit superior returns. We find evidence supporting the added value of funds adopting low-beta, small cap, and value strategies. We also find that the excess returns earned by these funds are sustainable and have not disappeared after the public dissemination of the anomalies: Not only do we find a positive relation between fund performance and the adoption of factor investing strategies during the first decade of our sample, but we also find this positive relation to be present over the second decade. However, we do not find consistent evidence supporting value added for funds adopting momentum and reversal strategies. For funds engaging in momentum strategies, we find mixed evidence of positive excess returns, and for funds engaging in short-term reversal strategies, we even find evidence of negative excess returns. We hasten to add that the insignificant results for momentum funds might be attributable to the very small sample size of momentum funds in our study.

The outperformances of funds adopting low-beta, small cap, and value strategies are not only significant from a statistical point of view, but are also economically highly significant. In terms of one-factor alpha against the market index, small cap and value funds deliver average alphas of 56 and 119 basis points per annum, respectively, after costs. And the returns of low-beta funds are indistinguishable from the market return, while these funds exhibit significantly lower levels of risk. In terms of success ratio (i.e., the probability of outperforming in the long run), we also find large differences between factor investing funds and the other funds in our sample: Only 20% of the funds not engaging in factor investing yield outperformance in the long run. For funds that do engage in factor investing, this figure is substantially more favorable, ranging up to 61% and 67% for small cap and value funds, respectively. All in all, we conclude that there can be large added value of funds incorporating academic knowledge in their investment processes by engaging in factor investing. However, the incorporation of academic knowledge does not always appear to result in adding value.

We hypothesize that the extent to which academic knowledge can successfully be adopted by mutual funds in their investment strategies depends on the strength of the empirical evidence supporting the underlying anomaly. Regarding both the momentum and short-term reversal anomalies, there are also several studies that challenge the hypothesis that strategies based on these anomalies actually earn positive excess return. Specifically, these studies argue that trading frictions (like transaction costs) might prevent profitable execution of these strategies. Also, the evidence supporting the existence of the long-term reversal anomaly is substantially weaker than the evidence supporting the low-risk, small cap, and value anomalies. Based on our results, we argue that it is less likely that new academic knowledge can successfully be adopted in the investment management industry if the empirical evidence on which the knowledge is based exhibits significant ambiguities.

Overall, our findings have important implications for the role of academic research and knowledge management in the investment management industry. First of all, our results indicate that investors who have adopted investment strategies based on asset pricing anomalies documented in the academic literature can earn consistent excess returns. Our results thereby provide a case to justify spending on research and development in the investment management industry. Our results also indicate that the excess returns earned by funds that have engaged in factor investing strategies are sustainable and do not disappear after the public dissemination of the anomalies. This result implies that investors do not have to worry that the added value of incorporating new knowledge is only short-lived and that mispricings are quickly arbitraged away once more investors adopt the knowledge. This implication is inconsistent with the conventional wisdom that financial markets quickly adapt and that investors should continuously search for the newest knowledge which they can exploit only for a short period of time (this line of reasoning is often referred to as the Adaptive Market Hypothesis of Lo [2004]). In fact, our empirical results point in the opposite direction: We find that factor strategies for which there is little documentation in the academic literature do not earn excess returns. Our results therefore support a more conservative approach to incorporating academic insights into investment processes and indicate that it is important that empirical evidence withstands a significant number of attempts of falsification before investment strategies are engineered that incorporate this knowledge.

Perhaps an even more important implication relates to the way academic research is conducted in the stream of literature on empirical finance. Typically, the characteristic of knowledge considered most important by the academic community when a study is considered for publication in an academic journal is the extent to which the knowledge is new. Consequently, little credit is typically given to studies that validate existing knowledge. However, our results indicate that attempts to validate existing knowledge provide an important contribution to the successful incorporation of academic knowledge into investment processes. We therefore argue that validation of existing knowledge should deserve more credits in the academic community because it plays an important role in applying the knowledge.

ACADEMIC LITERATURE, CHOICE OF FACTORS, AND SOME CONSIDERATIONS

The most important factors that have been documented, in our opinion, and the ones that are included in our study are 1) the low-risk factor (e.g., Haugen and Baker [1991]), 2) the small cap and 3) value factors (e.g., Fama and French [1992]), 4) the momentum factor [e.g., Jegadeesh and Titman [1993]), 5) the short-term reversal factor (e.g., Lehmann [1990]); and 6) the long-term reversal factor (e.g., De Bondt and Thaler [1985]). However, while (most of) the results of the above-mentioned anomalies have been confirmed by other studies, there are also several studies that postulate some important considerations regarding the practical applicability of the results of these studies. These studies in particular express their concerns regarding the real-life applicability of momentum and short-term reversal strategies. In light of the goal of our study, we believe it is important not only to discuss positive evidence for factors predicting stock returns, but also to discuss important considerations that have been put forward in the literature.

Specifically, several studies point out that momentum and short-term reversal strategies are concentrated in small cap stocks that typically exhibit large trading and require frequent portfolio rebalancing. As a consequence of these features of the strategies, several studies argue that the excess returns of momentum and short-term reversal strategies may be offset by the trading costs associated with the strategies costs (e.g., Lesmond et al. [2004]; Korajczyk and Sadka [2006]; and Avramov et al. [2006]). On the other hand, there are also some studies that argue that the anomalies are robust to trading costs and can be implemented in a real-life application once strategies are designed to reduce trading costs (e.g., Frazzini et al. [2012]; and De Groot et al. [2012]). There is also a stream of literature that argues that momentum strategies are associated with very high levels of risk, making it difficult to implement in a real-life investment strategy (e.g., Avramov et al. [2007]). Also, when we consider the long-term reversal anomaly, we note that the evidence supporting the existence of the anomaly is substantially weaker than the evidence supporting the existence of the low-risk, small cap, and value anomalies. For example, Fama and French [1996] show that the long-term reversal anomaly is largely encompassed by the value anomaly. Finally, the Adaptive Market Hypothesis of Lo [2004] postulates that factors documented in academic studies to predict stock returns might lose their predictive power after the public dissemination of the factors because professional arbitrageurs such as hedge funds might arbitrage away the premiums associated with the factors. For example, if many investors engaged in a small cap/value strategy, the excess returns of the strategies would eventually disappear because the increased demand for small cap/value stocks drives their prices up and drives expected returns down. However, this theory has not been confirmed by empirical studies. When evaluating the added value of investment managers engaging in factor investing, the considerations that have been put forward regarding some of the factors might be helpful to better understand in which cases the added value might be absent.

DATA AND METHODOLOGY

For our empirical analysis, we obtained return data on U.S. equity funds from the Morningstar database. Our database covers monthly returns for 6,814 U.S. equity funds over the period January 1990 to December 2010. Next, we estimate the single factor model for all funds in our database that have at least 36 consecutive return observations:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the return of fund i in month t, $r_{f,t}$ is the risk-free return in month t, $r_{m,t} - r_{f,t}$ is the Market-Rf factor of French [2012], which represents the return of the value-weighted CRSP universe in excess of the risk-free return, α_i and $\beta_{1,i}$ are parameters to be estimated, and $\varepsilon_{i,t}$ is the residual return of fund i in month t. We now select all funds that have an R-squared value for the single factor model specification above 60%. The reason that we exclude funds with an R-squared value below 60% is that these funds are likely invested in asset categories other than equities (e.g., fixed-income securities) and/or pursue market-neutral investment strategies, and their performance cannot reliably be evaluated using the factor models that we employ in this study. This brings our sample to 4,026 funds. For the first year in our sample, we have 7,809 monthly return observations available. This number steadily increases to 42,621 observations in the final year of our sample.

We obtained return data for the low-risk, small cap, value, momentum, short-term reversal, and long-term reversal anomalies from the webpage of Ken French over the period January 1990 to December 2010. We computed average factor returns and standard deviations over our sample period. Consistent with the results of the aforementioned studies, we observed large premiums associated with the factors: Over our sample period, we observed a small cap premium of 20 basis points per month, a value premium of 33 basis points, a momentum premium of 60 basis points, a short-term reversal premium of 25 basis points, and a long-term reversal premium of 43 basis points. When we consider average factor returns and standard deviations over the second decade in our sample, we observe that there is quite some variability in the magnitude of the premiums over time. For example, while the small cap factor earns a return of 7.50% per annum over the most recent half of our sample, the factor yields a negative return of −3.15% per annum over the first half of our sample period. In the following analysis, we investigate how many investment funds have adapted investment strategies based on these factors, and whether these funds earn consistent excess returns.

To indicate whether mutual funds have adopted investment strategies based on the asset pricing anomalies mentioned earlier, we apply a return-based approach throughout our empirical analysis. More specifically, for each fund, we estimate the six-factor model for their entire return history:

$$\begin{aligned} r_{i,t} - r_{f,t} = {} & \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i} SMB_t + \beta_{3,i} HML_t \\ & + \beta_{4,i} WML + \beta_{5,i} STR_t + \beta_{6,i} LTR_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

where $r_{m,t} - r_{f,t}$, SMB_t, HML_t, WML_t, STR_t, and LTR_t are the returns on factor-mimicking portfolios for the market, small cap, value, momentum, short-term reversal, and long-term reversal factors in month t, respectively, α_i, $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$ $\beta_{4,i}$, $\beta_{5,i}$, and $\beta_{6,i}$ are parameters to be estimated, and $\varepsilon_{i,t}$ is the residual return of fund i in month t.

Next we apply two approaches to indicate whether mutual funds follow investment strategies that are correlated with the return series for the small cap, value, momentum, short-term reversal, and long-term reversal anomalies. The main difference between the two approaches is that the first approach measures whether a fund's exposure to a specific asset pricing anomaly is statistically significant, while the second approach measures whether the exposure is economically significant. With the first approach, we indicate that a fund has statistically significant exposure to a specific style if the *t*-statistic of the beta of the fund to the style is larger than 2. For example, if a fund's *t*-statistic of its SMB beta is larger than 2, that fund is classified as a fund that follows an investment strategy that incorporates the small cap anomaly. And if a fund's *t*-statistic of its HML beta is larger than 2, that fund is classified as a value fund. With the second approach, we indicate that a fund has economically significant exposure to a specific style if the beta of the fund to the style is larger than 0.25. For example, if a fund's SMB beta is larger than 0.25, that fund is classified as a small cap fund. And if a fund's HML beta is larger than 0.25, that fund is classified as a value fund. We indicate that a fund follows a low-beta style if its market beta is smaller than 0.80. Funds can thus have multiple factor classifications simultaneously. Because our methodology requires only fund return data that are readily available, our sample basically covers all funds that existed during our sample period. Therefore, our analysis is free from selection and survivorship bias. In unreported tests, we also experimented with other threshold values (e.g., *t*-values of 1.8 and 2.5 and coefficients of 0.20 and 0.30) and found that our results do not materially change once we use these other values.

Using the above-mentioned classification schemes, we classify only a small portion of all funds as low-beta funds: Only 6% of the funds in our sample exhibit had a market beta lower than 0.8. More funds appear to follow small cap and value factor investing strategies. Depending on whether we consider the statistical significance of the factor exposures or the economic magnitude of the exposures, we find that between roughly 20% and 30% of the funds follow small cap and value investment strategies. When we consider the number of funds in our sample that have statistically significant exposures to the small cap and value factors, we find that 38% of the funds follow small cap investment strategies and 33% of the funds follow value investment strategies. When we consider the number of funds in our sample that have economically significant exposures to the factors, we find that 31% of the funds follow small cap investment strategies and 19% of the funds follow value investment strategies. So basically, regardless of whether statistical or economic significance is considered, it appears that a substantial number of mutual funds engage in small cap and value investment strategies.

Next, we consider how many funds follow momentum strategies. While we find that 25% of the funds do exhibit statistical significant exposure to the momentum factor, only a very small number of funds (2%) have economically significant exposure to the factor. Apparently, just a small number of funds engage in momentum strategies with high conviction. We find similar results for the number of funds engaging in short- and long-term reversal strategies: While some funds do have statistically significant exposure to the factors, only a very small number of funds appear to really engage in reversal strategies (1% to 2% of the funds in our sample).

To measure fund outperformance, we take the intercept from the single factor model in Equation (1). This intercept, known as Jensen's [1969] alpha, reflects a fund's return that is not due to its sensitivity to returns of the market portfolio (i.e., "beta"). To ensure that our results are not driven by outliers, we normalize and winsorize fund alphas:

$$z\_Alpha_i = \min\left(2, \max\left(-2, \frac{\alpha_i - \mu_\alpha}{\sigma_\alpha}\right)\right) \tag{3}$$

where μ_α is the average fund alpha obtained from the global market model and σ_α is the cross-sectional standard deviation. Next, we run the following regression to investigate whether funds that engage in factor investing exhibit differential performance:

$$\begin{aligned} z\_Alpha_i = a &+ b_1 LOW\_BETA \\ &+ b_2 SMALL\_CAP + b_3 VALUE \\ &+ b_4 MOMENTUM \\ &+ b_5 SHORT\_REVERSAL \\ &+ b_6 LONG\_REVERSAL + \varepsilon_i \end{aligned} \tag{4}$$

where LOW_BETA is an indicator variable that equals 1 if a fund is classified as a fund engaging in low-beta factor investing and zero otherwise; SMALL_CAP is an indicator variable that equals 1 if a fund is classified as a fund engaging in small cap factor investing; VALUE is an indicator variable that equals 1 if a fund is classified as a fund engaging in value factor investing; MOMENTUM is an indicator variable that equals 1 if a fund is classified as a fund engaging in momentum factor investing; SHORT_REVERSAL is an indicator variable that equals 1 if a fund is classified as a fund engaging in short-term reversal factor investing; and LONG_REVERSAL is an indicator variable that equals 1 if a fund is classified as a fund engaging in long-term reversal factor investing. We run the regressions for fund classifications based on both statistical and economic significance.

EMPIRICAL RESULTS

Proceeding further, we move to our empirical analysis. In our first analysis, we regress fund performance (*z_Alpha*) on the indicator variable that indicates whether the funds have economically significant factor exposures. We also base fund classification on the statistical significance of the funds' exposures, but since this analysis yields very similar results, we do not report them for the sake of brevity. Besides the multi-factor regression in Equation (4), we also run single-factor regressions for each indicator variable. Running both single- and multi-factor regressions helps us to detect any interaction effects. The results are presented in Exhibit 1.

When we consider the results in Exhibit 1 of Regressions 1, 2, and 3, we observe that funds engaging in low-beta, small cap, and value strategies earn significant excess returns. Low-beta funds earn alphas that on average are 0.24 standard deviations above the cross-sectional mean; small-cap funds earn alphas that are 0.59 standard deviations above the mean; and value funds earn alphas that are 0.69 standard deviations above the mean. These results are statistically highly significant. When we consider the results of Regressions 4, 5, and 6, we observe that funds that have adopted momentum and reversal strategies have not been successful in earning excess returns. In fact, short-term reversal funds have significantly underperformed the average fund. When we consider the results for the multi-factor regression (Regression 7), our conclusions remain unchanged. It does appear that some portion of the outperformance of value funds can be attributed to these funds being exposed to small-cap stocks.

Up to this point, we conclude that there is evidence supporting the added value of funds adopting factor investing strategies in some cases. In our follow-up analysis, we investigate whether this added value has been sustainable and economically significant. We finalize our analysis by making a first attempt at setting up a framework that might be helpful to determine the successful application of academic insights in the context of investment strategies and explain why some factor investing strategies are successfully implemented and others are not.

To investigate whether the excess returns earned by funds that engage in factor investing have been sustainable and have not disappeared after the public dissemination of the anomalies, we perform a subsample analysis and repeat our regression analysis for the second half of our sample period. Because we did not observe material differences between our results when we classify funds on the statistical or economic magnitude of their factor exposures, we base our fund classification through the remainder of this study on the economic magnitude of the funds' factor exposures. Specifically, we re-perform all analyses described earlier for the second subsample of our dataset. Hence, fund classifications in this analysis are based on fund and factor returns over the second subsample of our dataset. It does appear that the fund classifications are very consistent over our sample periods: In more than 90% of the cases, the classification of a fund over the second half of our sample

Exhibit 1

Fund (Economical) Factor Exposures and Outperformance

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5	Regression 6	Regression 7
Intercept	–0.01	–0.18	–0.13	0.01	0.01	0.01	–0.27
t-statistic	–0.69	–11.00	–8.54	0.43	0.78	0.56	–15.92
LOW_BETA	0.24	–	–	–	–	–	0.24
t-statistic	4.07	–	–	–	–	–	4.50
SMALL_CAP	–	0.59	–	–	–	–	0.52
t-statistic	–	20.43	–	–	–	–	18.06
VALUE	–	–	0.69	–	–	–	0.57
t-statistic	–	–	20.29	–	–	–	17.01
MOMENTUM	–	–	–	–0.07	–	–	–0.11
t-statistic	–	–	–	–0.72	–	–	–1.22
SHORT_REVERSAL	–	–	–	–	–0.98	–	–0.89
t-statistic	–	–	–	–	–5.62	–	–5.59
LONG_REVERSAL	–	–	–	–	–	–0.17	–0.09
t-statistic	–	–	–	–	–	–1.66	–0.98

is the same as over our entire sample period. When we consider our results for the second subsample of our dataset, it appears that our results become even stronger: While low-beta, small cap, and value fund outperformance is 0.24, 0.59, and 0.69 standard deviations above average fund performance over our entire sample period, these figures are 0.30, 0.93, and 0.88 standard deviations over the second half of our sample period, respectively. These results are inconsistent with the Adaptive Market Hypothesis, which states that financial markets quickly adapt and that investors should continuously search for the newest knowledge that they can exploit only over a short period of time, and indicate that investors do not have to worry that the added value of incorporating new knowledge is only short-lived and that mispricings are quickly arbitraged away once more investors adopt the knowledge. The systematic nature of the anomalies indicates that they probably originate from a persistent source and is consistent with either a risk-based explanation for the anomalies or systematic behavioral issues by actors in financial markets.

Continuing our analysis, we address the economic significance of the excess returns that are earned by funds engaging in factor investing. In our previous analysis, we compared the performance of factor investing funds relative to the performance of funds that do not engage in factor investing. While we found that factor investing funds do better than no-factor investing funds, it is still an open question whether factor investing funds outperform passive benchmark indexes. In other words, it is unclear how factor investing funds perform in a comparison vis-à-vis passively managed index funds and if they earn positive alphas relative to the market benchmark. To investigate this issue, we take fund alphas ($Alpha_i$) resulting from Regression (1) and regress the alphas on the indicator variables that indicate whether the funds engage in factor investing:

$$\begin{aligned} Alpha_i = {} & a + b_1 LOW\_BETA \\ & + b_2 SMALL\_CAP + b_3 VALUE \\ & + b_4 MOMENTUM \\ & + b_5 SHORT\_REVERSAL \\ & + b_6 LONG\_REVERSAL + \varepsilon_i \end{aligned} \tag{5}$$

when we consider the differential alphas for low-beta, small cap, and value funds, we observe that these funds earn significantly larger alphas than the other funds. Low-beta funds have a differential alpha of 91 basis points per annum (with a *t*-statistic of 3.94), small cap funds have a differential alpha of 211 basis points per annum (with a *t*-statistic of 18.11), and value funds even have a differential alpha of 259 basis points per annum (with a *t*-statistic of 19.00). The alphas of small cap and value funds are even significantly larger than zero, at 56 and 119 basis points per annum, respectively. On the other hand, factor investing funds engaging in momentum and reversal strategies do not display positive differential alphas. In fact, funds engaging in short-term reversal strategies even appear to earn a highly negative differential alpha of 453 basis points per annum (with a *t*-statistic of −6.53).

Another way to gauge the economic significance of funds incorporating factor investing insights into their investment strategies is to consider the funds' success ratios versus other funds. We therefore construct a dummy variable that indicates whether a fund has a positive alpha (1 if true and zero if false) and regress this dummy variable on the indicator variables that indicate whether the funds engage in factor investing:

$$\begin{aligned} SUCCES_i = {} & a + b_1 LOW\_BETA \\ & + b_2 SMALL\_CAP + b_3 VALUE \\ & + b_4 MOMENTUM \\ & + b_5 SHORT\_REVERSAL \\ & + b_6 LONG\_REVERSAL + \varepsilon_i \end{aligned} \tag{6}$$

when we consider the results of this analysis, we observe that both low-beta, small cap, and value factor investing funds have a significantly greater probability to yield outperformance than the average fund, as the coefficient estimates for *LOW_BETA*, *SMALL_CAP*, and *VALUE* are significantly positive. For funds engaging in momentum or reversal strategies, we do not find a positive differential success ratio. Besides average success ratios, we continue our analysis and consider the distributions of the alphas for various groups of funds. To this end, we construct a histogram that shows how fund alphas vary across a range of performance buckets. The results of this analysis are shown in Exhibit 2.

In the first two rows of Exhibit 2, the distribution of fund alphas is shown for funds that do not engage in factor investing. This group of funds is basically our

EXHIBIT 2
Distributions of Success Ratios

	< –5%	–5% to –4%	–4% to –3%	–3% to –2%	–2% to –1%	–1% to 0%	0% to 1%	1% to 2%	2% to 3%	3% to 4%	4% to 5%	< 5%
No exposures	10%	7%	13%	17%	17%	16%	10%	5%	2%	1%	1%	1%
Total	**80%**						**20%**					
LOW_BETA	7%	4%	6%	7%	17%	12%	13%	11%	6%	6%	5%	7%
Total	**53%**						**47%**					
SMALL CAP	9%	4%	4%	5%	7%	10%	11%	12%	9%	10%	7%	11%
Total	**39%**						**61%**					
VALUE	5%	1%	2%	6%	7%	13%	12%	16%	10%	10%	6%	12%
Total	**34%**						**66%**					
MOMENTUM	16%	8%	6%	8%	16%	9%	7%	11%	3%	6%	3%	7%
Total	**63%**						**38%**					
SHORT_REVERSAL	38%	19%	12%	12%	12%	4%	0%	0%	0%	0%	0%	4%
Total	**96%**						**4%**					
LONG_REVERSAL	18%	10%	9%	18%	8%	6%	6%	5%	6%	4%	3%	9%
Total	**68%**						**33%**					

control group for evaluating the performance of factor investing funds in our earlier analyses. Strikingly, it appears that only a very small group of funds that do not engage in factor investing are able to earn positive alphas. A total of 80% of these funds earn negative alphas, with the largest number of funds earning an alpha between minus 2% and minus 3% per annum. Only half of the funds earning positive excess returns earn an alpha smaller than 1% per annum, and only 5% of the funds earn an alpha larger than 2% per annum. We continue our empirical analysis by evaluating the alpha distributions for low-beta, small cap, value, momentum, and reversal funds separately.

In the next rows, the alpha distribution is shown for low-beta funds. Interestingly, we observe that the probability that low-beta funds earn a negative alpha is substantially smaller than for our control group: While 80% of the non-factor investing funds underperform the market index in the long run, this figure is 53% for low-beta funds. For small cap, value, and momentum funds, we also observe substantially smaller probabilities on underperformance of 39%, 34%, and 63%, respectively. Also, the probability of yielding a large outperformance is substantially larger for factor investing funds: While only 1% of the non-factor investing funds earn an alpha of more than 5% per annum, this figure is 7%, 11%, 12%, and 7% for low-beta, small cap, value, and momentum funds, respectively. For both short-term and long-term reversal funds, however, there is no evidence of outperformance. While the alpha distribution of long-term reversal funds is somewhat more favorable than for our control group of no-factor investing funds, almost all short-term reversal funds in our sample (96%) appear to deliver negative alphas.

When we consider all empirical results in this section together, we can conclude that there is compelling evidence supporting the added value of incorporating academic insights in the form of factor investing for mutual funds. In particular, low-beta, small cap, and value funds appear to deliver economically and significantly better returns than no-factor investing funds. For funds engaging in momentum strategies, we find mixed evidence. While the majority of these funds earn positive excess returns, there are also quite a few of these funds that earn highly negative alphas. Our interpretation of these mixed results is that some fund managers are able to cope with the trading frictions and risks associated with momentum investing, while others are not.

Apparently it is more difficult to successfully engage in momentum investing than in, for example, value investing. Furthermore, for reversal funds, we do not find evidence of these funds earning differential returns. In fact, for short-term reversal funds, the results seem to indicate that these funds destroy value.

Apparently, the incorporation of new knowledge does not always appear to result in adding value for investment funds. We hypothesize that the extent to which new academic knowledge can successfully be adopted by mutual funds in their investment strategies depends on the strength of the empirical evidence supporting the results. While numerous studies document momentum and reversal patterns in the data, there are also a number of studies that argue that trading frictions might prevent profitable execution of these strategies. We therefore postulate that it is less likely that new academic knowledge can successfully be adopted in the investment management industry if the empirical evidence on which the knowledge is based exhibits significant ambiguities.

This brings us to the final question that we address in this section: To what extent does incorporation of a certain academic insight generate added value above and beyond the value generated by another insight? For example, if a fund already engages in a small cap investment strategy, how would the probability of the fund yielding outperformance change if the fund also engaged in a value strategy? To investigate this research question, we proceed the following way: First, for all funds, we construct counter-variables that indicate to how many factors the funds are exposed. As in our previous analyses, we indicate that a fund is exposed to a certain factor if its loadings are larger than 0.25. So, for example, a fund that has a market beta of 1, a loading on SMB of 0.30, a loading of 0.30 on HML, and zero exposure to the other factor would be classified as a fund with exposure to two factors. Now, we regress (winsorized) alphas and success ratios on the indicator variables. For example, for winsorized alphas, we run the following regression:

$$z\_Alpha_i = a + b_1 1\_FAC + b_2 2\_FAC + b_3 3\_FAC + \varepsilon_i \tag{7}$$

where 1_*FAC*, 2_*FAC*, and 3_*FAC* are dummy variables that indicate whether a fund is exposed to one, two, or three factors, respectively. We have no fund in our sample that is exposed to more than three factors. The results of the analysis are presented in Exhibit 3.

EXHIBIT 3
Multiple Factor Exposures and Outperformance

	#	z_Alpha	Alpha	Success
Intercept	2146	–0.27	–1.89	0.20
t-statistic	–	–15.03	–26.26	20.67
1_FAC	1360	0.46	1.63	0.31
t-statistic	–	16.06	14.06	19.87
2_FAC	484	0.91	3.34	0.48
t-statistic	–	21.75	19.88	21.66
3_FAC	36	0.98	3.53	0.58
t-statistic	–	6.99	6.29	7.77

When we consider the results in Exhibit 3, we can see that for both (winsorized) alphas and success ratios, we have significant loadings on all indicator variables. More specifically, in all cases, the loading on 2_*FAC* is larger than the loading on 1_*FAC*, and the loading on 3_*FAC* in turn is larger than the loading on 2_*FAC*. To put it another way, the more strategies to which a fund is exposed, the higher its alpha and success ratio. For instance, no-factor investing funds have an average alpha of −189 basis points and a success ratio of 20%. For comparison, funds that are exposed to one factor have an average alpha of −26 (= −189 + 163) basis points per annum and a success ratio of 51% (= 20 + 31); funds that are exposed to two factors have an average alpha of 145 basis points and a success ratio of 68%; and funds that are exposed to three factors have an average alpha of 164 basis points and a success ratio of 78%. Hence, our results clearly indicate that incorporation of a certain academic insight can have incremental value above and beyond the added value of another insight.

CONCLUSION

In this study, we perform an in-depth analysis of the differential performance of adaptors of academic knowledge in the investment management industry. In particular, we investigate whether investors who have adopted investment strategies based on asset pricing anomalies documented in the academic literature (i.e., the low-beta, small cap, value, momentum, short-term reversal, and long-term reversal anomalies) earn consistent excess returns. For this purpose, we evaluate the performance of a large sample of U.S. equity mutual funds over the period 1990 to 2010 and use a regression-based method to indicate whether the funds follow factor investing strategies based on the low-beta, small cap, value, momentum, short-term reversal, and long-term reversal anomalies. We find evidence supporting the added value of funds adopting low-beta, small cap, and value strategies. We also find that the excess returns earned by these funds are sustainable and have not disappeared after the public dissemination of the anomalies: Not only do we find a positive relation between fund performance and the adoption of factor investing strategies during the first decade of our sample, we also find this positive relation to be present over the second decade of our sample. On the other hand, we do not find consistent evidence supporting added value for funds adopting momentum and reversal strategies. For funds engaging in momentum strategies, we find mixed evidence of positive excess returns, and for funds engaging in short-term reversal strategies, we even find evidence of negative excess returns. We conclude that there can be large added value of funds incorporating academic knowledge in their investment processes by engaging in factor investing. However, the incorporation of new knowledge does not always appear to result in adding value. We hypothesize that the extent to which academic knowledge can successfully be adopted by mutual funds in their investment strategies depends on the strength of the empirical evidence supporting the results. It is less likely that academic knowledge can successfully be adopted in the investment management industry if the empirical evidence on which the knowledge is based exhibits significant ambiguities.

Our findings have important implications for the role of academic research and knowledge management in the investment management industry. In the first place, our results provide a case to justify expenditures on research and development in the investment management industry. Our results also indicate that the excess returns earned by funds that have engaged in factor investing strategies are sustainable and do not disappear after the public dissemination of the anomalies. This result implies that investors do not have to worry that the added value of incorporating new knowledge is only short-lived and that mispricings are quickly arbitraged away once more investors adopt the knowledge. Our results therefore support a more conservative approach to incorporating academic insights into investment processes and indicate that it is important that empirical evidence has withstood a significant number of attempts of falsification before investment strategies are engineered that incorporate this knowledge.

Finally, our results indicate that attempts to falsify existing knowledge provide an important contribution to the successful incorporation of academic knowledge into investment processes. We therefore argue that falsification of existing knowledge deserves more credits in the academic community because it plays an important role in applying the knowledge.

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