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TIMING IS NOT EVERYTHING—ASSESSING MANAGER SKILL IN FACTOR TIMING

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We introduce an innovative framework to assess the contribution and persistence of factor timing within US large-cap equity funds. After decomposing active returns into three components—strategic factor contribution, tactical factor contribution and security selection—we find that they are all significant but security selection is the dominant contributor. We also find that the portfolio managers who rely on factor timing to drive performance do not seem to exhibit persistence in their abilities. Finally, across all funds, strategic and tactical factor tilts do not drive future active returns. Security selection is the key differentiator for future outperformance.

The asset management industry has a love-hate relationship with factor timing. On the one hand, investors are enamored by the allure of being able to predict the performance of factors and the potential to position portfolios towards the outperforming factors. Reality though is a lot harsher as portfolio returns are whipsawed by sudden and volatile factor returns over periods from one day to a few years. Indeed, for most investors, factor timing is not a part of the standard repertoire of tools to generate returns. Fundamental portfolio managers rely on bottom–up stock selection and largely ignore the un-intended factor exposures in their portfolios. These managers are willing to live through short-term factor fluctuations to achieve their longer-term predictions at the stock level. Quantitative portfolio managers generally target specific factors that they believe will outperform over time but they usually have consistent exposures to these factors most of the time. These systematic investors tend to believe that there is not enough "breadth" in factor timing to warrant varying exposures over shorter investment horizons. Indeed, strong long-term investment strategies may be undone with untimely factor bets.

With that as the backdrop, investors are nevertheless paying more attention to factor exposures and factor returns since the Global Financial Crisis. Given the extreme movements in factors like beta,

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Table 1 Long–short factor returns by year (%).

Factor	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Beta	27.7	6.0	8.0	−3.9	29.5	15.3	24.6	18.5	20.0	−16.8	−14.4	−22.4	30.4	10.6
Size	11.6	7.8	5.3	−2.9	−6.3	−2.8	−6.1	−23.1	5.9	3.4	25.3	5.3	17.8	7.1
Value	−10.2	22.3	17.5	−0.9	3.5	4.5	13.7	−8.1	−24.2	42.4	17.2	8.7	3.1	6.9
RMW	8.8	6.6	−6.6	5.3	0.9	13.4	8.4	0.3	−20.1	26.2	19.7	26.4	−14.5	6.2
CMA	−10.6	6.0	10.8	3.8	1.7	0.0	3.7	−4.9	−8.7	38.3	9.6	19.6	12.2	−6.5
Momentum	11.3	2.3	19.3	1.5	12.3	6.1	10.4	26.3	25.1	24.3	−2.8	26.7	−13.5	−0.3

Factor	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beta	2.9	10.1	1.0	−37.6	28.1	17.3	0.4	16.2	35.2	11.7	0.1	13.2	21.5
Size	−0.4	1.8	−7.4	5.0	7.4	12.2	−4.0	0.3	5.9	−6.9	−5.9	8.4	−4.5
Value	7.8	12.5	−13.6	4.6	−2.9	−3.4	−8.0	8.4	1.1	−1.9	−9.8	20.9	−11.0
RMW	1.5	2.1	3.7	25.2	0.9	−2.2	12.1	−4.6	−2.9	0.4	−1.2	3.1	6.1
CMA	−4.9	7.2	−7.5	5.4	−2.2	9.1	−1.1	7.8	0.7	−1.7	−8.8	8.5	−9.3
Momentum	17.0	−5.6	26.1	12.5	−50.9	6.2	11.3	−0.9	7.2	2.9	18.2	−18.5	8.6

size and momentum, investors are tempted to time factors in an attempt to generate higher returns (Table 1). Other investors may want to mitigate factor risks in their portfolios so being able to predict factor movements may help portfolio construction. Finally, the asset management industry has created research, strategies, products and vehicles to encourage and facilitate factor timing. These trends have made it more fashionable to not only conduct factor timing research but also to implement these ideas into actual strategies.

Despite the emergence of factor timing and factor products over the past decade, there has been a dearth of research into the return contribution of factor selection and the level of manager skill in this endeavor. Historically, various studies have explored market timing in funds but that has only focused on one factor, the market beta. In their pioneer paper on market timing, Treynor and Mazuy (1966) studied 57 open-end mutual funds from 1953 to 1962 and did not find any evidence of market timing skills. Henriksson (1984) evaluated 116 mutual funds from 1968 to 1980 based on the methodology developed in Henriksson and Merton (1981) but also did not find any evidence of successful market timing. Bollen and Busse (2001) found some evidence of successful market timing when using daily data instead of monthly observations. Finally, Jiang (2003) developed a nonparametric test for market timing but did not find superior timing abilities amongst portfolio managers. Numerous variations in the above-mentioned studies have also concluded that timing the markets is extremely difficult.

As portfolio managers have moved beyond market timing to utilize factor selection as a new tool to generate higher investment returns, it is critical that we develop frameworks and tools to evaluate the outcomes of their decisions. Holdings-based methods breaking down portfolio returns into allocation and selection effects can be extremely helpful in assessing how factor exposures in a portfolio impact returns. Indeed, various third-party risk vendors provide this service for their clients. One of the notable studies in this vein is from Jiang *et al.* (2007) where they analyzed holdings data for around 2,300 funds from 1980 to 2002 and found that the average portfolio manager exhibited market timing capabilities. The potential drawback in conducting holdings-based analyses is that holdings data may not be available, especially over shorter horizons. For example, while it may be trivial assessing a firm's internal strategies using holdings, it is significantly more difficult applying the same analysis to competitors. Holdings for competitors and external funds are often stale, incomplete or simply not available. In addition, factor timing by its very nature is short-term and needs to be evaluated over short-time horizons so it is important to obtain holdings that are consistent with this requirement. Quarterly or monthly holdings are not adequate for this task.

Returns-based analysis fulfills our needs nicely because this method only requires historical returns and can easily be applied to shorter horizons. We obtained daily returns for mutual funds from a variety of sources and thus are able to study factor timing over shorter time scales. Specifically, we believe that factor timing should be assessed over quarterly periods using daily data. This horizon strikes the right balance between data requirements (approximately 60 daily observations) and the period over which factor timing will likely be observable in portfolio manager processes. Our experience suggests that managers typically take active factor exposures over periods greater than one month and may rebalance monthly.

Solely using returns to imply manager decisions has drawbacks. Specifically, without any insights into the actual holdings it is difficult to discern if the results from a returns-based analysis are spurious—that is, relationships and correlations that we find in the data may simply be noise and therefore, not capture any true underlying trends. For example, if a strategy happens to outperform during a period when a certain factor also outperforms, we would conclude that the strategy is likely exposed to that factor. However, we know that there may be other effects in play—other factors may have also performed well during that period or there may be idiosyncratic stock-specific effects that drove the returns of certain stocks. This example highlights the potential drawback of returns-based analysis but on balance, this method can still provide useful insights into manager decisions and manager skill.

In Chin *et al.* [2018], we provided a framework to assess manager skill using returns-based analysis. We calculated *prime alpha* as the residual portfolio return after accounting for the benchmark return and a series of common factors. We find that prime alpha is persistent over time, unlike active returns, and thus is a useful indicator of manager skill because it strips out the cyclical factor returns that may influence investment results. In that paper, we showed that prime alpha captures manager skill and encompasses the various discretionary decisions at a portfolio manager's disposal—factor selection (which may include country and sector rotation) and stock selection. In this paper, we extend that research by separating out these components of manager skill.

We make a few contributions to the existing literature. First, we create a framework to assess the impact of three components in active returns: strategic factor contribution, tactical factor contribution and stock selection. Using this framework, we calculate these three components across US large-cap funds to determine their impact and significance over time. Our research suggests that all three components are significant in manager returns but security selection is the biggest driver. We then leverage this framework to assess manager skill along these three components and find that there is persistence in tactical factor contributions and in security selection. This suggests that on average, managers do seem to have processes or skills that give them the ability to repeat their historical successes or failures in factor timing and stock selection. However, when we analyze the "Factor Timers" (those funds where tactical factor contributors drove performance), we find there is no persistence in skill and conclude that factor timing is very difficult. Finally, we assess how these components drive future active returns and find that security selection is the dominant driver. Ultimately, our research suggests that stock selection is the biggest determinant of manager skill and investors should focus on that component before investing with a manager.

1 Data

To study factor timing, it is critical to obtain daily data to capture short-term decisions made by portfolio managers. Tilts in factors are by definition, temporary, and are meant to capture opportunities in short-term market movements. Across most funds in the industry, holdings are publicly available at quarterly intervals at best. However, this is not appropriate for studying portfolio manager decisions that occur over days or weeks. As a result, we use daily fund returns to gauge short-term factor decisions.

We use Morningstar's database of mutual fund returns from 1991 to 2017 as the data source for our analyses. We filtered the open-ended US large-cap equity mutual funds with at least one year's worth of history and benchmarked to one of the large-cap indices (S&P 500, Russell 1000, Russell 1000 Growth and Russell 1000 Value). For each fund, the share class with the longest history was used to represent the strategy. After making these adjustments, we have approximately 500 firms with almost 2,000 funds in our dataset.

The Morningstar database provides the assets under management (AUM) covered by the strategies. At the end of 2017, the AUM covered by the strategies in our study sample was approximately \$1.4 trillion for the approximately 300 funds for which data was available. We believe that this asset coverage is sufficiently large across the universe and therefore, our dataset is representative of the strategies used in the industry.

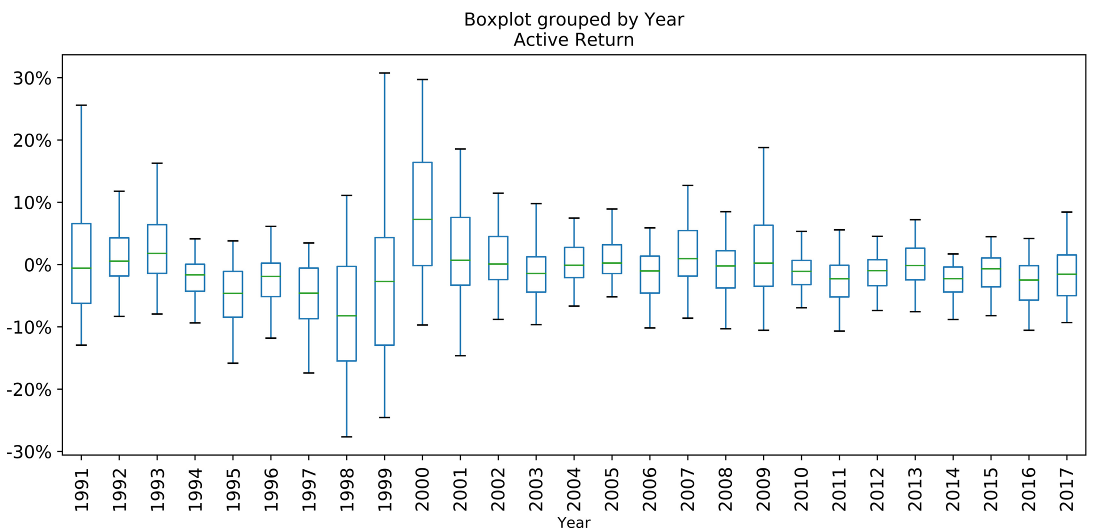

Figure 1 Distribution of active returns each year.

To decompose the manager returns, we use the five factors from Fama and French's (2015) paper and Carhart's (1997) momentum factor. We obtain the daily factor returns from the Fama–French website.

Figure 1 shows the distribution of active returns (after-fee portfolio returns minus benchmark returns) on an annual basis of all the funds in our dataset. In all of our figures showing distributions, we note the 5th, 25th, 50th, 75th and 95th percentiles. We can see that there is more dispersion amongst managers during periods of heightened market volatility, as exhibited during the Technology Bubble around the turn of the century and the Global Financial Crisis from 2007 to 2009. This should not be surprising because skilled managers can differentiate themselves more when the impact of their exposures is magnified. Similarly, unskilled managers are exposed during these periods.

2 Factor timing framework

We use the framework created by Chin *et al.* (2018) to decompose manager returns into strategic factor tilts and manager skill. This skill, called prime alpha, is the residual from a regression of manager returns against a series of common factors. In this paper, we further decompose manager skill into its two core drivers: factor timing and security selection.

For a strategy i during month T,

$$AR_{i,T} = R_{i,T} - B_{i,T} \tag{1}$$

where $AR_{i,T}$ is the relative return of strategy i during month T and is calculated as the difference between $R_{i,T}$, the absolute return of strategy i during month T, and $B_{i,T}$, the monthly return of strategy i's benchmark during month T.

We further decompose the active return $AR_{i,T}$ by running a regression using the Fama–French and Carhart factors:

$$AR_{i,T} = \alpha_i + \boldsymbol{\beta}_i' * \mathbf{F}_T + \varepsilon_{i,T} \tag{2}$$

where $\boldsymbol{\beta}_i$ is the vector of betas to the factors for strategy i ($\boldsymbol{\beta}_i'$ is the transpose of β_i) and $\mathbf{F}_T$ is the vector of factor returns during month T:

$$\beta_i = \begin{bmatrix} \beta_{i,Mkt-Rf} \\ \beta_{i,SMB} \\ \beta_{i,HML} \\ \beta_{i,RMW} \\ \beta_{i,CMA} \\ \beta_{i,MOM} \end{bmatrix} \tag{3}$$

$$F_T = \begin{bmatrix} F_{T,Mkt-Rf} \\ F_{T,SMB} \\ F_{T,HML} \\ F_{T,RMW} \\ F_{T,CMA} \\ F_{T,MOM} \end{bmatrix}. \tag{4}$$

In terms of the factors used in the regression, $F_{T,Mkt-Rf}$ is the return of the relevant benchmark minus the US 3-month T-Bill return during month T, $F_{T,SMB}$, $F_{T,HML}$, $F_{T,RMW}$ and $F_{T,CMA}$ are the returns from small minus big, value minus growth, robust minus weak and conservative minus aggressive factors respectively during month T, $F_{T,MOM}$ is the momentum factor return during month T, and $\varepsilon_{i,T}$ is the residual from the regression.

For each fund, Regression (2) is run over the life of the fund and we call the betas from the regression the "strategic betas." We then define prime alpha as the difference between the active return and the strategic factor returns:

$$PA_{i,T} = AR_{i,T} - \hat{\beta}_i' * F_T \tag{5}$$

where $\hat{\beta}_i$ is the vector of strategic betas estimated from the regression. Note that we can use the strategic betas of a fund to calculate the strategic factor impact and the prime alpha over the life of the funds as well as over shorter periods.

In this setup, prime alpha includes the returns to stock selection and factor timing. Strategic and persistent exposures to factors will be captured by the factor structure in Regression (2). On the other hand, the returns from tactical factor bets will not be captured by the factor structure and will therefore be included as part of the unexplained component of manager returns. This attribution is consistent with how the industry thinks about skill. Persistent factor exposures, by definition, do not change and therefore do not demonstrate skill while dynamic factor exposures result from changing manager views on factor opportunities and therefore, reflect a manager's capabilities.

To separate prime alpha into stock selection and factor timing, we need a method to capture changes in short-term factor tilts. Monthly returns do not provide enough granularity for this exercise because factor tilts tend to change over weeks, not months or years. As a result, we use daily returns to capture the dynamic factor tilts. Specifically, for each fund and for each calendar quarter q,[1] we use a variation of Regression (2) to decompose the return drivers over that quarter using daily returns denoted by t.[2]

Our formulation is represented as

$$AR_{i,t} = a_i + \mathbf{b}_i' * \mathbf{F}_t + \varepsilon_{i,t} \tag{6}$$

where $\mathbf{b}_i$ is similar to $\boldsymbol{\beta}_i$ in Regression (2) but is estimated over a quarter rather than over the life of the fund. We define $\mathbf{b}_i$ as the vector of short-term betas for fund i.

The betas from this regression represent the short-term factor exposures and we can compare these betas with the long-term strategic betas. We define the bet on factors during quarter q as the difference between the short-term beta ($\mathbf{b}$) in quarter q and the long-term strategic beta (β):

$$\widehat{\Delta}_{i,q} = \widehat{b}_{i,q} - \widehat{\beta}_i. \tag{7}$$

The tactical factor contribution is the return generated by varying factor exposures over time and thus captures factor timing in investment strategies. When portfolio managers deviate from their long-term strategic factor exposures, they are making bets on those factors. Our formulation captures those decisions.

An important point to note is that if a strategic beta for a factor is insignificant after running Regression (2), its value is considered to be zero in Equation (7). Similarly, if the short-term beta for a factor is insignificant from Regression (6), its value is also deemed to be zero in Equation (7). In both examples however, the *bet* can still be non-zero.

We are now ready to decompose strategy i's active return in quarter q into three components: strategic factor contribution (SC), tactical factor contribution (TC) and residual return (R):

$$SC_{i,q} = \hat{\beta}_i' * F_q \tag{8}$$

$$TC_{i,q} = \widehat{\Delta}_{i,q}' * F_q \tag{9}$$

$$R_{i,q} = AR_{i,q} - SC_{i,q} - TC_{i,q}. \tag{10}$$

We can then link the quarterly results over time to derive annualized and since inception contributions.

3 Results—Overall

The annual decomposition of active returns is shown in Figure 2. Over time, strategic factor selection, i.e., the persistent factor exposures in funds, slightly added to performance across all funds. This component ebbed and flowed through the years but long-term factor biases have helped.

Tactical factor selection is slightly negative over the study period. Note that 2007 and 2009 were

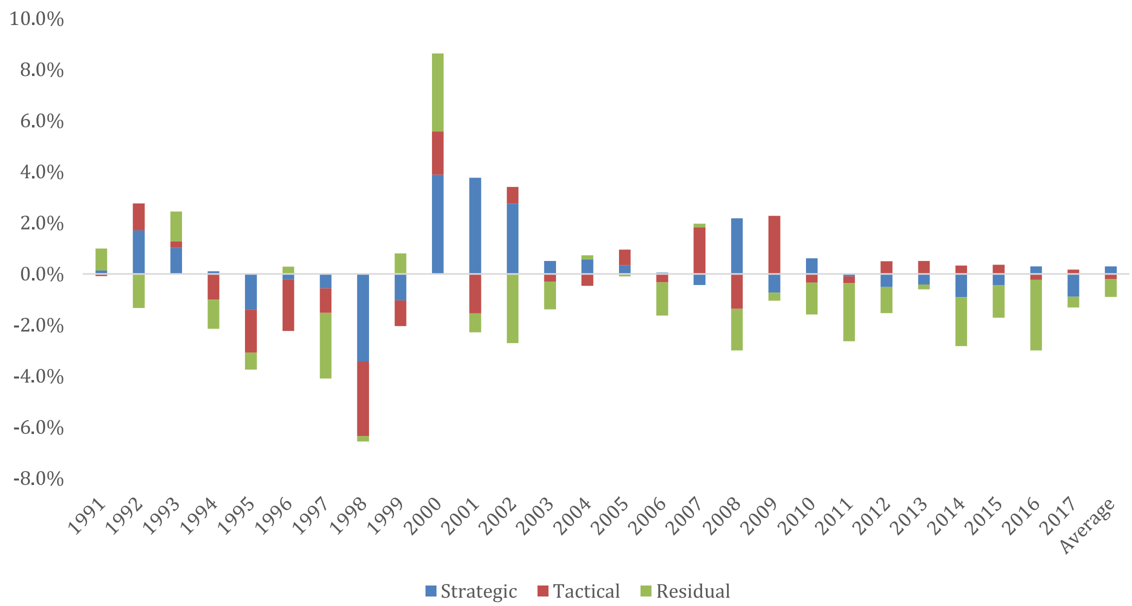

Figure 2 Decomposition of active returns.

exceptionally strong years for factor timing while managers struggled in the late 1990s.

The residual component largely captures stock selection and we will use these terms interchangeably. Over time, this component has detracted from performance and has deteriorated over the last ten years, suggesting that portfolio managers have had a difficult time delivering positive stock selection.

In terms of significance, Figure 3 shows that strategic and tactical factor contributions account for about 25–30% each while stock selection accounts for about 45%. These percentages vary across the funds in the dataset but for a vast majority of the funds, factor exposures play a significant role in manager performance. This reinforces the notion that even "stock pickers" have factor exposures and those exposures can significantly influence their returns.

3.1 Results—Strategic factor contribution

Figure 4 shows the importance of factors for the funds in our research universe. Specifically, about 75% of the funds have three or less significant factors out of the set of factors we used. This is consistent with industry expectations because the bulk of the strategies are still fundamentally driven and these strategies tend to be constructed bottom up through security selection. As a result, factors exposures in a portfolio may be indirectly driven from the underlying stocks, and depending on the collection of stocks in the portfolio, factor exposures can vary over time.

Figure 5 drills into the distribution of exposures for each factor. Several intuitive results appear in the results. First, over time, most funds have market betas (Mkt-Rf) less than one or similarly, *relative* market betas less than zero. This is not surprising given that many funds hold some cash to manage investor flows. Funds also have a small-cap bias, consistent with many other findings in literature. Finally, although the median fund is exposed to the other factors, the exposures across all the managers are more evenly distributed around zero.

Figure 6 shows the annual contributions by factor. Over the whole period, the underweight to

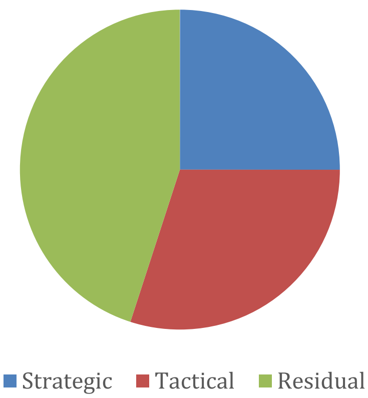

Figure 3 Average contribution of the three components in active returns.

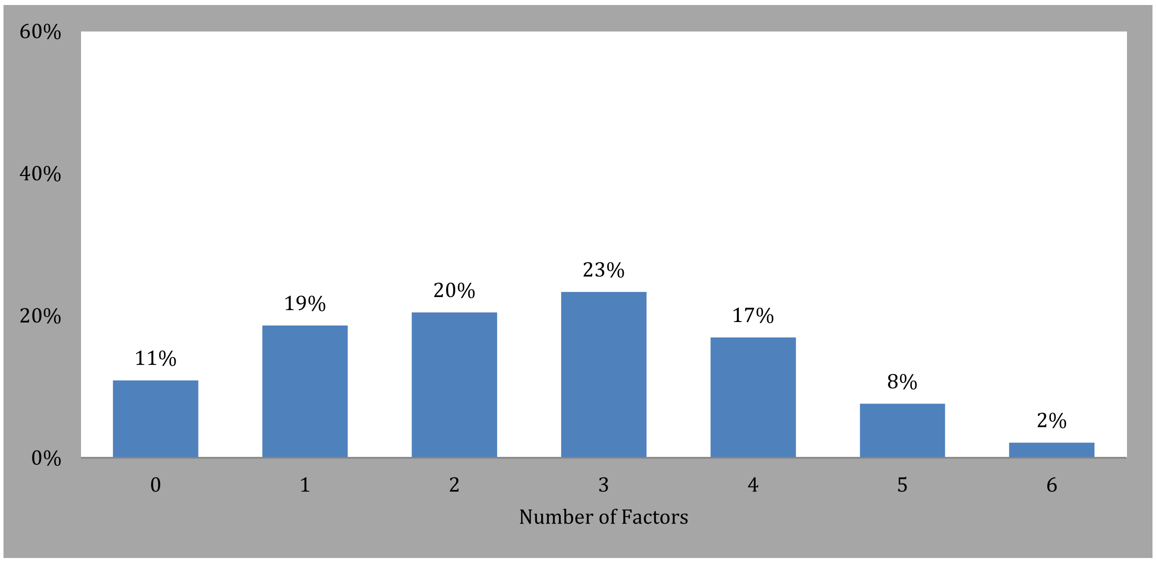

Figure 4 Number of significant strategic factors across funds.

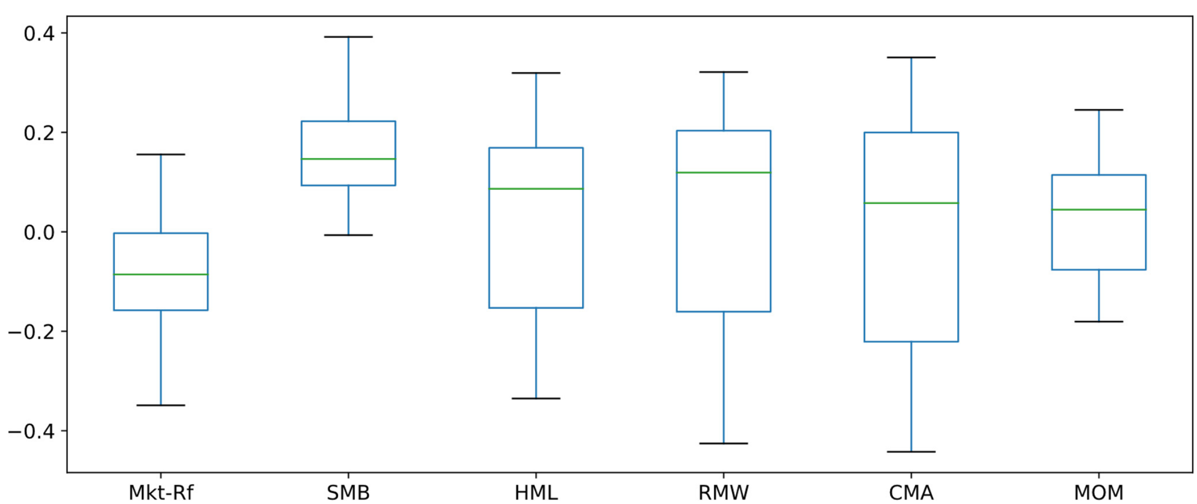

Figure 5 Distribution of strategic factor exposures.

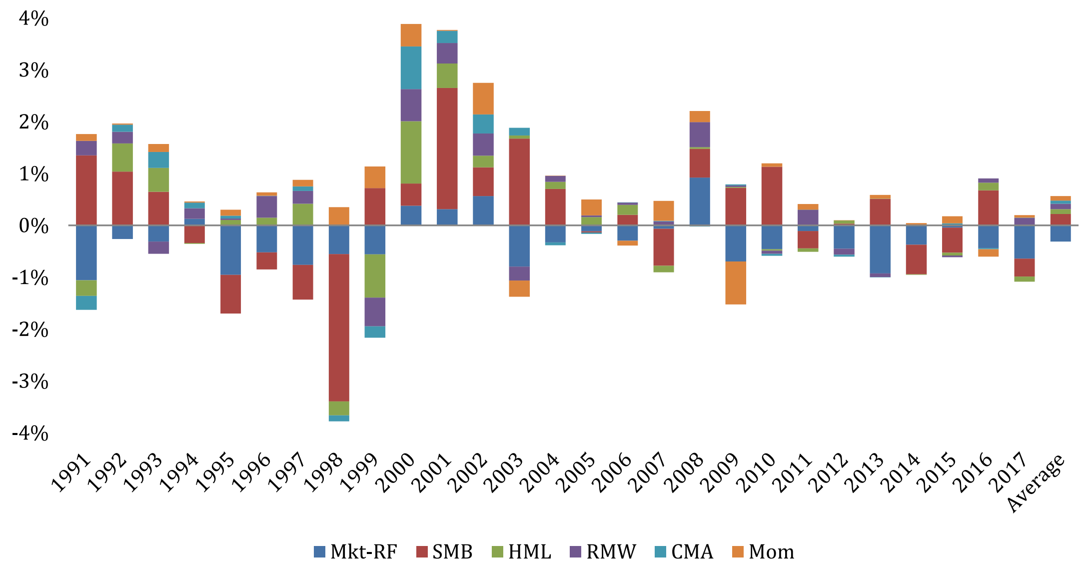

Figure 6 Annual contribution of strategic factors.

the market beta has detracted from performance because holding cash in rising equity markets has hurt returns. Also, given the long-term outperformance of small-cap stocks versus large-cap stocks, the small-cap preference in many funds has provided a tailwind for manager returns. It is worth noting the outsized gains from having small-cap exposures after the Technology Bubble and the Global Financial Crisis. The other factors are less impactful over the whole period but can play significant roles over shorter horizons.

3.2 *Results—Tactical factor contribution*

Figure 7 shows that about 75% of the time, funds have two or less significant short-term factors. Over a three-month period, funds may find it more practical to focus on a few factors rather than express views on a broad set of factors.

From Equation (7), we calculate the tactical factor bets as the difference between the short-term factor betas (shown later in Figure 9) and the long-term factor betas (Figure 5). The results shown in Figure 8 suggest that funds tend to have short-term factor exposures that are different from strategic exposures.

The distributions of tactical tilts (Figure 9) are fairly spread out around zero. The chart suggests that funds have wider differences in the CMA factor over time. In our experience, the Conservative Minus Aggressive factor (measured by asset growth) is less commonly monitored compared to the other factors so the resulting exposures to this factor may be accidental. We find that portfolio managers normally monitor many of the other well-known factors and as a result, exposures to those factors may be more tightly controlled.

In terms of individual factor contributions over time (Figure 10), there is huge variation in terms of impact. The aggregate impact from factor timing is close to zero for the full period but several factors had significant impact in some periods. For example, in 1999, during the build-up to the Technology Bubble, over-weights to HML (value) detracted significantly from performance. During the subsequent crash, managers were overweight CMA and this contributed to performance. Finally, at the height of the Global

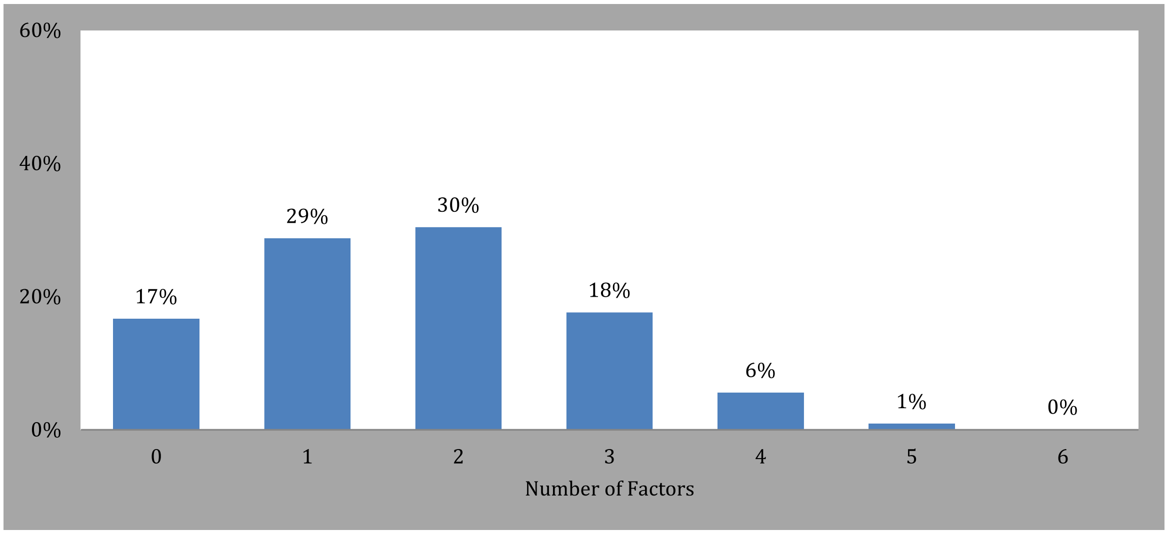

Figure 7 Number of significant short-term factors across funds.

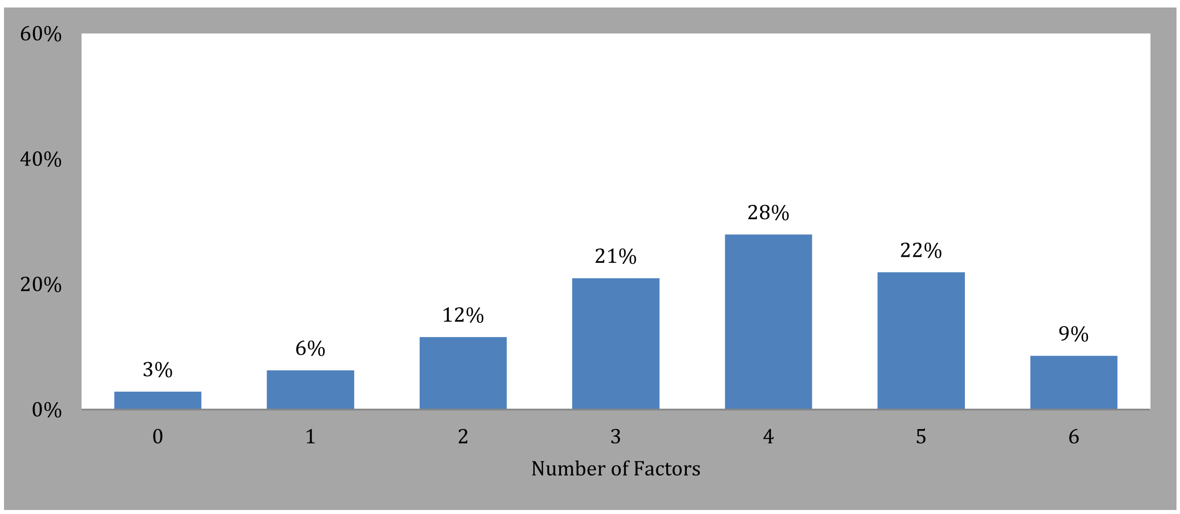

Figure 8 Number of significant tactical factors across funds.

Financial Crisis in 2008, funds were generally underweight RMW (robust minus weak, proxied by return on equity) and this hurt performance during the market turmoil.

3.3 *Results—Residual (security selection)*

The residual captures the impact of decisions after accounting for strategic and tactical factor exposures. While we have not explicitly controlled for industry exposures (regressions will likely be over-specified, given the limited number of observations), we suspect that some of the industry effects are captured by the factors in our framework. As a result, the bulk of the residual is security selection.

Figure 11 shows the annual distribution of returns from security selection. Recall that the fund returns we used are after fees so the residual also captures the expenses paid by investors. The average total expense ratio for US large-cap strategies

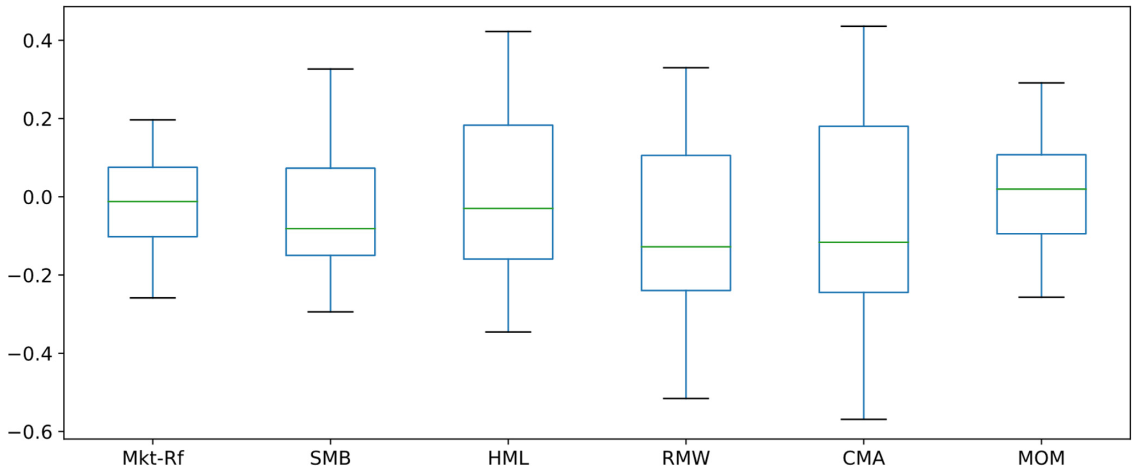

Figure 9 Distribution of tactical factor exposures.

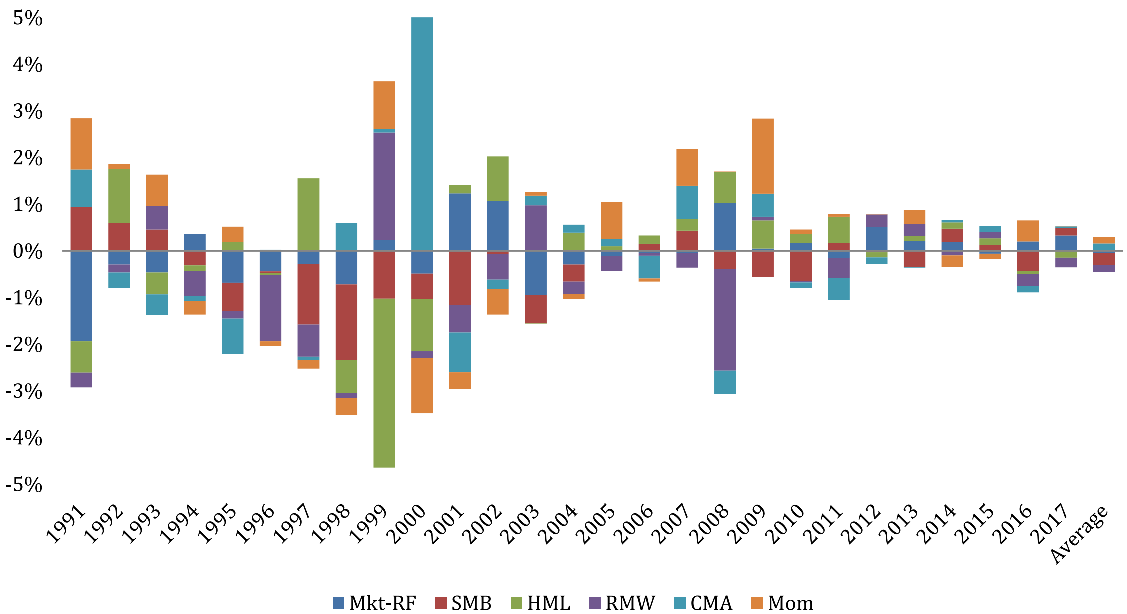

Figure 10 Annual contribution of tactical factors.

is in excess of 1% so positive security selection is largely offset by fees.

3.4 *Persistence of components*

To assess manager skill in factor positioning and security selection, we test for persistence in these components. The idea is that if there is persistence in these components for a fund, this may suggest manager skill. We test persistence by running regressions of future performance against trailing performance over three-year periods. We use rolling three-year periods because it is a common period used by the industry to assess manager performance and manager skill.

We run a pooled regression across all managers and across time

$$R_{i,q,q+11} = \alpha_i + \beta_i R_{i,q-12,q-1} + \varepsilon_i, \quad (11)$$

where $R_{i,q,q+11}$ represents the return component we are studying for strategy i calculated from

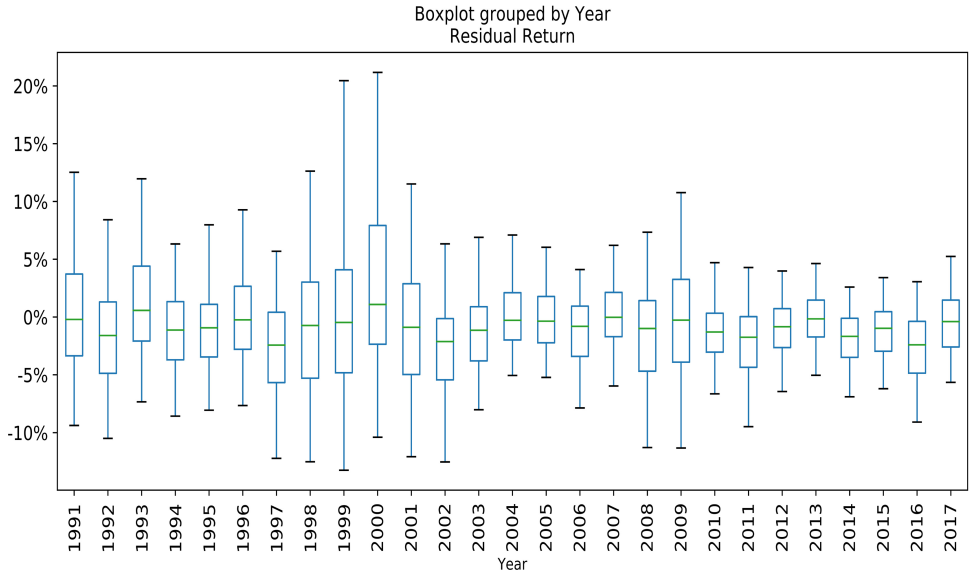

Figure 11 Annual contribution of security selection.

quarter q to quarter $q + 11$ (i.e., the next three years) and $R_{i,q-12,q-1}$ represents the return component we are studying for strategy i calculated from quarter q-12 to quarter q-1 (i.e., the last three years).

We apply the Newey–West method to adjust for multi-collinearity issues resulting from the overlapping three-year periods.

Table 2 shows the results of the persistence regressions on different components of returns. First, consistent with Chin *et al*. (2018), active returns exhibit mean-reverting tendencies; that is, high active returns tend to be followed by low active returns.

Table 2 Persistence regressions.

	Coefficient	t-Stat of coefficient
Active return	−0.07	−5.04
Strategic factor	−0.06	−3.20
Tactical factor	0.12	5.63
Residual (security selection)	0.10	5.61

Note: For each fund and for each month, we regress forward three-year returns against trailing three-year returns. We apply Newey–West to adjust for the multi-collinearity resulting from the overlapping periods.

There is also mean-reversion in strategic factor contributions. This is not surprising because factor returns ebb and flow over time so their impact on portfolio returns will follow the return patterns of the underlying factors.

Tactical factor contributions are persistent and statistically significant, suggesting that portfolio managers have skill in timing factors. This result is generally true across all managers and across all time periods but there might be differences amongst managers depending on their level of factor timing. We will analyze this in the next section.

Finally, the residual is persistent over three-year periods, suggesting that portfolio managers have skill in security selection.

3.5 *Factor Timers*

Up to now, we have looked at the whole universe of managers. Our experience suggests that many funds do not explicitly time factors and their factor exposures are byproducts of their underlying security selection. As a result, we want to study the subset of funds that seem to rely on factor timing to generate performance.

We define "Factor Timers" as follows:

— Rank all the funds by the percentage of significant factor bets over the life of each fund (i.e., number of significant short-term factor betas divided by the total number of possible factor betas) from high to low. We use this metric as a proxy for the intent to time factors. Since we are not using fund holdings in our analysis, it is difficult to discern precisely the objectives of the funds. By looking at the percentage of times a fund had statistically significant factor exposures over its life, we capture the fund's intent to vary factor exposures over short periods of time.
— Rank all the funds by the contribution to risk derived from factor timing from high to low. Specifically, for each fund, we calculate the variance of the quarterly short-term factor contributions and then determine the percentage of this contribution versus the total active variance of the fund versus its benchmark. This ranking methodology sorts the funds by the impact of factor bets over the life of the funds.
— Re-rank based on the average of the two rankings from high to low. The Factor Timers are the top 5% of these funds. This sort captures the intersection of those funds which exhibited intentions to time factors and whose active risk was driven by factor movements. We use the top 5% because we want to analyze the most active Factor Timers.

This definition may capture some funds which do not explicitly time factors. For example, concentrated funds (funds with low name counts) may have un-intended but significant short-term factor exposures from their held stocks. Even in this case however, we believe it is important to separate out the effects of factor selection and security selection because the un-intentional factor exposures are impacting fund returns. In other words, these funds are implicitly timing factors and even if the funds do not want to control these exposures, it is important to understand the contribution of these effects. To the extent that tactical factor bets and exposures are driving the performance of some of these funds, we want to include them in our definition.

Figure 12 shows the annual decomposition of returns for the Factor Timers. While the period average and the patterns are similar to the universe of funds in Figure 2, the impact of tactical bets is much larger for this cohort. This result should not be surprising, given our definition for Factor Timers but nevertheless, the annual results confirm the intentions of our construction methodology. Interestingly, the Factor Timers also have larger contributions from security selection through the years as compared to the broader universe of funds.

The contribution from factor timing was particularly large in the years before and during the Global Financial Crisis. This is also confirmed in Figure 13 where the distribution of tactical factor contributions across funds seems more disperse up to and including the recent financial crisis. Our research suggests the smaller impact over the last decade is a result of smaller factor bets rather than smaller factor movements.

Figure 14 shows the annual distribution of exposures by factor—the exposures have either become smaller or stayed about the same when comparing the first two decades with the last decade. This may reflect a stronger focus on risk management and portfolio construction across the industry. Commercial risk systems are being used

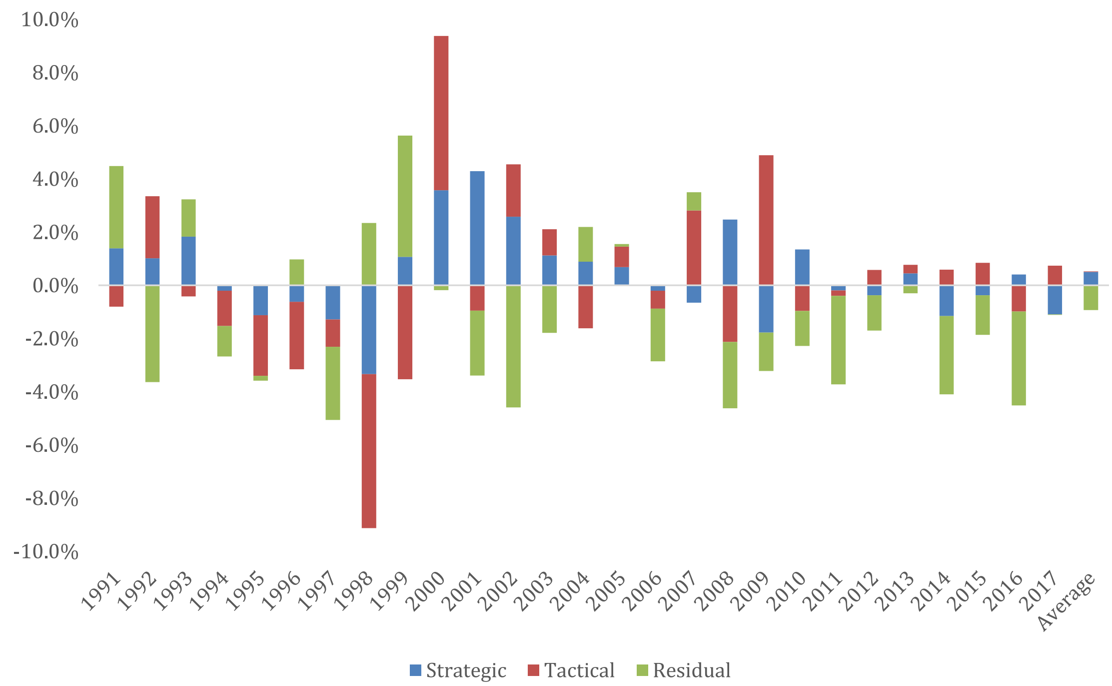

Figure 12 Decomposition of active returns (Factor Timers).

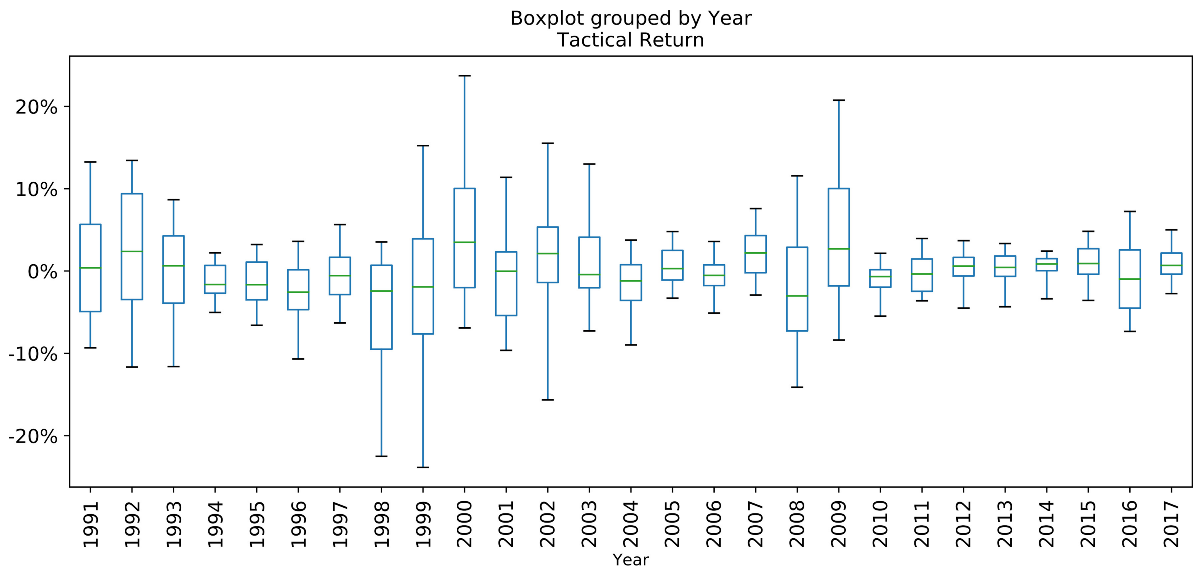

Figure 13 Distribution of tactical returns (Factor Timers).

to surface risks and factor exposures within strategies, and investment teams may be taking prudent steps to mitigate the un-intended risks emanating from factor tilts.

As for factor returns, we saw previously in Table 1 that different factors have driven performance over time. Momentum played a significant role in some periods (notably 2008 and 2009), value was a major contributor to performance during the Technology Bubble in the late 1990s and early 2000s, and other factors had large impacts in other periods. Looking over the last decade, the

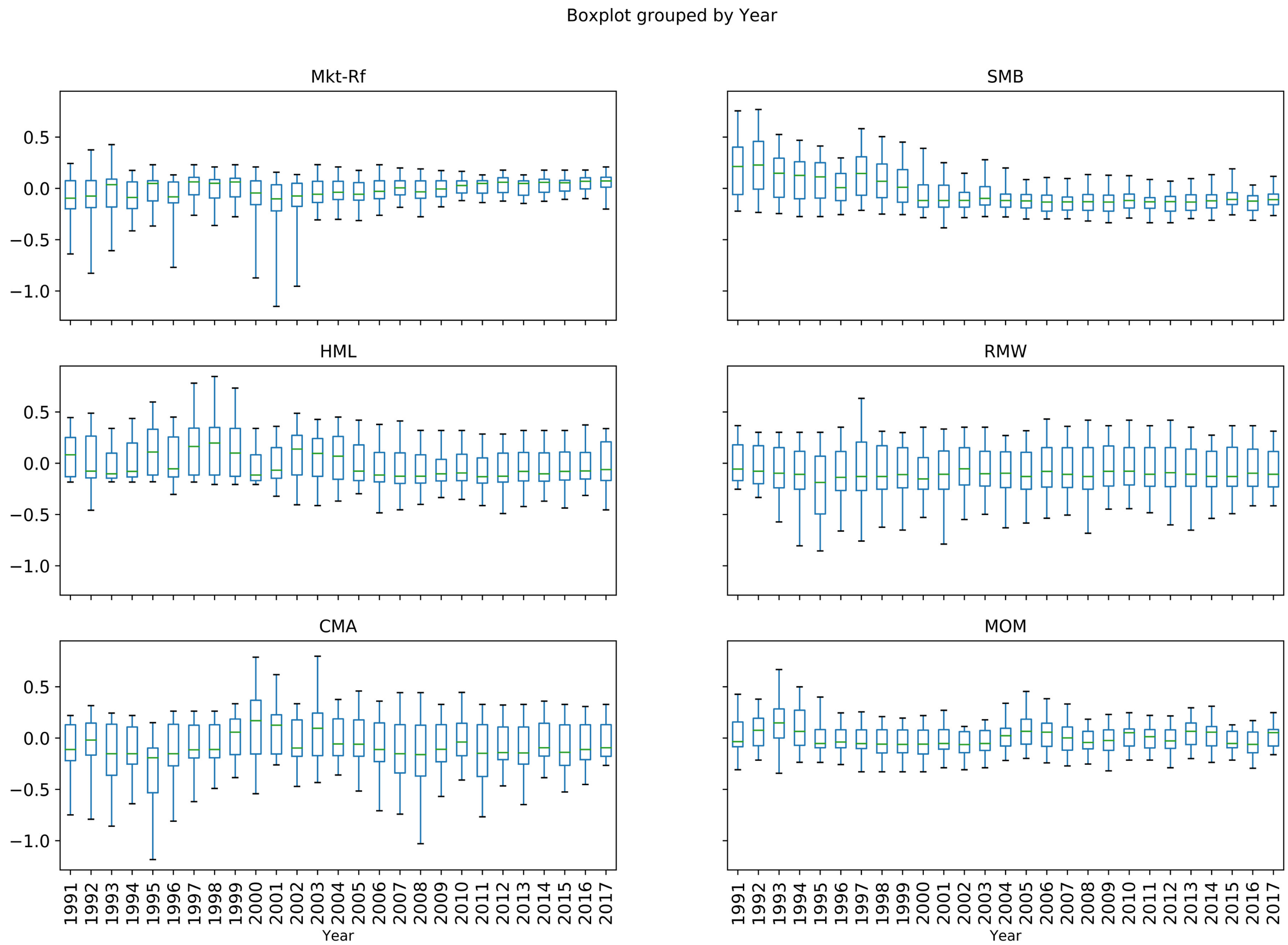

Figure 14 Distribution of factor exposures (Factor Timers).

dispersion of the returns in the six factors has not changed materially versus the prior period.

We also studied the skill of the Factor Timers and find that this cohort behaves differently from the funds in the broader universe. First, in Table 3, there is not mean-reversion in the active returns of the Factor Timers—indeed, the results suggest that there is no relationship between past and future active returns for this group. In addition, there seems to be persistence in the strategic factor contributions, suggesting that this cohort is skilled in creating a mix of strategic factor exposures that generally enhances returns. While factor returns ebb and flow over time, the Factor Timers have been able to combine the factors

Table 3 Persistence regressions (Factor Timers).

	Coefficient	*t*-Stat of coefficient
Active return	0.01	0.22
Strategic factor	0.15	2.69
Tactical factor	0.04	0.61
Residual (security selection)	0.07	1.06

Note: For each fund and for each month, we regress forward three-year returns against trailing three-year returns. We apply Newey–West to adjust for the multi-collinearity resulting from the overlapping periods.

in ways that produce persistent returns. The tactical factor result shows that there is no relationship between how the Factor Timers performed on factor tilts historically and how they did in the future. Even though this cohort bets on factors more often, there is no evidence that they have skill in this endeavor. Finally, unlike the findings for the broader universe, there is no persistence in the residual but this result is perhaps less surprising, given the smaller contribution of security selection for the Factor Timers (resulting from our definition). For these funds, they rely on factor timing rather than on security selection to drive active returns.

Table 4 Regression results for predicting active returns.

	Coefficient	*t*-Stat of coefficient
Strategic factor	−0.07	−3.64
Tactical factor	−0.14	−6.34
Residual (security selection)	0.02	0.90

Note: For each fund and for each month, we regress forward three-year active returns against different versions of trailing three-year returns (strategic factor, tactical factor, residual). We apply Newey–West to adjust for the multi-collinearity resulting from the overlapping periods.

Funds that rely on varying short-term factor exposures to generate alpha are often whipsawed by the performance patterns of factors. Whilst the industry has been rigorously researching more sophisticated techniques to time factors, we have not seen evidence that this research has been fruitful in aggregate. This may change in the future and our framework can be used to assess the evolution in our industry.

3.6 *What matters for active returns*

An important question is what drives active returns for a fund. Earlier, we found that strategic factor contributions, tactical factor contributions and security selection are all important components of active returns when explaining historical performance. However, which of these components predict *future* active returns, not just explain *historical* patterns of performance? Table 4 shows the results of the regressions of future active returns on trailing components of returns—we find that strategic and tactical factor contributions do not drive future active returns. The betas are negative, suggesting that successful strategic factor allocation or factor timing does not lead to positive active returns. This again highlights the difficulty and volatility of successfully allocating to factors, either over the long term or during shorter horizons. On the other hand, security selection seems to have a small positive relationship with future active returns (although the results are not statistically significant).

We now drill into the two components of manager skill—factor timing and security selection—and study whether they drive future skill (prime alpha). Chin *et al.* (2018) showed prime alpha captured manager skill so it is important to assess what drives that manager skill. The results in Table 5 show that security selection is the key driver for prime alpha, demonstrating that

Table 5 Regression results for predicting prime alpha.

	Coefficient	*t*-Stat of coefficient
Tactical factor	0.03	1.61
Residual (security selection)	0.13	7.16

Note: For each fund and for each month, we regress forward three-year prime alpha against different versions of trailing three-year returns (tactical factor, residual). We apply Newey–West to adjust for the multi-collinearity resulting from the overlapping periods.

manager skill is expressed through security selection rather than through factor timing.

4 Conclusions

Factor timing has garnered more interest since the Global Financial Crisis because of the divergent performance of popular factors. Portfolio managers, quantitative analysts and academics alike are drawn to the allure of successfully choosing the factors that will outperform going forward. Common techniques involve predicting the future regime (and then choosing the factors expected to perform well in that regime) or using statistical methods to analyze the historical or cross-sectional patterns of factor performance to predict future behaviors.

In addition, new investment vehicles and commercial software have made it easier for portfolio managers to understand and manage their factor exposures. Factor ETFs in particular have grown in popularity and are increasingly being used to gain or mitigate exposures to certain factors.

In light of these trends, we developed a simple yet innovative framework to assess the contribution of factor timing in manager returns. We defined factor timing as the difference between short-term and long-term factor exposures and used this technique to calculate the impact of strategic factor decisions, tactical factor bets and stock selection in historical manager returns.

Using this framework, we found that all three components are significant in manager returns but security selection is the most significant. We also found that on average, managers have persistent abilities in tactical factor timing and security selection. However, we do not see this same persistence amongst the cohort of funds which rely on factor timing to generate returns.

Finally, we found that security selection is the biggest driver of both future active returns and future prime alpha (manager skill). Portfolio managers may be tempted to time factors but the current evidence suggests security selection is the key determinant of manager skill.

We hope that our framework and findings create discussion and debate in the industry about the role and impact of factor timing in investment strategies. One area of further exploration is applying our framework to fixed income and multi-asset strategies, where there is more emphasis on factor timing.

Acknowledgment

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Notes

[1] We use calendar quarters in Regression (6), i.e. Jan–Mar, Apr–Jun, Jul–Sep and Oct–Dec, for simplicity but quarters can be defined over different periods.

[2] We use the Variance Inflation Factor to adjust for multicollinearity among the variables.

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