Deutsche Bank

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Signal Processing

Reviving Momentum: Mission Impossible?

Momentum still lives!
We analyze the 12-month price-return momentum factor and find that we can rescue the strategy by isolating its stock-selection component. Furthermore, we can improve the strategy further by shifting the price-return horizon according to information speed.

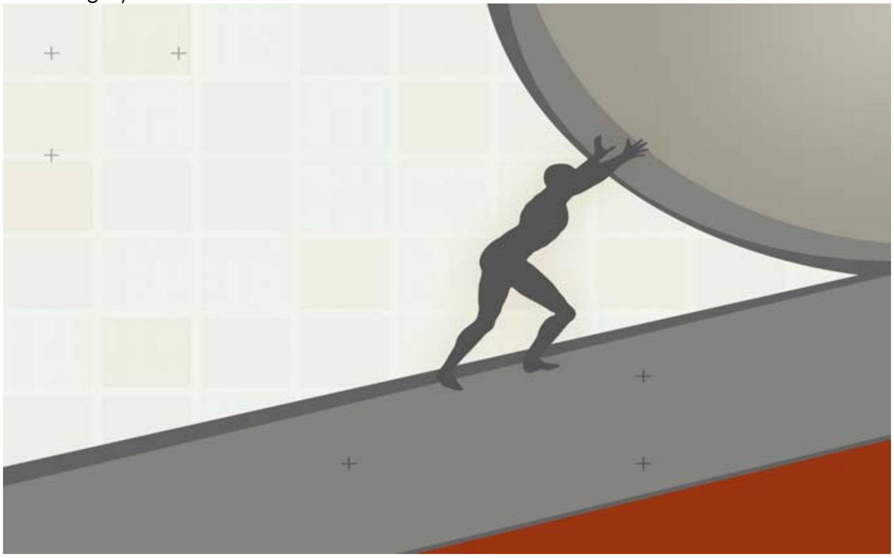
Momentum strategies for the new age of quantitative investing

Beta-timing vs. stock selection
We analyze the link between Beta and Momentum factor performance. Surprisingly, we find that Beta it is a major driver of risk and performance for Momentum strategies over time. In fact, Beta played a significant role in the drawdown experienced by the Momentum factor during the "junk" rally in 2009. We find that controlling Beta risk in the right way can lessen drawdowns and improve overall risk-adjusted performance.

Analyzing the Momentum term structure
We further analyze price return Momentum strategies constructed across various horizons and find that there are periods when shifting towards shorter price return horizons can improve performance.

Two new factors for Momentum
We use our analysis to develop two new factors that significantly improve momentum performance with added risk control:

- The first is constructed to capture pure stock-selection and takes advantage of relative distances within the momentum scores. In addition, we find that this factor suffers from less drawdowns and avoids the devastating performance caused to the traditional factor during and subsequent to the spring of 2009.
- The second improves the stock-selection factor by developing a framework to shift the strategy along the term-structure according to information speed. We find that this factor almost doubles the IR of the original 12-month momentum factor and it improves a basic 5-factor quant model portfolio IR by roughly 30%.



Source: Getty Images

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Letter to our readers

Is Momentum dead?

Undoubtedly, this is the question on the minds of many quantitative managers these days. Our belief is that momentum in general is not dead. What may be true is that the traditional 12-month price-return momentum strategy has long since seen its best days. However, we don't believe that the behavioral drivers responsible for momentum-type strategies have disappeared. Rather, we believe that capturing these effects will not be as simple as just buying last year's winners and selling last year's losers.

We believe that 12-month price return momentum has ceased to work consistently for two reasons. The first is simply due to overcrowding. The fact that 12-month price return momentum is so easy to construct and showed excellent past performance makes it a prime strategy for quantitative, fundamental and even retail investors. We believe, this will ultimately lead to smaller and less consistent profits in the strategy.

The second reason we believe momentum has ceased to outperform is due to the current risk-on/risk-off environment. Momentum is a strategy that relies on trend stability and tends to outperform when market conditions persist or change very slowly. On the other side of the equation, the strategy is susceptible to reversals in risk preferences and general sentiment. Therefore, the market turning points along with the risk-on/risk-off behavior since the summer of 2007 have had a detrimental effect on the traditional 12-month price return momentum strategy.

Do we give it up? Well, not necessarily – our philosophy is that the new age of quantitative investing calls for innovation across every aspect of the investment process and consideration of new techniques that would not have been contemplated in the past. For example, we could consider factors with less breadth but better skill such as those proposed in our research on industry specific factors, REIT and bond data[1]; or factors constructed from high frequency data such those suggested in our report on frequency arbitrage[2]; and even consider style timing as proposed in our report on style rotation[3]. In addition, we strongly believe that risk and portfolio construction research offers a bounty of potential for improving the quantitative investment process[4].

In this vein, we attack momentum from all sides and use a range of different techniques and methodologies to decompose, analyze, and reshape the factor. The goal is to make it more flexible to the speed of information while less susceptible to risk reversals and market turning points. In the end, we find that momentum still matters, just that it will require more sophistication to capture the relevant information.

Thanks and enjoy.

Yin, Rochester, Miguel, Javed & John

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[1] See Luo *et al.* [2010] "Industry Specific factors", Luo *et al* [2011] "A Quant Handbook on REIT Investing" and Cahan *et al* [2011] "Do Bonds Know Better?".

[2] See Cahan *et al* [2010] "Frequency Arbitrage".

[3] See Luo *et al* [2010] "Style Rotation".

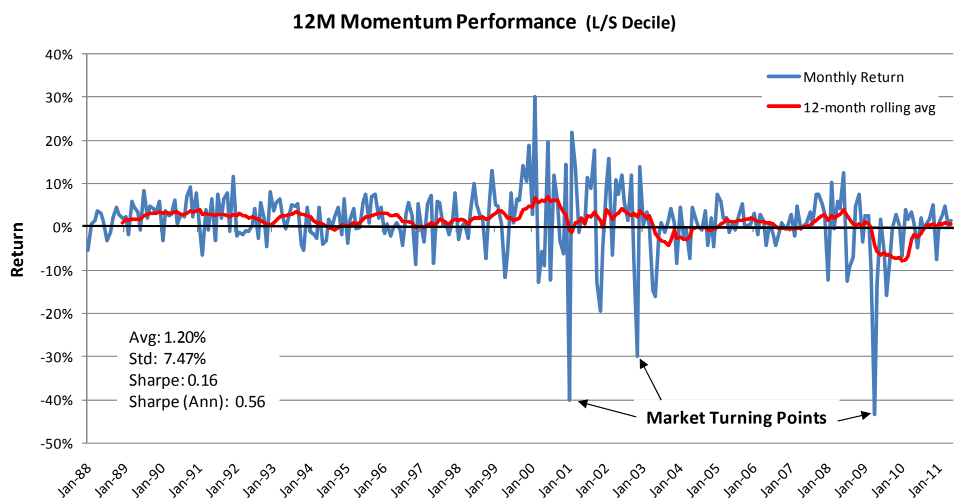
[4] See for example, Alvarez *et al* [2010] "Volatility=1/N", Luo *et al* [2011]"Robust factor models", Alvarez *et al* [2011] "Learning to Drive in the Fast Lane" and Luo *et al* [2011] "Tail Risk in Optimal Signal Weighting".

Dissecting Momentum

Why all the fuss?

Lately, the standard 12-month momentum[5] factor has come under considerable scrutiny. As with all second guessing this comes at a time when its performance over the last four years (post 2007) has been lackluster to say the least. The reason for all the negative attention is evident in Figure 1, which shows that over the past four years, the most conventional version of the strategy (the long/short decile strategy[6]) has had dismal performance and the drawdown associated with the factor during the "junk" rally in the spring of 2009 was tremendous. As the figure shows, 2009 was not the only significant drawdown the strategy has encountered over the sample period. As labeled in the figure, many of the drawdowns come at times of risk-aversion reversals or turning points in market sentiment.

Figure 1: Momentum L/S Decile Monthly and 12m Average Performance (Russell 3000)



Source: Compustat ,Russell, Deutsche Bank

The theoretical basis for momentum profits is well established. In their seminal paper, Jegadeesh and Titman (1993) showed that momentum or relative strength strategies were indeed profitable using price-return over horizons of 3 to 12 months. We will not focus too much on the hypotheses for the momentum effect, but they are based on behavioral arguments arising from either investor under-reaction or herd behavior (aka inertia).

From an empirical perspective, Momentum as the name implies, is contingent upon return persistence or continuation. In other words, Momentum performance depends on winners continuing to win and losers continuing to lose. Therefore, by definition, Momentum will underperform when past winners underperform relative to past losers. As we will see in the section below, there is very strong systematic component to the general Momentum

[5] All Momentum factors in this report use the standard construction. That is they are all constructed using total return over the indicated months excluding the last month to account for the short-term reversal effect.

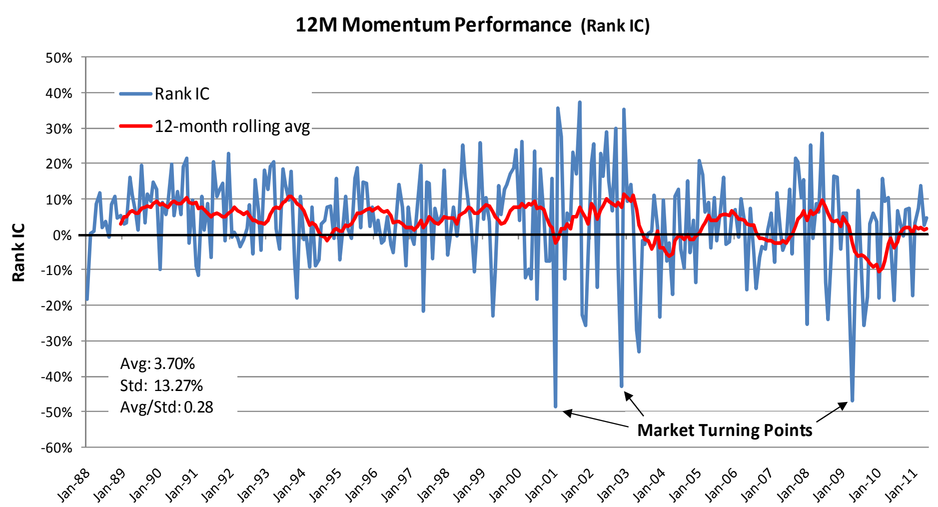
[6] This momentum strategy consists in ranking stocks by their 12-minus-1 month price return (last month is excluded to account for the reversal effect) and then going long an equal weighted basket in the top decile and short an equal weighted basket in the bottom decile. The strategy is rebalanced at the beginning of each month.

factor which has a significant impact on determining past winners and past losers and their performance going forward.

The results in Figure 1 showed the performance of 12-month price Momentum for the long/short decile strategy. However, in this report we focus on the information coefficient (IC) to assess the strategy so that we may assess the entire breadth of stocks in our universe (roughly the Russell 3000). Figure 2 shows the rank IC for Momentum for our universe over time (we will subsequently analyze performance in large cap versus small cap).

While not directly comparable, we can see some important differences between the L/S decile strategy in Figure 1 and the performance resulting from investing in the entire universe shown in Figure 2. First, the difference between the Sharpe ratio of the L/S decile strategy and the corresponding risk adjusted rank IC for the full-breadth strategy (see Figure 2) suggests that investing across the entire universe can yield significant added-value in risk-adjusted performance. Second, the drawdowns in the L/S decile strategy are much stronger relative to its historical volatility than that of the full-breadth strategy. Accordingly, given the evidence, we focus the rest of the report on the full-breadth strategy and work with rank IC (we will later work with factor-mimicking portfolios that will resemble the IC performance).

Figure 2: Momentum Monthly and 12m Average Rank IC (Russell 3000)



Source: Compustat ,Russell, Deutsche Bank

Figure 3: 12M Momentum Performance statistics across different periods

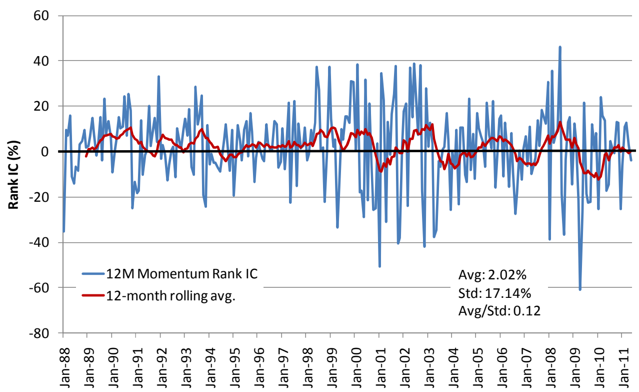
Period	Avg. Rank IC	Std Dev	Avg/Std
Jan 1988 - May 2011	3.70%	13.27%	0.28
Jan 1995 - May 2011	2.89%	14.60%	0.20
Jan 2007 - May 2011	0.77%	14.73%	0.05

Source: Compustat ,Russell, Deutsche Bank

Large versus small cap

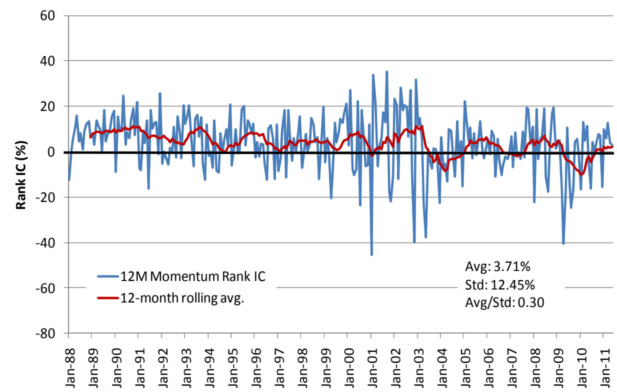
There is ample literature suggesting that Momentum behaves differently across small vs. large capitalization stocks (see Hong, Lim, and Stein [2000]). We analyze this further below, but at a high level, Figure 4 and Figure 5 show the rank IC of the 12-month Momentum signal across the Russell 1000 and Russell 2000, respectively. It is not hard to conclude that Momentum tends to be more effective in the small-cap relative to the large-cap universe. This is consistent with research which finds that momentum works best for more volatile stocks (see Zhang [2006] and Cahan *et al* "Harnessing the best ideas from academia" [2010]). This is not surprising given that most conventional (as well as unconventional) quant factors tend to work more effectively in small-cap universes where it is believed that mispricing and opportunity is greatest.

Figure 4: 12M Momentum Rank IC (Russell 1000)



Source: Compustat, Russell, Deutsche Bank

Figure 5: 12M Momentum Rank IC (Russell 2000)

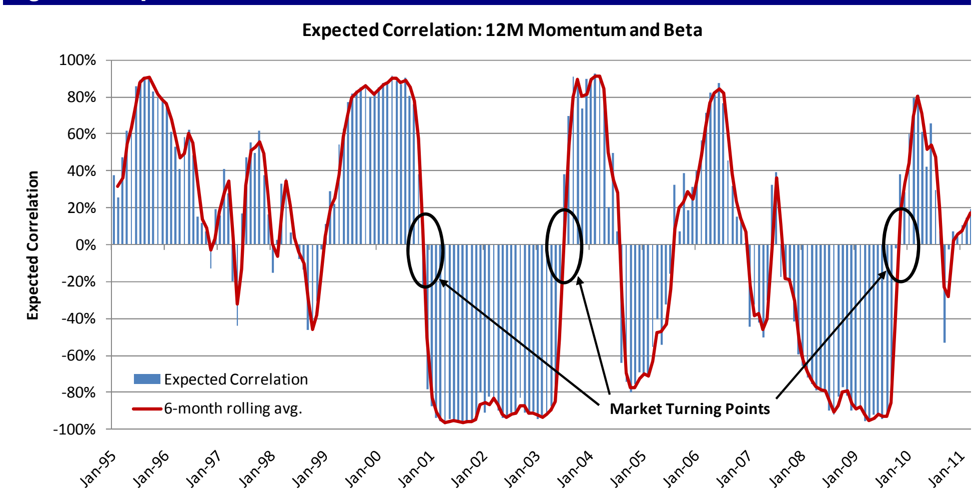


Source: Compustat, Russell, Deutsche Bank

The surprising correlation with Beta

Now we turn our analysis to a somewhat surprising and not well documented fact about the relationship between Momentum and Beta. An expected correlation analysis[7] over time (see Figure 6) shows that 12-month Momentum has a strong and dynamic correlation with Beta over time. We exposed this relationship in a past report (see Luo *et al* "Portfolios Under Construction: Volatility=1/N") and found that this was indeed the case for many other conventional quantitative factors as well.

Figure 6: Expected Correlation between 12M Momentum and Beta factors



Source: Axioma, Compustat ,Russell, Deutsche Bank

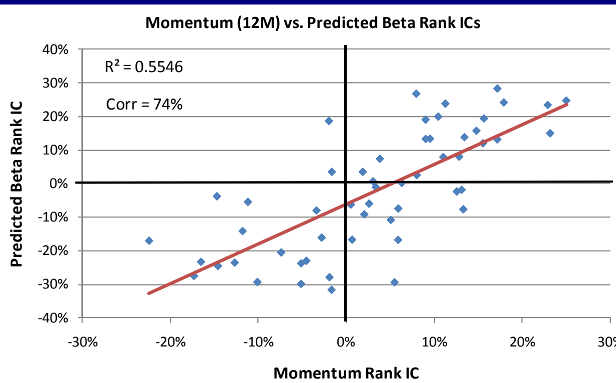
While somewhat surprising, the relationship is intuitive. When sentiment is bullish, investors tend to load up on higher Beta stocks, while periods of uncertainty drive

[7] The expected correlation is just the correlation of the two factors implied by the variance-covariance matrix of stock returns. We explored different types of correlation measures in the appendix of our paper "Portfolios Under Construction: Volatility=1/N" 2010. Specifically, the implied correlation between two factors $\mathbf{f_1}$, $\mathbf{f_2}$ is given by: $\mathbf{f'_1 V f_2} \,/\, [(\mathbf{f'_1 V f_1})^{1/2} (\mathbf{f'_2 V f_2})^{1/2}]$.

investors towards lower Beta stocks. We can see this relationship clearly in Figure 6, which shows the expected correlation between our 12-month momentum factor and Beta over time.

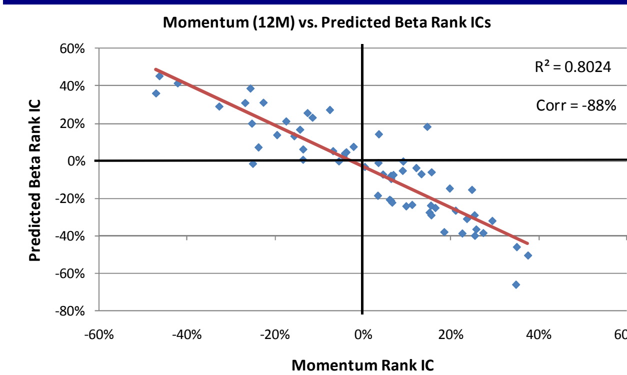
The relationship depicted in Figure 6 implies that the performance of the Momentum factor (both IC and return) will be driven mainly by performance of Beta during periods when the magnitude of the correlation between the two factors is large. Does our expected correlation measure correctly forecast the relationship in performance of the two factors? For out-of-sample verification, Figure 7 shows the realized rank IC of Momentum against Beta when the correlation is predicted to be large (greater than 50%). The strong realized correlation in rank IC implies that Beta is driving the majority of Momentum return during these periods. Similarly, Figure 8 shows the same relationship between the monthly rank IC of the two factors during periods when the correlation between the factors is expected to be strongly negative (less than -50%).

Figure 7: Momentum (12M) vs. Predicted Beta realized rank ICs for periods where expected correlation > 50%



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 8: Momentum (12M) vs. Predicted Beta realized rank ICs for periods where expected correlation < -50%



Source: Axioma, Compustat, Russell, Deutsche Bank

A common misperception we find in the Momentum literature is that the correlation or relationship with Beta is small. We find that this arises from two shortcomings:

1) Figure 6 shows the correlation of Momentum and Beta will average out over time (i.e. the unconditional correlation will be small in magnitude). Therefore, any time-series regression or correlation with a long enough window will obscure the fact that Momentum and Beta are strongly positively or negatively aligned over time.

2) The beta exposure of normalized Momentum factor scores will commonly be relatively small. This is falsely taken as a sign that momentum is uncorrelated or unaligned with Beta performance. However, Beta exposure is not enough to identify correlation; rather Beta exposure must be combined with specific risks and the variance levels of each factor to get a true sense of the correlation. In addition, it is well accepted that there are other factors which drive correlation that cannot be fully captured by Beta.

In the next section, we account for Beta exposure and correlation to analyze Momentum from a Beta-timing and stock-specific perspective.

Beta-timing vs. stock-specific

Momentum is a price related measure. Therefore, we can decompose any price momentum factor into a market momentum component and a stock-specific momentum component. To do this we follow the Capital Asset Pricing Model (CAPM) and argue that the price return of any stock over a given period of time arises from two sources:

1) Beta

2) Stock specific[8]

The Beta component will indicate whether momentum is aligned with higher or lower beta stocks and as we will see below, it can be used to measure Momentum's ability for beta-timing. The stock-specific component, as its name implies, determines Momentum's ability for stock-selection after controlling for systematic return via Beta.

There are various ways to go about this decomposition. Each method has its pros and cons and different levels of efficacy and complexity. We find overall, that the best method to decompose the factor is to use a weighted style-regression of the Momentum factor on a Beta factor. This method consists of splitting the Momentum factor into a piece that is aligned with Beta[9] and an orthogonal residual piece, which we will call stock-selection Momentum. In order to ensure that the residual factor is uncorrelated with Beta, we must use an accurate forecast of the stock-by-stock return covariance matrix[10].

In the following, we quickly describe three different methods to separate Momentum into a Beta-timing (aka Market) and a stock-specific (aka residual) component.

1) CAPM residual momentum

2) Beta exposure neutral

3) Beta correlation neutral (orthogonal)

CAPM Residual Momentum decomposition

This is the most intuitive decomposition of Momentum into a Beta and stock-specific component. Basically, this model decomposes the actual returns according to CAPM and then computes the 12-month price momentum of each return series. Specifically, at each point in time the return of each stock, $r_{i,t}$ is decomposed as follows:

$$r_{i,t} = \beta_{i,t} r_{m,t} + u_{i,t} \tag{1}$$

where $\beta_{i,t}$ is the Beta[8] of the i[th] stock at time *t*, $r_{m,t}$ is the return to the market at time *t*, and $u_{i,t}$ is the residual return from Beta. We will use the residual return as our stock specific return for time *t*. Then the 12-month stock-specific momentum from this method is simply[11]:

$$M_{i,t} = \sum_{k=2}^{12} u_{i,t-k} \tag{2}$$

Similarly, the Beta-timing score will be:

$$B_{i,t} = \sum_{k=2}^{12} \beta_{i,t-k} r_{m,t-k} \ . \tag{3}$$

[8] This is also termed the Beta-residual component since "stock-specific" is often taken to be the residual component to a set of common factors (e.g. industries, styles) that may capture the systematic component of returns.

[9] For Beta we will use the Predicted Beta from the Axioma US medium-horizon fundamental risk model.

[10] In our analysis we use the Axioma US medium-horizon fundamental risk model.

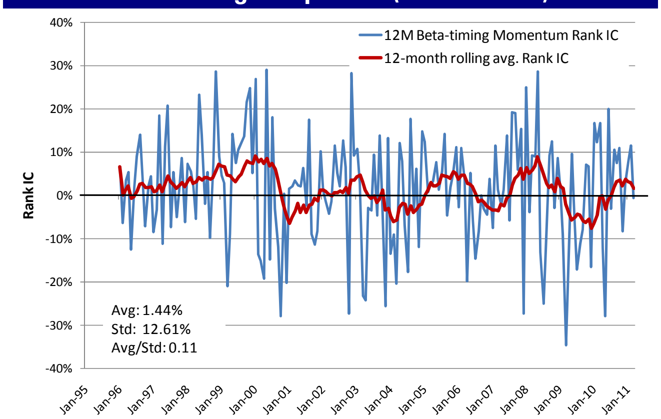
[11] We also tried compounding the returns and the results were practically the same.

The two components can be analyzed separately to determine the efficacy of the general 12-month Momentum signal for timing Beta and for stock-selection. Ideally, we would want it to serve both purposes, but due to the Fundamental Law of Active Management, we prefer stock selection because of the advantage in breadth.

To measure performance, we start by estimating the stock-selection scores in (2) and then simply compute rank IC of the scores. To measure the performance of the beta-timing component, we simply take the scores from (3) and measure the rank IC. While not an exact decomposition, it is adequate in that we are only interested in the direction of the Beta-timing component.

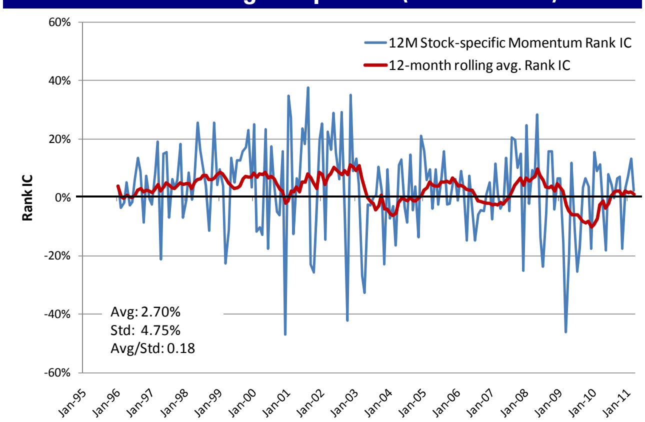
Figure 9 and Figure 10 show the rank IC performance for the Beta-timing and stock-selection component, respectively. We note a couple of points. First, the results suggest that both components seem to add value over time, with the stock-selection component being dominant in both rank IC and risk-adjusted rank IC. Second, both components seem to experience significant drawdowns during market turning points. Last, when comparing to the original Momentum results over the same period (see Figure 3) the decomposition does not add value relative to the original factor in terms of providing better risk-adjusted performance.

Figure 9: Rank IC: 12M Momentum CAPM Model Beta-timing component (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 10: Rank IC: 12M Momentum CAPM Model stock-timing component (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

OLS Beta neutral model

The next methodology we pursue to decompose Momentum is the commonly used Beta neutral technique in which the momentum scores are regressed (using OLS) against Beta to correct for the Beta bias. The methodology uses the same return model as in (1), but forces the scores between the factors to be orthogonal via the OLS regression procedure. Specifically we start with z-scores of our 12-month momentum scores, $\boldsymbol{f}_{mom}$, and posit the following model:

$$\boldsymbol{f}_{mom} = x_{mom}\boldsymbol{f}_{Beta} + \boldsymbol{u}_{mom} \tag{4}$$

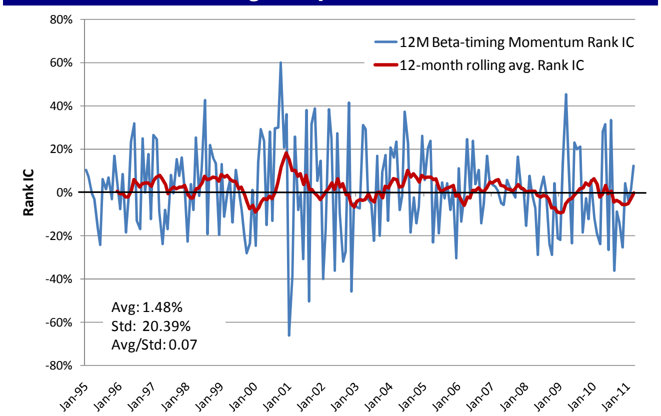
In equation (4), $\boldsymbol{f}_{Beta}$ is the vector of z-scores of our Beta factor; $\boldsymbol{u}_{mom}$ is the vector of residual momentum scores (stock-selection component) which we are after; and x_{mom} is the exposure of the momentum factor to Beta, which is estimated via OLS regression as follows:

$$\hat{x}_{mom} = \left(\boldsymbol{f}'_{Beta}\boldsymbol{f}_{Beta}\right)^{-1}\boldsymbol{f}'_{Beta}\boldsymbol{f}_{mom}\,. \tag{5}$$

One thing to note about the equation in (5) is that $\hat{x}_{mom} = \boldsymbol{f}'_{Beta}\boldsymbol{f}_{mom}$ in the case that we are using z-scores. This expression is just the exposure of the momentum factor to Beta and as we discussed above, the magnitude of this exposure can be deceivingly small while the correlation can be quite large.

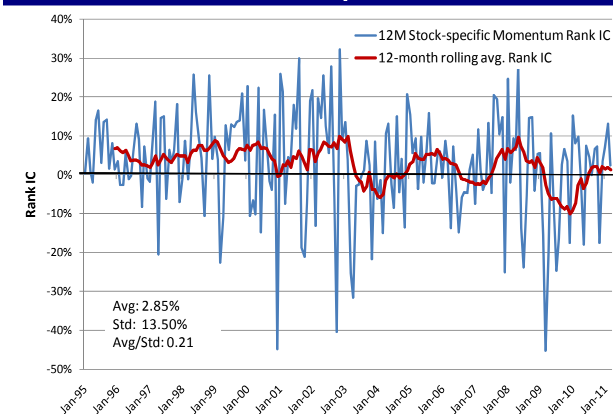
To see the latter assertion more clearly, we can compare the performance statistics from Figure 12 to those in the second row of Figure 3. Note that the mean and more importantly the standard deviation of the monthly rank IC numbers have not changed much. What this tells us is that the OLS regression is not capturing much signal and does not provide the real neutrality to Beta we would desire. Last it is worthy to note that this decomposition does not provide any risk control as can be seen by the drawdowns in Figure 12 due to the fact that it does not effectively capture the dynamic relationship between Momentum and Beta.

Figure 11: Rank IC: 12M Momentum OLS Beta-neutral Beta-timing component (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 12: Rank IC: 12M Momentum OLS Beta-neutral stock-selection component (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Beta correlation-neutral decomposition

This method was detailed in our "Volatility=1/N" (2010) report so we will briefly describe the procedure here and leave the details for those interested to that document. Basically, the returns model is the same as in (1) and the estimation model is the same to that in (4), but instead of using OLS to estimate the Beta exposure, we use a variant of weighted regression to account for the expected covariance between the stock returns. This is accomplished by infusing the estimate in equation (5) by the stock-by-stock covariance matrix, $\boldsymbol{V}$ [12]. The estimate of the Beta exposure, x_{mom}, then takes the form:

$$\tilde{x}_{mom} = \left(\boldsymbol{f}'_{Beta}\boldsymbol{V}\,\boldsymbol{f}_{Beta}\right)^{-1}\boldsymbol{f}'_{Beta}\boldsymbol{V}\,\boldsymbol{f}_{mom} \tag{6}$$

Finally, plugging this result into equation in (4) the stock-selection scores are determined by:

$$\tilde{\boldsymbol{u}}_{mom} = \boldsymbol{f}_{mom} - \tilde{x}_{mom}\boldsymbol{f}_{Beta} \tag{7}$$

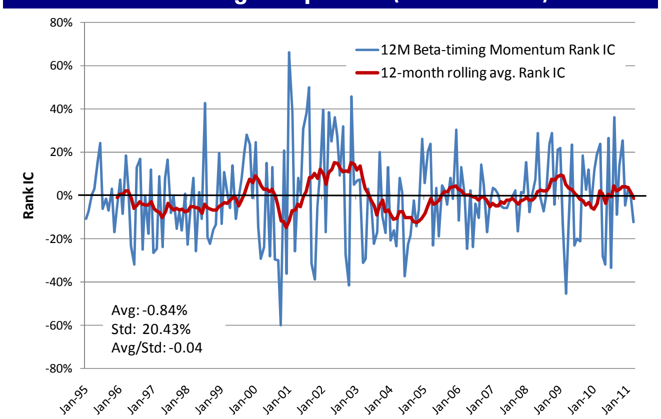
Figure 13 and Figure 14 show the performance for the Beta-timing and stock-selection components, respectively. We note a few observations. First, the results show that only the stock selection component is effective at capturing performance over time. However, once we have controlled for the correlation to Beta, the stock-selection component now

[12] We are using the stock-by-stock covariance matrix from the Axioma US fundamental medium horizon risk model.

outperforms the original factor on a risk-adjusted basis over the same sample period (see Figure 3). Best of all, many of the drawdowns are no longer present in the stock-selection component; rather they have been absorbed by the Beta-timing component as we expected. In particular the drawdown associated with the "junk" rally of spring 2009 has been reduced significantly, albeit the factor still shows negative performance over this period. This result also shows that controlling for Beta in the proper manner can protect the stock-selection ability inherent in the Momentum strategy from the volatility caused by the risk-on/risk-off environment we face today.

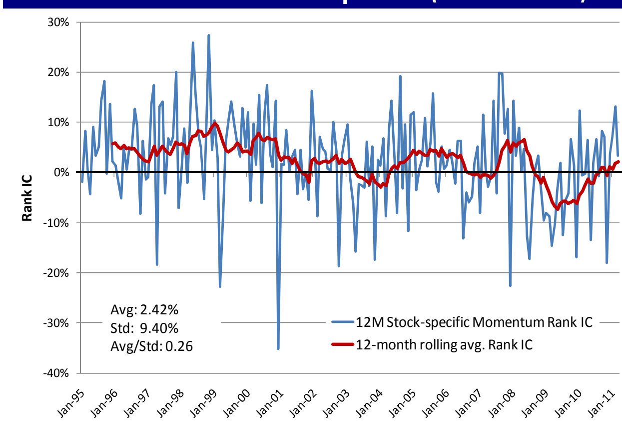
Last we note that while the correlation-neutralization technique improves the overall risk-adjusted performance of the factor over time, it still does not mend the current underperformance of the factor, which we will address in the following sections.

Figure 13: Rank IC: 12M Momentum correlation-neutral Beta-timing component (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 14: Rank IC: 12M Momentum correlation-neutral stock-selection component (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

The Momentum term structure

The 12-minus-1 month horizon is among the most commonly used momentum strategy by quantitative investors. The origin of this preference can be traced back to Jegadeesh and Titman (1993). In their seminal paper, they analyzed momentum strategies across 3, 6, 9 and 12 month horizons and found that they produced significant excess returns above standard risk premia factors. However, it was most likely Carhart (1997) that cemented the 12-month horizon strategy as the standard bearer for Momentum. In addition, most early risk model vendors (Barra and Northfield) adopted the 12-month Momentum factor in their risk models due to its strong explanatory power of cross-section return dispersion.

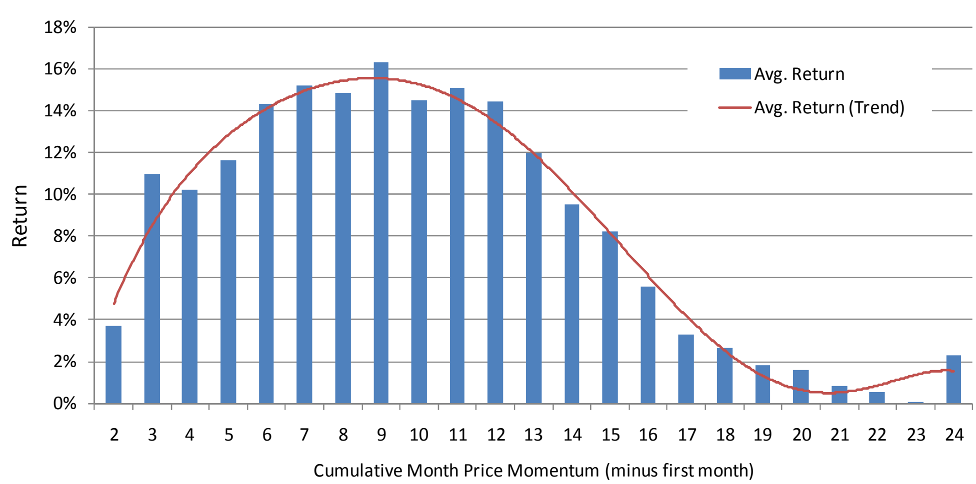
However, hypotheses behind the outperformance of momentum strategies don't necessarily specify a particular horizon, just one which is *long enough* to capture the effect of the mispricing. Therefore, in this section we look at the *term-structure* of Momentum performance and analyze its properties across various horizons. The purpose is two-fold. First, we want to identify which horizon has consistently worked best over time; second, but more importantly, we aim to gain insight into the relationship between the strategy across different horizons and how this can help us identify periods of dislocation, which may be detrimental to the strategy. The impetus for the latter arises from the observation that momentum strategies across different horizons should have some *steady state* relationship. Intuitively, we would expect that stocks which rank high according to 12-month momentum should also rank high in 11-month momentum. Similarly, 6-month momentum should be more correlated to 9-month momentum rather than to 12-month momentum. If indeed there exists some type of *steady state* or stable behavior across different Momentum horizons, then deviations from the steady state could provide information for future momentum performance across different horizons.

Before we continue it is worthy to note that all else equal, investors should prefer a longer Momentum horizon to implement the strategy. This is because longer horizon price-momentum will be "stickier" than shorter horizon price-momentum and will consequently produce less turnover. However, the latter is true when return volatility is stable and momentum is working.

Historical performance of the term-structure

We begin the analysis by looking at the L/S decile performance for price-return momentum strategies spanning horizons starting at 2-months through to 24-months[13]. The sample period for this analysis starts in January 1988 ending in May 2011. Figure 15 shows the results of the average returns[14] over the different horizons. Note that return peaks at the 9-month horizon, but it should be clear that differences are not significant across 6-12 month horizons.

Figure 15: Momentum L/S Decile Average Return Term Structure Russell 3000 Universe (Jan 1988 – May 2011)



Source: Compustat, Russell, Deutsche Bank

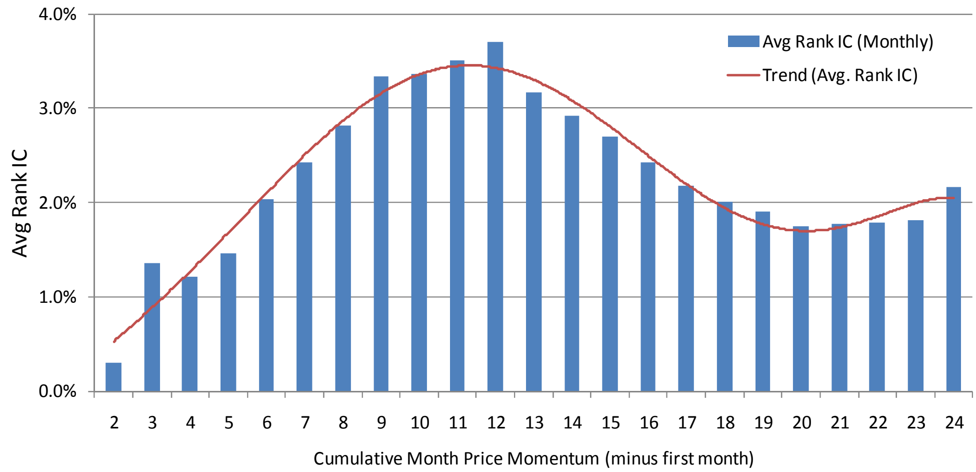
The second analysis in Figure 16 shows the term-structure of the rank IC computed across the entire breadth of stocks in our universe. In this case, performance[15] numbers peak for the 12-month horizon, which verifies the frequent use of the 12-month Momentum factor in quantitative analysis.

[13] We ignore the first month to avoid the reversal effect.

[14] Sharpe ratios follow a very similar pattern to returns and can be provided upon request.

[15] The risk-adjusted IC's have a similar profile.

Figure 16: Momentum Average Rank IC Term Structure
Russell 3000 Universe (Jan 1988 – May 2011)



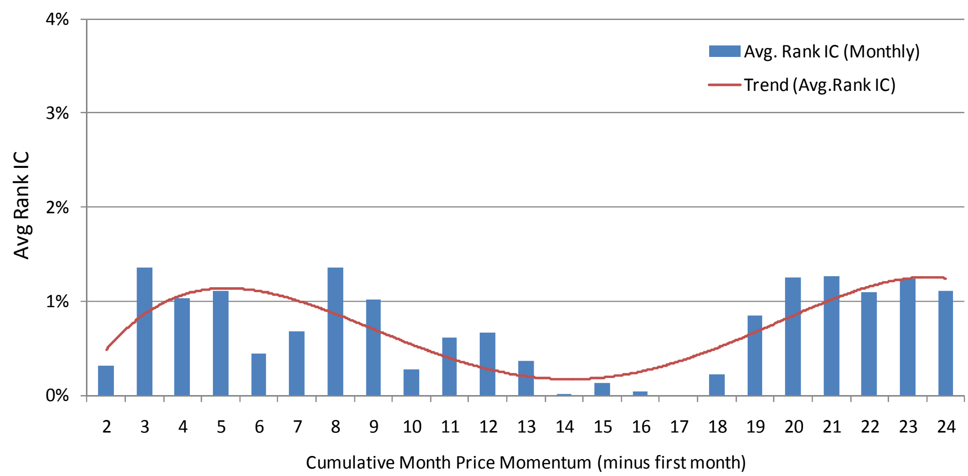
Source: Compustat, Russell, Deutsche Bank

The new reality

The term-structure of momentum performance shown in Figure 15, Figure 16, Figure 18 and Figure 20 all suggest that the conventional 12-month price return horizon is optimal. However, those results are heavily influenced by a period (Jan 1988 through Dec 2006) during which quantitative factors had spectacular performance and whose behavior over time did not show strong deviations from expectations.

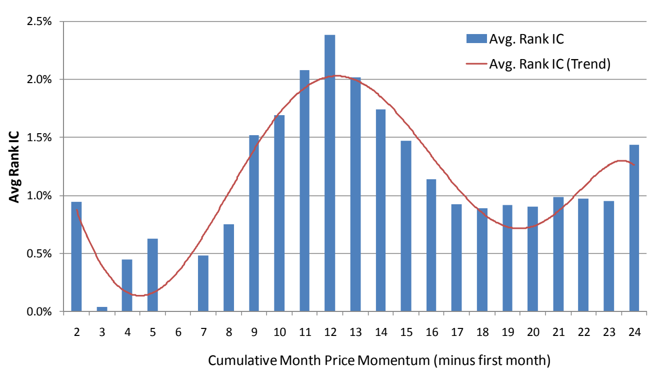
The new reality is quite different. Beginning in 2007, we have seen most of the conventional quantitative factors underperform and behave in strange and unexpected ways. Momentum factors have not been spared. Figure 17 shows the same average rank IC Momentum term-structure from Jan 2007 to May 2011. Note the vast difference relative to the shape of the term-structure curve in Figure 16 and how the better performance across Momentum strategies has shifted toward those with shorter horizons. In addition, the rank IC values as well as the risk-adjusted rank ICs have all decreased dramatically; an indication that predictive power is not what it used to be. In fact Figure 19 suggests that the predictive power for any Momentum horizon strategy in large cap stocks is negligible.

Figure 17: Momentum Average Rank IC Term Structure Russell 3000 Universe (Jan 2007 – May 2011)



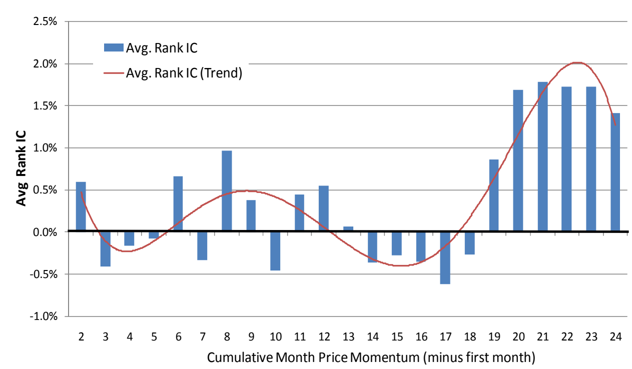
Source: Compustat, Russell, Deutsche Bank

Figure 18: Momentum Average Rank IC Term Structure Russell 1000 Universe (Jan 1988 – May 2011)



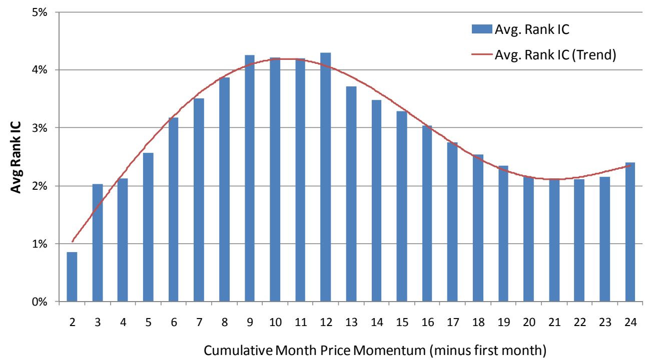
Source: Compustat, Russell, Deutsche Bank

Figure 19: Momentum Average Rank IC Term Structure Russell 1000 Universe (Jan 2007 – May 2011)



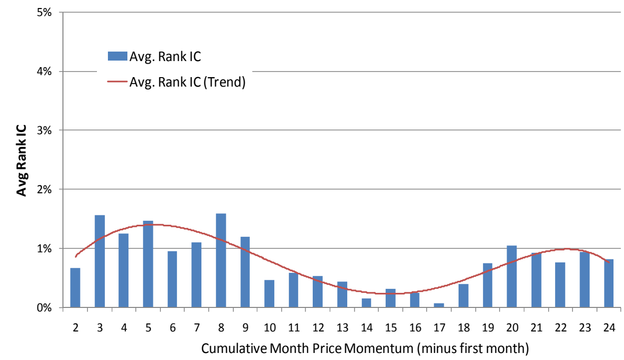
Source: Compustat, Russell, Deutsche Bank

Figure 20: Momentum Average Rank IC Term Structure Russell 2000 Universe (Jan 1988 – May 2011)



Source: Compustat, Russell, Deutsche Bank

Figure 21: Momentum Average Rank IC Term Structure Russell 2000 Universe (Jan 2007 – May 2011)



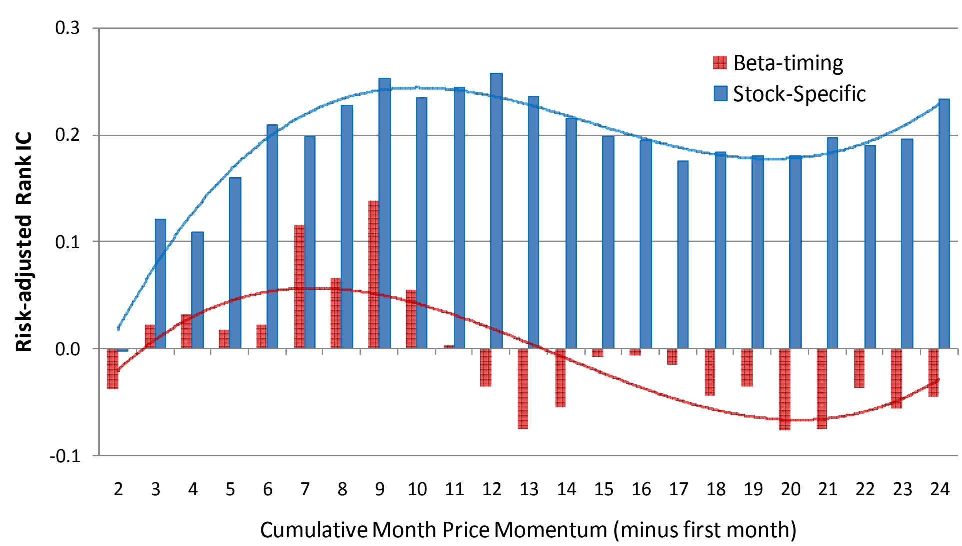
Source: Compustat, Russell, Deutsche Bank

The recent shift towards faster Momentum could be a consequence of various factors. For example, it could be due to the strong and sudden risk reversals the market has experienced over the last four years. It could also be that investors are better informed and mispricing due to investor under-reaction has diminished due to faster information flow.

Beta-timing & stock specific momentum across the term-structure

In the previous two sections, we saw two different ways to analyze Momentum. The first consists of decomposing Momentum into a Beta-timing versus a stock-selection component, while the second looks at the term-structure across Momentum strategies for different horizons. We can go further and combine these two perspectives to analyze momentum. This consists in simply analyzing the term-structure for both the Beta-timing and stock-specific components over the different Momentum horizons.

Figure 22: Beta-timing vs. stock-specific risk adjusted rank IC across Momentum term-structure Russell 3000 (Jan 1995 – May 2011)



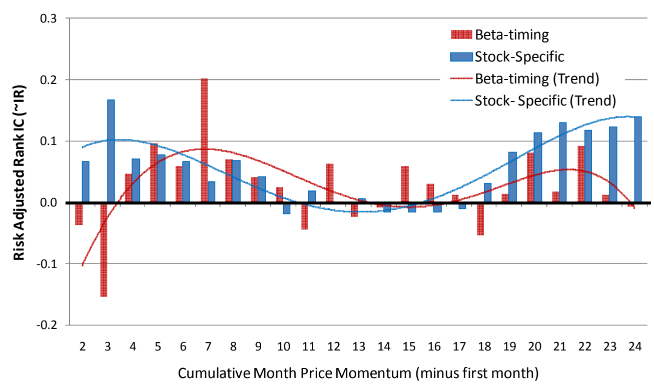
Source: Axioma, Compustat, Russell, Deutsche Bank

Is stock-specific momentum dead?

This new reality as shown in the last section leads us to question whether traditional stock price momentum can be used as a viable strategy going forward. Figure 23 and Figure 24 below add even more bad news to the already dismal picture. They show that recent performance for stock-selection has seen a significant downshift relative to the past. In addition, the performance after the spring 2009 "junk rally" shows overall negative performance for both stock-selection and Beta-timing across most conventional horizons.

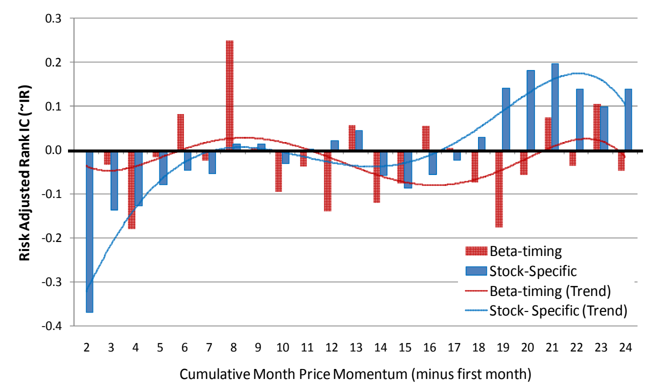
Do these results mark the grave for Momentum strategies? Not necessarily as we will see in our next section.

Figure 23: Beta-timing vs. Stock-specific risk-adjusted Rank IC for Momentum Term-Structure Russell 3000 (Jan 2007 – May 2011)



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 24: Beta-timing vs. Stock-specific risk-adjusted Rank IC for Momentum Term-Structure Russell 3000 (Jun 2009 – May 2011)



Source: Axioma, Compustat, Russell, Deutsche Bank

Re-constructing Momentum

Stock-selection and multiple-horizon factors

We look at two new factors that arise from the framework and the analysis done in the prior sections. Our first factor is simple and is linked to the analysis on Beta-timing and stock selection, while our second factor relies on a key insight from the term-structure analysis.

However, we add a twist at this point for measuring performance. Up to now our factor performance metric has been the rank IC. However, as we will argue below this metric is not optimal to measure the performance of Momentum strategies.

Distance matters

Momentum performance is contingent upon investors buying past winners and selling past losers. If buying and selling is based on past performance, then the distances between the raw momentum scores should possess some level of information. In other words, we argue that the fact that stock A is ranked next to stock B matters less than *how far* stock A's momentum score is from stock B's.

For example, take a group of ten stocks and suppose that nine out of ten stocks have price-return momentum scores that are not very different from each other, but the tenth stock is outperforming the other nine by a wide margin. Then a momentum focused investor would most likely think of the ten stocks as two groups. The first group consisting of the nine stocks for which there is not enough information to pick future winners over losers, and a second group consisting of the tenth stock that should outperform the other nine.

The latter implies that distance matters, but also that there may be less breadth than we imagined given that some of the information in the scores may not be valuable to discern outperformers versus underperformers.

Using a factor-mimicking portfolio to measure performance

In the first part of the report, we focused on the rank IC of factors to measure their performance. The rank IC as its name implies is a measure of how well the ranking of the momentum scores match the ranking of forward returns. The measure is intended for robustness because it is not significantly affected by outliers or data errors. However, it can have its drawbacks. One major drawback of the metric is that it does not account for the distances between the factor scores and the magnitude of forward returns. As we argued above, distance should matter so we must use a different metric than the rank IC.

One alternative is to trim for outliers and use regular IC. However, a very similar but more tactical route is to form a factor-mimicking portfolio. The two will be very similar (correlations are in the 90% levels), but the portfolio route has the advantage that it is more realistic and lends itself to traditional portfolio return analytics such as computing risk, Sharpe ratio and IR without the need for intermediary assumptions.

To construct the factor-mimicking portfolio is quite simple. Basically, we take the raw momentum scores (after trimming outliers) and scale them to have unit risk (see below). Then center the factor and form a long/short portfolio using the factor scores as the holdings to the factor-mimicking portfolio. The returns to this factor mimicking portfolio will actually be highly correlated with rank IC, but will account for the distance between the Momentum scores. The process to scale a factor to have unit risk is detailed in the following.

$$\textit{factor-mimicking portfolio} \equiv \textit{factor-scores} \,/\, \hat{\sigma}_{\textit{factor-score return}} \quad (8)$$

where $\sigma_{\textit{factor-score return}}$ is the expected risk of the factor-score return - not to be confused with the cross-sectional standard deviation of the scores. This risk can be estimated in different ways. The simplest is to use the sample standard deviation of the factor-score returns over time. The factor-score returns for each point in time are simply:

$$R_{f,t} = \sum_i f_{i,t} \cdot r_{i,t} \quad (9)$$

where $f_{i,t}$ is the factor score for stock *i* at time *t*, and $r_{i,t}$ is the return to stock *i* at time *t*[16]. Then the sample standard deviation of the factor scores is given by:

$$\hat{\sigma}_{\textit{factor-score return}} = \frac{1}{T}\sqrt{\sum_t \left(R_{f,t} - \mu_f\right)^2} \quad (10)$$

Of course other and more sophisticated estimation methods may be used in place of (10) to capture the standard deviation of the factor scores. However, a more sophisticated way to compute the forecast is to use the stock-by-stock covariance matrix of returns. This has the benefit that it uses the full risk structure of the stocks and is best when evaluating a large universe. The forecast for factor-score risk is then given by:

$$\hat{\sigma}_{\textit{factor-score return}} = \left(\boldsymbol{f}'\, \boldsymbol{V}\, \boldsymbol{f}\right)^{1/2} \quad (11)$$

where $\boldsymbol{f}$ is the vector of factor-scores and $\boldsymbol{V}$ is the stock-by-stock covariance matrix. We use this method for constructing the factor-mimicking portfolios going forward.

Stock-selection Momentum Factor

This factor is modeled after the stock-specific component from the correlation-neutral decomposition in equation (7). However instead of using Predicted Beta for the neutralization, we find it best to use a similar, but more effective factor developed in our "Volatility=1/N" (2010) report. In that report, we introduced the contribution-to-risk factor as our preferred measure to capture risk seeking or risk-adverse behavior. It is very similar to Beta both in substance and mathematically. The benefit is that we construct the factor using the stock-by-stock covariance matrix, which provides better systematic risk control in that it is more aligned than Beta with stocks that have exposure to riskier industries, styles and specific risk.

Specifically, our new stock-selection Momentum factor-mimicking portfolio is constructed as follows:

1) Take the 12-month price momentum scores and trim outliers at 99.5% levels.

2) Scale the momentum factor to unit risk[17] as done in (8).

3) Neutralize for the contribution-to-risk factor as done in equation (7).

[16] Intuitively and mathematically this return is very similar to the IC of the factor. To see this recall that IC is the correlation of the signal-scores and forward return. Then write the correlation as the covariance divided by the standard deviations of the factor-scores and forward returns and note that if the factors scores are normalized (z-scored) then the numerator (the covariance portion) of the IC becomes the factor-score return depicted in (9). The factor-score return then becomes the driver of IC direction and relative performance.

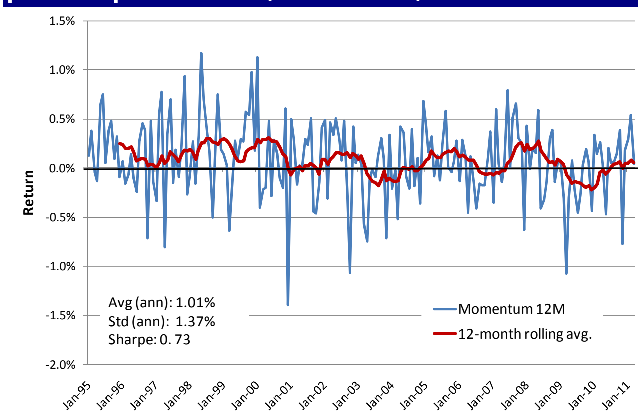
[17] Actually, we scale them to have 1% risk. This scale is completely arbitrary.

4) Use the resulting scores as the factor-mimicking portfolio weights.

One important note about the factor construction process described above is that we do not fully normalize the scores cross-sectionally. The reason is because we want to preserve the natural distances between the scores. Therefore, if the scores are skewed to the left then we will probably have more of the weight distribution allocated to the negative tail; rather if the factor-score distribution is heavily fat-tailed but symmetric, then we will have the weights concentrated in the tails of the factor-scores. The factor is neutralized for Beta-type risk so the concentration of the weights towards one or both tails of the distribution should not cause any significant risk downside[18]. Furthermore, we let the neutralization scheme center the factor and do not re-center because it will alter the risk correction carried out by the neutralization.

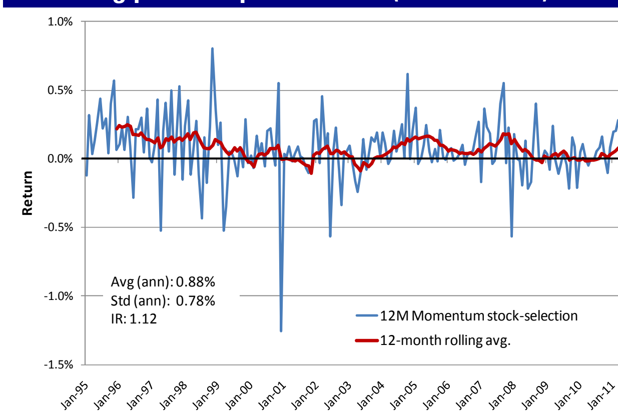
To compare against the traditional Momentum factor, we construct the same factor-mimicking portfolio except that we use the conventional method of standardizing the z-scores. Figure 25 shows the performance to the generic 12-month Momentum factor using standardized z-scores, while our new Momentum stock-selection factor performance is shown in Figure 26. Note that it only suffers from one large drawdown in January 2001, but is not affected by the "junk" rally in spring 2009, which is quite devastating for the traditional 12-month momentum factor.

Figure 25: Generic Momentum factor-mimicking portfolio performance (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 26: Stock-selection Momentum factor-mimicking portfolio performance (Russell 3000)



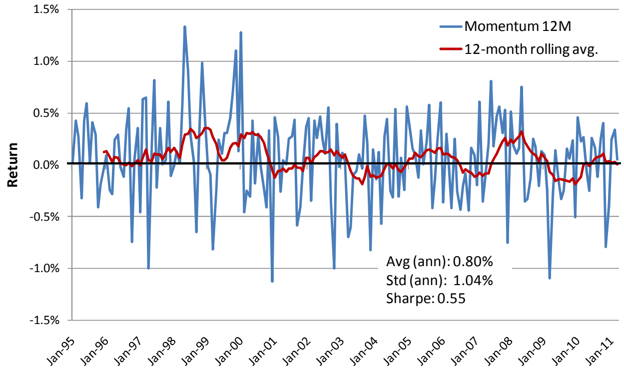
Source: Axioma, Compustat, Russell, Deutsche Bank

Vast improvement the large cap universe

Interestingly enough, we find that this factor improves significantly on the traditional Momentum factor in the large cap space. In particular, we find that the new factor benefits mainly from added risk control, especially on the downside. Figure 27 and Figure 28 show the performance of the traditional and new stock-selection momentum factors for the Russell 1000. As we did for the full universe, the traditional factor is standardized, while our stock-selection factor is not allowing it to allocate more weight towards the tails. The Sharpe ratio almost doubles and we can see that negative performance is limited on the downside.

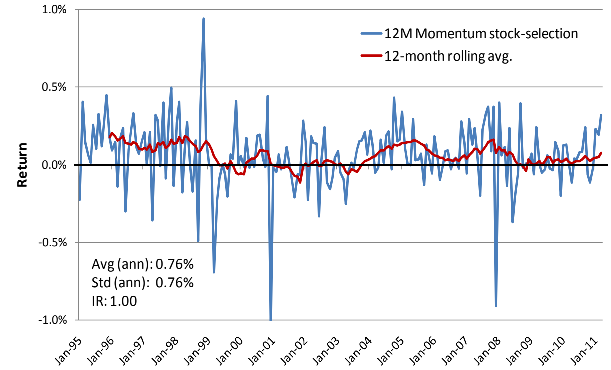
[18] There is the downside of less breadth, which is what happens when weights are concentrated too heavily in too few assets. However, to control systematic risk we do not need breadth, just a good risk model.

Figure 27: Generic Momentum factor-mimicking portfolio performance (Russell 1000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 28: Stock-selection Momentum factor-mimicking portfolio performance (Russell 1000)



Source: Axioma, Compustat, Russell, Deutsche Bank

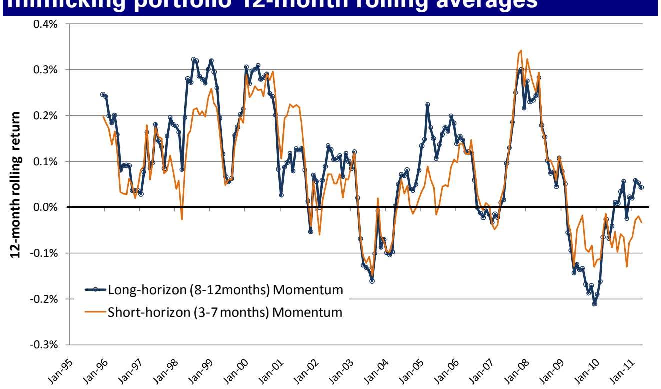
A term-structure factor: Momentum principal component factor (MPC factor)

Our next factor is constructed using insights from the term-structure analysis in the second section of the report. There we saw that the term-structure of momentum performance peaked at the 12-month strategy over the entire period (see Figure 16), but in recent times has seen radical changes and that performance has shifted towards the front and back end of the term-structure (see Figure 17).

At a high level, we can see the shift in the term-structure by looking at the performance over time across the upper-half and lower-half of the term structure. To do this, we simply aggregate the strategies into two groups: a long-horizon group consisting of the momentum strategies from 8-12 months; and a short-horizon group consisting of the momentum strategies across 3-7 month horizons.

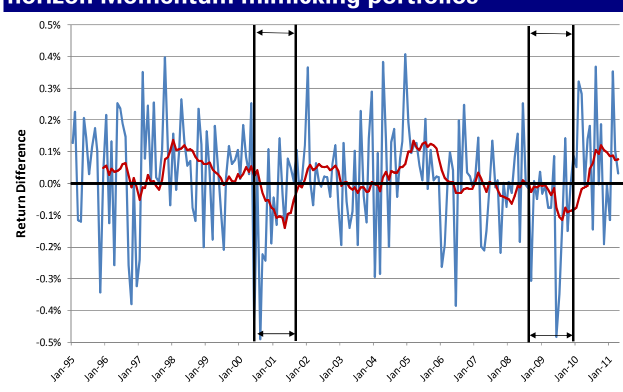
Figure 29 shows that the longer-horizon momentum strategies have dominated throughout most of the sample, but have underperformed the shorter-horizon strategies during two periods.

Figure 29: Long-horizon vs. Short-horizon Momentum mimicking portfolio 12-month rolling averages



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 30: Difference between long-horizon and short-horizon Momentum mimicking portfolios

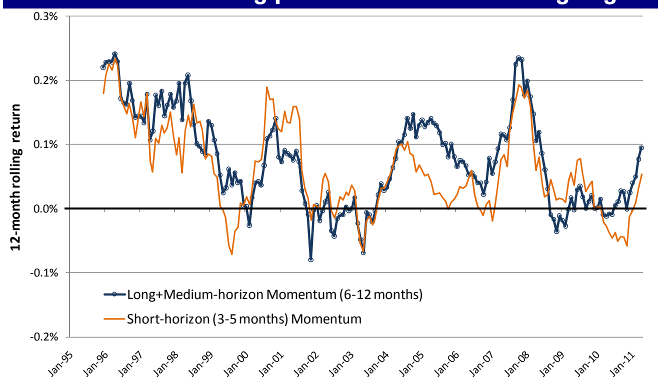


Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 30 shows the difference between the long-horizon and the short-horizon strategies where it is easier to see the two periods in which shorter-horizon strategies outperformed those of longer horizon. The figures suggest that short-term horizon strategies outperform those of longer-horizon during and subsequent to episodes of strong risk-reversals or market turning points. These are times when macro dominates stock returns and the "risk-on/risk-off" investment behavior is the norm.

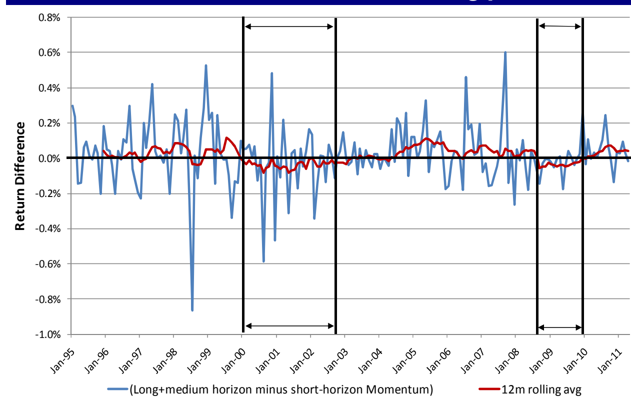
The next question is whether we see similar alternating behavior across the momentum stock-selection strategy horizons? To examine, Figure 31 shows the 12-month rolling average returns of long and medium-horizon stock-selection momentum strategies (6-12 months) compared to those of short-horizon (3-5 months). Note that there are two periods when the shorter-horizon strategies outperform the long-horizon. The first is during the bear market of 2001-2003. The second occurs during the recent period of Momentum underperformance (Nov 2008 – Jan 2010).

Figure 31: Long+medium-horizon vs. Short-horizon Momentum mimicking portfolio 12-month rolling avg



Source: Axioma, Compustat, Russell, Deutsche Bank

Figure 32: Difference between long+medium-horizon and short-horizon Momentum mimicking portfolios

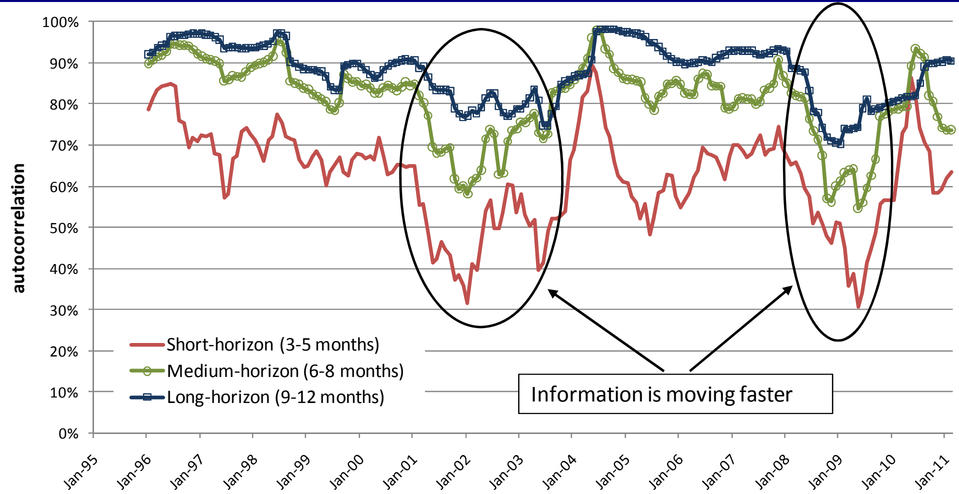


Source: Axioma, Compustat, Russell, Deutsche Bank

The fact that there are sustained periods when shorter-horizon momentum strategies outperform those of longer horizon may be attributed to faster information flow or consistent and rapid reversals in the market environment. Either way, information entering into shorter-term signals seems to possess more value than older information that has been accumulated into the longer-horizons.

How do we verify that indeed information is flowing more rapidly through these strategies during those periods? Ultimately, we need some measure or indication of information flow. One way to measure this is to look at the turnover of the portfolios across each horizon or equivalently, we can look at the autocorrelation of the factor-mimicking portfolio returns for each horizon. The autocorrelation will indicate how new information has changed the portfolio from one month to the other. If autocorrelations are abnormally low from steady-state across all horizons then information is moving relatively faster, while higher autocorrelations indicate that information is not changing much or moving more slowly. To see this we first aggregate the strategies into three groups: a short-horizon (3-5 months), medium-horizon (6-8 months), and long-horizon (9-12 months) group and measure the average autocorrelation of the strategies within each group (see Figure 33). Note that episodes when short-horizon strategies outperformed those of longer-horizon (see Figure 31), correspond to periods when the autocorrelations across all momentum horizons dropped substantially (see Figure 33).

Figure 33: Average autocorrelation of momentum strategies across different horizons



Source: Axioma, Compustat, Russell, Deutsche Bank

Naturally, the next question is whether we can use information from the term-structure to dynamically shift our horizon so that we are better positioned for changes in term-structure performance.

One way to do this is to use principal component analysis. The impetus for this procedure arises from the intuition that the horizon with the highest potential for momentum profits will be the one with the most correlation across all the different horizon strategies. To more generally implement this theme, a principal component technique would allocate factor weights according to levels of correlation

The construction of the factor mimicking portfolio follows:

1) Start with the stock-selection factor-mimicking portfolios (neutralized) from the last section for horizons starting from 2-months to 12-months and scale to unit risk.

2) Compute the correlation matrix of the 11 factors using a forecast of the stock-by-stock covariance matrix as follows.

$$\boldsymbol{\rho} = \boldsymbol{D}^{-1/2} \left(\boldsymbol{F}' \boldsymbol{V} \boldsymbol{F}\right) \boldsymbol{D}^{-1/2} \tag{12}$$

where $\boldsymbol{F}$ is an Nx11 matrix where each column is the vector corresponding to the factor-mimicking portfolios for the Momentum horizons and $\boldsymbol{D}$ is a diagonal with the expected variances of each of the portfolios as computed (11).

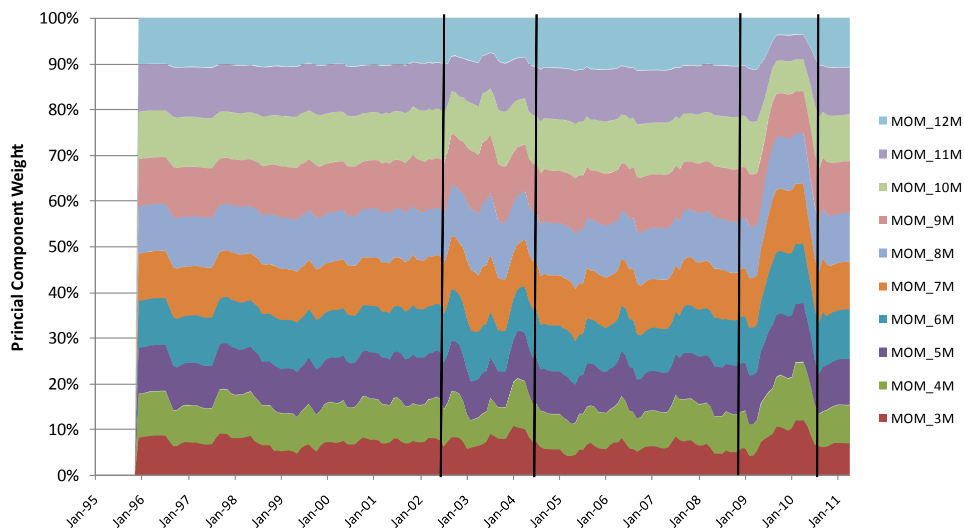
3) Take the singular value decomposition of the correlation matrix in (12) and use the first eigenvector as the weights to allocate to each of the factor-mimicking portfolios – i.e. take the first principal component as the new factor-mimicking portfolio[19]. Scale the new portfolio to have unit risk. The resulting portfolio is our Momentum Principal Component factor (MPC).

[19] This can be computed using any common statistical package via a few lines of code.

What we have done using this analysis is to allocate weights to each of the horizons depending on each horizon's level of correlation relative to the other horizons. This is an attempt to allocate more exposure towards momentum strategies that have the most momentum information. Therefore, if information is moving rapidly then the shorter horizon strategies will be correlated amongst each other. In contrast when information is moving slowly then the correlations will concentrate towards the longer horizon strategies. This is because the longer horizon strategies will have more concentration of momentum when information is moving slowly; and will have less momentum (thus less correlation) when information is moving rapidly.

To see the latter, we can look at the weights implied by the first eigenvector over time. Figure 34 shows the 12-month rolling average weights to each momentum strategy over time. It is obvious from the figure that the higher horizons tend to have higher weight allocation over time. This is intuitive in that during times when information is moving slowly the longer-horizon strategies will be more correlated because their compositions will be "stickier" over time. However, we note the two periods enclosed in the bars. These are periods in which macro dominated and if we look at the area of each strategy what we see is that the weights shift from higher horizons to lower horizons and then back to higher horizons.

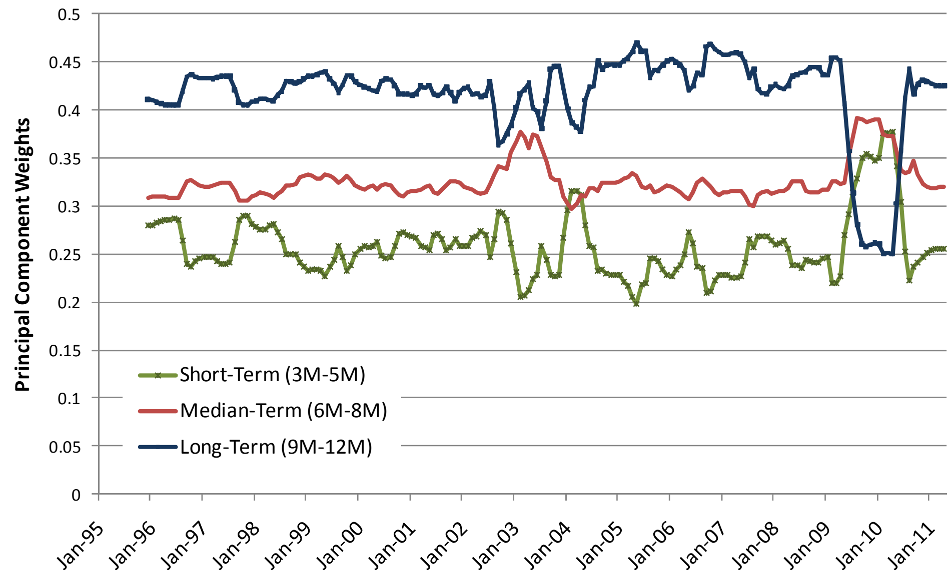
Figure 34: Principal Component factor weights (12-month rolling average)



Source: Axioma, Compustat, Russell, Deutsche Bank

We can gain more insight by grouping the momentum strategies into three groups: short, median and long horizon. Figure 35 shows the aggregate weights to each of these groups over time. What we see is very interesting. It suggests that there is indeed a steady state of information flow, which concentrates heavily into the longer horizon strategies. However, during periods of risk-reversals and strong macro influence, information moves faster trending towards the medium and shorter-term strategies. Finally, we note that the last divergence from the steady state behavior suggests that stock-selection information became heavily concentrated in the shorter and medium horizon strategies. However, the divergence has recently subsided and the term-structure seems to be in steady state once again. This may explain the more recent (Jan 2011 – May 2011) outperformance of longer-horizon Momentum.

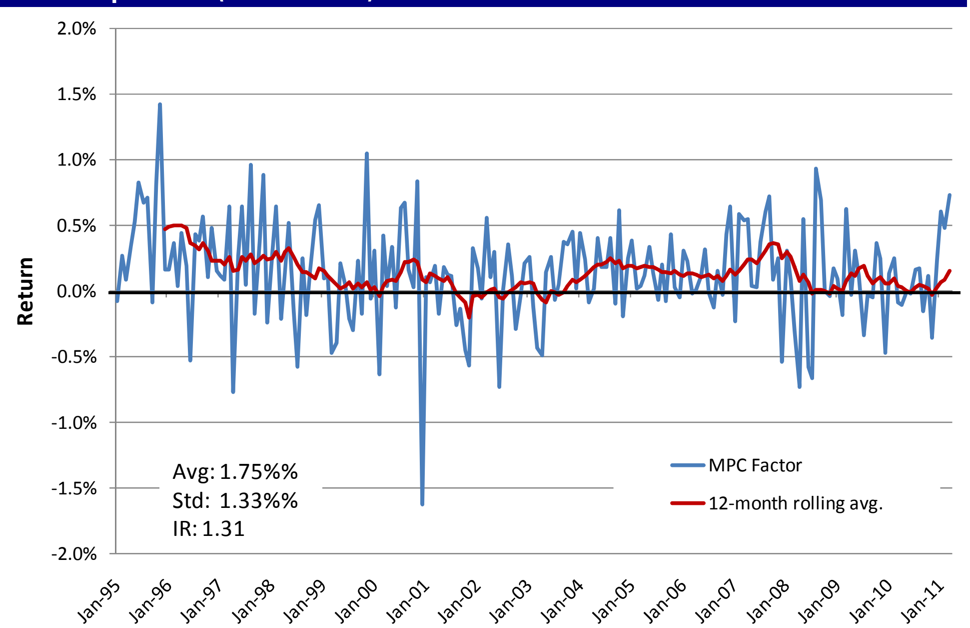
Figure 35: Principal Component Weights aggregated across short, median and long horizon frequencies (12-month rolling average)



Source: Axioma, Compustat, Russell, Deutsche Bank

The practical question however is whether or not we can capture the shifts early enough to improve performance. The answer can be seen in Figure 36 where we show the performance of the factor-mimicking portfolio across time. Note that it is superior to any of the other of the Momentum factors we have developed above and more impressively it is the only Momentum factor to have positive performance from Jan 2009 to the present (the stock-selection factors were flat and the conventional 12-month factor was negative).

Figure 36: Performance of Momentum Principal Component (MPC) factor mimicking portfolio (Russell 3000)



Source: Axioma, Compustat, Russell, Deutsche Bank

Portfolio considerations

Alpha and risk model misalignment

Investors using risk models and optimization in the portfolio construction process have yet another obstacle to overcome when trying to implement Momentum into their strategy. The risk-alpha misalignment phenomenon is a well documented effect (see Lee and Stefek [2008]), which can cause the final risk-adjusted portfolio to become adversely misaligned with the intended alpha exposure. The effect of this phenomenon on 12-month Momentum is particularly strong, which was well documented by Lee and Stefek (2008). While the research on this topic is still in its early stages, it is well known that the problem is brought about by using similar (not exactly the same) factors in both the alpha and risk model. Therefore, the fact that most fundamental risk model vendors include some version of Momentum into their risk models this phenomenon is particularly common in the case of 12-month Momentum[20].

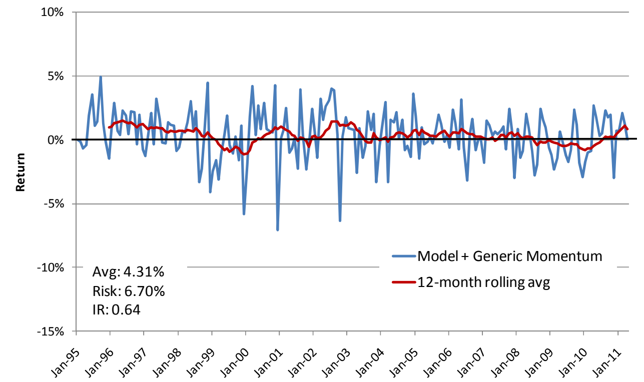
Optimized portfolio example

Now we run a full optimized portfolio to assess the real-world applicability of our MPC factor. We start with a basic four-factor model, which consists of FY1 Earnings Yield, EPS YoY Growth, Revisions, and ROE. We then add a Momentum factors and weigh all the factors on an equal risk basis. To test the efficacy of our MPC factor relative to the generic 12-month Momentum we add each to a model separately. To avoid issues with the risk-alpha alignment phenomenon, we take the Momentum factor out of the risk model before the optimization. The optimization settings are standard:

- 3% risk target
- 30% two-way turnover per month
- 3% maximum holding
- Beta neutral (+/-10%)
- Sector neutral (+/-20%)
- 2xLeverage
- Take out Momentum Risk factor from the Risk Model.

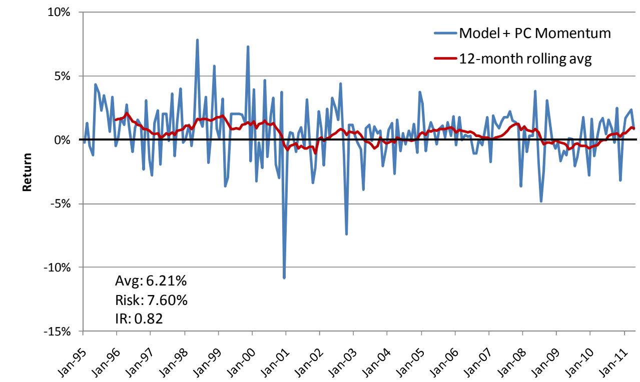
[20] Indeed, Momentum is often used as the prime example of the problem.

Figure 37: Portfolio performance: Generic 12-month Momentum + Basic four factor model



Source: Axioma, Compustat, Russell, IBES, Deutsche Bank

Figure 38: Portfolio performance: Term Structure PC Momentum + Basic four factor model



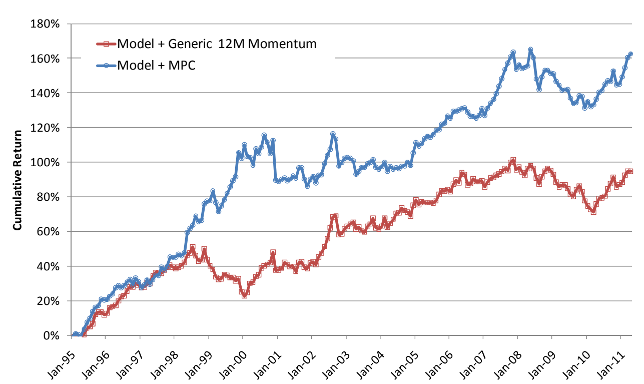
Source: Axioma, Compustat, Russell, IBES, Deutsche Bank

As we expected, the results in Figure 37 and Figure 38 show that the basic model factor performance improved by using our new PC Momentum factor. Interestingly enough, in both cases, the risk came out to more than double of our risk target. This is due to the fact that Momentum was taken out of the risk model and so the optimizer was fooled into having less risk than we actually did.

We also see a dramatic benefit when looking at cumulative performance across our backtest period. Figure 39 shows the difference between adding the generic 12-month Momentum factor versus out MPC factor to the generic four-factor model. Note that there are various periods when the MPC model outperforms the generic Momentum model. Specifically, we see a strong improvement in the late 90's as well as post 2007.

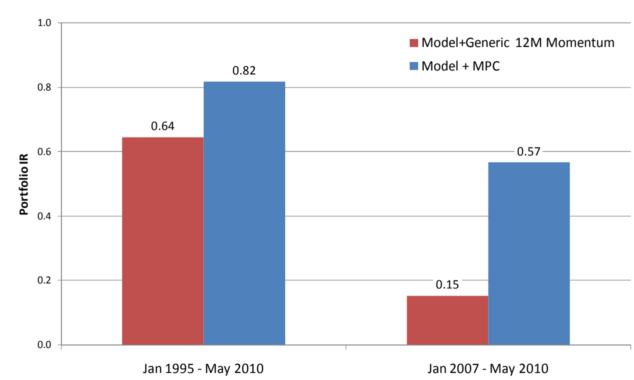
Last, Figure 40 shows the information ratios of the two portfolios over the full sample, and post 2007. We note that the model, which includes the MPC adds significant value over the entire sample, but even more strongly so after Jan 2007, when generic 12-month Momentum as well as most other conventional factors underperformed or were flat.

Figure 39: Cumulative performance



Source: Axioma, Compustat, Russell, IBES, Deutsche Bank

Figure 40: Portfolio IR over different periods



Source: Axioma, Compustat, Russell, IBES, Deutsche Bank

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Appendix 1

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