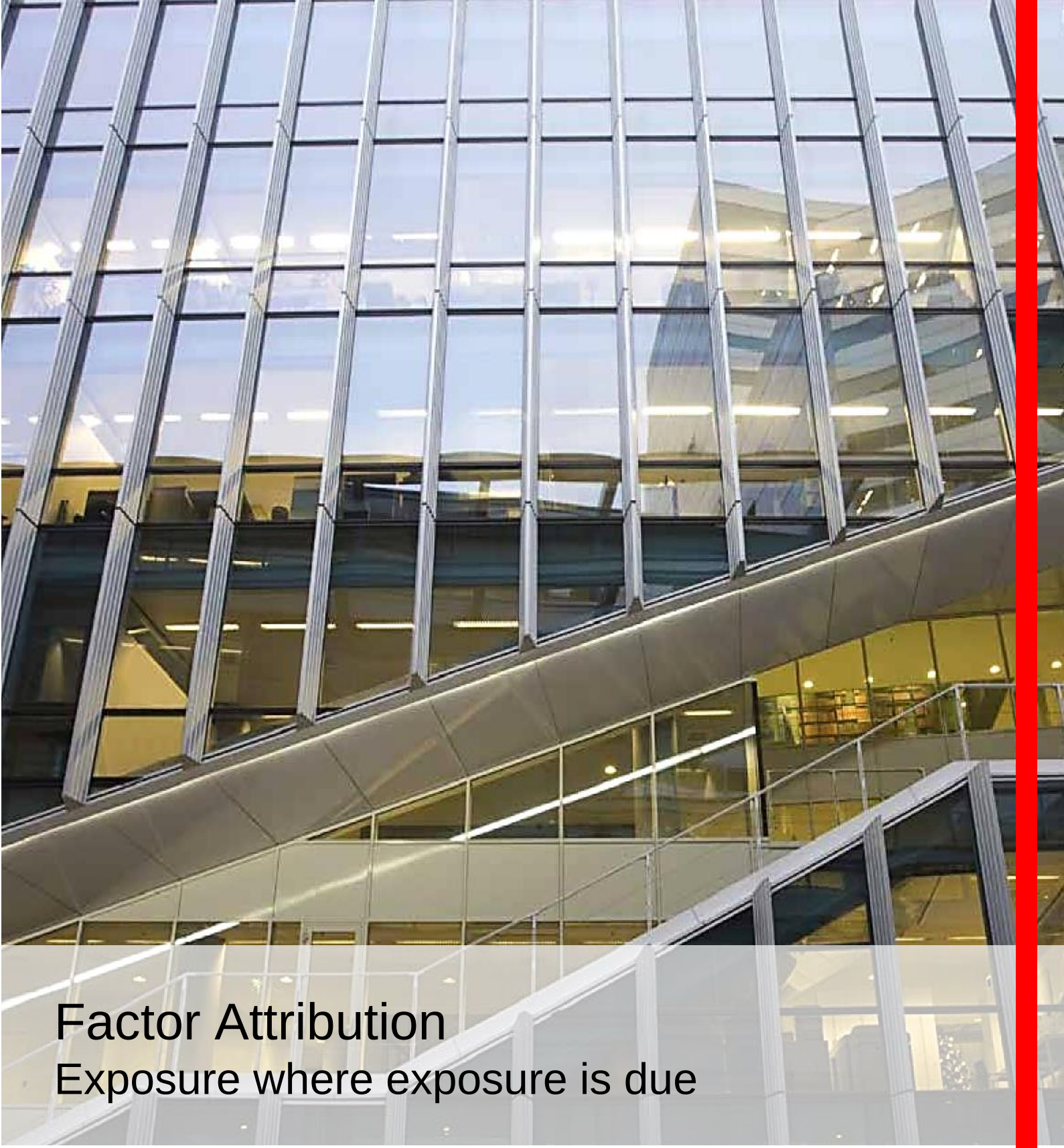


Factor Attribution

Exposure where exposure is due

HSBC Quantitative Research Team

July 2017

HSBC Global Asset Management

Factor Attribution

Exposure where exposure is due

Whilst benchmarking and peer grouping have served as intuitive indications of portfolio performance, they have left fund managers blind to the underlying drivers of return and potential areas of unintended risk exposure. In contrast, performance and risk attribution enables investors to quantify the contributions of each performance factor, equipping them with the potential to:

- Identify and act upon undesirable or unnecessary exposures
- Distinguish between systematic performance and stock-specific contributions indicative of stock selection skill
- Combine historical factor return contributions with forecasts to implement well-grounded views on future factor performance

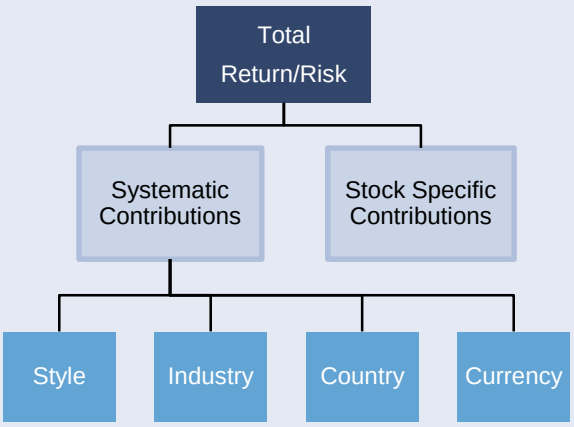
What does attribution entail?

Factor models can be used to attribute risk and performance. In our view, the most relevant groups of active systematic components that help determine return and tracking error are factors, countries, industries and currencies. Factors themselves can be categorised into different groups, e.g. value, momentum, quality, low volatility, leverage, growth, size, earnings variability, trading activity, etc. Any residual risk or non-factor return can be attributed on an individual stock basis.

In our factor investing solutions, we use customised alpha factor composites whose definitions are the product of rigorous theoretical and empirical research. This enables us to harvest these premia in an accurate way that captures the various dimensions of each factor. Likewise, our active solutions make use of systematic screening processes that provide a tailwind to performance.

In such scenarios, attribution requires a risk model that permits flexible addition or deletion of factors and can be calculated using stock universes specific to the fund under analysis. This is the case with our own in-house factor and performance attribution. Later on in this paper, we will discuss how our Custom Risk models (CRISK) allow us to combine our proprietary factors with other common risk factors, providing superior insight into the performance of our strategies.

Our performance attribution models are implicit fundamental models – stock-level factor exposures are calculated using fundamental data and used in cross-sectional regressions across the fund's entire stock universe to derive factor returns. These returns are then combined with the aggregate portfolio factor exposures to determine each factor's historical contribution to return. Our risk attribution process considers the decomposition of ex-ante tracking error. This provides a forward-looking indication of factors' potential contributions to risk, which is more valuable to portfolio improvement than simply observing the factor contributions ex-post[1].



[1] Practical Financial Econometrics by Carol Alexander includes a comprehensive guide to the underlying mathematics behind factor models.

Getting what you desire

The straightforward and transparent nature of factor investing strategies has generated significant inflows in recent years. Investors have benefitted from the commoditisation of academically supported risk premia through accessible, cost-effective products. However, excessive focus on performance metrics and faith in the simplicity of systematic strategies have at times distracted investors from ensuring that factor solutions provide optimum, uncontaminated exposure to the factor advertised. As smart beta represents a growing segment in client portfolios and solutions become more sophisticated, the quality of factor construction ought to be of growing concern. However, fiduciary duty continues to lie with the investment manager, not index constructors, and investors need to ensure they are aware of the underlying return and risk profile of any factor weighting scheme they follow.

Naïve, "raw" factor strategies are constructed by overweighting stocks exhibiting a certain characteristic and can lead to a trail of inadvertent exposures to unrewarded factors. This can occur even when exposure to the target factor seems impressively high. Portfolio-level exposures can be a coincidental result of how stock-level exposures happen to aggregate. However, some factors are inherently related and it is hard to obtain exposure to one without gaining some exposure to another. It is a well-appreciated fact that a value strategy constructed from the top quintile of value names is likely to demonstrate a high exposure to small caps.

When it comes to factor investing, transparency demands that a factor strategy should provide pure access to the advertised factor alone. Portfolio risk management and diversification are a common application of these products and managers need to control exposure to the target factor confidently without the possibility of concentrating other positions.

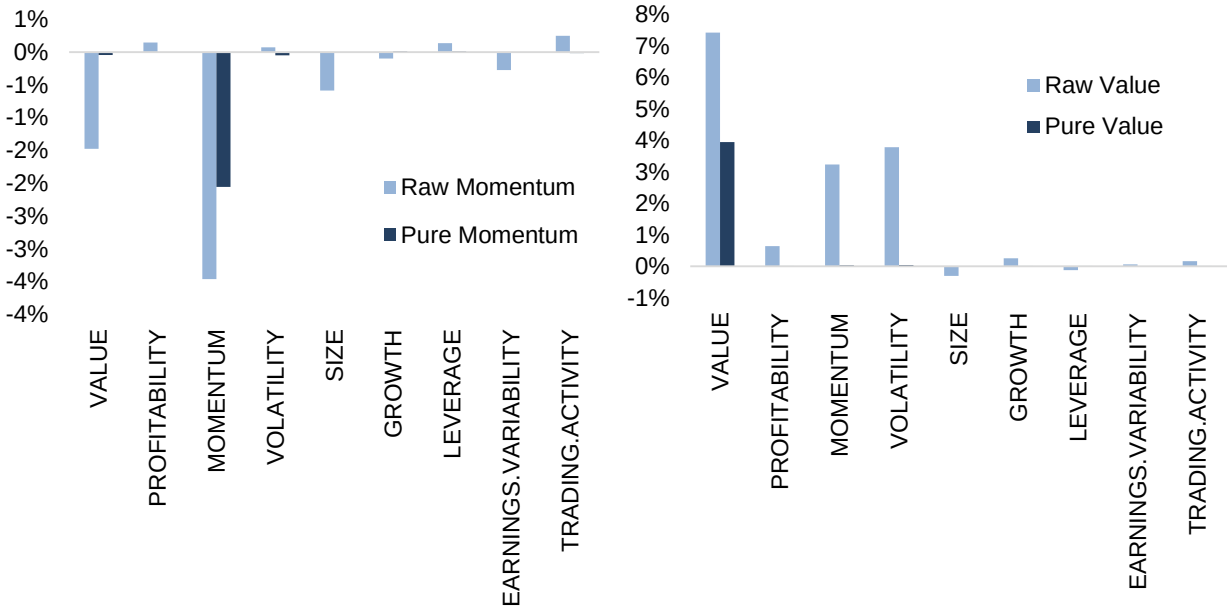
Why are unnecessary exposures such bad news?

Non-target exposures can have a positive contribution to return; the factor-only return attribution of the raw value strategy on page 5 shows that momentum and volatility have enhanced performance significantly. However, it is hard to justify its classification as a value strategy when such a great share of return originates from momentum exposure.

2016 saw a fundamental shift in factor performance as defensive factors retreated (e.g. quality and low volatility) and cyclical factors (e.g. value and size) outperformed. Unintentional systematic exposures are most likely to attract attention when the target factor itself suddenly underperforms or generates weak returns.

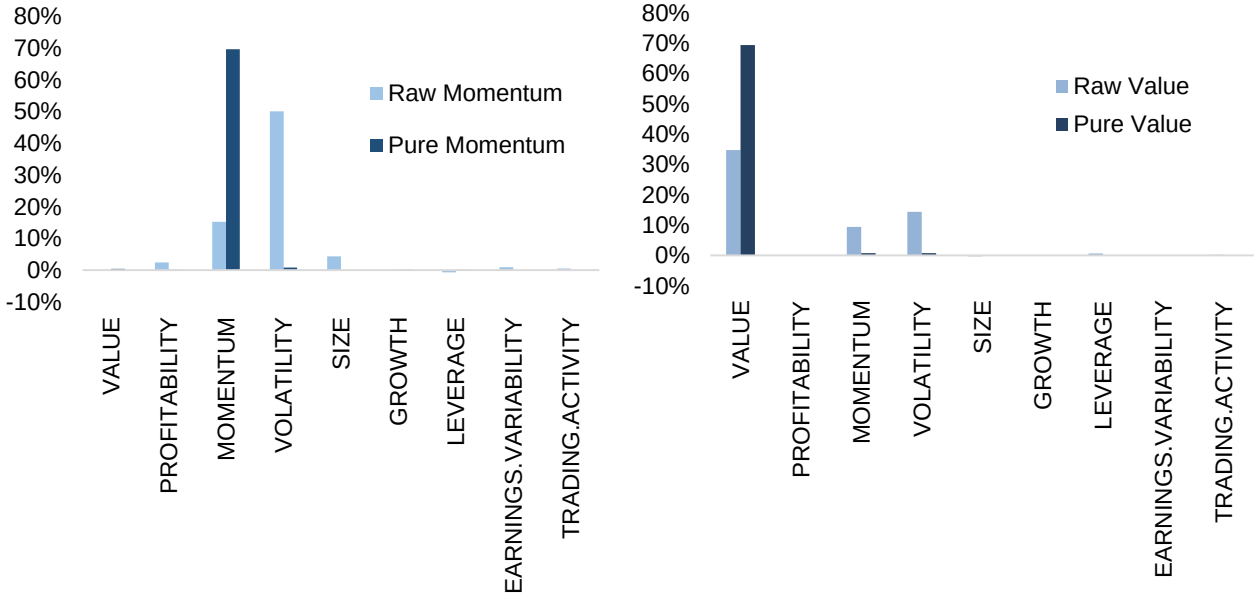
In the example of raw momentum on page 5, the targeted factor posts a strong negative return of -3.5%. However, the client ends up enduring an even worse style return contribution as value and size accentuate the negative return to -5.3%. The pure factor strategies presented demonstrate the benefit of a pure factor construction process that purposely constrains non-target exposures, leaving the advertised factor as the dominant driver of return. It is easier to communicate to investors the poor performance of their target factor than to explain poor performance at odds with the factor's theoretical return.

Figure 1: Total return factor-only contributions to momentum (left) and value (right) strategies' performance between February 2016 and February 2017 from factor exposures. "Raw" construction captures the top quintile of MSCI World constituents according to target factor exposure. "Pure" construction heavily constrains non-target systematic exposures whilst maximising exposure to the advertised factor.



However, unintended exposure can be just as destructive when these factors are not generating a significant return premium. Bertrand (2005) highlights the fact that performance attribution considered alone can be misleading. This is because the volatility in the factors' returns can still contribute to total risk, thereby diluting the strategy's risk adjusted returns. In the example of the raw momentum strategy below, factor risk attribution is dominated by the volatility factor, which contributes over 3x as much active risk to the portfolio than momentum. Similarly, whilst most non-target risk contributions to the raw value strategy are relatively small, momentum and volatility contribute significantly to the risk profile.

Figure 2: Ex-ante risk attribution of momentum and value strategy performance using weights as at 28 February 2017.



Source: All graphs use data from Thompson Reuters, IBES, Worldscope and MSCI as of 28 February 2017.

What is the best way to assess the purity of strategies?

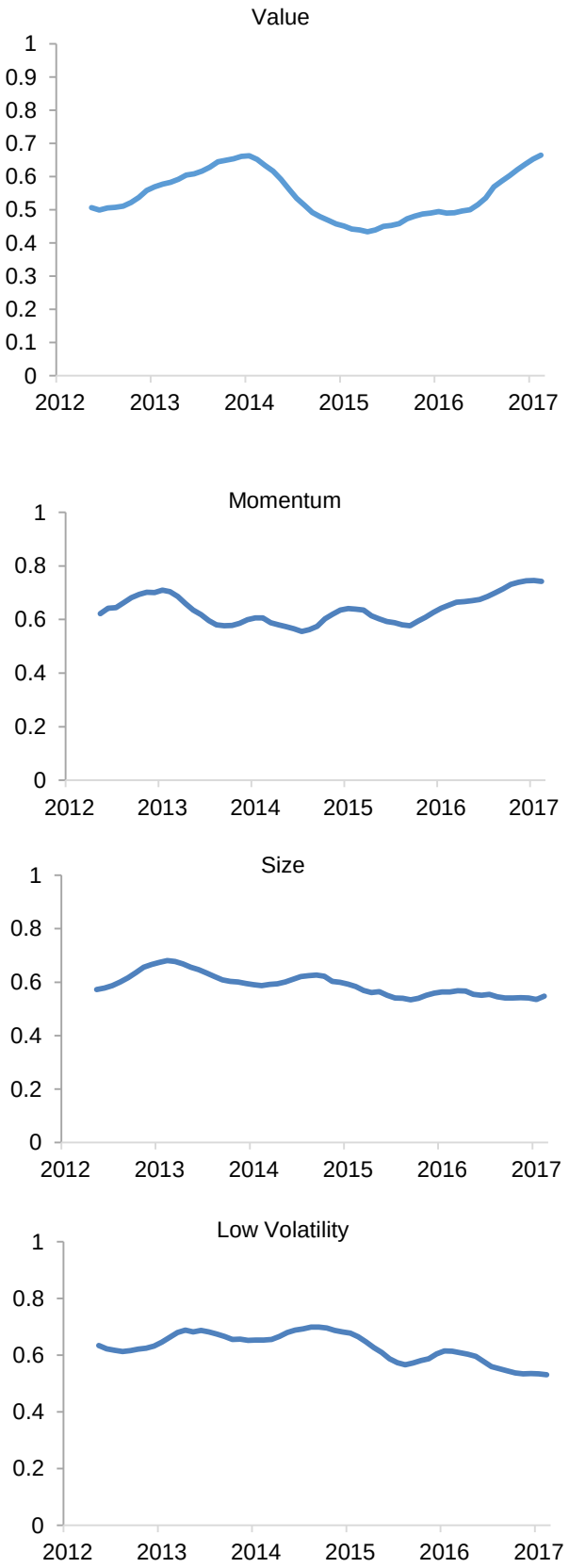
A risk attribution profile can therefore provide a more complete picture of the purity of a factor strategy than target-factor exposure or return attribution alone. We use the percentage contribution of the target factor to total active risk, or the "Factor Purity Ratio"[2] as a measure of the efficiency of the risk budget allocation in a given strategy construction methodology. This intuitive metric enables quick comparison of the purity of different factor strategies.

Constant monitoring of factor purity is important. Factor purity is not necessarily stable, indeed the charts on this page demonstrate how it can fluctuate over time. Investors need to consider the historical variance in purity, as well as its current level to cast a reasonable judgment of a strategy's risk allocation efficiency.

Figure 3: Factor purity ratios for raw and pure strategies as of 28 February 2017. Purity varies considerably across different factors but in all cases, constraining non-target factor exposures enhances efficiency.

Factor Efficiency	Raw	Pure
Value	35%	69%
Momentum	15%	70%
Low Volatility	37%	51%
Size	27%	57%

Figure 4: The evolution of pure factor purity ratios over time.



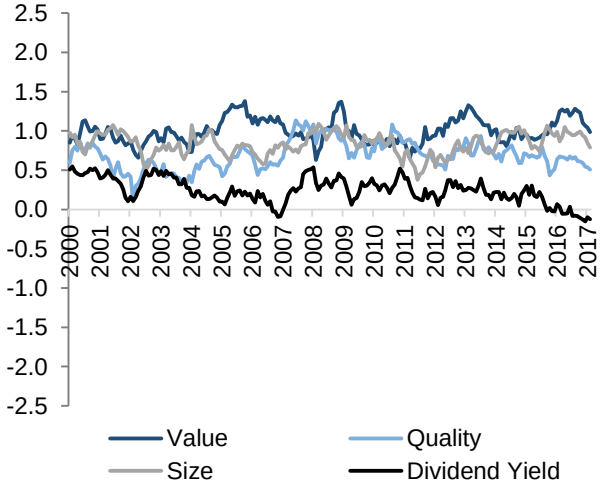
[2] See *Factor Purity*, HSBC Global Asset Management 2017.
Source: All graphs and tables use data from Thompson Reuters, IBES, Worldscope and MSCI as of 28 February 2017. Data from 31 May 2012 to 28 February 2017.

What has attribution got to offer active management?

Purity is a valuable quality in factor investing. However, in the broader realm of active investing, conscious management of factor exposures can be used intelligently in portfolio construction strategies to provide a tailwind to performance. Return attribution educates the manager about past successful factor exposures, knowledge that may be combined with forecasts to form astute views on future systematic performance. Goldberg, Leshem and Geddes (2013) use return attribution to demonstrate how minimum variance strategies have typically benefitted from negative exposures to size and positive exposures to value. In recent years, rapid inflows into minimum variance strategies have encouraged value tilts to reverse and momentum tilts to increase, harming performance. In response, they recommend introducing a positive value exposure constraint in the portfolio optimisation process to restore performance.

HSBC's core active management equity process evaluates stocks in the context of their enterprise value, ranking them according to their Return On Invested Capital (ROIC) and EBIT yield (EBIT/EV) – see the box on the right. High ranking stocks are then included in construction processes that either maximise average rank or minimise portfolio variance. The ranking process induces an inherent quality and value bias into portfolios.

Figure 5: Factor exposures exhibited by our core EV-ROIC process in the absence of style constraints.



Source: All graphs use data from Thompson Reuters, IBES, Worldscope and MSCI as of 28 February 2017. Data from 1 January 2000 to 28 February 2017.

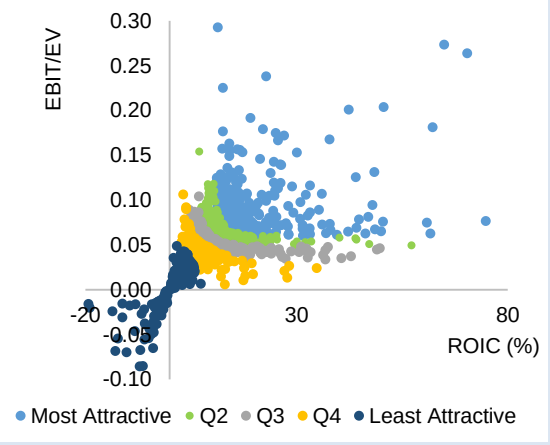
Our Enterprise Value Model – EV-ROIC

Joel Greenblatt's "Little Book that Beats the Market" was influential in getting investors, especially value investors, to pay attention to capital productivity in addition to valuation. The emphasis of Greenblatt's "magic formula investing" is on combining quality and value, in the spirit of Graham's belief in buying good firms at low prices. His approach ranks stocks in both ROIC and earnings yield, then buys those with the highest combined rank. The formula is explicitly intended to ensure that investors are "buying good companies…only at bargain prices."

In our EVROIC model, we use the ratio of EBIT to enterprise value as our measure of earnings yield. Both these quantities are measured with respect to the total capital of the firm, rather than only the equity portion. We refer to this ratio as "EV."

The measure of profitability (quality) is Return On Invested Capital (ROIC), one of the most fundamental financial metrics. Despite its importance, it does not receive the same kind of attention as earnings per share (EPS), return on equity (ROE), EBITDA or operating margin. One reason is probably because you cannot read ROIC straight off financial statements. However ROIC shows a company's cash rate of return on capital invested, i.e., it aims to measure the cash-on-cash return of a firm.

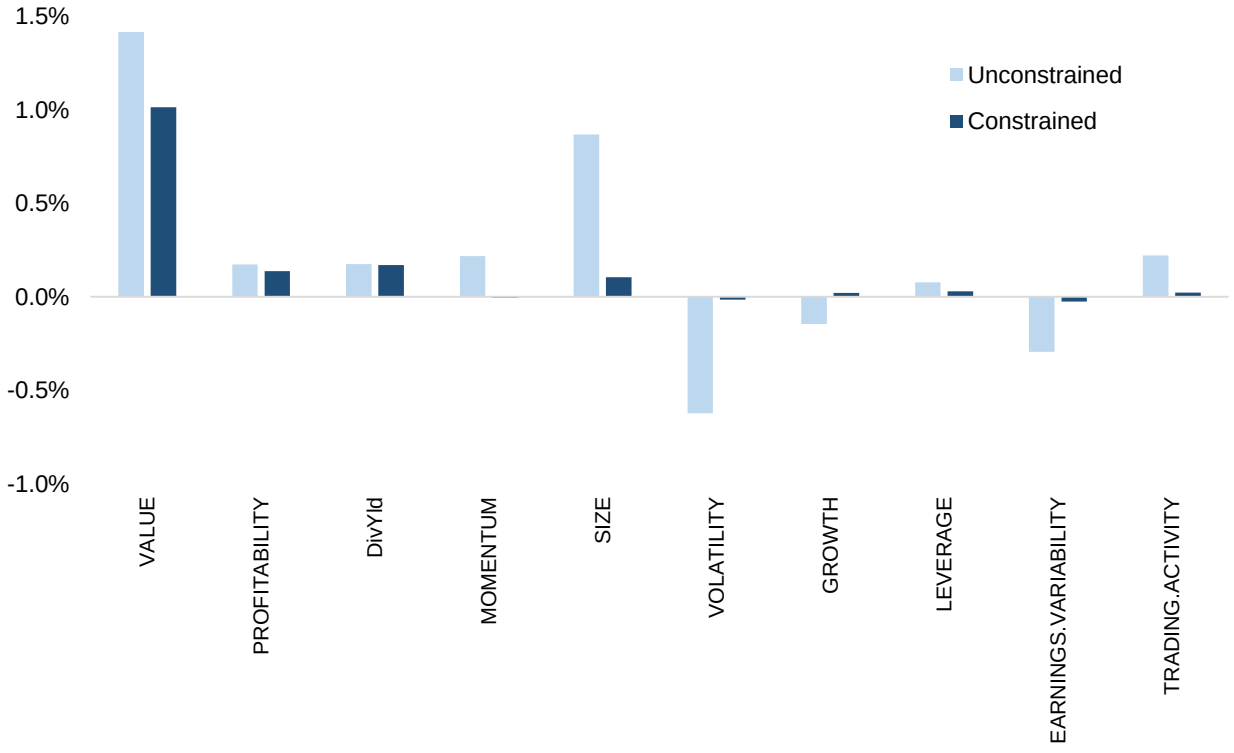
Companies are ranked by EBIT yield and ROIC separately. We then add the square of these ranks to determine a final, overall EV-ROIC hierarchy of stocks. This determines the order of preference for fundamental analysis and for consideration by our portfolio construction tools.



These quality and value exposures are preserved as we do not constrain them in the optimisation process. By default, all other factor exposures are minimised with the exception of dividend yield. The traditional role of the active fund manager is to improve upon the returns of such portfolios by maximising idiosyncratic return through superior stock selection skill. However, they also have the freedom to vary the default parameters in the portfolio construction process to take a particular view on expected factor returns or to loosen/restrict active country and sector exposures. Performance and risk attribution allow us to determine the relative successes of core systematic exposures, country/sector constraint adjustments, short-term factor views and stock selection and to incorporate any feedback into subsequent portfolio construction.

The graph below compares the factor return attribution of an unconstrained global optimised portfolio versus one subject to the default constraints over the period January 2000 to February 2017. It confirms our belief that the default constraints captured three drivers of positive return (value, profitability and dividend yield) over this period whilst protecting the portfolio from negative contributions from earnings variability, growth and volatility. However, the significant positive contribution from size in the unconstrained portfolio suggest that there may have been opportunities for managers to add value by relaxing some constraints over appropriate periods.

Figure 6: Factor return attribution of our core active process using MSCI World as the investment universe, covering the period 1 January 2000 to 28 February 2017. The unconstrained portfolio allows all factor exposures to vary freely, whilst the constrained portfolio suppresses all factor exposures except value, profitability and dividend yield.



Source: All graphs use data from Thompson Reuters, IBES, Worldscope and MSCI as of 28 February 2017.

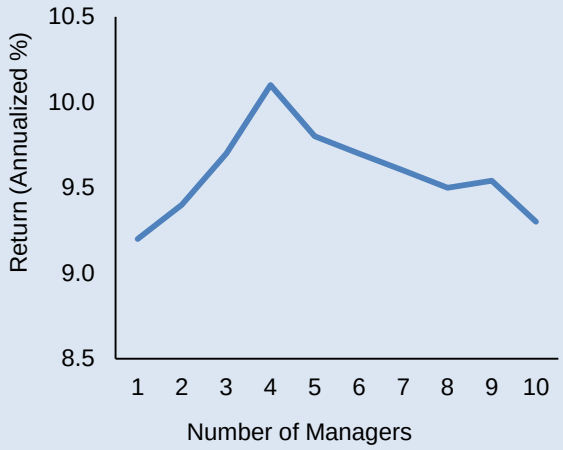
A comment on manager diversification

A study from RVK showed that manager diversification (i.e., increasing the number of funds in a multi-manager portfolio basket) could potentially lead to negative effects. As more managers are added to a portfolio:

- Portfolio active share declines
- Cost increases
- There is minimal diversification benefit

Ultimately returns suffer:

Median Seven-Year Return by Number of Managers in Portfolio



Source: RVK, Inc. (3 June 2015). For illustrative purposes only.

Avoiding this problem requires a parsimonious approach of building thematic blocks and identifying the point of diminishing returns.

Typically additional managers are added to the roster to bring complementary, uncorrelated exposures to the overall portfolio. Our pure factor strategies provide a useful set of tools to achieve this. They are designed to represent independent sources of risk and return at low cost. This provides the opportunity to control overall factor exposure without affecting true “active” share or introducing new unwanted risk exposures.

Customising Risk Models

HSBC in-house risk models equip us with the tools necessary to build superior portfolios by being fully aware of their underlying risk profile and observing feedback from historical return attribution.

Our Custom Risk models (CRISK) allow us to combine our proprietary stock signal factors (profitability and valuation) with other common risk factors. The result is a system that measures the tilts applied by our managers and allows them to utilise their risk budget more effectively.

There are four main benefits to the CRISK model:

- More efficient portfolios: a manager can allocate risk to the factors that lead to outperformance while avoiding risk they don’t want exposure to.
- Improved accuracy of risk forecasts: our profitability and valuation factors drive the “alpha” forecasts but contain risk themselves. A custom model measures risk factors more closely because we can precisely define the factors ourselves. A standardised off-the-shelf model may not exactly measure our risks. For example our alpha factor for value is price-to-book in many regions while a system like Bloomberg PORT will use a blended measure for value.
- Improved performance attribution: this is particularly true in identifying what drives portfolio returns. By clearly identifying the tilts being employed by the manager, we can attribute performance to the exact factor being exploited.
- Direct factor returns calculation: a CRISK model can calculate factor returns and potentially use them for pure factor products. This is more useful than simple quintile spreads, etc.

Building Robust Risk Models

We cannot evaluate the risk characteristics of a portfolio without a sample covariance matrix to map how individual constituents' risk exposures interact. The development of this matrix amounts to a trade-off between a tolerable level of standard error and a manageable number of estimated parameters. Unfortunately, an acceptable compromise is hard to find for large portfolios. We have three techniques at our disposal to tackle this challenge.

- As we explained previously, our models are implicit factor models. Re-expressing a stock-by-stock problem from the perspective of factor exposures requires fewer estimation parameters. Implicit factor models are more intuitive than explicit and statistical models and their structure improves risk model performance.
- We impose a greater degree of structure into the covariance matrix by appropriately combining the original with a target matrix that possesses a lot of structure. This process is known as "shrinkage" and enables us to create an estimator that performs better than its parents.
- The third technique applies random matrix theory. This allows us to minimize noise whilst protecting real correlation information. It is not mathematically applicable in all cases, but we can use it to "cleanse" the initial factor covariance matrix in our CRISK model.

The factor covariance matrix in our CRISK model uses all three techniques, whilst carefully considered weighting schemes ensure larger stocks exert more influence on the end result and correlations evolve more slowly than individual volatilities.

The result is an intuitive model which allows managers to keep track of a full range of systematic risk exposures, including factors, industries, countries and currencies.

Evaluating Custom Risk Models

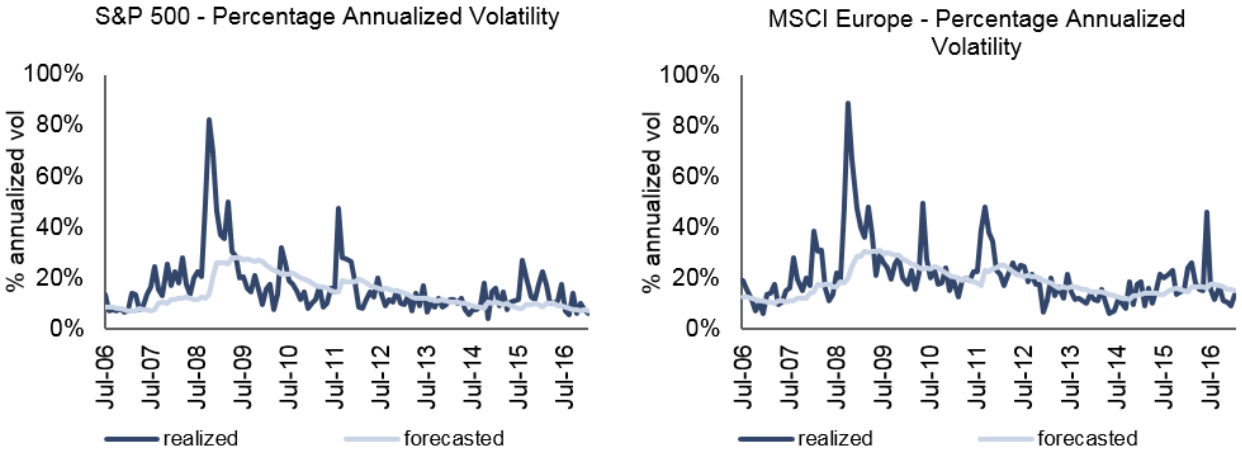
To develop efficient, accurate CRISK models, we need an approach that enables us to evaluate how well the model captures the dynamics of the universe in question.

In our evaluation process, we need to choose carefully the test metrics and portfolios used. For example, if a risk model misses a particular factor, the test will only expose this issue if the assets in a chosen test portfolio also share exposure to this missing factor. For this reason, we tend to apply widely available benchmark portfolios in our evaluation process.

We conduct our risk model evaluation by assessing its volatility forecasting ability. We can't measure the "true" volatility of the market; all we can do is approximate this measure by observing the historical realized volatility. However, we can improve upon our estimation by subdividing our observation period into smaller and smaller grids.

In the charts below, we directly compare our CRISK model's forecast percentage annualized volatility against the market's realized equivalent. Our model forecasts realized portfolio risks very well and responds to changes in the risk environment.

Figure 7: Direct comparisons of CRISK model forecast percentage annualized volatility versus realized volatility for S&P 500 and MSCI Europe.



Raw data sources: MSCI, S&P Dow Jones Indices, Thompson Reuters, IBES and Worldscope as of 30 June 2016.

Attribution enhances competitiveness in an increasingly sophisticated market

In the world of factor investing, return and risk attribution should be used in tandem to identify those products that deliver the targeted factor return in the most purest manner. Our pure factor strategies perform very well in this regard as they are specifically constructed to minimise non-target exposure. Meanwhile, active fund managers can control factor exposures in their portfolio construction and are therefore able to add value through opinions on expected systematic returns as well as expected stock specific returns. Return attribution identifies successful historic exposures, information that may be combined with forecasts to form well-informed judgments of future systematic performance. The result of our exposure-conscious approach is a series of solutions that match the client's specifications with precision, delivering returns that are commensurate with the performance of their investment views.

For more information go to http://www.global.assetmanagement.hsbc.com/canada

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Data Sources

All graphs use data from Thompson Reuters, IBES, Worldscope and MSCI.

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