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The most pressing issues facing investment professionals

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Introduction

It is a pleasure to introduce this latest issue of the EDHEC-Risk Institute supplement to *AsianInvestor*. The supplement aims to analyse the most relevant issues for investment professionals through the lens of academic research.

If exposure to the right factors is the main source of performance of alternative equity, or "smart beta," indices, the important question that arises is how best to reward investors for their choices of risk. Drawing on illustrations from Japan and Developed Asia Pacific ex Japan, we show that a good smart beta index is one which diversifies away the specific risks and manages the exposure to equity risk factors. We then analyse the performance of smart factor indices in other developed economies (at a local level) and in the global developed stock universe.

Considerable empirical evidence exists on the presence of multiple risk factors in Asia-Pacific stock markets. In our article on the performance and implementation benefits of multi smart beta allocation in Asian equity markets, we analyse the potential benefits of combining factor tilts.

In the domain of commodities investing, we look at the importance of the structural shape of crude oil futures curves. Crude oil futures contracts typically traded in "backwardation" (with a near-month futures contract trading at a premium to deferred-delivery futures contracts) during the 1990's. From 2004 to 2007, however, the contracts traded in "contango" (front-month price trading at a discount to the deferred-delivery contract). The question arises as to whether a return to the backwardation norm of the 1990's is now being experienced.

Finally, we examine the question of alpha and the choice of rate of return in regressions. The results reported in the article show that whether or not a series of portfolio returns exhibits a significantly positive alpha depends on the arbitrary choice of whether the returns are measured as holding-period returns or continuously-compounded returns.

We extend our warmest thanks to *AsianInvestor* for their collaboration on the supplement. We hope that all readers will find it both useful and enjoyable.

Noël Amenc
Professor of Finance, EDHEC Business School, and Director, EDHEC-Risk Institute

Smart Factor Indexing in Asian Markets: Assessing the Performance of Well-Diversified Factor Indices for Japan and Developed Asia Pacific ex Japan

When allocating to equity factors, it is important to construct a well-diversified index. Smart diversification of factor tilts results in higher risk-adjusted returns.

By Felix Goltz and Ashish Lodh

Alternative forms of equity indices, which draw from a wide range of portfolio construction practices, have become increasingly popular in recent years. For example, using fundamental or accounting-based metrics for size instead of market price to weight stocks is a popular approach. On the other hand, scientific diversification-based approaches exist that either have a deconcentration objective (such as maximum deconcentration or maximum decorrelation) or a risk-return objective (such as maximum Sharpe ratio and minimum volatility). A consensus is forming in the asset management industry that the exposure to the right factors is the main source of performance of smart indices. Therefore, the important question that arises is how best to reward investors for the risk choices they wish to make? In this article, we show that a good smart beta index is one which diversifies away the specific risks and manages the exposure to equity risk factors. We introduce the methodology for constructing well diversified factor indices and illustrate their performance in two stocks markets - Japan and Developed Asia Pacific ex Japan – which show quite contrasting performance over last 10 years.

Theoretically, cap-weighted (CW) indices do not qualify as efficient benchmarks when evaluated based on the findings of two Nobel laureates - Harry Markowitz and Eugene Fama, who respectively postulated the benefits of diversification of unrewarded risk (Modern Portfolio Theory) and empirically showed the existence of rewarded risk factors other than the market factor. Furthermore, it has been shown that cap-weighted indices do not provide "fair compensation" for the amount of risk taken (Haugen and Baker (1991), Grinold (1992)). All alternative beta indices, directly or indirectly, address either or both of the two major drawbacks of cap-weighted indices. Firstly, cap-weighted indices do not efficiently diversify te unrewarded risks as they are highly concentrated in the largest stocks. The Mean Effective Number of Stocks for the Japan CW index is just 119, whereas the nominal number is 500 (Exhibit 2).[1] Secondly, they fail to benefit from rewarded systematic risk factors (such as size, value and momentum). Exhibit 1 shows that the CW indices tilt towards low value (book-to-market) and large-cap stocks, and therefore do not capture the value and small size risk premiums (Fama and French (1993)).

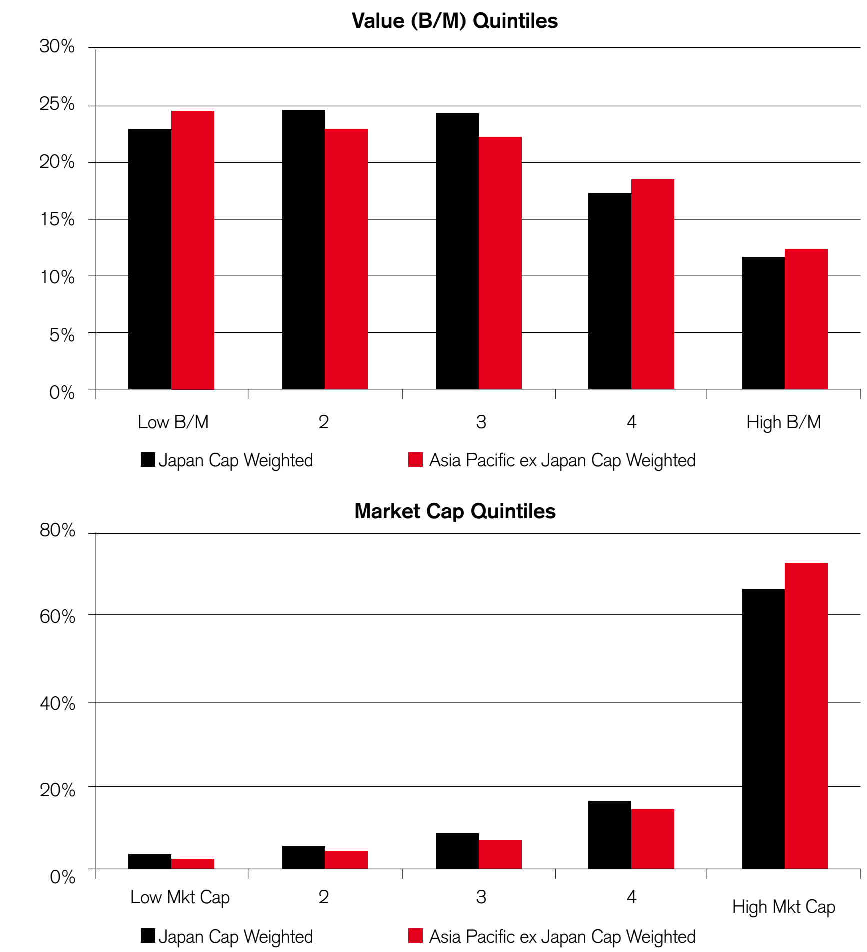
Specific and systematic risks

All smart beta strategies are exposed to systematic risk factors and strategy-specific risks. Systematic risks refer to the exposure to risk factors that can be rewarded or not. They arise from the characteristics of the underlying stock universe and also from the portfolio construction methodology. For example, an index formed on a selection of value stocks will have an explicit value tilt. Similarly, any weighting scheme which underweights larger cap stocks relative to a CW index will inevitably lead to an increase in the exposure to smaller stocks, such as mid-cap stocks.

The non-rewarded or specific risk constitutes all the risks that do not have

Exhibit 1: Drawbacks of CW Indices - All statistics are based on average quarterly weights in the period 31-Dec-2003 to 31-Dec-2013

The total number of stocks in the Japan (Developed Asia Pacific ex Japan) universe is 500 (400).



Source: www.scientificbeta.com.

a premium in the long run, and are therefore not ultimately desired by the investor. The first kind of specific risk is the exposure to unrewarded financial risk factors, such as commodity, currency, or sector risks. For example, minimum volatility portfolios tend to overweight certain defensive sectors. Another kind of non-rewarded financial risks are specific financial risks (also called idiosyncratic stock risks) which are related to the risks that are specific to the company itself. Similarly, all weighting schemes have specific operational risk that is specific to the implementation of the diversification model. For example, the robustness of the Maximum Sharpe Ratio scheme depends on a good estimation of the covariance matrix and expected returns.

Five standard weighting schemes offered by ERI Scientific Beta are – Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio (Gonzalez and Thabault (2013)). Each weighting scheme, despite being smart, is exposed to these strategy-specific risks. Portfolio theory suggests that specific risks are neither predictable nor rewarded, so one is better off completely avoiding them by investing in a well-diversified portfolio. The Diversified Multi-strategy approach, which combines the five different weighting schemes in equal proportion, is based on this specific risk diversification principle (Tu and Zhou (2010), Kan and Zhou (2007)). Moreover, since single strategies' performance shows dependency on market conditions, a multi-strategy approach can help investors smooth the overall performance across market conditions (Amenc *et al.* (2012)).

Smart factor indices: the Smart Beta 2.0 approach

Stocks earn a risk premium through their exposure to certain rewarded factors (Ross (1976)). The economic intuition for the existence of a reward for a given risk factor is that exposure to such a factor is undesirable for the average investor because it leads to losses in bad times (i.e. when marginal utility is high, see e.g. Cochrane (2001)). Fama and French have identified that value (book-to-market) and size (market cap) explain average asset returns, as a complement to the market beta (Fama and French (1993)). Zhang (2005) provides a rationale for the value premium by arguing that value firms suffer more in bad times because their stock price is mainly made up of tangible assets. Similarly, the small size premium is often explained by low liquidity (Amihud and Mendelson (1986)) and high downside risk (Chan, Chen and Hsieh (1985)). Carhart (1997) empirically proved the existence of another priced factor – the momentum factor. Momentum is explained by the sensitivity of past winner stocks to expected growth (Liu and Zhang (2008)) and by the short-term over-reaction of investors (Daniel *et al.* (1998)). The low volatility factor, which qualifies as an anomaly rather than a risk factor, is the result of the famous 'volatility puzzle,' which states that low-volatility stocks tend to outperform high-volatility stocks in the long run (Ang *et al.* (2006)). The anomaly has been recognised as a persistent phenomenon and has been explained through leverage constraints and the lottery preferences of investors (Baker, Bradley and Wurgler (2011)).

These findings have given rise to factor indices, which fall into two major categories. The first involves selecting stocks that are most exposed to the desired risk factor and the application of a weighting scheme to this selection. While this approach responds to one limitation of cap-weighted indices, namely the choice of exposure to a good factor, the problem of poor diversification arising from high concentration in a small number of stocks remains unanswered. The second method involves maximising the exposure to a factor, either by

[1] Effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which is defined as the sum of squared weights across portfolio constituents. $ENS = 1/\sum_{i=1}^{N} W_i^2$

weighting the whole of the universe on the basis of the exposure to this factor (score/rank weighting), or by selecting and weighting by the exposure score of the stock to that factor. Here again, the maximisation of the factor exposure does not guarantee that the indices are well diversified.

To overcome these difficulties, index providers that generally offer factor indices on the basis of the first two approaches have recently sought to take advantage of the development of smart beta indices to offer investors a new framework for smart factor investing (Bender *et al.* (2013)). This approach recognises that smart betas have implicit risk exposures and aims to select and combine them according to these varying exposures. The drawback of this approach is that it maximises neither factor exposure nor diversification of the indices.

For example, a minimum volatility index on a broad universe does not guarantee either the highest exposure to low volatility stocks or the best diversification of this low volatility portfolio. Similarly, seeking exposure to the size factor through equal weighting of a broad universe is certainly less effective than selecting the smallest size stocks in the universe and then diversifying them, including with an equal-weighted weighting scheme. Finally, seeking to be exposed to the value factor through a value-weighted index will not produce a well-diversified index, simply because the integration of the attributes characterising the value exposure into the weighting does not take the correlations between these stocks into account.

In view of these problems, EDHEC-Risk Institute has promoted the concept of smart factor investing using the Smart Beta 2.0 approach. The idea is to construct a factor-tilted portfolio to extract the factor premia most efficiently and is based on two pillars: 1) explicitly selecting appropriate stocks for the desired beta and 2) using a diversification-based weighting scheme

Exhibit 2: Performance and Risk Analysis - Broad cap-weighted index, containing 500 (400) stocks for Japan (Developed Asia Pacific ex Japan) is used as the benchmark. 95% tracking error is the 95th percentile of the tracking error computed using a rolling window of one year and step size of one week. Maximum relative drawdown is the maximum drawdown of the long-short index, whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Probability of outperformance (5Y) is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 5 years and is computed using a rolling window analysis with 1-week step size. Japan Gensaki T-bill (1M) is the risk-free rate for Japan. Secondary Market US Treasury Bill (3M) is the risk-free rate for Dev Asia ex Japan. All statistics are annualised. GLR measure is the ratio of the portfolio variance to the weighted variance of its constituents. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which in turn is defined as the sum of squared weights of portfolio constituents. The analysis is based on daily total returns and quarterly weights from 31-Dec-2003 to 31-Dec-2013 (10 years).

Japan	Broad Cap Weighted	Mid Cap		High Momentum		Low Volatility		Value	
		CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy
Ann. Returns	4.09%	4.97%	5.72%	3.64%	5.31%	5.34%	7.15%	5.65%	6.86%
Ann. Volatility	22.62%	21.21%	19.26%	22.39%	19.95%	19.50%	17.42%	22.60%	20.15%
Sharpe Ratio	0.17	0.23	0.29	0.15	0.26	0.26	0.40	0.24	0.33
Ann. Excess Returns	-	0.89%	1.64%	-0.45%	1.22%	1.26%	3.06%	1.56%	2.77%
Ann. Tracking Error	-	6.62%	7.73%	5.28%	7.48%	5.95%	8.65%	3.84%	6.22%
95% Tracking Error	-	11.75%	14.46%	10.66%	15.39%	9.90%	15.44%	6.11%	11.68%
Information Ratio	-	0.13	0.21	-0.09	0.16	0.21	0.35	0.41	0.45
Max Rel. Drawdown	-	16.85%	16.50%	17.49%	17.02%	12.84%	14.39%	12.54%	11.28%
Outperf. Prob. (5Y)	-	62.6%	96.9%	4.2%	92.0%	94.3%	97.3%	92.4%	97.3%
GLR Measure	36.71%	29.83%	27.10%	37.75%	29.83%	35.39%	29.36%	39.19%	32.06%
Mean ENS	119	217	191	70	193	53	200	65	198

Dev Asia Pacific ex Japan	Broad Cap Weighted	Mid Cap		High Momentum		Low Volatility		Value	
		CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy
Ann. Returns	12.91%	15.31%	15.91%	16.12%	18.01%	13.86%	14.24%	14.92%	16.82%
Ann. Volatility	23.93%	23.08%	20.72%	25.45%	22.13%	22.85%	17.74%	24.36%	21.93%
Sharpe Ratio	0.47	0.60	0.69	0.57	0.74	0.54	0.71	0.55	0.70
Ann. Excess Returns	-	2.40%	2.99%	3.21%	5.10%	0.94%	1.33%	2.01%	3.91%
Ann. Tracking Error	-	6.98%	7.55%	4.73%	6.85%	4.05%	8.21%	5.70%	6.77%
95% Tracking Error	-	13.18%	15.15%	8.00%	12.78%	5.69%	14.96%	10.23%	12.40%
Information Ratio	-	0.34	0.40	0.68	0.74	0.23	0.16	0.35	0.58
Max Rel. Drawdown	-	24.33%	18.52%	7.84%	13.36%	10.46%	16.97%	11.81%	10.76%
Outperf. Prob. (5Y)	-	72.1%	85.5%	95.8%	99.2%	84.0%	78.6%	100.0%	92.0%
GLR Measure	30.85%	20.37%	18.22%	32.86%	21.37%	35.66%	20.61%	31.89%	22.35%
Mean ENS	63	166	142	33	143	39	148	44	147

(Amenc *et al.* (2013)). ERI Scientific Beta constructs ***smart factor indices*** by using diversified multi-strategy weighting on characteristics-based half universes – small size, high momentum, low volatility, and value.[2] The Smart Beta 2.0 approach allows investors to not only manage systematic risks but also diversify strategy-specific risk by combining different strategies.

Comparing the performance of smart factor indices to tilted cap-weighted indices

Exhibit 2 shows that smart factor indices outperform tilted cap-weighted indices on both an absolute and risk-adjusted basis. In both Japan and Developed Asia Pacific ex Japan and for each factor tilt, the excess returns of smart factor indices are higher than those of tilted CW indices. In Japan, the Low Volatility Diversified Multi-strategy index outperforms by 3.06% compared to the 1.26% outperformance of its tilted CW counterpart. Similarly in Developed Asia Pacific ex Japan, the outperformance ranges from 1.33% for the Low Volatility Diversified Multi-strategy index to 5.10% for the High Momentum Diversified Multi-strategy index. It should be noted that the momentum factor does not outperform in Japanese markets and therefore the momentum-tilted CW index does not outperform (Chui *et al.* (2000)). Similarly Developed Asia Pacific ex Japan has experienced rather bullish markets during the analysis period (return of CW index = 12.91%) which has led to poor performance of its Low Volatility factor – a factor which is known to outperform in bearish conditions.

The Sharpe ratios of smart factor indices are systematically higher than those of tilted CW indices and broad CW indices. It shows that for each sub-universe of stocks the Diversified Multi-strategy weighting scheme, by virtue of being well diversified, results in superior risk-adjusted performance compared to cap-weighting.

The GLR measure[3] - a measure of diversification benefits – shows that smart factor indices benefit from risk reduction by exploiting imperfect stock correlations, which tilted CW fails to do as it ignores any information on correlations. The reduction in GLR measure is significant between tilted CW indices and smart factor indices. With the exception of the mid-cap universe[4] , smart factor indices are more deconcentrated, as suggested by their higher ENS numbers.

Exhibit 3: Investability - Weighted average market capitalisation of index is in $million and turnover is mean annual 1-way and is averaged across 40 quarters in the period from 31-Dec-2003 to 31-Dec-2013 (10 years). The net returns are the relative returns over the cap-weighted benchmark net of transaction costs. Two levels of transaction costs are used - 20 bps per 100% 1-W turnover and 100 bps per 100% 1-W turnover. Days to Trade is the number of days necessary to trade the total stock positions, assuming USD1bn AUM and that 100% of the Average Daily Dollar Traded Volume can be traded every day.

Japan	Broad Cap Weighted	Diversified Multi-Strategy				High Liquidity Diversified MultiStrategy			
		Mid Cap	High Momentum	Low Volatility	Value	Mid Cap	High Momentum	Low Volatility	Value
Wgt Avg Mkt Cap (m$)	23 743	1 566	5 848	5 794	4 656	1 767	8 595	8 196	6 730
Days to trade for $1bn Initial Investment (Quintile 95%)	0.38	4.83	2.83	3.78	4.02	2.73	1.11	1.63	1.74
1-Way Annual Turnover	3.23%	32.45%	74.91%	28.51%	30.09%	38.17%	80.15%	28.94%	29.24%
Ann Excess Returns	-	1.64%	1.22%	3.06%	2.77%	2.00%	0.89%	3.54%	2.97%
Net Returns (20 bps)	-	1.57%	1.07%	3.01%	2.71%	1.92%	0.73%	3.48%	2.92%
Net Returns (100 bps)	-	1.31%	0.47%	2.78%	2.47%	1.61%	0.08%	3.25%	2.68%

Dev Asia Pacific ex Japan	Broad Cap Weighted	Diversified Multi-Strategy				High Liquidity Diversified MultiStrategy			
		Mid Cap	High Momentum	Low Volatility	Value	Mid Cap	High Momentum	Low Volatility	Value
Wgt Avg Mkt Cap (m$)	28 083	1 056	4 715	5 624	4 285	1 143	7 074	8 586	6 571
Days to trade for $1bn Initial Investment (Quintile 95%)	0.77	13.76	7.17	8.95	7.91	8.07	2.51	3.37	3.05
1-Way Annual Turnover	5.39%	48.41%	74.07%	27.15%	33.24%	50.27%	75.91%	27.99%	31.58%
Ann Excess Returns	-	2.99%	5.10%	1.33%	3.91%	3.43%	3.78%	0.11%	3.90%
Net Returns (20 bps)	-	2.90%	4.95%	1.28%	3.84%	3.33%	3.63%	0.06%	3.84%
Net Returns (100 bps)	-	2.51%	4.36%	1.06%	3.58%	2.93%	3.03%	-0.17%	3.58%

[2] The smart factor indices are available for nine geographical universes: USA, UK, Eurozone, Europe ex-UK, Japan, Asia Pacific ex-Japan, Developed, Developed ex-US, and Developed ex-UK.

[3] GLR measure – which can be used to measure the diversification benefit - is the ratio of portfolio variance to the weighted variance of its constituents (Goetzmann, Li and Rouwenhorst (2001)).

[4] The mid cap universe has quite a flat market cap profile. Therefore in this selection cap weights do not pose the problem of high concentration in few stocks.

Particularly in Developed Asia Pacific ex Japan, the tilted CW indices are highly concentrated; they have effectively around 40 stocks in the portfolio. Even the broad CW index has an ENS of 63, while the nominal number is 400. The smart factor indices are much more deconcentrated with ENS in the range of 140-150.

Assessing the investability of smart factor indices

ERI Scientific Beta applies weight adjustments to limit liquidity issues that may arise upon investing and upon rebalancing. The indices are also governed by an optimal turnover control technique based on rebalancing thresholds, the objective of which is to reduce turnover and associated transaction costs.[5] To meet the needs of investor who have high liquidity constraints, ***high liquidity smart factor indices*** can be constructed. These indices make a highly liquid stock selection (top 60% liquid stocks) on top of the existing factor-tilted selection and then use the appropriate weighting scheme.

Since the Developed Asia Pacific ex Japan universe is much less liquid than Japan, the extreme values for 'days to trade' for smart factor indices is relatively high. This problem is controlled to a large extent in the high liquidity version. The High Liquidity Diversified Multi-strategy indices show improvement in weighted average market cap and require lower days to trade when compared to their standard versions. In Japan, the High Liquidity Diversified Multi-strategy indices need on average 1.80 days to trade compared to 0.38 days for the broad CW index.

With the exception of the momentum tilt,[6] all smart factor indices have manageable levels of turnover. Transaction costs of 20 bps per 100% 1-way turnover represents the worst case observed historically and 100 bps per 100% 1-way turnover represents an 80% reduction in market liquidity. Except for the Momentum factor in Japan and the Low Volatility factor in Developed Asia Pacific ex Japan, which have been shown to be unrewarded during the analysis period, all smart factor indices show significant outperformance (>130 bps) net of unrealistic transaction costs. This shows that the performance benefits of smart factor indices are so high that their seemingly high turnover does not erode the excess returns that these indices bring over the CW benchmark.

The Smart Beta 2.0 framework allows for efficient management of exposures to rewarded risks while avoiding unrewarded (specific) risks. The smart factor indices that result from this framework show pronounced improvements in risk-adjusted performance compared not only to compared to broad cap-weighted indices, but also compared to cap-weighted factor tilted indices. Certain factor tilts have not been well rewarded in the equity universes we study here (notably in the case of momentum in Japan and low volatility in Asia ex Japan), which highlights the importance of selecting the right factors. However, across the factor tilts we analyse, smart diversification for a given factor tilt results unequivocally in higher risk-adjusted returns (Sharpe ratios), highlighting the importance of constructing well diversified factor indices. Such smart factor indices provide suitable building blocks for the implementation of static or dynamic factor allocation decisions, which may incorporate views on the reward associated which each factor. ■

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5 For more information on turnover and liquidity rules, please refer to the white paper "Overview of Diversification Strategies" by Gonzalez and Thabault (2013).

6 Persistence in price movement is a short-term phenomenon and mean-reversion is observed in longer horizons Therefore, to extract the momentum premium, the momentum score assignment is done semi-annually, which results in higher turnovers (Chan *et al.* 1999).

Smart Factor Indexing Around the World

The performance of smart factor equity indices can be analysed both at a local level in developed economies and in the global developed stock universe.

By Felix Goltz and Ashish Lodh

Smart factor indexing approach

The exposure to the right (rewarded) factors is a key source of long-term performance for smart beta strategies. In addition to harvesting the risk premia associated with the long-term rewarded factors (such as value, momentum, etc.), factor indices need to avoid taking unrewarded risks, such as stock-specific risk or the model risks inherent in a particular index weighting scheme. In the previous article, we emphasised the two important pillars in smart factor investing, which are i) the choice of the right risk factor and ii) the choice of a diversification-based weighting scheme to best extract the risk premium.

ERI Scientific Beta offers five robust diversification schemes - *Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio*. However, these schemes are exposed to non-rewarded operational risks that are specific to the implementation of the diversification model. For example, the robustness of the Maximum Sharpe Ratio scheme depends on a good estimation of the covariance matrix and expected returns. Also, these weighting schemes have residual exposure to other financial risk factors (e.g. commodity, currency, sector risks) and specific financial risks (company-level idiosyncratic risks) which can be reduced by diversification. The Diversified Multi-strategy approach combines the five different weighting schemes to reduce the non-rewarded strategy-specific risks (Amenc *et al.* (2012)) and is thus used for

'Factor indices need to avoid taking unrewarded risks, such as stock-specific risk or the model risks inherent in a particular index weighting scheme.'

the construction of smart factor indices.[7] We assess the performance of smart factor indices on four well known factors - mid cap (as a proxy for small cap), high momentum, low volatility, and value.

A performance analysis of smart factor indices for Asian equity markets is reported in a dedicated article in the current *AsianInvestor* supplement.[8] In this article, we analyse the performance of smart factor indices in other developed economies (at a local level) and in the global developed stock universe. For the USA we are able to assess long-term data (40 years) while for other countries we assess the past 10 years due to more limited depth of historical data.

Assessing the performance of local smart factor indices

The Scientific Beta Developed Universe consists of 2,000 securities and is divided into 8 non-overlapping basic geographic blocks, each comprising a fixed number of securities. Eligibility of securities for each basic geographic block is determined by various criteria such as country classification, exchange on which they are traded, and issue date. The eligible securities are subject to free-float market-cap screens and liquidity screens to select the largest and most liquid securities available to non-domestic investors – the basic geographic blocks. Each Scientific Beta Investable Universe is an aggregate of one or more of these geographic blocks.[9] The local developed universes analysed and their respective stock universe sizes are: USA (500), Eurozone (300) and UK (100). We provide this analysis to complement our analysis of the smart factor indexing approach in the Japan universe (500 stocks), and Asia Pacific ex Japan universe (400 stocks).

Exhibit 1 presents performance statistics of smart factor indices in different geographies. The benchmark used is the cap-weighted (CW) index constructed using all stocks in the respective region (broad CW index). Tilted cap-weighted indices are portfolios which are based on the same characteristics-based stock selection as respective smart factor indices, and are cap-weighted. They represent poorly-diversified factor-tilted portfolios. All smart factor indices in all regions

7 For more details on the weighting scheme methodology, please refer to the ERI Scientific Beta white paper – "Scientific Beta Diversified Multistrategy Index" by Badaoui and Lodh (2013).

8 Please refer to the article – "Smart Factor Indexing in Asian Markets: Assessing the Performance of Well-Diversified Factor Indices for Japan and Developed Asia Pacific ex Japan" in the current AsianInvestor supplement.

9 More information on the Scientific Beta stock universe can be found in the ERI Scientific Beta white paper – "ERI Scientific Beta Universe Construction Rules."

Exhibit 1: Absolute Performance and Risk of Local Smart Factor Indices – the benchmark is the Cap-Weighted index on the full universe for each region. The risk-free rates used for these regions are the Secondary Market US T-bill (3M), Euribor (3M), and UK T-bill (3M) respectively. All statistics are annualised. The analysis is based on daily total returns from 31-Dec-2003 to 31-Dec-2013 (10 years.) For the USA long-term analysis the analysis is based on simulated long-term track records over the period 31-Dec-1972 to 31-Dec-2012 (40 years).

	Broad Cap Weighted	Mid Cap	High Momentum	Low Volatility	Value				
		CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy
USA Long-Term Track Record									
Ann. Returns	9.74%	12.54%	14.19%	10.85%	13.30%	10.09%	12.64%	11.78%	14.44%
Ann. Volatility	17.47%	17.83%	16.73%	17.60%	16.30%	15.89%	14.39%	18.02%	16.55%
Sharpe Ratio	0.24	0.39	0.52	0.30	0.48	0.29	0.50	0.35	0.54
Eurozone									
Ann. Returns	6.35%	7.99%	8.41%	9.09%	10.60%	8.39%	9.19%	6.09%	7.68%
Ann. Volatility	20.58%	18.63%	16.69%	19.74%	16.66%	18.35%	14.96%	22.81%	20.26%
Sharpe Ratio	0.21	0.32	0.38	0.35	0.51	0.34	0.47	0.18	0.28
UK									
Ann. Returns	8.32%	11.76%	11.10%	9.46%	12.71%	8.19%	11.86%	6.04%	10.09%
Ann. Volatility	19.18%	19.67%	17.95%	20.57%	17.99%	16.57%	15.33%	21.35%	19.43%
Sharpe Ratio	0.30	0.46	0.47	0.33	0.56	0.34	0.60	0.16	0.38

'Smart factor indices show attractive performance on both an absolute and risk-adjusted basis in different developed markets.'

outperform the broad cap-weighted index. For example, in the UK the improvement in returns over the cap-weighted reference index ranges from 1.77% for the Value factor to 4.39% for the Momentum factor.

Moreover, all smart factor indices exhibit superior Sharpe ratios and have higher returns than tilted CW indices (with the exception of Mid Cap UK). For example, Eurozone high momentum and UK Value smart factor indices outperform their respective tilted CW indices by 1.52% and 4.04% respectively. The results show that having chosen the right factor tilt one could procure additional benefit by using a diversification-based weighting scheme rather than simple cap-weighting. Due to the use of the Diversified Multi-Strategy weighting scheme, which aims to diversify not only stock-specific risk but also strategy-specific risk, one is able to extract the risk premium of each factor at low levels of portfolio risk.

Since broad cap-weighted indices are default benchmarks for most active and passive managers, the relative risk of smart factor indices becomes important. Smart beta offerings are sold on the basis of outperformance over CW indices, thus generating a reputation risk for index providers and passive managers in the event of underperformance. Due to the importance of such reputation risk, the risk-adjusted performance in relative terms (i.e. the information ratio) becomes a key performance measure for such strategies. Exhibit 2 shows that information ratios of the four smart factor indices are usually higher than those of tilted cap-weighted indices and often reach impressive levels such as 0.81 for USA Value and 0.69 for UK Momentum. Outperformance Probability is an intuitive measure to show how often the strategy has managed to outperform the cap-weighted reference index in the past. It is reported for investment horizons of five years by using a rolling window analysis with one-week step size. The smart factor indices achieve high levels of outperformance probability and in general deliver more robust outperformance than tilted CW indices.

Global smart factor indices

Smart factor indices show attractive performance on both an absolute and risk-adjusted basis in different developed markets. A next logical question is how this outperformance translates when investors construct global portfolios. It is interesting to note that none of the smart factor indices for the global developed universe posted excess returns of less than 200 bps. This is because the results of relatively poorly performing local smart factor indices can be compensated by the value added that is generated in other regions. Sharpe ratios of developed smart factor indices lie in the range of 0.50 to 0.65 compared to a mere 0.36 for the global developed broad cap-weighted index. For each risk factor, the smart factor indices outperform the tilted CW indices in both relative returns and Sharpe ratio. Moreover, due to international diversification, we also obtain low levels of tracking error, leading to information ratios ranging from 0.62 for the low volatility smart factor index to 1.03 for the value smart factor index. The 5-year outperformance probability is extremely high (95%-100%), meaning that outperformance is both high and robust across these four factors. ■

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Ashish Lodh, Senior Quantitative Analyst, ERI Scientific Beta

Exhibit 2: Relative Performance and Risk of Local Smart Factor Indices – the benchmark is the Cap-Weighted index on the full universe for each region. Outperformance Probability is defined as the historical probability of outperforming the cap-weighted reference index over a 5-year investment horizon and is computed using a rolling window analysis with 5-year length and 1-week step size. All statistics are annualised. The analysis is based on daily total returns from 31-Dec-2003 to 31-Dec-2013 (10 years). For the USA long-term analysis the analysis is based on simulated long-term track records over the period 31-Dec-1972 to 31-Dec-2012 (40 years).

	Mid Cap		High Momentum		Low Volatility		Value	
	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy
USA Long-Term Track Records								
Excess Returns	2.80%	4.45%	1.10%	3.56%	0.35%	2.90%	2.04%	4.70%
Tracking Error	5.99%	6.80%	3.50%	4.88%	4.44%	6.17%	4.74%	5.82%
Information Ratio	0.47	0.66	0.32	0.73	0.08	0.47	0.43	0.81
Outperformance Probability (5Y)	75.3%	78.9%	86.8%	91.2%	54.3%	85.0%	72.0%	88.3%
Eurozone								
Excess Returns	1.64%	2.05%	2.73%	4.25%	2.04%	2.84%	-0.26%	1.33%
Tracking Error	6.28%	7.07%	4.82%	7.05%	4.48%	7.27%	3.96%	4.55%
Information Ratio	0.26	0.29	0.57	0.60	0.45	0.39	-0.07	0.29
Outperformance Probability (5Y)	70.2%	95.0%	100.0%	100.0%	100.0%	100.0%	30.5%	42.4%
UK								
Excess Returns	3.44%	2.78%	1.14%	4.39%	-0.13%	3.54%	-2.27%	1.77%
Tracking Error	7.17%	7.29%	5.95%	6.37%	5.53%	7.60%	4.93%	5.78%
Information Ratio	0.48	0.38	0.19	0.69	-0.02	0.47	-0.46	0.31
Outperformance Probability (5Y)	88.5%	67.2%	69.1%	95.0%	38.9%	100.0%	0.0%	29.0%

Exhibit 3: Scientific Beta Developed Smart Factor Indices – the number of stocks in the Scientific Beta Developed universe is 2,000. The benchmark is the Cap Weighted index on the full universe. The risk-free rate is the Secondary Market US T-bill (3M). Outperformance Probability is defined as the historical probability of outperforming the cap-weighted reference index over a 5-year investment horizon and is computed using a rolling window analysis with 5-year length and 1-week step size. All statistics are annualised. The analysis is based on daily total returns from 31-Dec-2003 to 31-Dec-2013 (10 years).

Scientific Beta Developed	Broad Cap Weighted	Mid Cap		High Momentum		Low Volatility		Value	
		CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy
Ann. Returns	7.80%	10.18%	10.45%	8.90%	10.30%	8.67%	10.54%	7.82%	10.21%
Ann. Volatility	17.09%	17.80%	16.12%	17.23%	16.09%	15.07%	13.79%	18.80%	17.23%
Sharpe Ratio	0.36	0.48	0.55	0.43	0.54	0.47	0.65	0.33	0.50
Excess Returns	-	2.38%	2.65%	1.09%	2.49%	0.86%	2.73%	0.01%	2.40%
Tracking Error	-	3.46%	3.33%	3.16%	3.70%	3.14%	4.40%	2.82%	2.34%
Information Ratio	-	0.69	0.79	0.35	0.67	0.27	0.62	0.00	1.03
Outperformance Probability (5Y)	-	100.0%	100.0%	84.0%	100.0%	87.8%	100.0%	19.8%	95.0%

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Multi Smart Beta Allocation in Asian Equity Markets: Performance and Implementation Benefits

An allocation to multiple equity factors using several weighting schemes can prove highly beneficial.

By Felix Goltz and Antoine Thabault

Multi-smart beta allocation: a new source of value added in investment management

Many investors are seeking to improve the performance of their equity portfolios by capturing exposure to rewarded factors. A key to selecting relevant and persistent factors is to rely on factors for which there is extensive empirical evidence, as well as a compelling economic rationale as to why the attached premia should continue. In their study dedicated to the quality of popular Asian stock market indices, Padmanaban *et al.* (2013) report that a large body of empirical evidence exists on the presence of multiple risk factors in Asia-Pacific stock markets (see, for instance, Daniel *et al.* (2001), Chiao and Hueng (2004) and Pham (2007) for evidence of strong size and value premia in Japanese stock returns, or Chui *et al.* (2000) on the momentum premium in Asia). The issue of selection of factors and the ways to effectively capture the premia they carry through factor indices is dealt with in dedicated articles in this supplement. In this article, we analyse the potential benefits of combining factor tilts.

Combinations of tilts to different factors may be of interest for two reasons. First, multi-factor allocations are expected to result in improved risk-adjusted performance. In fact, even if the factors to which the factor indices are exposed are all positively rewarded over the long term, there is extensive evidence that they may each encounter prolonged periods of underperformance. More generally, the reward for exposure to these factors has been shown to vary over time (see e.g. Harvey (1989); Asness (1992); Cohen, Polk and Vuolteenaho (2003)). If this time variation in returns is not completely in sync for different factors, allocating across factors allows investors to diversify the sources of their outperformance and smooth their performance across market conditions. Exhibit 1 provides an illustration of the time-varying premia of Carhart factors: it shows that the cyclicality of returns differs from one factor to the next. In other words, the different factors work at different times.

Intuitively, we would expect pronounced allocation benefits across factors which have low correlation with each other. As shown in Exhibit 2, the relative returns of the four smart factor indices over the cap-weighted benchmark are not perfectly correlated. It follows in particular that a combination of these indices will exploit these imperfect correlations to lower the overall tracking error of the portfolio significantly.

Second, investors may benefit from allocating across factors in terms of implementation. Some of the trades necessary to pursue exposure to different factors may actually cancel each other out. Consider the example of an investor who pursues an allocation across a value and a momentum tilt. If some of the low valuation stocks with high weights in the value strategy start to rally, their weight in the momentum-tilted portfolio will tend to increase at the same time as their weight in the value-tilted portfolio will tend to decrease. The effects will not cancel out completely, but some reduction in turnover can be expected through such natural crossing effects.

We now turn to a detailed analysis of the two key benefits of multi-factor allocations, notably the performance benefits and the implementation benefits. We provide practical illustrations of multi-factor allocations drawing on Scientific Beta smart factor indices (see the articles on smart factor investing in this supplement for more information), representing a set of four main risk factors, notably value, momentum, low volatility and size. In a nutshell, our results suggest that multi-beta indices present new opportunities for active managers and multi-managers to enhance their performance at very low marginal cost.

Performance benefits of allocating across factors

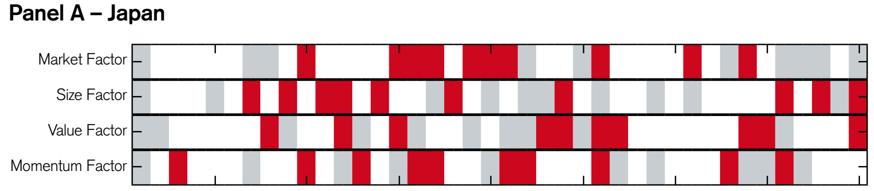
Investors may use allocation across factor tilts to target an absolute (Sharpe ratio, volatility) or relative (information ratio, tracking error with respect to broad cap-weighted index) risk objective. We show in Exhibit 3 the performance and risk characteristics of two multi-beta allocations over the last 10 years. The first one is an equal-weight allocation of the four smart factor indices (low volatility, mid cap, value, and momentum). This allocation is an example of a simple and robust allocation to smart factors, which is efficient in terms of absolute risk. The second one combines the four smart factor indices so as to obtain equal contributions (see Maillard *et al.*, 2010) to the tracking error risk from each component index. This approach is an example allocation with a relative risk objective. Both multi-beta allocations are rebalanced quarterly. Of course, the multi-beta multi-strategy equal weight (EW) and equal risk contribution (ERC) indices are starting points in smart factor allocation. More sophisticated allocation approaches (e.g. conditional strategies, or strategies that have views on the rewards of the different smart factor indices) can be deployed using smart factor indices as ingredients to reach more specific investment objectives (see Amenc, Deguest, Martellini, 2013).

Exhibit 3 shows that both the multi-beta multi-strategy EW and ERC indices present returns that are close to the average performance of the constituents but lower absolute and lower relative risk than the average constituent index. Both allocations thus deliver improvements in the Sharpe ratio compared to the average constituent index. Furthermore, compared to the Sharpe ratio of the cap-weighted reference (0.17 in Japan, 0.47 in Developed Asia Pacific ex. Japan), the multi-beta allocations bring a gain in Sharpe ratio of about 55% and 88% in the Japan and Developed Asia Pacific ex Japan universes, with Sharpe ratios of around 0.32 and 0.73 respectively. However, the most impressive gains compared to the average of components are witnessed in relative risk, where the reduction in the tracking error is more than 1% for both the EW and ERC allocations in the Developed Asia Pacific ex. Japan case (which represents a risk reduction of about 15% relative to the average tracking error of the component indices). This

Exhibit 1- Conditional Returns of the Factors – The plot shows for each factor through the 10-year history the 25% most bullish quarters in green, the 25% most bearish in red, and the 50% of quarters with medium factor return realisations in white.

Factors are based on SciBeta Japan Universe (Panel A) and SciBeta Developed Asia-Pacific Ex Japan Universe (Panel B). The Market factor is the daily return of the cap-weighted index of all stocks that constitute the index portfolio in excess of the risk-free rate. Small size factor is the daily return series of a cap-weighted portfolio that is long the 30% smallest market caps and short the 30% largest market-cap stocks of the extended universe (i.e including small caps). Value factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest B/M ratio stocks in the investable universe. Momentum factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest 52 weeks (minus most recent 4 weeks) past return stocks in the investable universe. The yields on the "Japan Gensaki T-Bill (1M)" and the "Secondary Market US Treasury Bills (3M)" are used respectively as the risk-free rate in Japanese Yen and US Dollars. All statistics are annualised. The analysis is based on daily total returns from 31/12/2003 to 31/12/2013.

Panel A – Japan



Panel B - Developed Asia-Pacific Ex Japan

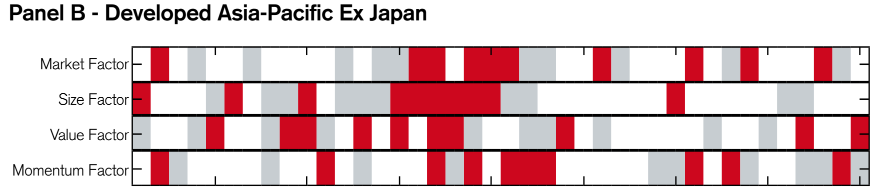


Exhibit 2 – Correlation of Relative Returns across Factor-Tilted Multi-Strategy Indices – The table shows the correlation of the relative returns of four Scientific Beta Multi-Strategy Smart Factor Indices (mid cap, momentum, low volatility, and value) over the 10-year period. The analysis is based on daily total return data from 31-December-2003 to 31-December-2013 (10 years).

The SciBeta Japan CW index and the SciBeta Dev. Asia Pacific Ex. Japan are used respectively as the cap-weighted reference in Panels A and B.

Panel A –Relative Returns Correlation Matrix Japan Indices

SciBeta Investable Japan Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy			
	Low Volatility	Mid Cap	Value	Momentum
Low Volatility	100%	84%	87%	77%
Mid Cap		100%	86%	86%
Value			100%	73%
Momentum				100%

Panel B – Relative Returns Correlation Matrix Dev. Asia Pacific Ex Japan Indices

SciBeta Investable Developed Asia-Pacific ex Japan Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy			
	Low Volatility	Mid Cap	Value	Momentum
Low Volatility	100%	64%	45%	49%
Mid Cap		100%	78%	77%
Value			100%	69%
Momentum				100%

Exhibit 3 – Performances and Risks of Multi-Beta Multi-Strategy Allocations vs Single Factor Tilts – The table compares performance and risk of Scientific Beta Diversified Multi-Strategy indices on SciBeta Japan Indices (Panel A) and SciBeta Dev. Asia Pacific Ex. Japan Indices. The Multi-Beta Multi-Strategy EW Allocation is the equal combination of the four Diversified Multi-Strategy Smart Factor Indices (low volatility, mid cap, value, and momentum). The Multi-Beta Multi-Strategy ERC Allocation is an optimised combination of the same four Smart Factor indices in which beginning of quarter optimal allocations to the component indices are determined from the covariance of the daily relative returns of the component indices over the last 6 quarters (18 months), so as to obtain (in-sample) equal contributions to the (tracking error) risk. The analysis is based on daily total return data from 31-December-2003 to 31-December-2013 (10 years).

The SciBeta Japan CW index and the SciBeta Dev. Asia Pacific Ex. Japan are used respectively as the cap-weighted reference in Panels A and B. The yields on the "Japan Gensaki T-Bill (1M)" and the "Secondary Market US Treasury Bills (3M)" are used respectively as the risk-free rate in Japanese Yen and US Dollars.

Panel A

SciBeta Investable Japan Indices (Dec 2003 – Dec 2013)	Cap Weighted	Scientific Beta Diversified Multi-Strategy						
		Smart Factor Indices				Average of 4 Smart Factor Indices	Multi-Beta Allocations	
		Low Vol	Mid Cap	Value	Momentum		Equal Weight	ERC
Ann. Returns	4.09%	7.15%	5.72%	6.86%	5.31%	6.26%	6.30%	6.22%
Ann. Volatility	22.62%	17.42%	19.26%	20.15%	19.95%	19.20%	19.01%	19.12%
Sharpe Ratio	0.17	0.40	0.29	0.33	0.26	0.32	0.32	0.32
Max DrawDown	60.13%	43.05%	53.92%	50.39%	52.37%	49.93%	49.26%	49.57%
Excess Returns		3.06%	1.64%	2.77%	1.22%	2.17%	2.21%	2.14%
Tracking Error		8.65%	7.73%	6.22%	7.48%	7.52%	7.00%	6.89%
95% Tracking Error		15.44%	14.46%	11.68%	15.39%	14.24%	13.83%	13.75%
Information Ratio		0.35	0.21	0.45	0.16	0.29	0.32	0.31
Outperf. Prob. (1Y)		58.94%	57.02%	52.98%	60.00%	57.23%	57.66%	58.09%
Outperf. Prob. (3Y)		83.33%	72.40%	83.88%	86.07%	81.42%	78.69%	78.42%
Max Relative DrawDown		14.39%	16.50%	11.28%	17.02%	14.80%	12.24%	12.29%

Panel B

SciBeta Investable Developed Asia-Pacific ex Japan Indices (Dec 2003 – Dec 2013)	Cap Weighted	Scientific Beta Diversified Multi-Strategy						
		Smart Factor Indices				Average of 4 Smart Factor Indices	Multi-Beta Allocations	
		Low Vol	Mid Cap	Value	Momentum		Equal Weight	ERC
Ann. Returns	12.91%	14.24%	15.91%	16.82%	18.01%	16.25%	16.32%	16.41%
Ann. Volatility	23.93%	17.74%	20.72%	21.93%	22.13%	20.63%	20.32%	20.30%
Sharpe Ratio	0.47	0.71	0.69	0.70	0.74	0.71	0.73	0.73
Max DrawDown	65.62%	56.80%	66.86%	64.28%	66.29%	63.56%	63.28%	62.65%
Excess Returns	-	1.33%	2.99%	3.91%	5.10%	3.33%	3.41%	3.50%
Tracking Error	-	8.21%	7.55%	6.77%	6.85%	7.34%	6.26%	6.21%
95% Tracking Error	-	14.96%	15.15%	12.40%	12.78%	13.82%	12.57%	12.51%
Information Ratio	-	0.16	0.40	0.58	0.74	0.47	0.54	0.56
Outperf. Prob. (1Y)	-	60.21%	70.85%	72.55%	79.15%	70.69%	81.49%	82.55%
Outperf. Prob. (3Y)	-	70.49%	79.78%	86.34%	95.36%	82.99%	96.17%	97.27%
Max Relative DrawDown	-	16.97%	18.52%	10.76%	13.36%	14.90%	11.05%	11.43%

TE reduction yields an increase in the information ratios to levels of 0.32 in the Japan universe and 0.55 in Developed Asia Pacific ex. Japan, from an average information ratio for the constituent indices of 0.29 and 0.47 respectively for each zone.

Such improvements in the information ratio, around 16% and 20% for the EW and ERC allocations respectively in the Developed Asia Pacific ex. Japan universe, are significant and support the idea of diversification between smart factors. Additionally, the multi-beta multi-strategy indices exhibit significantly lower extreme relative risk (95% Tracking Error) and maximum relative drawdown compared to the average of their constituent indices. The maximum relative drawdown is reduced by more than 2.5% in Japan and by about 3.6% in the Developed Asia Pacific ex Japan case. It is noteworthy that – due to its focus on balancing relative risk contributions of constituents – the ERC allocation generally provides greater reductions in the relative risk measures such as the tracking error and the extreme tracking error risk.

Additionally, the benefits of allocation across different factors can be seen in

Exhibit 4 – Implementation of EW Allocation across Standard or Highly Liquid Factor-Tilted Indices The analysis is based on daily total return data from 31-December-2003 to 31-December-2013 (10 years) in panels A and B. Days to Trade is the number of days necessary to trade the total stock positions, assuming a USD1bn AUM and that 100% of the Average Daily Dollar Traded Volume can be traded every day. The weighted average market capitalisation of index is in $million and averaged over the 10-year period. The net returns are the relative returns over the cap-weighted benchmark net of transaction costs. Two levels of transaction costs are used - 20 bps per 100% 1-Way turnover and 100 bps per 100% 1-Way turnover. The first case corresponds to the worst case observed historically for the large and mid-cap universe of our indices while the second case assumes 80% reduction in market liquidity and a corresponding increase in transaction costs.

The SciBeta Japan CW index and the SciBeta Dev. Asia Pacific Ex. Japan are used respectively as the cap-weighted reference in Panels A and B.

Panel A

SciBeta Investable Japan Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy					
	All Stocks			Multi-Beta Allocations		
	Average of 4 Smart Factor Indices	EW Multi Beta	ERC Multi Beta	Average of 4 Smart Factor Indices	EW Multi Beta	ERC Multi Beta
1-Way Turnover	41.49%	35.77%	37.41%	44.13%	38.67%	41.12%
Internally Crossed Turnover	-	5.91%	7.82%	-	5.85%	7.94%
Days to Trade for $1bn Initial Investment (Quantile 95%)	3.87	2.48	2.43	1.80	0.88	0.85
Weighted Avg. Market Cap ($m)	4 466	4 466	4 538	6 322	6 322	6 460
Information Ratio	0.29	0.32	0.31	0.35	0.41	0.44
Relative Returns	2.17%	2.21%	2.14%	2.35%	2.41%	2.49%
Relative Returns net of 20 bps transaction costs (historical worst case)	2.09%	2.14%	2.06%	2.26%	2.34%	2.41%
Relative Returns net of 100 bps transaction costs (extreme liquidity stress scenario)	1.76%	1.85%	1.76%	1.91%	2.03%	2.08%

Panel B

SciBeta Investable Developed Asia-Pacific ex Japan Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy					
	All Stocks			Multi-Beta Allocations		
	Average of 4 Smart Factor Indices	EW Multi Beta	ERC Multi Beta	Average of 4 Smart Factor Indices	EW Multi Beta	ERC Multi Beta
1-Way Turnover	45.72%	40.01%	40.33%	46.44%	41.09%	41.03%
Internally Crossed Turnover	-	6.06%	7.28%	-	5.86%	7.53%
Days To Trade for $1bn Initial Investment (Quantile 95%)	9.45	5.13	4.97	4.25	1.80	1.70
Weighted Avg. Market Cap ($m)	3920	3920	4017	5843	5843	6356
Information Ratio	0.47	0.54	0.56	0.36	0.49	0.46
Relative Returns	3.33%	3.41%	3.50%	2.81%	2.92%	2.57%
Relative Returns net of 20 bps transaction costs (historical worst case)	3.24%	3.33%	3.42%	2.71%	2.84%	2.49%
Relative Returns net of 100 bps transaction costs (extreme liquidity stress scenario)	2.88%	3.01%	3.10%	2.34%	2.51%	2.16%

Source: scientificbeta.com.

the probability of outperformance, which is the historical frequency with which the index will outperform its cap-weighted reference index for a given investment horizon. The probability of outperformance increases considerably for the multi-beta indices compared to the component indices, especially at short horizons. The higher probabilities of outperformance reflect the smoother and more robust outperformance resulting from the combination of different rewarded factors within a multi-beta index.

Implementation benefits of allocating across factors

The multi-beta indices analysed above were designed not only to provide efficient management of risk and return but also for genuine investability. Each of the smart factor indices has a target of 30% annual one-way turnover which is set through optimal control of rebalancing (with the notable exception of the momentum tilt, which allows for a 60% turnover). In addition, the stock selections used to tilt the indices implement buffer rules in order to reduce unproductive turnover due to small changes in stock characteristics. The component indices also apply weight and trading constraints relative to market-cap weights so as to ensure high capacity. Finally, these indices offer an optional High Liquidity feature which allows investors to reduce the application of the smart factor index methodology to the most liquid stocks in the reference universe.

In addition to these implementation rules, which are applied at the level of each smart factor index, the multi-beta allocations provide a reduction in turnover (and hence of transaction costs) compared to a separate investment in each of the smart factor indices. This reduction in turnover arises from different sources. First, when the renewal of the underlying stock selections takes place, it can happen that a stock being dropped from the universe of one smart factor index is being simultaneously added to the universe of another smart factor index. Second, for constituents that are common to several smart factor indices, the trades to rebalance the weight of a stock in the different indices to the respective target weight may partly offset each other.

Exhibit 4 displays statistics relative to the investability of the multi-beta equal-weight and relative ERC allocations along with the average of the mid cap, momentum, low volatility and value smart factor indices. For comparison, we also show the same analytics for their Highly Liquid counterparts. We see that the turnover of multi-beta indices is very reasonable. In fact, managing a mandate on each smart factor index separately would yield a turnover which is higher than the average turnover across the smart factor indices. This is due to the fact that rebalancing each component index to the allocation target would induce extra turnover. However, implementing the multi-beta index in a single mandate exploits the benefits of natural crossing between the different component indices and actually reduces the turnover below the average level observed for component indices. We provide in the table for each multi-beta allocation the amount of turnover that is internally crossed in multi-beta indices as compared to managing the same allocations separately. We see that about 5.9% turnover is internally crossed by the EW allocation while the relative ERC allocation internally crosses around 7.6%.

In addition to turnover, the exhibit also shows the average capacity of the indices in terms of the weighted average market-cap of stocks in the portfolio. This index capacity measure indicates decent levels with an average market-cap of around US$4.5bn for the standard multi-beta index, while the highly liquid version further increases capacity to levels of around US$6.4bn in the case of the Japan universe. In the case of the Developed Asia Pacific ex. Japan region, the weighted average market caps are slightly lower, around US$4bn for the standard indices and US$6.1bn for the highly liquid ones. In both regions, we provide an estimate of the time that would be necessary to set up an initial investment (i.e. full weights) of US$1bn AUM in the indices, assuming that the average daily dollar traded volume can be traded (100% participation rate) and that the number of days required grows linearly with the fund size.

Overall, this does highlight the ease of implementation of the multi-beta indices and the effectiveness of the high liquidity option. Indeed, the Days to Trade required for the initial investment on Japan indices are quite manageable (about 2.45 days for the standard multi-beta indices, and 0.87 days with the highly liquid feature). Even in the Developed Asia Pacific ex. Japan universe, the initial investment in highly liquid multi-beta indices amounts to less than two days of trading. In addition, one should keep in mind that the number of days needed to rebalance the indices (i.e. trade the weight change rather than the full weight on each stock) would be much lower. It should be noted that the highly liquid multi-beta indices also maintain a reasonable level of performance (information ratio) of the standard multi-beta indices in the Developed Asia Pacific ex. Japan case and it provides even stronger information ratios in the Japan universe. Finally, even when assuming unrealistically high levels of transaction costs, all the smart factor indices deliver significant outperformance net of costs in both regions. Compared to the average stand-alone investment in a smart factor index, the multi-beta indices almost always result in higher average returns net of costs due to the turnover reduction through natural crossing effects across its component smart factor indices. ■

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The Importance of the Structural Shape of Crude Oil Futures Curves

What is the typical shape of the price curve for oil futures contracts? There is no definitive answer but strong clues exist.

By Hilary Till

Structural shape of crude oil futures curves

In the past, one could confidently discuss how crude oil futures contracts typically trade in "backwardation." By backwardation, one means that a near-month futures contract trades at a premium to deferred-delivery futures contracts. For example, Litzenberger and Rabinowitz (1995) pointed out that the NYMEX West Texas Intermediate (WTI) crude oil futures contract's front-to-back futures spreads were backwardated at least 70% of the time between February 1984 and April 1992. This pattern was so persistent that these authors theorised why this should be the typical shape of the crude oil futures price curve.

This structural feature of the crude oil futures market persisted for another 11 years. Goldman Sachs (2003) reported that from March 1983 through February 2003, the WTI futures contract had "been in backwardation 62% of the time[,] delivering an average yield of 0.78% per month."

Because of the persistence of backwardation in the crude oil futures market, practitioners could come up with the concept of a positive "roll yield," which is earned from continuously buying and rolling crude oil futures contracts. The idea is that even if the front-month price of a crude oil futures contract is stable, there can be a positive return since one is continuously buying deferred futures contracts at a discount to where they eventually converge to, resulting in an accumulating "roll yield" over time.

Roll yields in performance attribution

Further, Anson (1998) shows that from 1985 through 1997, roll yields accounted for essentially all of the futures-only returns in an investment indexed to the petroleum-complex-heavy (S&P) Goldman Sachs Commodity Index.

Anson's article showed how the total returns of a collateralised commodity futures program can be ascribed to (1) spot return; (2) roll yield; and (3) the T-Bill return. The spot return and the roll yield account for the "futures only" return of the program. Once one includes the T-Bill return from fully collateralising the program, one arrives at the total return of such a program. We should emphasise that both the spot return and the roll yield are artifacts of this particular method of performance attribution. In a futures program, one cannot directly receive the spot return separate from the roll yield; and correspondingly, one cannot directly receive the roll yield separate from the spot return. Again, though, the advantage of this type of performance attribution is it makes clear that buying and rolling a structurally backwardated commodity futures contract can have positive returns, even when its spot price is stable (or mean-reverts).

> *'The act of rolling from one contract to the next does not in itself generate returns, just as selling Ford stock to buy GM stock does not in itself generate returns..'*

Rolling a futures contract does not actually generate returns

Now, both practitioners and academics have recently pointed out that one needs to be very careful in defining commodity futures "roll yields." The act of rolling from one contract to the next does not in itself generate returns, just as selling Ford stock to buy GM stock does not in itself generate returns, as explained by Sanders and Irwin (2012). Instead, roll yields are an artifact of one type of performance attribution, as discussed above.

But the commodity futures curve's structural shape can be predictive of futures returns

That said, there is comfort in the peer-reviewed literature with treating a commodity futures contract's curve shape as *predictive* of future returns. For example, amongst the research covering this topic, Gorton, Hayashi, and Rouwenhorst (2013) examine 31 commodity futures over the period, 1971 to 2010. They find that "a portfolio that selects commodities with a relatively high basis … significantly outperforms a portfolio with a low basis …" The authors define "basis" as "the difference between the current spot price and the contemporaneous futures price." In other words, the winning portfolios contain futures contracts that are relatively more backwardated than the losing portfolios. The authors provide a fundamental rationale for their results, linking relatively high-basis futures contracts with relatively low inventories (and correspondingly, relatively more scarcity.)

2004's structural break in the oil futures markets

Prior to 2004, if there were scarcity in the crude-oil market, one could expect two outcomes: (1) increasing spot prices; and (2) for the front-month price to trade at an ever larger premium to deferred-delivery contracts. Reflecting this relationship, there had been a +52% correlation between the level of outright crude prices and the level of front-to-back-month calendar spreads from December 1986 through December 2003.

As discussed at the outset of this article, when the front-month price trades at a premium to the deferred-delivery contracts, this is known as *backwardation*. When a futures curve instead trades in contango, the front-month price trades at a discount to the deferred-delivery contract. In times of surplus, inventory holders receive a return-to-storage, as represented by the size of the contango, since they can buy the crude oil immediately at a lower price and lock in positive returns to storage by simultaneously selling the higher-priced contract for a future delivery. If inventories breach primary storage capacity, the crude curve will trade in deeper contango, so as to provide a return for placing the commodity in more expensive, secondary storage (and eventually, tertiary storage.)

The WTI crude curve's structural relationship changed from 2004-to-the-summer-of-2007. During that time period, the level of crude-oil prices became -75% correlated with its corresponding calendar spread.

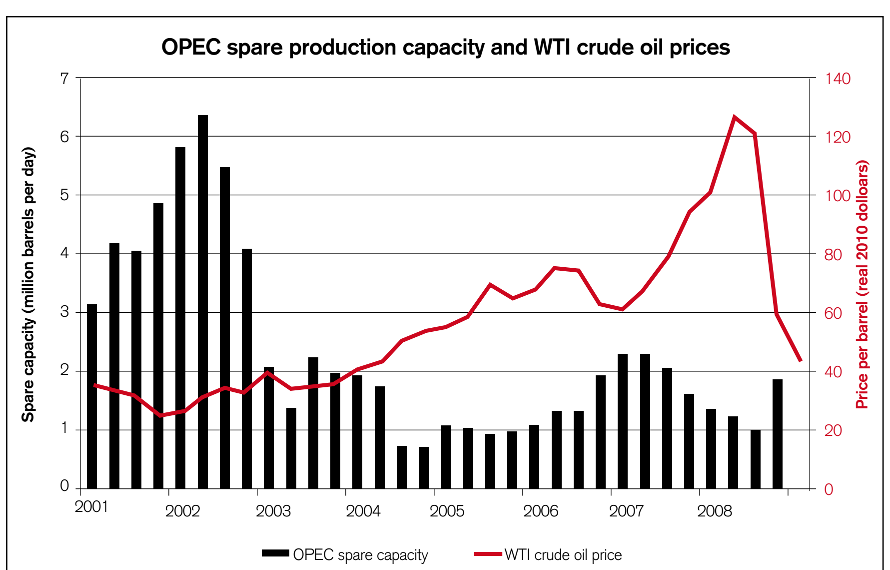
Through the summer of 2007, the structural rigidities in the crude oil market translated into large contangos and high flat prices. What changed during 2004? Please see Figure 1. During mid-2004, OPEC's immediately-deliverable spare capacity *collapsed*. The International Monetary Fund later explained in IMF (2005) that this occurred because of "[s]ynchronised global growth, high oil demand (especially from China), and a series of supply disruptions …"

Why does this matter?

In contrast, during 2004, the oil market's excess supply cushion dropped to sufficiently low levels that there were two resulting market responses: (1) there were continuously high spot prices to encourage consumer conservation, and (2) the market undertook precautionary stock building, which arguably led to the persistent (but not continuous) contangos that the crude oil market began experiencing in late 2004.

By July 2008 the excess-capacity cushion became exceptionally small relative to the risk of supply disruptions due to naturally-occurring weather events as well as due to well-telegraphed-and-perhaps-well-rehearsed geopolitical confrontations. At that point, the role of the spot price of oil was arguably to find a level that would bring about sufficient demand destruction to increase spare capacity, which did occur quite dramatically, starting in the summer of 2008, after which the spot price of oil spectacularly dropped by about $100 per barrel by the end of 2008.

Figure 1



Graph is excerpted from EIA (2014), Slide 12.

U.S. Energy Information Administration (EIA): "The extent to which OPEC member countries utilise their available production capacity is often used as an indicator of the tightness of global oil markets … EIA defines spare capacity as the volume of production that can be brought on within 30 days and sustained for at least 90 days. … OPEC spare capacity provides an indicator of the world oil market's ability to respond to potential crises that reduce oil supplies."

As explained in Harrington (2005), the true inventories for crude oil should be represented as above-ground stocks plus excess capacity. Historically, the markets had been able to tolerate relatively low oil inventories because there was sufficient swing capacity that could be brought on stream relatively quickly in the case of any supply disruption.

Possible return in importance of roll yields

Could we be in a state-of-the-world where fears on worryingly low OPEC spare capacity are diminishing? There is definitely not universal agreement on this topic, but at least according to the International Energy Agency (IEA), "OPEC's spare crude oil production capacity will surge 25 percent in the next two years as rising U.S. shale output crimps demand for the group's supplies," reported Nguyen (2013) in *Bloomberg News*.

If OPEC spare capacity were not in question, then there would not be a need for precautionary stock building, which would mean that relatively low oil inventories would be tolerable. And typically when there have been low crude oil inventories, the oil futures curve has been backwardated, leading to positive "roll yields."

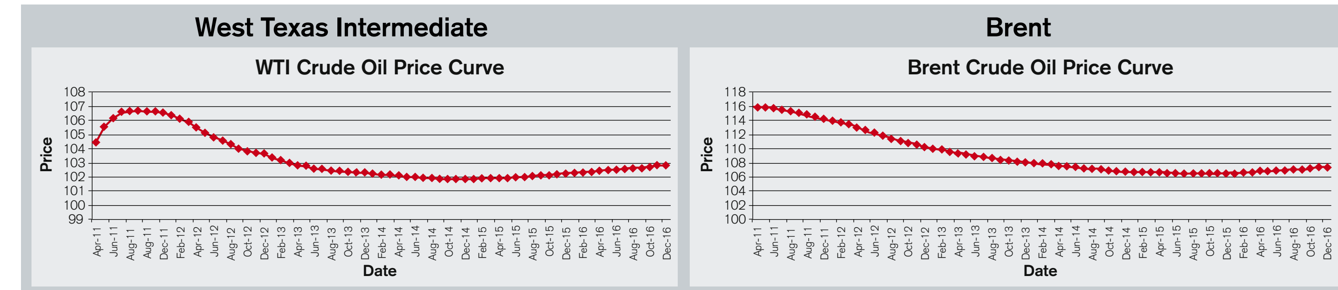
The above analysis applies to any oil futures contract that is seamlessly connected to the global oil markets. This is because we are using a measure of global oil market tightness, OPEC spare capacity, as a plausible explanatory variable for whether one can expect positive roll yields. As noted in Blas (2011) in a *Financial Times article*, "From time to time, the [WTI] contract [has] disconnect[ed] from the global oil market due to logistical troubles at its landlocked point of delivery in Cushing, Oklahoma." The result has been a different curve shape and different returns from buying and holding Brent crude futures contracts versus WTI crude futures contracts. For example, please see Figure 2.

That said, Platts (2013) has noted that "many pieces of the logistical puzzle" in North America are now falling into place, due to the "ingenuity of logistical engineers," in managing the increase in

Figure 2

12/31/08 to 2/28/11 Annualised Excess Returns:

WTI: 3.5% **Brent 27.4%**



Source of Data: The Bloomberg. Futures Curves as of March 4, 2011.[Bloomberg Tickers for Return Calculations – WTI: SPGCCLP and Brent: SPGCBRP.]

> *'It may be that a whole host of systematic futures strategies and indexes that exploit structural backwardation in the crude oil futures markets might properly become in vogue again.'*

U.S. domestic crude supplies. Further, in JP Morgan (2013), the bank's commodity analysts have written that "the boom in … [domestic oil] production has been well absorbed by existing U.S. infrastructure … [T]ruck, rail, and barge have all served to move the large increase in domestic crude supplies to U.S. refineries," whom, in turn, can export petroleum *products* abroad. This has been the mechanism for connecting the U.S. oil markets to global markets since exporting crude oil *itself* is presently illegal with some minor exceptions. To the extent that this logistical ingenuity continues, one could be justified in seeing a return in the importance of roll yields as an ongoing driver of returns for holding WTI oil futures contracts, just as has been the case for Brent oil futures contracts. Both the WTI and Brent oil curves are currently trading in backwardation.

Going forward: backwardation, swing capacity, and roll yield

It may be that a whole host of systematic futures strategies and indexes that exploit structural backwardation in the crude oil futures markets might properly become in vogue again. For example, JP Morgan (2013) noted that amongst 65 commodity index products, two of the indexes, which emphasise backwardation, may have excellent prospects over the next two years.

Further, PIMCO's commodity portfolio managers noted in Johnson and Sharenow (2013) that "as long as Saudi Arabia maintains the ability to manage imbalances in the market and shale extraction prospects remain good, we expect the oil market roll yield to look similar to that in the 1990s …"

In conclusion, we may be returning to a Litzenberger-and-Rabinowitz state-of-the-world of structurally backwardated oil futures curves. In that case, it may be useful to revisit research done in the 1990s on structural drivers of both oil-futures and commodity-index returns.

Endnotes

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Alphas and the Choice of Rate of Return in Regressions

Whether or not a series of portfolio returns exhibits significantly positive alpha depends on how the returns are measured.

By Michael Edesess

Alpha has had a remarkably long run as the Holy Grail of investment. Many investment managers claim to have alpha, and all desire it. A top investment web site is called Seeking Alpha. The *Financial Times*'s daily news commentary on financial markets is named Alphaville. Journalist Sebastian Mallaby, in his 2010 paean to hedge funds, “More Money than God,” rests his case for the superiority of hedge funds in general on one academic study's conclusion that although the average hedge fund trailed the S&P 500, it earned three percentage points of alpha.[1] The persistence of the impression that small company stocks are superior to large company stocks is due chiefly to a finding of positive small-cap stock alpha in a 30-year-old paper. It is no coincidence that “alpha” is to investment machismo what “alpha male” is to manhood.

Yet arguments for the value of alpha are tenuous. Evidence for alpha can only be found in past returns data; past records of outperformance, however, are unreliable guides to the future. Most runs of unusually good performance, sometimes called anomalies, tend to go the way of the Schwert rule: “After they are documented and analysed in the academic literature, anomalies often seem to disappear, reverse, or attenuate.”[2] Alphas can be no more than a result of excessive data-mining. Even if the data are random, one out of twenty empirical alphas will spuriously be found to be significant in a t-test at the .05 level; those who wish to find alphas in a strategy's past performance can often try variations on the strategy and different time periods and data series until they find a significant alpha. Alpha is so easy to conjure up and tout that economists Nouriel Roubini and Stephen Mihm, in their 2010 book, “Crisis Economics,” ridiculed it by calling it “schmalpha.”

Consummating these weaknesses, we shall show that the standard method of calculating alphas from rate of return series may well be flawed, in such a way that it causes alphas to be found where they don't exist, especially in highly volatile portfolios.

Assumptions of ordinary least squares (OLS) regression

The standard mathematical tool used to compute alpha is ordinary least squares (OLS) regression. The method assumes that the rate of return r for the test portfolio or strategy is a linear function of one or more reference variables (the “independent variables” – usually index returns), v_i, i=1,…, m, plus a randomly-distributed error term ε.

When n measurements of the variables r and v_i, i=1,…, m are made, sample values R_j, j=1,…, n and V_{ij}, i=1,…, m; j=1,…, n are obtained. The assumed relationship in the j'th measurement between R_j and the V_{ij}'s is

$$R_j = \alpha + \beta_1 V_{1j} + \beta_2 V_{2j} + \ldots + \beta_m V_{mj} + \varepsilon_j$$

where ε_j is a random variable. The fundamental assumptions of regression analysis are that the expected value of each ε_j is zero and the ε_j are mutually independent and have the same variance. These assumptions suffice for the regression formula estimators of α and the β_i's to be unbiased and efficient.

Most mathematical developments of regression analysis in textbooks and courses also assume that the error terms are normally distributed. This assumption is necessary for the valid use of t-statistics and confidence intervals, which measure how confident we can be that the estimates are close to the real values. Without these statistics we do not have, for example, a reliable measure of how likely it is that α is not really zero.

Rates of return and non-normality

The analysis is nevertheless somewhat robust to non-normality; it is not necessary to be absolutely certain that the error terms are drawn from exactly a normal distribution. An arcane niche of mathematical statistics investigates such matters in depth, but we needn't delve into it here. It is on the other hand, however, generally assumed that if the distributions are substantially skewed, then the results may not be dependable.

It is well known that the distribution of holding-period returns[3] (HPRs) is skewed – that is, it is asymmetrical. It has a longer tail on the upside than the downside. The skew appears greater when depicted graphically, the longer the time interval over which returns are measured; but that is just due to compounding of the skewed distribution of short-term returns to obtain the long-term returns.

The distribution of continuously-compounded returns (CCRs), on the other hand – the logarithm of one plus the HPR – is not skewed. Many statistics textbooks recommend that when the distribution of a regression variable is skewed it should be transformed to a related variable whose distribution is not skewed, and is more like a normal distribution, before a regression is run. In the case of holding-period returns that transformed variable is the CCR, the continuously-compounded return.

The CCR is the rate of return if it is compounded continuously over a holding period, while the HPR is the rate if it is not compounded. Neither the HPR nor the CCR can claim to be the more correct measure of rate of return. While the difference between the two for short periods will be seemingly insignificant, the difference between using one or the other in a regression analysis can, as we shall see, be great. Surprisingly, the matter of the choice of type of rate of return – HPR or CCR – to use in regression analyses is not discussed even in the most mathematically sophisticated textbooks of finance, for example that of Campbell, Lo, and MacKinlay (2012).

On the grounds of better agreement with the normality assumption, it is arguably preferable to use CCRs. If it made no difference which was used it wouldn't matter; but we shall see that it does make a difference.

Small cap stocks and the Miller-MacKillop study

Over thirty years ago, a paper by Rolf W. Banz (1981), then a professor at Northwestern University, appeared in the *Journal of Financial Economics*, stating “The results show that, in the 1936-1975 period, the common stock of small firms had, on average, higher risk-adjusted returns than the common stock of large firms.” Banz's method was least-squares regression, which found a significantly positive alpha for small-cap stocks when regressed against the market portfolio over that time period. This result fueled an enduring belief in the benefits of small-cap stocks, although later studies found that this alpha often did not exist in the time period after the publication of Banz's 1981 article.

A recent article by Miller and MacKillop (2011) in *Financial Advisor Magazine* made the surprising claim that Banz was wrong. Miller and MacKillop compiled data on the Center for Research in Security Prices (CRSP) small-cap 9-10 index and regressed it against the Standard & Poors 500 index over four time periods since 1926: the years 1982-2010 since the Banz study; the years 1926-1981 up to the study; the same period 1936-1975 that Banz studied; and the whole time period 1926-2010. In none of these time periods did Miller and MacKillop find any alpha for small-cap stocks.

Miller and MacKillop attributed the differences between the results of their study and those of Banz over the same time period to several possible factors. First, they did not use the exact same portfolios as Banz did for the market and for small-cap stocks. Second, the CRSP data change continually, so the data for small-cap stocks are not the same as the data that Banz used. Third, Miller and MacKillop say they use “annualised” returns while Banz used monthly returns.

A little investigation revealed[4] that what Miller and MacKillop actually used was not “annualised” returns but continuously-compounded returns (CCRs). In other words, they used the form of the returns that is better suited to the regression model.

Replication of Miller and MacKillop's results

The present study used Miller and MacKillop's data to see if the difference between their results and Banz's could be entirely explained by the fact that Banz used HPRs while Miller and MacKillop used CCRs.

The result is clear: the difference in the measure used does explain all of the differences between Banz's findings and those of Miller and MacKillop. The results are shown in Table 1.

The monthly excess return (over Treasury-bill returns) of the small-cap CRSP 9-10 index was regressed against the excess return on the S&P 500. In the second column of Table 1 the HPRs were used, while in the third column the CCRs were used. The calculated alpha ranges from 1.2% to 2.6% greater for the HPRs than for the CCRs.

Table 1– HPR vs. CCR alphas in regressions of small-cap stock returns against market returns

	Annualised Alphas	
Time Period	Holding-Period Returns	Continuously-Compounded Returns
1926-2010	2.51%	0.41%
1926-1981	3.72%	1.01%
1936-1975	1.70%	-0.29%
1982-2010	1.08%	-0.13%

Simulations

The result above could have been unique to the particular data set. Hence, a simulation was conducted to see if a similar pattern could be observed by comparing any randomly-generated set of HPRs and CCRs.

Ten thousand random series of 1020 monthly premium CCRs were generated for the market and for small-cap stocks (1020 = 85 years x 12 months, paralleling the 85-year time period 1926-2010).

Assumptions for the market returns were that each CCR was drawn independently from a normal distribution with 6% annual expected premium return (0.5% monthly) and 20% standard deviation (20%/$\sqrt{12}$ or 5.7735% monthly).

The following relationship was then assumed between small-cap and market CCRs:

$$r_s = 1.5r_m + \varepsilon$$

where r_s is the small-cap CCR, r_m is the market CCR, ε is a normally-distributed random variable independent of r_m with zero mean, and the annualised standard deviation of r_s is 35% (35%/$\sqrt{12}$ or 10.1036% monthly). These assumptions imply that the monthly standard deviation of ε is 5.2042%.

By construction, r_s has a beta of 1.5 against the market, and a zero alpha. Thus, as expected, the average alpha when the simulated small-cap CCRs were regressed against the market CCRs was approximately zero. As expected – with only small discrepancies, due to the large number of simulations – 5% of the t-statistics for the alphas were significant at the .05 level, 2.5% at the .025 level, 1% at the .01 level, and 0.5% at the .005 level. The average beta was 1.5.

The CCRs for both the small-cap and market returns were then converted to HPRs, in the usual manner by raising e, the base of natural logarithms, to the power of the CCR and subtracting one. The small-cap HPRs were then regressed against the market HPRs.

While the betas averaged about the same – 1.51 instead of 1.5 – the alphas for the HPRs were very different. The monthly alphas averaged 0.26%, about 3.1% annualised. Of the 10,000 t-statistics for the alphas, 46% were significant at the .05 level, 34% at the .025 level, 21% at the .01 level, and 15% at the .005 level. Hence, the regressions of the HPRs found many significantly positive alphas, while the regressions of the CCRs found only the number of significantly positive alphas that would occur at random.

The effect of volatility

This effect – the spurious detection of alphas, or at least very different alphas

1 Ibbotson *et al.* (2010)
2 Schwert (2003) p. 940
3 We use the rate of return terminology of Bodie, Kane and Marcus (2009)
4 Gary A. Miller, personal communication.

when HPRs are used than when CCRs are used – dies down as the dependent variable becomes less volatile.

The simulations were run again using smaller assumed betas and smaller standard deviations for the dependent variable. Table 2 summarises the results.

The pairs of rows for CCRs and HPRs in Table 2 show results for portfolios with declining volatility. The spurious alpha effect declines as volatility decreases, finally dying out when beta = 0.7 and portfolio standard deviation = 16.75%.

An illustration

A stylised illustration with exaggerated values of beta and the standard deviation of the dependent variable helps to see why results are so different for the CCRs than for the HPRs. In Figure 1 the assumptions for beta and standard deviation of the small-cap premium CCR have been exaggerated (beta = 4, standard deviation = 100%) and the number of years of monthly data has been reduced to 5 for visual clarity.

The squares represent the HPRs, while the diamonds represent the corresponding CCRs. Note the upward skew of the HPRs relative to the CCRs at high and low values. The result is that the regression line for the CCRs goes through the origin (alpha = 0) while the regression line for the HPRs has a positive alpha.

Conclusion

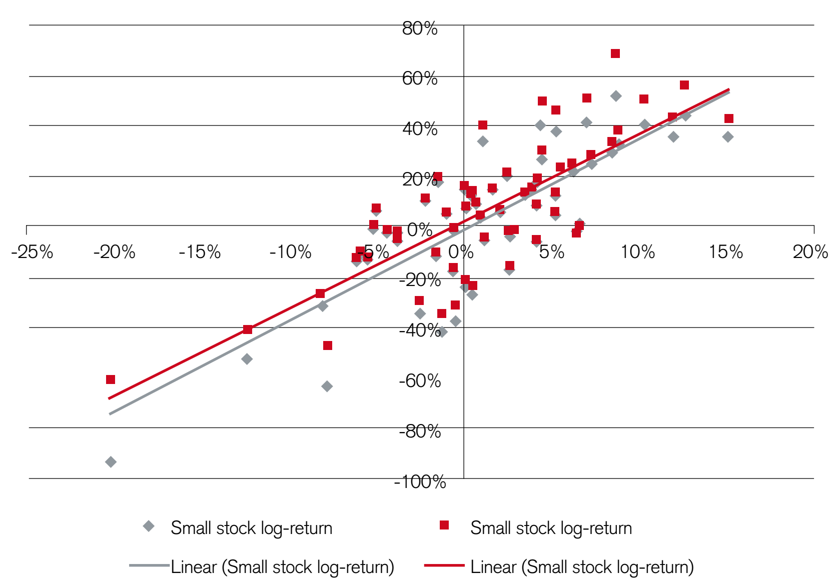
The results reported above show that whether or not a series of portfolio returns exhibits a significantly positive alpha depends on the arbitrary choice of whether the returns are measured as HPRs (holding-period returns) or CCRs (continuously-compounded returns). Since the distribution of the CCRs is more in keeping with the assumptions of regression analysis, it would seem appropriate to run regressions on the CCRs rather than the HPRs. Almost invariably, however, when regressions are run in financial studies of one return series against one or more others, it is the HPRs that are used, not the CCRs. This choice may result in the finding of spurious significantly positive alphas in many studies, especially when the portfolio being regressed against one or more market indices is highly volatile.

This observation further undermines alpha's already shaky underpinnings – for its use either in the prediction of future performance or the evaluation of past performance. ■

Table 2 – HPR vs. CCR alphas in regressions of simulated returns

Parameters			Avg regr. coeffs		% of alphas signif. at level:			
10,000 simulations			**Alpha (ann.)**	**Beta**	**0.05**	**0.025**	**0.01**	**0.005**
Small stocks - highly volatile								
CCR α = 0	Portfolio ß =1.5	CCR:	0.00%	1.50	5.2%	2.6%	1.1%	0.6%
Market ⊠ = 20%	Portfolio ⊠ = 35%	HPR:	3.15%	1.51	45.7%	33.9%	21.3%	14.5%
Less volatile								
CCR α =0	Portfolio ß =1.0	CCR:	0.01%	1.00	5.0%	2.4%	1.0%	0.5%
Market =20%	Portfolio ⊠ = 25%	HPR:	1.14%	1.00	16.3%	9.6%	4.7%	2.6%
Market volatility								
CCR α = 0	Portfolio ß =0.8	CCR:	0.01%	0.80	5.4%	2.6%	1.0%	0.5%
Market ⊠ = 20%	Portfolio ⊠ =20%	HPR:	0.41%	0.80	9.0%	5.0%	2.2%	1.1%
Below-market volatility								
CCR α =0	Portfolio ß =0.7	CCR:	0.00%	0.70	4.8%	2.3%	1.1%	0.6%
Market ⊠ =20%	Portfolio ⊠ =16.75%	HPR:	0.01%	0.70	4.8%	2.2%	1.1%	0.5%

Figure 1. – HPR and CCR regression lines



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