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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.

In the equity universe, we look at how to constitute a well diversified smart beta index that diversifies away specific risks and manages exposure to equity risk factors. The results show that smart factor indices allow high-performance allocations to be constructed either in terms of absolute return (Sharpe ratio) or in relative terms (information ratio) compared to cap-weighted indices, which remain the performance reference for long-only passive investment. Multi-beta multi-strategy indices, which allow smart factor indices to be chosen and combined flexibly, present themselves as more transparent and cost efficient ways for active managers and multi-managers to generate outperformance.

We explore the long-term performance and risks of selected smart beta strategies in order to examine the consistency of the performance of these strategies over the long run. Our results show that all strategies analysed not only achieve their respective objectives in the long term but also show high levels of outperformance probability with limited risk of underperformance.

Consequently, we also look at the robustness of the outperformance of smart beta equity strategies. Our article specifically provides a relative risk analysis and an analysis of conditional performance properties of a set of smart beta strategies in the Asian equity universe. Interestingly, the diversified multi-strategy index, which combines five different weighting schemes, shows less dependence on market conditions than its component strategies, since the different conditional performance profiles counterbalance each other when diversifying across strategies.

We analyse the diversification of pension fund portfolios and its relationship with subsequent portfolio performance, and find that better diversified policy portfolios, in the sense of a higher number of uncorrelated bets, tend to perform better on average in bear markets. Our analysis suggests that a better assessment of the degree of diversification of a portfolio in terms of effective number of bets would provide useful insights regarding the risk and return profile of the portfolio in various market conditions.

Looking at the extreme risk of Asian stock market indices, we find higher tail risk for Asian markets compared to European and North American ones. The higher tail risk of Asian markets indicates the key difference over the long run is in the levels of volatility of the market returns and possibly in the variability of the extreme losses. This conclusion underlines the importance of volatility management techniques for managing tail risk.

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

Multi-Beta Multi-Strategy Approach: an Asian Perspective

By Ashish Lodh, Noel Amenc and Felix Goltz

There has been a significant increase recently in the number of alternative forms of equity indices. Most of these indices are marketed based on their outperformance over the cap-weighted benchmark. It is true that cap-weighted indices are the default benchmark choice for active and passive managers, but they have two major drawbacks which lead to inferior risk-adjusted performance compared to popular alternative beta indices. Firstly, they do not efficiently diversify unrewarded (specific) risks due to an excessive concentration in the largest cap stocks. For example, TEPCO had a weight of 1.24% in the TOPIX 1000 index (cap-weighted) as of March 2011 when the Fukushima disaster caused its shares to plunge by 20.3% between February 15 and March 15. In the same period, the TOPIX 1000 index incurred a loss of 20.2%. Second, they provide limited access to other rewarded risks (like size and value). Exhibit 1 shows that the cap-weighted indices tilt towards low value (book-to-market) and large-cap stocks, and therefore do not capture value and small size risk premia (Fama, French (1993)). Therefore an important question that arises is – how to constitute a well diversified smart beta index? We show that it is an index which diversifies away the specific risks and manages the exposure to equity risk factors.

Managing unrewarded risk factors: diversified multi-strategy

The specific risks constitute all the risks that do not have a premium in the long run, and are therefore not ultimately desired by the investor. Specific risks can correspond to important ***financial risk factors*** that do not have, over the long term, a positive long-term premium. Examples of these factors from the academic literature include commodity, currency, or sector risks. These factors can have a strong influence on the volatility, tracking error, maximum drawdown or maximum relative drawdown over a particular period, which might sometimes be greater than that of systematically rewarded risk factors (e.g. exposure to the financial sector during the 2008 crisis or to sovereign risk in 2011). Other kinds 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. Portfolio theory suggests that these risks are neither predictable nor rewarded, so one is better off completely avoiding them by investing in a well-diversified portfolio. Specific or non-rewarded risks can also correspond to ***specific operational risks*** that are specific to the implementation of the diversification model and are usually analysed using the concept of parameter estimation error.

A globally effective diversification weighting scheme aims to reduce the quantity of non-rewarded financial risk factors and non-rewarded specific financial risks. However, due to imperfections in the model there remain residual exposures to these risks. For example, minimum volatility portfolios are often exposed to significant sector biases. Similarly, in spite of all the attention paid to the quality of model selection and the implementation methods for these models, the specific operational risk remains present to a certain extent. For example, the robustness of the maximum Sharpe ratio scheme depends on a good estimation of the covariance matrix and expected returns. Therefore, it seems interesting to be able to reduce even further the exposures that each weighting scheme, even if it is smart, is not able to diversify. The diversified multi-strategy approach, which combines five different weighting schemes, enables all of the non-rewarded risks associated with each of the weighting schemes to be well diversified (Amenc et al. (2012)). Exhibit 2 shows, for USA long term data, that the diversified multi-strategy index smoothes out the outperformance across different market conditions and obtains lower tracking error.

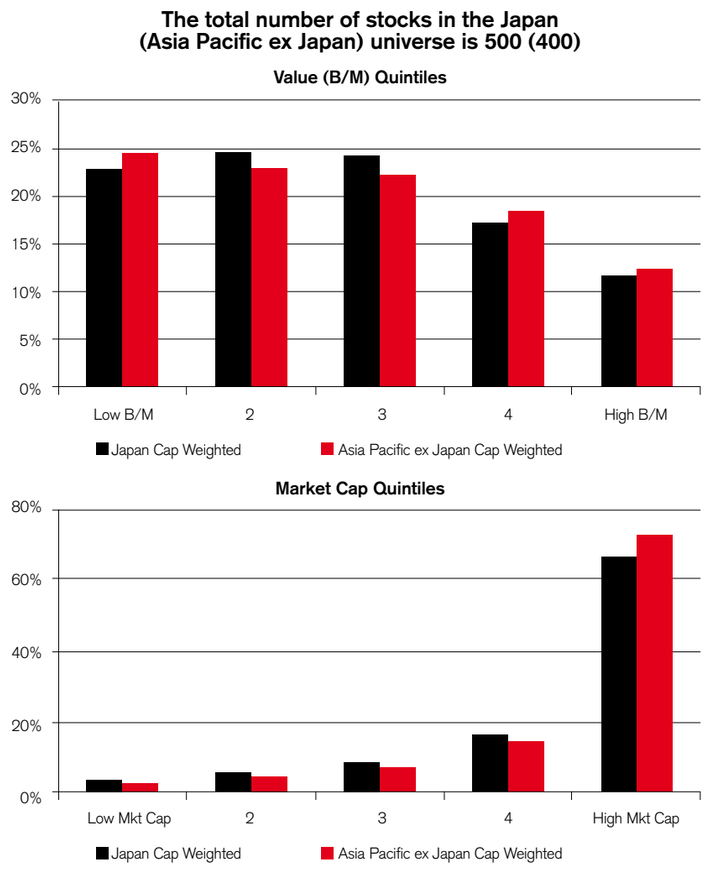
Managing rewarded risk factors: smart factor indices and multi-beta multi-strategy

First generation smart beta indices have focused on addressing the problem of unrewarded risks by constructing naively (equal weighted or risk parity) or scientifically (minimum volatility or maximum Sharpe ratio) diversified portfolios. But most such indices, being a pre-packaged bundle of factor exposures and methodological choices, leave the second problem unattended. The Smart Beta 2.0 approach proposes a solution for this in the form of smart factor investing. The idea of smart factor investing is to construct a factor-tilted portfolio to extract the factor premia most efficiently and is based on two pillars: 1) selecting appropriate stocks for the desired beta and 2) using a diversification-based weighting scheme (Amenc et al. (2013)).

We construct ***smart factor indices*** – building blocks which use diversified multi-strategy weighting on characteristics-based half universes. Stock selection choices are made to gain exposure to three well-known equity risk factors – small size, value, and momentum (Carhart (1997)) along with the low volatility factor, which is commonly accepted to have a positive risk premium (Ang et al. (2006)). The choice of diversified multi-strategy provides efficient diversification of unrewarded strategic risks for a given factor tilt. The value addition of the four smart factor indices over respective cap-weighted tilted portfolios is illustrated using long-term USA data in Exhibit 3.

'The multi-strategy approach enables all of the non-rewarded risks associated with each of the weighting schemes to be well diversified'

Exhibit 1: Cap Weighting and Rewarded Risk Factors - All statistics are based on average quarterly weights in the period 21-June-2002 to 31-Dec-2013.



Source: www.scientificbeta.com

Exhibit 2: Diversified Multi-strategy - Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. All statistics are annualised and the analysis is based on daily total returns (with dividends reinvested) in the period 31-Dec-1972 to 31-Dec-2012.

The total number of stocks in the USA universe is 500

	Scientific Beta USA Long Term Indices						
	Maximum Deconc.	Maximum Decorr.	Efficient Min Volatility	Efficient Max Sharpe	Diversified Risk Parity	Average of 5 Single Strategies	Diversified Multi-strategy
Ann Relative Returns							
Full Period	2.39%	2.42%	2.46%	2.69%	2.45%	2.48%	2.50%
Bull Market	4.34%	3.33%	-0.07%	2.33%	3.17%	2.62%	2.63%
Bear Market	-0.08%	1.16%	5.38%	2.91%	1.41%	2.16%	2.15%
Ann Tracking Error							
Full Period	4.32%	4.36%	5.29%	4.54%	4.23%	4.55%	4.28%
Bull Market	3.85%	3.87%	4.51%	3.86%	3.69%	3.96%	3.72%
Bear Market	5.15%	5.23%	6.61%	5.69%	5.17%	5.57%	5.25%

Source: www.scientificbeta.com and CRSP

Exhibit 3: Smart Factor Indices - Factor tilted indices contain 50% stocks sorted by the characteristics (size, momentum, volatility, and B/M ratio). The yield on Secondary Market US Treasury Bills (3M) is a proxy for the risk-free rate. 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. All statistics are annualised and the analysis is based on daily total returns (with dividends reinvested) in the period 31-Dec-1972 to 31-Dec-2012.

The total number of stocks in the USA universe is 500

		Mid Cap Momentum		High Momentum		Low Volatility		Value	
	USA Long Term Cap Weighted	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy
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%w
Sharpe Ratio	0.24	0.39	0.52	0.30	0.48	0.29	0.50	0.35	0.54
Max Drawdown	54.53%	60.13%	58.11%	48.91%	49.00%	50.50%	50.13%	61.20%	58.41%
Ann Excess Returns		2.80%	4.45%	1.10%	3.56%	0.35%	2.90%	2.04%	4.70%
Ann Tracking Error		5.99%	6.80%	3.50%	4.88%	4.44%	6.17%	4.74%	5.82%
95% Tracking Error		9.38%	11.55%	6.83%	8.56%	9.20%	11.51%	8.70%	10.15%
Information Ratio		0.47	0.66	0.32	0.73	0.08	0.47	0.43	0.81
Max Rel Drawdown		35.94%	42.06%	14.44%	17.28%	33.82%	43.46%	20.31%	32.68%
Outperf. prob (1Y)		61.2%	67.9%	63.0%	68.4%	50.3%	67.8%	61.8%	70.9%
Outperf. prob (3Y)		70.1%	74.1%	78.2%	84.4%	50.1%	76.3%	69.8%	78.8%

Source: www.scientificbeta.com and CRSP

Having shown the long term robustness of smart factor indices, one could construct similar smart factor indices for other geographies too (like Japan and Asia Pacific ex Japan). Furthermore, to manage factor allocation, we construct a multi-beta multi-strategy index which combines the four smart factor indices in equal proportion.[1] This is an example of efficient diversification of (i.e., efficient allocation to) systematic rewarded risk factors achieved through a mix of smart weighting schemes applied to selected factor tilts.

Exhibit 4 shows that the multi-beta multi-strategy index results in tracking error which is below the average tracking error of the constituting indices. Since its performance is close to the average performance of the constituents, its Information Ratio shows a significant improvement. Results show that diversification across factors also helps in controlling extreme relative risks.

'Multi-beta, multi-strategy indices present themselves as more transparent and cost efficient ways for active managers and multi-managers to generate outperformance'

Conclusion

The objective of Smart Beta 2.0 is the management of both unrewarded (specific) risk and rewarded risks. Smart factor indices allow high-performance allocations to be constructed either in terms of absolute return (Sharpe ratio) or in relative terms (information ratio) compared to cap-weighted indices, which remain the performance reference for long-only passive investment. Multi-beta multi-strategy indices, which allow smart factor indices to be chosen and combined flexibly, present themselves as more transparent and cost efficient ways for active managers and multi-managers to generate outperformance. ■

By Ashish Lodh, Senior Quantitative Analyst, ERI Scientific Beta
Noel Amenc, Professor of Finance, EDHEC Business School, Director, EDHEC-Risk Institute, CEO, ERI Scientific Beta
Felix Goltz, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta

Exhibit 4: Multi-beta Multi-strategy – The four smart factor indices contain 50% stocks sorted by the characteristics (size, momentum, volatility, and B/M ratio) and Multi-beta Multi-strategy is an equal weighted combination of them. The yield on Secondary Market US Treasury Bills (3M) is a proxy for the risk-free rate. 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. All statistics are annualised and the analysis is based on daily total returns (with dividends reinvested) in the period 21-June-2002 to 31-Dec-2013.

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

	Japan CW	Mid Cap	Momentum	Low Volatility	Value	Avg of 4 Smart Factor Indices	Multi Beta Multi Strategy
Ann Returns	4.16%	6.43%	6.10%	7.04%	7.70%	6.82%	6.86%
Ann Volatility	22.40%	18.88%	19.38%	17.00%	19.61%	18.72%	18.54%
Sharpe Ratio	0.18	0.33	0.31	0.40	0.38	0.36	0.36
Rel. Returns	-	2.27%	1.94%	2.88%	3.54%	2.66%	2.70%
Tracking Error	-	8.02%	7.66%	8.87%	6.65%	7.80%	7.32%
Information Ratio	-	0.28	0.25	0.32	0.53	0.35	0.37
95% Tracking Error	-	14.14%	15.11%	15.24%	11.65%	14.03%	13.50%
	Scientific Beta Asia Pacific ex Japan Diversified Multi-strategy						
	Asia Pacific ex Japan CW	Mid Cap	Momentum	Low Volatility	Value	Avg of 4 Smart Factor Indices	Multi Beta Multi Strategy
Ann Returns	11.82%	17.41%	19.61%	16.24%	18.71%	17.99%	18.06%
Ann Volatility	23.20%	19.89%	21.17%	16.94%	21.05%	19.76%	19.45%
Sharpe Ratio	0.44	0.80	0.85	0.87	0.82	0.83	0.85
Rel. Returns	-	5.59%	7.79%	4.42%	6.89%	6.17%	6.24%
Tracking Error	-	7.77%	7.21%	8.68%	6.96%	7.65%	6.66%
Information Ratio	-	0.72	1.08	0.51	0.99	0.83	0.94
95% Tracking Error	-	14.97%	12.42%	14.80%	12.31%	13.63%	12.36%
	Scientific Beta USA Long Term Diversified Multi-strategy						
	USA Long Term CW	Mid Cap	Momentum	Low Volatility	Value	Avg of 4 Smart Factor Indices	Multi Beta Multi Strategy
Ann Returns	9.74%	14.19%	13.30%	12.64%	14.44%	13.64%	13.72%
Ann Volatility	17.47%	16.73%	16.30%	14.39%	16.55%	15.99%	15.76%
Sharpe Ratio	0.24	0.52	0.48	0.50	0.54	0.51	0.52
Rel. Returns	-	4.45%	3.56%	2.90%	4.70%	3.90%	3.98%
Tracking Error	-	6.80%	4.88%	6.17%	5.82%	5.92%	5.24%
Information Ratio	-	0.66	0.73	0.47	0.81	0.67	0.76
95% Tracking Error	-	11.55%	8.56%	11.51%	10.15%	10.44%	8.93%

Source: www.scientificbeta.com

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[1] In theory, the choice of weighting across the smart factor indices depends on the risk preference of the investor. Other weightings such as equal risk contribution can also be used. In this article, we only illustrate the simple equal weighting approach.

Long-Term Performance of Scientific Beta Indices

By Ashish Lodh, Noel Amenc and Felix Goltz

Recent years have witnessed increasing interest in alternative beta or smart beta equity strategies. Different directions have been taken to depart from cap-weighted equity indices and address some of their known shortcomings, such as the issue of high concentration in the larger capitalisation stocks (Malevergne, Santa-Clara and Sornette (2009)) or their lack of risk/return efficiency (Ferson, Kandel and Stambaugh (1987), Goltz and Le Sourd (2011)). Most smart beta indices are marketed on the basis of outperformance, but usually their back-tests are conducted over a limited time period. Critics of smart beta often question the robustness of these strategies over the long term. Economic and financial market conditions may have a considerable impact on how different equity strategies perform (Ferson and Qian (2004). Therefore in this article, we explore the long-term performance and risks of selected smart beta strategies.

Scientific Beta weighting schemes

There are two distinct approaches to diversification: either an *ad-hoc* diversification objective that matches the investor's views and preferences, or strategies which are based on the theoretical framework of Modern Portfolio Theory and aim to achieve efficient frontier portfolios, i.e. portfolios that obtain the lowest level of volatility for a given level of expected return. Heuristic or ad-hoc strategies, which have objectives different from Sharpe ratio maximisation, can be further categorised into *deconcentration* and *decorrelation*-based approaches. *Deconcentration*-based strategies simply focus on reducing the weight and risk concentration of portfolios by spreading out the constituents' weights or their risk contributions equally[2]. Decorrelation strategies focus on risk reduction that stems from the fact that assets are imperfectly correlated.

In contrast to these heuristic approaches, scientific or *efficient diversification* methodologies aim to proxy the portfolios located on the efficient frontier. The Minimum Volatility portfolio corresponds to a particular spot on the efficient frontier representing the portfolio that has the lowest level of volatility among all feasible portfolios. The Maximum Sharpe Ratio (MSR) portfolio is an implementable proxy for the tangency portfolio – the portfolio with the highest level of risk-adjusted returns.

> *'Most smart beta indices are marketed on the basis of outperformance, but usually their back-tests are conducted over a limited time period'*

ERI Scientific Beta proposes three heuristic diversification weighting schemes (Maximum Deconcentration, Diversified Risk Parity and Maximum Decorrelation), *two efficient diversification strategies* (Efficient Minimum Volatility and Efficient Maximum Sharpe) and a combination of these five weighting schemes – Diversified Multi-strategy[3]. Additionally, ERI Scientific Beta applies turnover control and liquidity rules to all its indices to ensure that they take into account practical investment constraints. In order to further foster liquidity, additional adjustments of weights are implemented to achieve two objectives: one is to limit liquidity issues that may arise upon investing and another is to limit the liquidity issues that may occur upon rebalancing a smart beta strategy. Moreover, all indices are governed by an optimal turnover control technique which is based on rebalancing thresholds (Leland (1999); Martellini and Priaulet (2002)).

Table 1 shows that in the long-term (40 years), all the diversification strategies deliver annualised outperformance of more than 2.3% and Sharpe ratios ranging from 0.38 to 0.45 (compared to 0.24 for the cap-weighted reference index). The Efficient Minimum Volatility index delivers a volatility of 14.73% compared to 17.47% for the cap-weighted benchmark. The Efficient Maximum Sharpe Ratio index results in a Sharpe ratio of 0.43, which is well above that of the cap-weighted index (0.24). Similarly, Maximum Deconcentration fulfils its deconcentration objective with an effective number of stocks equal to 485.[4] The Maximum Decorrelation objective can be accessed by computing the GLR measure, which can be viewed as the contribution of average pair-wise correlations to the volatility of the portfolio compared to that of a portfolio composed of uncorrelated stocks.[5] One-way annual turnover of all diversification strategies is below 30%, showing the effectiveness of turnover rules. All strategies are adequately liquid as their weighted average market capitalisation is about one quarter of that of the cap-weighted index, which is itself highly liquid by construction[6].

Table 1: Overview of Diversification Strategies - The analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years). The regression coefficients statistically significant at the 95% level are highlighted in bold The Small Size factor is the daily return series of a cap-weighted portfolio that is long the CRSP cap-weighted market portfolios 6-8 (NYSE, Nasdaq, AMEX) and short the largest 30% of stocks from the CRSP S&P 500 universe by market cap. The Value factor is the daily return series of a cap-weighted portfolio that is long the highest 30% and short the lowest 30% of B/M ratio stocks in the CRSP S&P 500 universe. The Momentum factor is the daily return series of a cap-weighted portfolio that is long the highest 30% and short the lowest 30% of 52-week (minus most recent 4 weeks) past return stocks of CRSP S&P 500 universe. Turnover is mean annual 1-way. All statistics are annualised.

	Cap Weighted	Max Deconcentration	Max Decorrelation	Efficient Min Vol	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-Strategy
Ann Returns	9.74%	12.13%	12.16%	12.20%	12.43%	12.19%	12.24%
Ann Volatility	17.47%	17.49%	16.67%	**14.73%**	15.99%	16.78%	16.28%
Sharpe Ratio	0.24	0.38	0.40	0.45	**0.43**	0.40	0.41
ENS	113	**485**	305	247	296	457	399
GLR	26.51%	19.75%	**18.29%**	18.99%	18.42%	20.23%	18.95%
Max DD	54.53%	58.70%	54.16%	50.03%	53.22%	56.36%	54.55%
Ann Alpha	0.00%	**1.24%**	**1.23%**	**1.87%**	**1.58%**	**1.49%**	**1.49%**
Market Beta	**1.00**	**0.99**	**0.95**	**0.82**	**0.91**	**0.95**	**0.93**
Small Size Beta	-	**0.21**	**0.20**	**0.11**	**0.16**	**0.17**	**0.17**
Value Beta	-	**0.11**	**0.09**	**0.10**	**0.11**	**0.11**	**0.11**
MOM Beta	-	**-0.05**	0.01	**0.01**	**0.01**	**-0.04**	**-0.01**
Capacity (m$)	44 967	10 730	10 745	12 741	11 492	11 515	11 445
1-Way Turnover	2.66%	19.19%	27.65%	28.59%	26.31%	20.90%	19.12%

Diversified multi-strategy weighting scheme

All smart beta strategies contain some specific or unrewarded risks – all the risks that do not have a premium in the long run, and are therefore not ultimately desired by the investors. Specific risks include financial risk factors such as commodity, currency, or sector risks; or idiosyncratic risks which are specific to companies; or specific operational risks which are specific to the implementation of the diversification model and are usually analysed using the concept of parameter estimation error. It is possible, to some extent, to diversify risks that are specific to each strategy (Tu and Zhou (2010), Kan and Zhou (2007)). The Diversified Multi-strategy approach, which combines the five different weighting schemes in equal proportion, is based on this specific risk diversification principle.

An interesting measure of downside relative risk – maximum relative drawdown – is the maximum relative loss experienced by the index between a peak and the subsequent valley. The relative drawdowns of 30%-40% occurred in the late '90s, the period when cap-weighted indices continued to load on overpriced stocks and/or the momentum factor delivered attractive short-term gains. Not surprisingly, the Efficient Minimum Volatility strategy, being the most defensive strategy, lagged behind the most in this period. A quite robust method to measure the consistency of outperformance is to compute outperformance probabilities for investment horizons of 3 (or 5) years. This measure is the historical empirical probability of outperforming the benchmark over a typical investment horizon irrespective of the entry point in time. It is remarkable that over a period of 40 years all strategies deliver extremely high outperformance probabilities (5Y) of between 78% and 83.5%. Compared to the average of its constituents, the Diversified MultiStrategy index achieves a lower tracking error and a higher Information Ratio. Also, its outperformance in bull and bear markets is quite similar, while most other strategies are favoured in either bull or bear markets.

[2] The risk contribution of a constituent is defined as the product of the constituent's weight and the marginal contribution of this constituent to the total portfolio volatility.

[3] A detailed description of all index methodologies can be found in Gonzalez and Thabault (2013).

[4] Effective number of stocks (ENS) is the inverse of the Herfindahl Index, $ENS = 1/\sum_{k=1}^{N} W_k^2$

[5] $GLR = \frac{Var(R_p)}{\sum_{i=1}^{N} W_i Var(R_i)}$ where N is the number of stocks in the portfolio, R_p is the return of the portfolio, W_i is the weight of stock i and R_i is the return of stock i.

[6] *Weighted Average Market Cap of index i*$= \sum_{k=1}^{N} W_{k,i} \cdot Market\ Cap_k$ where $W_{k,i}$ is the weight of stock k in index i, N is the total number of stocks in the index, and $Market\ Cap_k$ is the float-adjusted market cap of stock k.

Table 2: Diversification across Weighting Schemes - The analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years). The benchmark is the cap-weighted index on the CRSP S&P 500 universe and all relative performance and relative risks measures are reported relative to it. Probability of outperformance is the historical empirical probability of outperforming the benchmark. It is computed using a rolling window analysis with 3/5-year window length and one-week step size. 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. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. All statistics are annualised.

	Max Deconcentration	Max Decorrelation	Efficient Min Volatility	Efficient Max Sharpe	Diversified Risk Parity	Average of 5 single strategies	Diversified Multi-Strategy
Ann Rel Returns	2.39%	2.42%	2.46%	2.69%	2.45%	2.48%	2.50%
Tracking Error	4.32%	4.36%	5.29%	4.54%	4.23%	4.55%	4.28%
Information Ratio	0.55	0.55	0.46	0.59	0.58	0.55	0.58
Outperf Prob (3Y)	72.3%	79.0%	79.6%	79.9%	76.3%	77.4%	78.6%
Outperf Prob (5Y)	78.3%	82.1%	79.9%	83.5%	80.6%	80.9%	81.4%
Max Rel DD	30.07%	30.00%	40.10%	30.66%	34.10%	32.98%	32.89%
Period of Max Rel DD	Mar '94-Mar '00	Mar '94-Mar '00	Jul '89-Mar '00	Mar '94-Mar '00	Mar '94-Mar '00	Mar '94-Mar '00	Mar '94-Mar '00
95% Trk Error	7.69%	7.20%	9.43%	7.29%	8.17%	7.96%	7.67%
Excess Ret (Bull)	4.34%	3.33%	-0.07%	2.33%	3.17%	2.62%	2.63%
Excess Ret (Bear)	-0.08%	1.16%	5.38%	2.91%	1.41%	2.16%	2.15%
TE (Bull)	3.85%	3.87%	4.51%	3.86%	3.69%	3.96%	3.72%
TE (Bear)	5.15%	5.23%	6.61%	5.69%	5.17%	5.57%	5.25%

It is understood that any deviation from cap-weighting will induce systematic risks (as shown in Table 1), but it is misleading to assume that the outperformance of a strategy can simply be explained by these factor premiums alone. In fact, one can still benefit from diversification without taking a particular risk exposure and/or while taking a desired risk exposure. In the smart beta 2.0 approach, a clear distinction between the stock selection phase and the weighting phase allows management of implicit factor tilts that may arise from the weighting scheme through an explicit choice of the universe in which the strategy invests (Amenc et al. (2013)). Table 3 shows how diversified multi-strategy weighting can be used to best harvest the associated risk premia for a given equity risk factor (beta).

All strategies analysed not only achieve their respective objectives in the long term but also show high levels of outperformance probability with limited risk of underperformance. It is useful to understand that all strategies have some implicit specific risk, which can be diversified by allocating across strategies in the form of a diversified multi-strategy index. Diversified multi-strategy is a good starting point for investors who are agnostic about either their capacity to identify the model with superior assumptions or their capacity to take the risk of choosing a particular model in the wrong market conditions. We also show that one can always add value through diversification even for a restricted characteristics-based stock selection. ■

'One can still benefit from diversification without taking a particular risk exposure and/or while taking a desired risk exposure'

Table 3: Smart Factor Indices - Factor tilted indices contain 50% stocks sorted by the characteristics (size, momentum, volatility, and B/M ratio). The yield on Secondary Market US Treasury Bills (3M) is a proxy for the risk-free rate. The benchmark is the cap-weighted index (CW) on the CRSP S&P 500 universe and all relative performance and relative risks measures are reported relative to it. 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. All statistics are annualised and the analysis is based on daily total returns (with dividends reinvested) from 31/12/1972 to 31/12/2012.

The total number of stocks in the USA universe is 500

		Mid-Cap		High Momentum		Low Volatility		Value	
	USA Long Term Cap Weighted	CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy
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
Max Drawdown	54.53%	60.13%	58.11%	48.91%	49.00%	50.50%	50.13%	61.20%	58.41%
Ann Excess Returns		2.80%	4.45%	1.10%	3.56%	0.35%	2.90%	2.04%	4.70%
Ann Tracking Error		5.99%	6.80%	3.50%	4.88%	4.44%	6.17%	4.74%	5.82%
95% Tracking Error		9.38%	11.55%	6.83%	8.56%	9.20%	11.51%	8.70%	10.15%
Information Ratio		0.47	0.66	0.32	0.73	0.08	0.47	0.43	0.81
Max Rel Drawdown		35.94%	42.06%	14.44%	17.28%	33.82%	43.46%	20.31%	32.68%
Outperf. prob (1Y)		61.2%	67.9%	63.0%	68.4%	50.3%	67.8%	61.8%	70.9%
Outperf. prob (3Y)		70.1%	74.1%	78.2%	84.4%	50.1%	76.3%	69.8%	78.8%

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How Robust is the Outperformance of Smart Beta Equity Strategies?

By Ashish Lodh, Noel Amenc and Felix Goltz

Accounting for the risks of smart beta

There has been increasing interest in so-called *smart beta strategies*, which try to generate outperformance over the standard market indices. These indices are being marketed on the basis of a number of shortcomings of cap-weighted indices, which have been documented to be overly concentrated (see Tabner (2007) and Malevergne *et al*. (2009)) and to provide poor risk-adjusted returns (see Goltz and Le Sourd (2010) for a literature review). As an alternative to cap-weighted indices, numerous advanced beta equity offerings have been launched, which either draw on firm fundamentals or on risk/return parameters to construct systematic equity portfolios.

Providers of such indices have widely documented the superior performance of their respective approaches compared to the corresponding cap-weighted indices. In early papers, such performance comparisons have fallen short of fully accounting for risks of such strategies (see Arnott, Hsu, and Moore (2005) as an example of a paper which does not even report the exposure of the strategy to standard risk factors such as small cap and value factors[7]).

While it is now commonly accepted that moving away from cap-weighting tends to enhance diversification and improve risk-adjusted performance over long horizons, it has to be recognised that each alternative weighting scheme will expose an investor to a risk of underperforming cap-weighted reference indices over short investment horizons. Moreover, it seems reasonable to assume that certain market conditions may influence the capacity of a given weighting scheme to provide outperformance over cap-weighted reference indices. It is thus crucial for investors to assess the risk of underperformance as well as the conditional performance profile of any smart beta strategy so as to gain a better picture of the robustness of the potential outperformance of a strategy.

'It is crucial to assess the risk of underperformance as well as conditional performance of any smart beta strategy'

The remainder of this article provides a relative risk analysis and an analysis of conditional performance properties of a set of smart beta strategies in the Asian equity universe. In particular we analyse the following weighting schemes:

- Maximum Deconcentration: Equal Weighting attributes a weight of 1/N to each of N constituents in the index to achieve a naive form of diversification. It can be understood as the maximisation of the effective number of stocks. Maximum Deconcentration consists of equal-weighting subject to adjustments that allow for sufficiently high liquidity and capacity.
- Diversified Risk Weighted: Equal Risk Contribution aims to equalise risk contributions from different assets in the portfolio. If we make the assumption of identical correlations across all pairs of components, inverse volatility weighting leads to equal risk contributions.
- Maximum Decorrelation: This scheme maximises the use of the correlation features of the stock universe to create a well-diversified portfolio. Maximum Decorrelation minimises portfolio volatility with the assumption that volatilities are identical across stocks. The only differences across stocks that the optimiser then takes into account are differences in correlations.
- Efficient Minimum Volatility aims at providing the lowest possible portfolio volatility. Required optimisation inputs are correlations and volatilities. We apply constraints in order to avoid concentration in low volatility stocks.
- Efficient Maximum Sharpe Ratio is about maximising the Sharpe ratio while avoiding direct return estimation. It uses indirect estimation of expected returns through a stock's riskiness.

We also assess a Diversified Multi-strategy index which consists of an equal-weighted allocation to each of these five weighting schemes.

Global relative risk

Alternative index construction schemes lead in principle to an exposure to risk that deviates substantially from that of cap-weighted reference indices, as they lead to choices of factor exposure that are different from those of cap-weighted indices. Investment professionals who deviate from cap-weighted indices take on considerable reputation risk, as cap-weighted indices represent a common reference for their peer group. It is thus crucial to properly analyse

[7] While the paper shows results for a single factor regression, in particular the alpha of the alternative index with respect to a single market factor, and provides a detailed discussion of these results, it only loosely refers to the existence of small cap and value exposure, without however showing any results to the reader.

Relative Performance and Risk Analysis of Smart Beta Strategies Probability of outperformance is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 1, 3 or 5 years irrespective of the entry point in time. It is computed using a rolling window analysis with 1, 3, or 5-year window length and one-week step size. Maximum relative drawdown is the maximum drawdown of the long-short index, the return of which is given by the fractional change in the ratio of the strategy index to the benchmark index. Based on daily total returns from 21/06/2002 to 31/12/2013.

The stock universe consists of 500 stocks with the highest free-float market capitalisation for Japan and the 400 stocks with the highest free-float market capitalisation for Developed Asia ex Japan, which consists of the following countries: Australia, Hong Kong, Korea, New Zealand, and Singapore.

	Max Deconcentration	Max Decorrelation	Efficient Min Volatility	Efficient Max Sharpe	Diversified Risk Weighted	Diversified Multi-Strategy
			Japan			
Ann Relative Returns	2.04%	1.78%	2.31%	2.05%	2.25%	2.12%
Tracking Error	4.27%	5.54%	8.08%	5.93%	4.70%	5.45%
Information Ratio	0.48	0.32	0.29	0.35	0.48	0.39
Outperf Prob (1Y)	63.5%	59.8%	54.5%	59.6%	66.0%	60.9%
Outperf Prob (3Y)	75.8%	71.7%	69.6%	74.4%	80.7%	75.8%
Outperf Prob (5Y)	99.4%	96.5%	87.4%	96.2%	98.5%	97.4%
Max Relative Drawdown	10.27%	11.08%	14.59%	10.10%	9.57%	10.44%
			Developed Asia ex Japan			
Ann Relative Returns	3.13%	4.63%	5.54%	4.41%	3.48%	4.26%
Tracking Error	5.24%	6.23%	7.46%	6.57%	5.23%	5.83%
Information Ratio	0.60	0.74	0.74	0.67	0.67	0.73
Outperf Prob (1Y)	67.3%	71.6%	75.5%	72.0%	61.5%	70.9%
Outperf Prob (3Y)	63.5%	89.0%	96.9%	85.9%	70.6%	87.9%
Outperf Prob (5Y)	69.3%	91.5%	99.7%	96.8%	74.0%	95.6%
Max Relative Drawdown	17.70%	11.19%	14.11%	10.91%	10.92%	9.12%

Data obtained from www.scientificbeta.com

'Investors also pay attention to extreme realisations of relative risk, relative drawdowns and probability of outperformance'

this relative risk. A common relative risk measure is the tracking error. However, in addition to such an average measure of relative risk, investors also pay attention to extreme realisations of relative risk, relative drawdowns and probability of outperformance. The table below provides a set of global relative risk measures which indicate the risk of deviating from the performance of a cap-weighted reference index for a range of smart beta indices for Japan and Developed Asia ex Japan equities.

Of particular interest is the information on the probability of outperformance, which is defined as the historical probability of outperforming the cap-weighted reference index over a given investment horizon. This measure is reported for investment horizons of 5 years by using a rolling window analysis with 1-week step size. It is an intuitive measure to show how often the strategy has managed to outperform the cap-weighted reference index in the past. It is calculated by computing the probability of obtaining positive excess returns if one invests in the strategy for a period of 1, 3 and 5 years at any point during the complete history (in other words, after inception) of the strategy.

Another intuitively appealing measure of relative risk is the Maximum Relative Drawdown, which measures the maximum relative loss experienced by a strategy between a peak and a valley over a specified period. The relative drawdown measure highlights the downside risk exposure experienced by a strategy index over time with respect to its cap-weighted reference index. It first forms a portfolio that goes long the strategy index and short the reference index. The cumulative returns of this portfolio can be interpreted as the relative cumulative returns of the strategy with respect to its reference index.

It is clear that – while all smart beta strategies show pronounced outperformance – they all face significant drawdowns during the period under analysis, with the worst drawdowns exceeding 10% for most strategies. The probability of outperformance over any one year holding period is less than 60 percent for some strategies. However, when increasing the holding period to five years, outperformance probabilities exceed 90% for many strategies, showing the importance of investors being aware of the short-term risks and able to sustain their investment in smart beta strategies during periods of drawdowns.

Conditional Performance of Smart Beta Equity Strategies Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. High Volatility market comprises the top 50% of quarters sorted on the quarterly cap-weighted benchmark's volatility and the Low Volatility market comprises the rest. All statistics are annualised. Based on daily total returns from 21/06/2002 to 31/12/2013.

The stock universe consists of 500 stocks with the highest free-float market capitalisation for Japan and the 400 stocks with the highest free-float market capitalisation for Developed Asia ex Japan, which consists of the following countries: Australia, Hong Kong, Korea, New Zealand, and Singapore.

Japan	**Max Deconcentration**	**Max Decorrelation**	**Efficient Min Volatility**	**Efficient Max Sharpe**	**Diversified Risk Weighted**	**Diversified Multi-Strategy**
			Bull Markets			
Ann Rel Returns	-0.51%	-4.17%	-10.93%	-5.81%	-2.96%	-4.89%
Tracking Error	4.03%	5.00%	6.93%	5.22%	4.34%	4.86%
Information Ratio	-0.13	-0.83	-1.58	-1.11	-0.68	-1.01
			Bear Markets			
Ann Rel Returns	3.53%	5.49%	11.14%	7.04%	5.44%	6.51%
Tracking Error	4.50%	6.08%	9.17%	6.63%	5.05%	6.02%
Information Ratio	0.78	0.90	1.21	1.06	1.08	1.08
Developed Asia ex Japan	**Max Deconcentration**	**Max Decorrelation**	**Efficient Min Volatility**	**Efficient Max Sharpe**	**Diversified Risk Weighted**	**Diversified Multi-Strategy**
			Bull Markets			
Ann Rel Returns	4.74%	4.80%	0.70%	2.30%	3.12%	3.15%
Tracking Error	4.41%	5.37%	6.21%	5.51%	4.41%	4.90%
Information Ratio	1.08	0.89	0.11	0.42	0.71	0.64
			Bear Markets			
Ann Rel Returns	0.75%	3.65%	10.74%	6.19%	3.32%	4.87%
Tracking Error	7.06%	8.18%	10.71%	8.92%	7.07%	7.88%
Information Ratio	0.11	0.45	1.06	0.69	0.47	0.62

Data obtained from www.scientificbeta.com

Conditional performance

Comparing performances under different market conditions provides insight into the drivers of an index's performance. Moreover, an analysis of the dependence of a strategy's short-term performance on market conditions allows the robustness of a strategy's performance to be assessed. The table below conducts a performance analysis separately for periods during which the cap-weighted reference index displays high returns (bull markets) and periods with low returns for the cap-weighted reference index (bear markets).

The conditional performance properties of different smart beta strategies show pronounced differences. For example, the Efficient Minimum Volatility strategy shows strong dependence on market conditions. It generates strong outperformance during bear markets both for Japan and Developed Asia ex Japan, underperformance in bear markets for Japan, and almost flat relative performance in bear markets for Developed Asia ex Japan. The diversified multi-strategy index, which combines five different weighting schemes, shows less dependence on market conditions than its component strategies, as the different conditional performance profiles counterbalance each other when diversifying across strategies. It is important for investors choosing a smart beta strategy to be informed of such dependencies so that they can make an appropriate choice of smart beta strategy or combination of strategies. ■

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'The conditional performance properties of different smart beta strategies show pronounced differences'

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Measuring Pension Fund Diversification

By Romain Deguest and Lionel Martellini

Measures of diversification

While the benefits of diversification are intuitively clear in terms of reduction/elimination of unrewarded risks, which leads to an enhancement of risk-adjusted performance, it is not straightforward to provide a quantitative measure of how well or poorly diversified a portfolio is. The most common intuitive explanation of diversification is that it is the practice of not "putting all your eggs in one basket". Having eggs (dollars) spread across many baskets is, however, a rather loose prescription in the absence of a formal definition for what is the true meaning of "many" and "baskets."

Fortunately, recent advances in financial engineering have paved the way for a better understanding of the true meaning of diversification. In particular, the *effective number* of (*uncorrelated factor*) bets (ENB), formally defined in Meucci (2009) as the dispersion (entropy) of the factor exposure distribution (see also Deguest, Martellini and Meucci (2013)), provides a more meaningful assessment of how well-balanced an investor's dollar (egg) exposure is to various uncorrelated risk factors (baskets).

In recent research supported by CACEIS in the context of the "New Advances in Risk Measurement and Reporting" research chair at EDHEC-Risk Institute (Carli, Deguest and Martellini (2014)), we analyse the diversification of the portfolio held by US pension funds and its relationship with subsequent portfolio performance, and we find that better diversified policy portfolios, in the sense of a higher number of uncorrelated bets, tend to perform better on average in bear markets. On the other hand, we confirm that top performers are, as expected, policy portfolios highly concentrated in the best performing asset class for the sample period under consideration.

Overall, our results suggest that the effective number of (uncorrelated) bets could be a useful risk indicator to be added to risk reports of policy portfolios.

Data collection and empirical methodology

We use the *P&I* Top 1,000 database to obtain information on the asset allocation of each of the largest 1,000 US pension funds as of September 30, 2002, September 30, 2007 and September 30, 2012. We exclusively focus on the portion allocated to their defined benefit plan; if they also have a defined contribution plan, we do not analyse the amount they allocate to this plan. We are left with 750 pensions funds in 2002, 780 in 2007 and 320 in 2012 (the last figure is quite low because less than half of the 1,000 pension funds in the database filled in *P&I's* survey).

> *'The effective number of (uncorrelated) bets could be a useful risk indicator to be added to risk reports of policy portfolios'*

In order to represent the different asset classes pension fund assets are invested in, we consider the following, arguably somewhat arbitrary, partition of the asset allocation: domestic fixed income, international fixed income, high-yield bond, inflation-linked bond, domestic equity, international equity, global equity, private equity, real estate, commodity, mortgage, and cash. Once the partition is completed, we choose appropriate benchmarks for each asset class and use *the minimal linear torsion approach* (Meucci et al. (2013)), which is an alternative to standard principal component analysis approaches to turn correlated asset class returns into uncorrelated factor returns that generates implicit factors that are closest to each corresponding asset class with the resulting enhancement of the stability and interpretation for these factors.

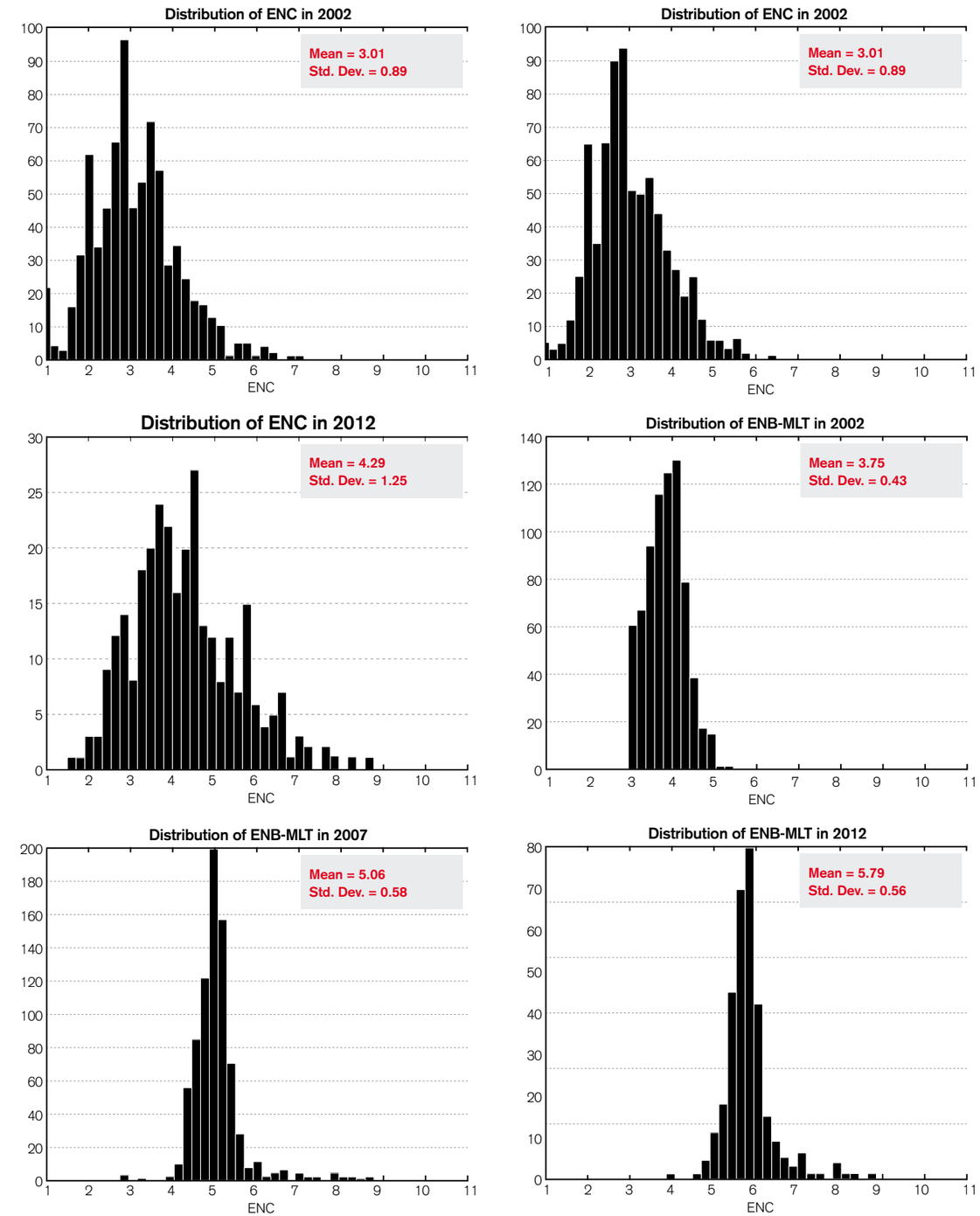
We estimate the ENB diversification measure for each pension fund in the database at the end of September 2002, at the end of September 2007 and at the end of September 2012. We also compute the Effective Number of Constituents (ENC), defined as the entropy of the asset class exposure, at the same dates. This definition, which is maximised for the equally weighted portfolio, is a naïve diversification measure that does not account for the presence of differences in risk and correlation levels within the set of asset classes. This is in contrast with the ENB measure, which is based on normalised uncorrelated factors. On the other hand, the ENB measure is an instantaneous observable quantity, while the ENC measure requires an estimate for the covariance matrix of asset returns so as to apply the minimum torsion methodology. In order to estimate the covariance matrix needed to compute the ENB measure, we use 5 years of historical weekly returns before the date at which we perform the computation.

Diversification measures for the 1,000 largest U.S. pension funds

In Figure 1, we display the distributions of the ENC and ENB measures.

Figure 1: Distribution of Diversification Measures of U.S. Pension Funds

These figures display the distribution of the effective number of constituents (ENC) and the effective number of bets (ENB) for the U.S. pension funds in the P&I database in years 2002, 2007 and 2012.



'A better assessment of the degree of portfolio diversification in terms of effective number of bets would provide useful insights regarding the risk and return profile of portfolios in various market conditions.'

When looking at the evolution of each diversification measure, it seems that a change occurred between 2007 and 2012, as most U.S. pension funds seem to have increased the diversification level in their portfolio between these two dates. For instance, between 2002 and 2007, the mean of the distribution of the ENCs increases by 1.3%, while between 2007 and 2012 it increases by 40.7%. Therefore, it seems that U.S. pension funds dedicated some effort between 2007 and 2012 to improve their level of diversification. However, we note that while U.S. pension funds increase their ENC by 40.7% in five years, they only increase their ENB by 14.4% between 2007 and 2012.

We then analyse whether the diversification measures computed for these pension funds at the end of September 2007 can give insights on the returns of U.S. pension funds in subsequent months.[8] In our test, we compute the fund returns over two different periods: over the year directly following the date of computation of the diversification measures (from 28/09/2007 to 26/09/2008), and over the worst period of the subprime crisis for the financial sector (from 05/09/2008 to 27/02/2009). For each diversification measure, we first plot the relationship between the U.S. pension funds' annualised performances at date *t+n* months according to their level of diversification measure at date t (end of September 2007). Then we statistically test the degree of significance of our results. We replicate this test for each diversification measure and for the two periods of time considered.

We display our results in Figure 2. It is first striking to see that the relationship between U.S. pension fund performances and their level of ENB is positive, and this relationship is statistically significant. This result holds true for the two periods of performance computation. Overall, these results mean that, at the end of September 2007, a pension fund that had a higher ENB (hence holding a better diversified portfolio) was more likely to achieve better performance (lower loss levels) during 28/09/2007-26/09/2008 and during 05/09/2008-27/02/2009 than a pension fund that had a lower ENB, assuming the policy portfolio weights remain constant. On the other hand, higher levels of ENC for a pension fund at the end of September are likely to have no impact, if not negative effects, on its performances during 28/09/2007-26/09/2008 and during 05/09/2008-27/02/2009 compared to another pension fund with lower levels of ENC. This result is consistent with the interpretation of the ENB as a more meaningful diversification measure compared to the ENC.

Nevertheless, we also find that the pension funds that enjoyed the very highest levels of performance during the two periods considered seem to behave differently to the others. For these pension funds, there seems to be a negative, as opposed to positive, relationship between their performances and their level of ENB at the end of September 2007. When analysing which asset classes these pension funds were invested in, we find that the pension funds that perform the best are the ones that allocate more than 80% on average to U.S. bonds. Hence these pension funds performed best during the two periods considered simply because they were fully invested in safe asset classes that resisted well during the crisis. These pension funds were very poorly diversified in terms of asset classes since their aim is not to diversify their portfolio so as to maximise their risk reward but to invest in a safe, low risk-rewarding asset class. In other words, they seem to maintain a focus on *liability hedging*, as opposed to p*erformance diversification*. In this context a useful extension of the research would be to repeat the analysis we have conducted for pension funds for endowments. Pension funds manage assets against liabilities within the context of a liability-driven investing strategy, and therefore seek to achieve diversification for one component of their portfolio only, the performance-seeking component, while another component of the portfolio is dedicated to liability-hedging, which requires concentration on assets that can match the liabilities' risk factor exposures. Endowments, on the other hand, typically operate in an asset-only context, and the search for a well-diversified portfolio should therefore apply to their entire portfolio. We leave these as well as other potentially useful extensions for further research.

Overall, our analysis suggests that a better assessment of the degree of diversification of a portfolio in terms of effective number of bets would provide useful insights regarding the risk and return profile of the portfolio in various market conditions. In unreported results, we have also shown that it would be a useful indicator for equity portfolios as well, since we find statistical evidence of a positive (negative) time-series and cross-sectional relationship between ENB risk diversification measures and portfolio performance in bear (bull) markets. As such, it appears that the ENB measure could be a useful addition to the list of risk indicators reported for policy and equity portfolios. ■

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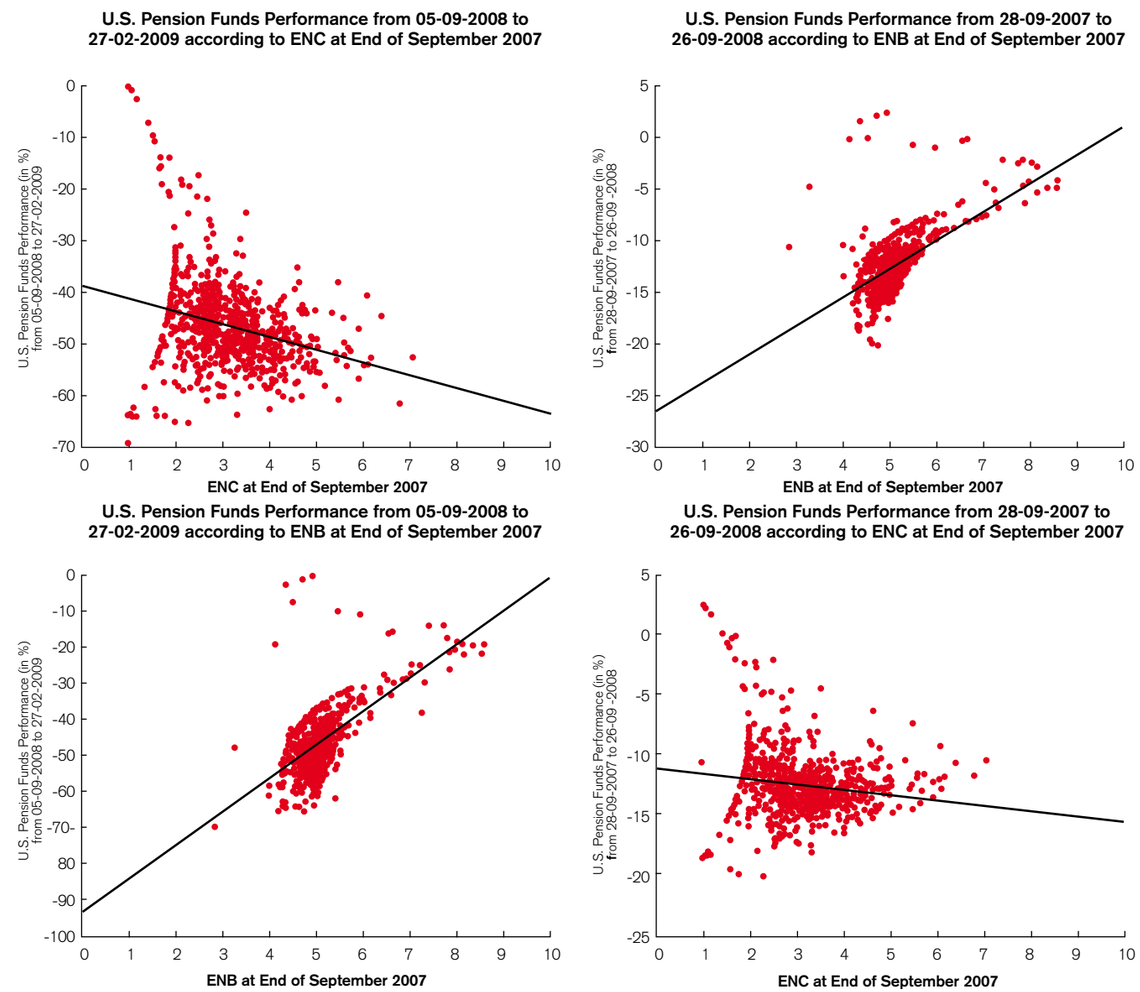
[8] We do not use actual pension fund performance in our analysis and assume instead that the fund asset allocation remains constant over the months following the computation of the diversification measures at date *t*. We use this methodology for two main reasons. First, we have information about pension fund allocation only at the end of calendar years or at the end of fiscal years (end of June). Secondly, this approach allows us to preserve a stronger link between diversification measures computed at a date *t* and pension funds' performances at *t+n* months.

Figure 2: Performances of U.S. Pension Funds with respect to their Diversification Measures at the end of September 2007

These figures display the annualised performances of the U.S. pension funds in the P&I database computed over two different periods with respect to their diversification measures at the end of September 2007. The annualised performances are calculated for the year immediately following the date of computation of the diversification measures (from 28/09/2007 to 26/09/2008) and during the worst of the subprime crisis (from 05/09/2008 to 27/02/2009). We consider that pension funds' asset allocations have not changed since the end of September 2007, therefore, the performances displayed here are only estimates.



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The Extreme Risk of Asian Indices

By Lixia Loh and Stoyan Stoyanov

Value-at-risk (VaR) and conditional value-at-risk (CVaR) have become standard choices for risk measures in finance. Both VaR and CVaR are examples of measures of *tail risk*, or *downside risk*, because they are designed to exhibit a degree of sensitivity to large portfolio losses, whose frequency of occurrence is described by what is known as the tail of the distribution: a part of the loss distribution away from the central region geometrically resembling a tail. In practice, VaR provides a loss threshold exceeded with some small predefined probability, usually 1% or 5%, while CVaR measures the average loss higher than VaR and is, therefore, more informative about extreme losses.

An interesting practical question explored in recent research[9] is to compare tail risk as measured by VaR and/or CVaR across different markets. It is a challenging problem for a couple of reasons. First, for practical purposes the frequency of extreme losses is calculated unconditionally while it is a well-known fact that in different states of the market the likelihood of extreme loss varies, i.e. more turbulent markets are more likely to experience higher losses. As a result, tail risk would be affected by the temporal behaviour of volatility, which is characterised by clustering: elevated levels of volatility are usually followed by similar volatility levels.

Apart from the dependence on the state of the market, a second more subtle challenge is that any downside risk measure (including VaR and CVaR) is sensitive to the tail of the portfolio loss distribution. A stylised fact for asset returns is that they exhibit fat tails; that is, the frequency of observed extreme losses is higher than that predicted by the normal distribution. CVaR, being the average of the extreme losses, is more sensitive to the way the relative frequency of extreme losses is reflected in the risk model. Thus, a model such as the normal distribution underestimates this frequency and, therefore, underestimates tail risk as well.

'It is important to understand how much residual tail thickness remains after explaining away the dynamics of volatility'

Constructing a realistic risk model

To compare tail risk across markets, we need to adopt a conditional measure which can take into account at least the clustering of volatility effect and also the tail behaviour of portfolio losses having explained away the dynamics of volatility. This decomposition into two components is important from a risk management perspective because the dynamics of volatility contribute to the unconditional tail thickness phenomenon and techniques do exist for volatility management. Thus, it is important to understand how much residual tail thickness remains after explaining away the dynamics of volatility. The standard econometric framework taking into account the clustering of volatility effect is that of the Generalised Autoregressive Conditional Heteroskedastic (GARCH) model.

The academic literature on modelling VaR and CVaR indicates that a successful approach for modelling the high quantiles of the portfolio loss distribution is to combine a GARCH model with extreme value theory (EVT). EVT originated in areas other than finance and is used in problems related to rare events. In finance, such problems include estimation of probabilities of extreme losses. In essence, EVT provides a model for the extreme tail of the loss distribution, which turns out to have a simple structure approximated through a distribution known as the generalised Pareto distribution (GPD). To illustrate the method, consider a time series of portfolio losses at a given frequency in a given time window. If we set a high loss threshold and take the losses that exceed it, their probabilistic properties are described approximately through GPD. In fact, GPD describes extreme losses in terms of two parameters: the shape parameter measuring the thickness of the tail and a scale parameter measuring the variability of extreme losses.

As a result, the constructed risk model has two components. The GARCH part is responsible for capturing the dynamics of volatility, while EVT provides a model

[9] Loh, L, and S. Stoyanov, August 2013, Tail Risk of Asian Markets: An Extreme Value Theory Approach, EDHEC-Risk Institute Publication.

Table 1. The fitted shape parameter of GPD (larger values indicate higher probability of extreme losses), the forecasted daily 1% CVaR, and the realised losses beyond 1% VaR on a daily basis averaged over two 10-year periods. The loss figures represent percentages.

	Mar 1993-Dec2002			Jan 2003-Dec 2012		
	Avg fitted shape parameter	Avg 1% CVaR	Avg realised losses beyond 1% VaR	Avg fitted shape parameter	Avg 1% CVaR	Avg realised losses beyond 1% VaR
Asia						
China	NA	NA	NA	0.0188	0.0545	0.0519
Hong Kong	0.0513	0.0519	0.0464	0.0240	0.0458	0.0373
India	NA	NA	NA	0.0416	0.0529	0.0514
Indonesia	0.1427	0.0551	0.0488	0.0998	0.0508	0.0498
Japan	0.0458	0.0462	0.0431	0.0424	0.0464	0.0461
Korea	0.0501	0.0555	0.0557	0.0397	0.0475	0.0490
Malaysia	0.0641	0.0397	0.0371	0.0872	0.0273	0.0258
Philippines	0.0496	0.0470	0.0452	0.0357	0.0439	0.0457
Singapore	NA	NA	NA	0.0182	0.0370	0.0318
Thailand	0.0980	0.0523	0.0526	0.1263	0.0469	0.0523
Taiwan	0.0449	0.0511	0.0463	0.0399	0.0440	0.0394
Europe						
Finland	0.0885	0.0571	0.0557	0.1044	0.0471	0.0453
France	0.0333	0.0430	0.0365	0.0331	0.0424	0.0340
Germany	0.0549	0.0450	0.0367	0.0245	0.0421	0.0333
Netherlands	0.0411	0.0417	0.0355	0.0190	0.0396	0.0330
Switzerland	0.0392	0.0370	0.0309	0.0134	0.0344	0.0292
UK	0.0217	0.0341	0.0308	0.0107	0.0355	0.0322
North America						
Canada	0.1080	0.0347	0.0304	0.0418	0.0341	0.0288
US	0.0799	0.0377	0.0293	0.0457	0.0380	0.0278

for the behaviour of the extreme tail of the residual. Not only does this approach allow reliable estimation of VaR and CVaR, but it also provides insight into the tail thickness through the fitted value of the shape parameter of GPD. To measure tail risk, we choose VaR and CVaR at 1% tail probability, which is a standard choice.

Testing the risk model

We run a VaR back-testing for 19 markets (11 Asian, 6 European, and 2 North American) covering periods of different length ranging from 13 to 62 years depending on the market. The statistical tests indicate that VaR at 1% tail probability is modelled reliably through the GARCH-EVT model for all markets. Dropping the EVT part in the model and employing the normal distribution results in too many VaR violations in the back-testing, cases in which the realised loss exceeds the predicted VaR, which indicates the presence of significant residual tail thickness uncaptured by the normal distribution. As a by-product, we can also conclude that the observed fat tail in the unconditional distribution is not an artefact of the clustering of volatility effect, which is consistent with other academic studies.

To compare the average tail risk across markets, we calculate two 10-year averages of the estimated shape parameter of the GPD, averages of the forecasted daily VaR, CVaR and the CVaR/VaR ratio at 1% tail probability. The two periods in question are 1993-2002 and 2003-2012. Further on, we calculate the out-of-sample average of the observed losses exceeding the forecasted 1% VaR for the two periods and also the corresponding ratio to the forecasted VaR. Some of the aggregated statistics are provided in Table 1.

Conclusion

Our findings can be classified into two groups. First, we find that the fitted shape parameter exhibits time variation for all markets but the averages over the two 10-year periods in Table 1 (larger values represent heavier tails) reveal no geographical structure; that is, there is nothing specific about the residual tail thickness of Asian markets. Second, the comparison of the in-sample and out-of-sample tail risk measures reveals higher tail risk for Asian markets. This holds in both time periods and for both the forecasted risk numbers and the realised losses. The higher tail risk of Asian markets indicates that the key difference over the long run is in the levels of volatility of the market returns and possibly in the variability of the extreme losses rather than in the residual tail thickness as measured by the shape parameter. This conclusion underlines the importance of volatility management techniques for management of tail risk. ■

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'The higher tail risk of Asian markets indicates that the key difference over the long run is in the levels of volatility of the market returns and possibly in the variability of the extreme losses'