What Is Smart Beta?

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Smart Beta Investing

How to Appreciate the Performance and Risks of New Forms of Equity Benchmarks

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Introduction

Blurring the Line Between Active and Passive

- Cap-weighted (CW) indices have been widely criticised for being overly concentrated, trend-following, and providing inefficient risk-reward properties.
- Smart Beta Strategies move away from CW indices, by applying a **systematic** set of constituent selection and stock weighting rules.
- There are two main categories:
  - Fundamental approaches: selecting and/or weighting stocks on the basis of fundamental measures.
  - Diversification approaches: selecting and/or weighting stocks on the basis of risk measures (max deconcentration (MDC), equal weighting (EW), risk parity (RP), risk weighting (RW), max decorrelation (MDC), global minimum variance (GMV), max Sharpe ratio (MSR), etc.).
- Smart beta investing is sold not on the basis of market performance, but of **outperformance**: manager substitution versus benchmark substitution (exchanging manager risk for **strategy risk**).

Introduction

Evaluating Performance and Risks of Smart Beta

- Providers of smart beta strategies have documented outperformance of these strategies without necessarily documenting the risks.
  - Commercial Offerings are pre-packaged bundles of methodological choices. Their focus is on generating performance over cap-weighted indices without a main concern on risk transparency and risk choice.

- As Smart Beta strategies gain importance in the investment process, the question of the impact of Smart Beta strategies on the risk of the investor’s allocation arises, both in terms of absolute risk and relative risk.

Introduction

Measuring and Controlling Risks of Smart Beta

- Three key ingredients are available to get a clearer assessment of smart beta performance or a more suitable strategy that takes into account an investor's preferences and beliefs.
  - **Measurement and control of systematic risks**
  - **Measurement and management of the specific risk of a weighting scheme**
  - **Ex ante control of potential deviations with respect to a cap-weighted reference index**

- We discuss these three issues in the remainder of this presentation.

Outline

The systematic risks of smart beta strategies

Controlling systematic risks in smart beta investing

How to evaluate the specific risks of the new smart beta strategies

Controlling the relative risk of the smart beta approaches

The Systematic Risks of Smart Beta Strategies

Introduction on Systematic Risk

- Any deviation from the standard cap-weighting approach will potentially lead to exposures to equity risk factors that are different from the cap-weighted references.
- It is therefore sometimes argued that such strategies simply consist of style tilts towards small cap, value, and low volatility stocks (see Scherer (2011) or Chow et al. (2011)).
- Many studies have underlined the importance of such exposures for explaining part of the outperformance over cap-weighted indices (see for example Jun and Malkiel (2007), Kaplan (2008), Blitz and Swinkels (2008), or Amenc, Goltz and Le Sourd (2009)).
- We illustrate this phenomenon drawing on two particular cases, namely Fundamental weighting and Equal-weighting under liquidity and turnover constraints (Maximum Deconcentration).

The Systematic Risks of Smart Beta Strategies
Fundamental Benchmark Case

- Here we assess the exposure of popular fundamental weighted indices to systematic risk factors.
- The value and small size exposure is highly significant. Weighting by firm size is thus similar to selecting small cap and value stocks.

	FTSE RAFI US 1000 Index	Russell Fundamental Index	Dow Jones Select Dividend Index	S&P 500 Dividend Aristocrats
Ann Alpha	-0.40%	1.20%	-1.70%	1.93%
Market Exposure	**0.97**	**0.97**	**0.85**	**0.83**
Small Cap Exposure	**0.16**	**0.18**	**0.15**	**0.10**
Value Exposure	**0.15**	**0.03**	**0.20**	**0.04**
Momentum Exposure	**-0.11**	**-0.06**	**-0.12**	**-0.11**
R-square	0.98	0.99	0.89	0.89

Carhart four factor model - *The market factor is the daily return of cap-weighted index of all stocks that constitute USA Scientific Beta universe. The small cap factor is the daily return series of a cap-weighted portfolio that is long 30% smallest market-cap stocks and short 30% largest market-cap stocks. The value factor is the daily return series of a cap-weighted portfolio that is long 30% highest B/M ratio stocks and short 30% lowest B/M ratio stocks. The momentum factor is the daily return series of a cap-weighted portfolio that is long 30% highest 2 year past return stocks and short bottom 30% lowest 2 year past return stocks. The risk free rate is the return of 3 months US Treasury Bill. Betas significant at the 5% confidence level are highlighted in bold and alphas are annualized. T-statistic is computed using paired difference testing on the ordinary least square (OLS) estimates of betas. The analysis is based on daily total return data from 21 June 2002 to 31 December 2012, obtained from www.scientificbeta.com and from Datastream.*

The Systematic Risks of Smart Beta Strategies

Maximum Deconcentration Benchmark Case

- Here we perform factor analysis on Maximum Deconcentration benchmarks across different geographical regions to see if it is exposed to any systematic risks.
- Moving away from cap-weighting to deconcentrate leads to a small cap bias. The table shows that this is true for all geographical regions.

	Scientific Beta Max Deconcentration				
	USA	UK	Eurozone	Japan	Dev Asia Pac ex Japan
Ann Alpha	0.41%	1.08%	0.10%	0.60%	0.18%
Market Exposure	**1.01**	**0.99**	**1.00**	**1.00**	**0.98**
Small Cap Exposure	**0.44**	**0.43**	**0.46**	**0.46**	**0.46**
Value Exposure	**-0.01**	**-0.02**	**-0.02**	**-0.01**	**0.07**
Momentum Exposure	**0.01**	**-0.01**	0.00	0.00	**0.05**
R-square	1.00	0.99	1.00	1.00	0.99

Carhart four factor model - *The market factor is the daily return of cap-weighted index of all stocks that constitute the universe. The small cap factor is the daily return series of a cap-weighted portfolio that is long 30% smallest market-cap stocks and short 30% largest market-cap stocks. The value factor is the daily return series of a cap-weighted portfolio that is long 30% highest B/M ratio stocks and short 30% lowest B/M ratio stocks. The momentum factor is the daily return series of a cap-weighted portfolio that is long 30% highest 2 year past return stocks and short bottom 30% lowest 2 year past return stocks. Betas significant at the 5% confidence level are highlighted in bold and alphas are annualized. T-statistic is computed using paired difference testing on the ordinary least square (OLS) estimates of betas. The geographical regions and total number of stocks in each region are – USA (500), UK (100), Eurozone (300), Japan (500) and Developed Asia Pacific x Japan (400). The analysis is based on daily total return data from 21 June 2002 to 31 December 2012, downloaded from www.scientificbeta.com.*

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Controlling Systematic Risks in Smart Beta Investing

Disentangling Constituent Selection and Weighting

- Commercial Advanced Beta Offerings are mostly pre-packaged bundles of methodological choices.
- Control of systematic risk can be conducted in two manners:
  - Distinction between **stock selection** and weighting scheme: favoured in plain vanilla indices due to its simplicity. Below we consider the example of controlling size exposure.
  - Implementation of **constraints** within weighting scheme: allows creating indices with specific constraints on multiple risk factors or sectors/countries. Below we consider an example of constraining sector exposures.

The following text and illustrations draw on material of a recent Journal of Portfolio Management article by Amenc, Goltz and Lodh (2012).

Disentangling Constituent Selection and Weighting

Stock Selection for Correction of Style/Factor Biases

- It is straightforward to correct factor or style tilts through the selection of stocks with appropriate characteristics, while maintaining the improvement in objective that is due to the respective diversification approach.
- To demonstrate this, we divide the S&P 500 universe into three equal groups by **size** (small, medium and large) and construct Minimum Volatility portfolios.
- For the three sub-universes and the broad universe based minimum volatility portfolios, we assess:
  - The resulting size tilts
  - The attainment of the low volatility objective
- Amenc, Goltz and Lodh (2012) show similar results when using stock selection to neutralise **volatility** and **value** exposure of smart beta strategies, and when using other smart beta strategies such as Maximum Sharpe Ratio and Maximum Decorrelation.

Disentangling Constituent Selection and Weighting

Stock Selection for Correction of Style/Factor Biases

- It is possible to reduce or cancel implicit factor tilts of a weighting scheme through an appropriate stock selection decision.

- Risk/return properties of smart beta strategies may stay attractive even after correcting for factor tilts (Amenc, Goltz and Lodh 2012).

	Global Minimum Volatility (GMV)			
Universe	All stocks	Small size universe	Medium size universe	Large size universe
Size (Big - Small) exposure of excess returns over CW	**-19.00%**	**-43.75%**	**-19.32%**	1.83%
Annual Volatility	12.40%	13.67%	12.67%	12.59%
% Reduction in Volatility relative to S&P 500	19.8%	11.6%	18.0%	18.6%

Size exposure and attainment of low volatility objective on different size-based stock selections - *The table shows the excess (over S&P 500) risk factor exposures of GMV portfolio based on broad S&P 500 stock universe and three size based stock selections. Stock selection is done at each rebalancing. We run the following regressions to identify factor exposures*

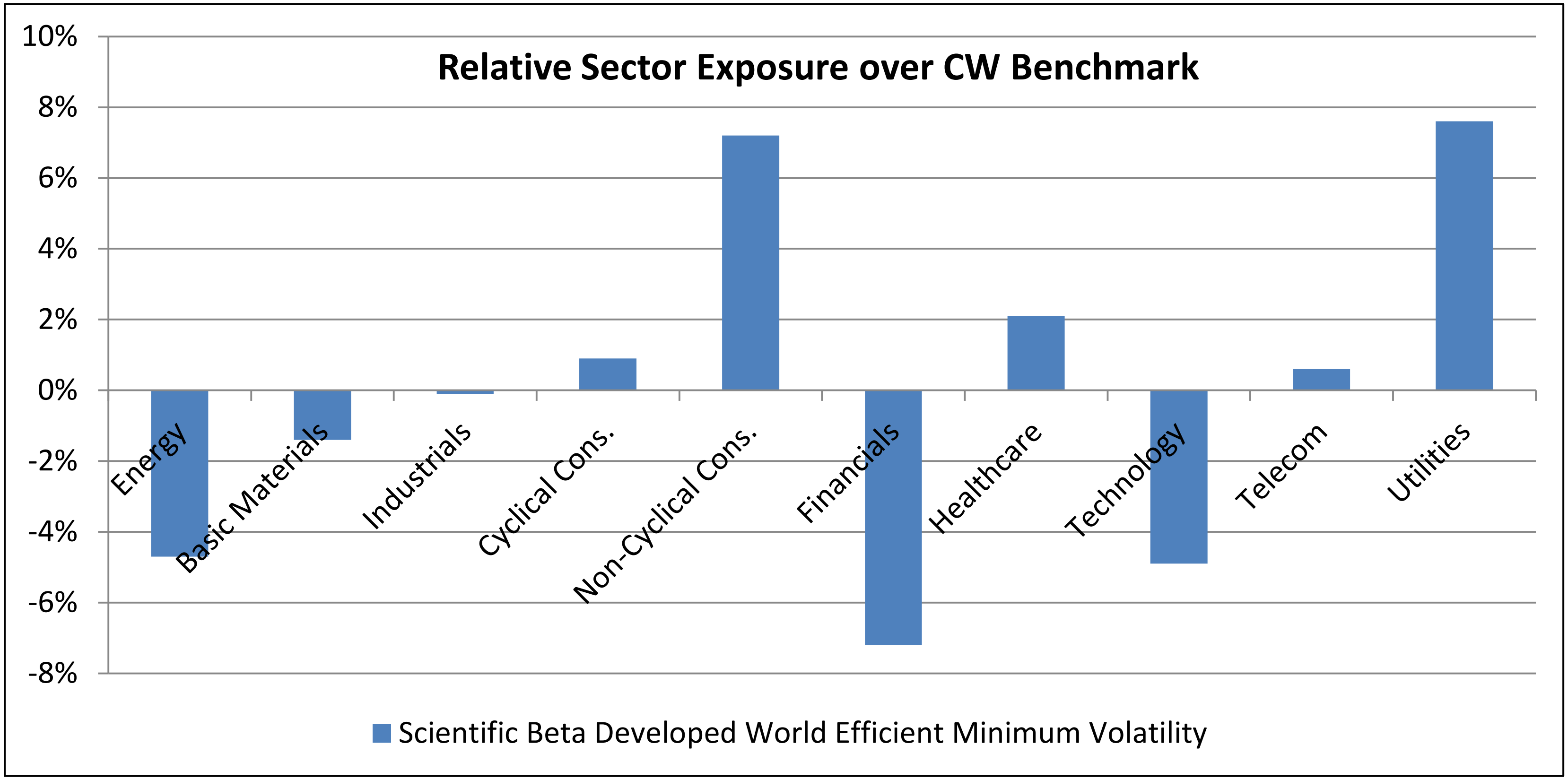
$$R_P - R_{CW} = \alpha + \beta_M . R_{CW}$$
$$Res = \beta_S . R_S$$

R_P is time series of test portfolio returns, R_{CW} is S&P 500 time series returns, β_M is market beta, β_S is size (big-small) beta, R_S is size factor which is return of a portfolio (cap-weighted) long in 1/5th largest cap stocks and short in 1/5th smallest cap stocks that constitute the NYSE, AMEX and NASDAQ universe, and Res is residual time series from equation 2 regression. This two-step process is used for each risk factor and for each test portfolio. Betas significant at the 1% confidence level are highlighted in bold. T-statistic is computed using paired difference testing on the ordinary least square (OLS) estimates of betas. The analysis is based on weekly total return data from 5th July 1963 to 31st December 2010, obtained from CRSP. Source: Choose Your Betas: Benchmarking Alternative Equity Index Strategies. Amenc N., F. Goltz and A. Lodh. Journal of Portfolio Management, Fall 2012.

Smart Beta Strategies and Sector Constraints

Minimum Volatility Example

- The overweighting of defensive sectors (like Utilities and non cyclical consumer goods) and underweighting of Financials and Technology is a well known issue with Minimum Volatility strategies.



The figure displays excess sector exposures (in excess weight %) of the Scientific Beta Developed World Minimum Volatility index with respect to the cap-weighted reference index, based on portfolio's stock weight profile at the last rebalancing date (21 December 2012). Total number of stocks in the Developed World scientific beta universe is 2000. Source: www.scientificbeta.com.

Smart Beta Strategies and Sector Constraints

Minimum Volatility Example (continued)

	Scientific Beta Developed World		
	Efficient Min Volatility	Efficient Min Volatility (Sector Neutral)	Cap Weighted
Ann Returns	9.66%	9.03%	6.95%
Ann Volatility	14.44%	15.27%	17.66%
% Reduction in Vol.	18.2%	13.5%	-
Sharpe Ratio	0.55	0.48	0.30

The table compares the performance statistics of Scientific Beta Developed World Minimum Volatility index with and without sector neutral constraints with their cap-weighted benchmark. The risk free rate is the return of 3 months US Treasury Bill. All statistics are annualised. Total number of stocks in the Developed World scientific beta universe is 2000. The analysis is based on daily total return data from 21 June 2002 to 31 December 2012, downloaded from www.scientificbeta.com.

- We compare the performance statistics of Cap-Weighted and Minimum Volatility portfolios with and without sector neutrality constraints.
- Imposing sector neutrality constraints does affect the performance of the strategy but maintains considerable benefits versus cap-weighting.
- In particular, while the unconstrained portfolio shows 18% volatility reduction (compared to the CW benchmark), the sector constrained portfolio still achieves 13% reduction.

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Evaluating the Specific Risks of Smart Beta Strategies

Parameter Estimation Risk and Optimality Risk

- In addition to systematic risk, smart beta strategies come with strategy specific risk. The specific risk inherent in each strategy is related to the risk and return parameters it uses.

- In portfolio construction, a trade-off between estimation risk and ignorance risk exists.
  - **Parameter estimation risk** is the risk of a substantial difference between the estimated parameter value and the true parameter value.
  - **Optimality risk** is the risk that the heuristic benchmark (such as Equal Weighting or Global Min Volatility) can be very far from the optimal Max Sharpe Ratio (MSR) benchmark.
  - The benefits of using information on risk/return parameters may be entirely offset by parameter estimation risk. For example, an investor could be better off investing in an EW portfolio (which completely ignores risk/return information) than investing in a *proxy* for the true MSR (which relies on necessarily imperfect estimates of risk/return parameters) [see DeMiguel et al, 2009].

Evaluating the Specific Risks of Smart Beta Strategies

Managing Specific Risk

- Martellini, Milhau and Tarelli (2013) propose an analysis of the trade-off between optimality risk and parameter estimation risk:
  - They consider a large number of possible true population values for risk and return parameters, and measure the difference of Sharpe ratios (based on true parameter values) between various portfolio strategies.
  - Their results suggest that specific risk of smart beta strategies may be diversified away by combining different strategies.

Portfolio strategy	Avg. Sharpe ratio without estimation risk	Avg. Sharpe ratio with estimation risk	St. dev. of Sharpe ratio with estimation risk
Max Sharpe Ratio	13.34	0.56	0.61
Minimum Volatility	2.49	0.89	0.57
Equal Weighting	0.60	0.60	0.00
Cap-Weighting	0.50	0.50	0.00
50% Min Vol + 50% Equal Weighting	1.08	0.94	0.30

Sharpe ratios in the presence of estimation errors in expected excess returns and covariances – Results from Martellini, Milhau and Tarelli (2013). The table shows the time-average of the annualised Sharpe Ratio of portfolio strategies computed according to the "true" expected excess returns, as well as the time-averages of the mean values and standard deviations of the distributions of Sharpe Ratios, obtained for each time-window. Estimation errors on expected excess returns have an impact only on MSR strategies.

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Why is Relative Risk is Important

Practical motivations

- Even if investors are convinced that alternative weighting schemes deliver higher performance, they may be well advised to limit the *risk of periodic underperformance* compared to their peer group.

  - In contrast to comparisons of active managers, comparisons of performance across alternative indices rarely take into account the *tracking error budgets* that have been used to achieve this outperformance.

  - The CIOs who adopt alternative weighting scheme take considerable *reputation risk*. While termination of active managers in case of underperformance is part of the logic of the delegation process in investment management (Goyal & Wahal 2008), CIOs will not have anyone else but themselves to blame for the choice of a new type of index.

How much relative risk is there in Smart Beta Strategies?

Smart Beta Indices with and without TE Control

- Smart beta strategies show **pronounced relative drawdowns** and **extreme tracking error**
- **Relative risk controlled strategies** (involving relative risk constraints and hedging) capture part of the performance benefits of smart beta with a well-defined risk level.

Panel 1: No TE Control	Scientific Beta USA			
	Max Deconc.	Max Decorr.	Efficient Min Volatility	Efficient Max Sharpe
Excess Returns over CW	2.02%	1.53%	2.16%	1.72%
Tracking Error	3.62%	3.57%	4.60%	3.39%
95% Tracking Error	6.36%	5.58%	8.01%	5.28%
Max Rel Drawdown	13.76%	12.29%	7.12%	9.15%

Panel 2: 3% TE Control	Scientific Beta USA (3% TE)			
	Max Deconc.	Max Decorr.	Efficient Min Volatility	Efficient Max Sharpe
Excess Returns over CW	0.90%	0.99%	0.71%	0.68%
Tracking Error	1.86%	2.03%	2.10%	1.83%
95% Tracking Error	2.83%	3.55%	4.30%	3.01%
Max Rel Drawdown	6.60%	8.36%	3.86%	6.33%

The 3% target tracking error portfolio is obtained by combining a 5% TE controlled (and beta constrained) satellite with the cap-weighted core. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of strategy index to the benchmark index. 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 annualized. Total number of stocks in the USA scientific beta universe is 500. The analysis is based on daily total return data from 21 June 2002 to 31 December 2012, downloaded from www.scientificbeta.com.

Conclusion
The Risks in Smart Beta Strategies

- A given smart beta index does not give a definite view on possible risk choices for the strategy it uses.
  - **Pre-packaged indices** ignore that several choices can be made within a given strategy.
  - For example, one could create an infinite number of Minimum Volatility indices, representing a large **variety of choices** of risk.

- Risk choices can be made on two dimensions:
  - **Systematic risks** can be controlled using the following ingredients:
    - stock selection decisions in favour of relevant stock characteristics
    - constraints on factor exposures
  - **Specific risks** have to be measured and can be managed using the following approaches
    - robust estimation approaches to reduce parameter estimation risk
    - diversification across strategies

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Question and Answer Session

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