SCIENTIFIC BETA
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Defensive Equity Investing Without the Implicit Bets

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About the Authors

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Daniel Aguet serves as Index Director and Deputy CEO at Scientific Beta, where he plays a central role in the development and design of factor, climate and enhanced equity strategies. With extensive experience in quantitative finance and index design, he has been instrumental in advancing Scientific Beta's mission of providing research-backed systematic equity strategies to institutional investors. His expertise spans both the theoretical foundations of factor and climate investing and their practical implementation in institutional portfolios. Prior to his current role, Daniel worked as a Quantitative Investment Manager in the asset management industry for more than 10 years. Daniel has authored several papers published in practitioner journals on the design of systematic strategies. Daniel is a Chartered Alternative Investment Analyst (CAIA) and holds a master's degree in finance with a specialisation in Financial Engineering and Risk Management from HEC Lausanne.

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Vera Cady is Senior Investment Specialist for Europe at Scientific Beta. She has over 15 years of experience in sustainability and quantitative Equity investment strategies, with expertise spanning research, product management, and client advisory. Before joining Scientific Beta, she served as Senior Director of Product Management at STOXX. Previously, she spent 11 years at FTSE Russell and 3 years at Nomura International plc, focusing on research and product management in quantitative finance. Vera holds a Bachelor's degree in Mathematical and Computer Modelling from the University of West Bohemia (Czech Republic).

Executive Summary

Many equity investors opt for defensive strategies to strike a balance between capitalising on market upswings and mitigating the impact of market downturns. Their goal is to create a more stable and resilient investment portfolio. However, pursuing a defensive stance often results in inadvertent exposure to specific sectors and regions, along with overweighting stocks that possess unfavourable characteristics, such as high valuation or low profitability.

The Scientific Beta Defensive Equity index distinguishes itself from traditional defensive equity strategies by strategically avoiding implicit bets. This index steers clear of industry biases, regional imbalances, and exposure to expensive or unprofitable securities. By sidestepping these implicit biases, the index not only protects capital but also delivers smooth risk-adjusted returns over the long term.

Our innovative two-step approach to portfolio construction combines the simplicity of stock selection with the power of robust risk models. This approach enables a comprehensive evaluation of each stock's contribution to the defensiveness of the portfolio to be made, ensuring a highly effective risk reduction for investors. In essence, the Scientific Beta Defensive Index targets better risk-adjusted returns by effectively reducing risk and avoiding the biases present in standard defensive strategies.

Introduction

Traditional defensive strategies have been popular for many decades. Investors looking for defensive equity strategies want to participate in bullish markets while protecting their capital in bear periods by limiting their losses relative to the cap-weighted index. This desire for capital protection, or capital preservation, typically leads equity investors to invest in equity strategies whose main objectives are to offer defensive payoff profiles. There is substantial evidence that such risk reduction does not lead to a proportional reduction in returns, resulting in superior risk-adjusted performance by defensive strategies relative to cap-weighted benchmarks over the long-term (the low-risk effect).

There are two main approaches to designing a defensive portfolio.

- The first is based on Modern Portfolio Theory and tries to build the portfolio with the lowest risk on the efficient frontier (Markowitz, 1952) by accounting for stock's volatilities and pairwise correlations.
  This minimum volatility portfolio, achieved through an optimisation, is known to produce very concentrated portfolios. This is why most commercial solutions use very tight constraints (such as imposing minimum and maximum weights for each stock) to force the optimiser to generate less concentrated allocations. Moreover, optimisers, used to solve minimum volatility allocations, are very sensitive to outliers and to parameter estimation errors that can lead to dramatic changes to the optimal weights, leading to high turnover and sub-optimal allocations that do not necessarily reach minimum volatility ex-post (Michaud, 1989). In addition, investors cannot easily tract optimal solutions which depend on many ad-hoc parameter choices used in the optimisation, such as weight constraints, turnover constraints, and numerical specifications of the algorithm.
- The second approach is a pure selection approach, where one simply selects a percentage of stocks that have the lowest volatility in the reference universe. The advantage of this approach is its tractability. The drawback is that, by ignoring correlations across stocks, investors give up on some of the risk reduction potential available in equity markets.

At Scientific Beta, we pursue a different approach, one which offers the advantages of each of the two approaches above while mitigating their drawbacks. Our approach favours a clear separation of the selection and weighting of stocks. The objective of the selection phase is to focus on stocks with the lowest volatility in the investment universe, those which have been shown to offer higher risk-adjusted returns over the long-term than cap-weighted benchmarks[1]. The objective of the weighting phase, meanwhile, is to account for correlations between stocks to build a portfolio with the lowest possible volatility out-of-sample. We thus maintain the tractability of approaches selecting low volatility stocks while also exploiting the risk reduction benefits of accounting for correlation.

1
Friend and Blume (1970), Black, Jensen and Scholes (1972), Miller and Scholes (1972) and Haugen and Heins (1972, 1975) highlighted a negative or flat relationship between systematic risks and expected returns in the cross-section of stock returns, which is in contradiction with the Capital Asset Pricing Model theory.

Mitigating the Biases of Conventional Defensive Equity Strategies

Whether selecting low volatility stocks or optimising weights of the minimum volatility portfolio, defensive strategies suffer from a wide range of well-known biases:

- First, only assessing the low volatility features of stocks might lead to selecting stocks that are unfavourable for investment according to other characteristics. For example, some stocks may offer low risk but also come with high valuation or low profitability, driving down their long-term return potential.
- Second, global portfolios that seek a defensive positioning often find themselves with regional biases, favouring stocks in markets with low volatility. For instance, the MSCI World Minimum Volatility index has a strong overweight to Japan; the country weight in the index is 11.2%, almost twice its weight in the cap weighted MSCI World index (6%). The same is true for Switzerland, with a weight of more than 6% in the Minimum Volatility index but only 2.6% in the parent benchmark. Unexpected shocks related to these countries can lead to unintended losses in defensive strategies.
- Third, it is well known that defensive strategies heavily overweight defensive industries, such as utilities and consumer staples. While such exposures do have lower volatility in the long run, they might lead to important unintended risk. One example is that regulation in the utilities industry, such as the exit from nuclear energy imposed on utilities companies in Germany in 2011, might cause unexpected losses in such portfolios with heavy industry concentration.

The Scientific Beta Defensive Equity index relies on four controls to account for major drawbacks of traditional minimum volatility strategies:

- First, we select stocks with the lowest volatility of the investment universe within each sector of the economy. This has the advantage of promoting a sufficient diversity of stocks in each sector of the economy; investors avoid being overly concentrated in a few sectors such as Utilities or Non-Cyclical Consumer, which are typical defensive sectors.
- Second, we remove low volatility stocks that have the worst valuation or quality scores, since they could drag down the potential for superior risk-adjusted performance.
- Third, we apply a minimum volatility optimisation, where correlations among stocks are estimated via a robust statistical procedure, and by applying a deconcentration constraints to avoid being invested in only a few stocks.
- Finally, we build indices by combining regional building blocks with weights that are neutral relative to the reference cap-weighted benchmark. This avoids any regional biases, such as overweighting Japan in a global equity index.

A Robust Defensive Framework

The Scientific Beta Defensive Equity indices deliver defensive characteristics whilst strategically mitigating implicit bets such as regional imbalances, exposure to expensive or unprofitable securities and industry concentration. Robustness of their index design ensures that they deliver superior risk-adjusted returns over the long term. The following section provides more detail on the implementation of the Scientific Beta Defensive Equity indices.

SELECTION OF DESIRABLE LOW VOLATILITY STOCKS

The first step consists of selecting companies with low volatility characteristics. We measure a company's volatility as the standard deviation of weekly returns over the past two years. Our approach focuses on a model free measure that does not involve modelling the idiosyncratic and systematic components of risk[2]. However, focusing only on selecting stocks with the lowest volatility can also lead to ignoring some of their unwanted features which may have a negative impact on their long- term return potential. For example, a low volatility company may have poor profitability due to factors such as operating in a competitive market, high operating costs, or economic downturns. A low volatility company can also have a high valuation due to investor preferences for stable and predictable earnings, perceived safety during market downturns or potential for consistent dividend payments. In our construction approach, we select 30% of low volatility companies as well as remove[3] one-third of unwanted companies from the initial selection with the worst valuation or quality characteristics. Exhibit 1 below shows the improvement in the average book-to-market and gross profitability of the Defensive Equity index when compared with the same index where we have not removed companies with poor characteristics.

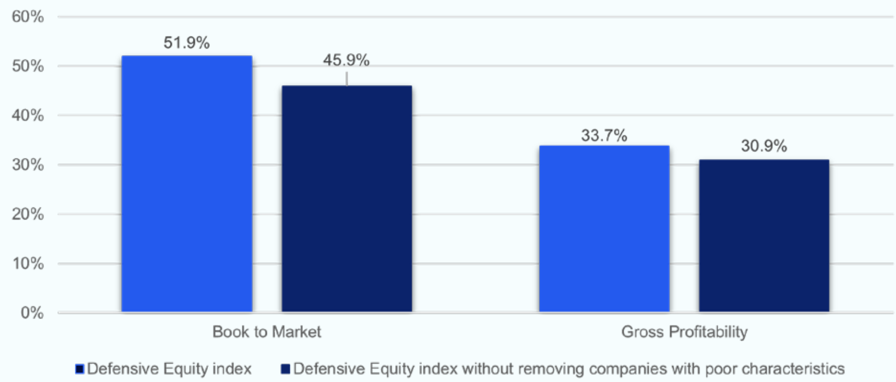
2
Some research comes to a result that either idiosyncratic volatility (Stambaugh, Yu and Yuan, 2015) or beta (Hong and Sraer, 2016) are negatively related to risk-adjusted returns in the broad cross-section of stock returns when analysed on a stand-alone basis. It should be noted that some research argues that the main driver of this negative relationship with risk-adjusted returns is idiosyncratic volatility rather than beta (Liu, Stambaugh and Yuan, 2018). To avoid reliance on components of risk when implementing low risk stock selections, a reasonable approach is thus to use the overall volatility of each stock.

3
Scientific Beta uses a High-Factor-Intensity (HFI) filter, which eliminates stocks with the worst multi-factor scores. These multi-factor scores are composed of the value, momentum, volatility, investment, and profitability scores. Stocks with the lowest multi-factor scores are removed.

EXHIBIT 1

Average Book to Market and Gross Profit

Exhibit 1 shows the average Book to Market and Grow Profit calculated from quarterly ratios from June 1984 to December 2023 for both the SciBeta Developed Defensive Equity Index as well as the SciBeta Developed Defensive Equity Index without removing companies with poor characteristics.

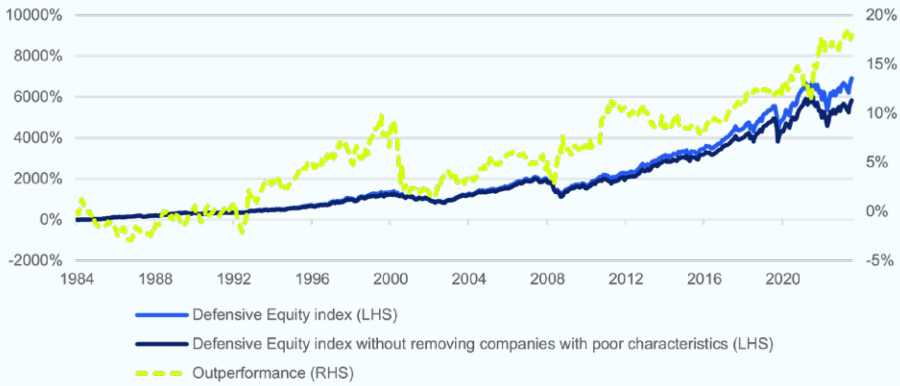


Over the years, the book-to-market ratio has been identified by numerous academics as a key driver of stock returns, including Fama and French (1993), Chan, Hamao and Lakonishok (1991), and Rosenberg, Reid and Lanstein (1985). The outperformance of a strategy exposed to the higher book-to-market ratio can be explained by the higher risk of value stocks compared to growth stocks (Zhang, 2005; Petkova and Zhang, 2005). Regarding gross profitability, it has been demonstrated that profitable firms generate significantly higher returns than unprofitable firms, despite having significantly higher valuation ratios (Novy-Marx, 2013). Therefore, removing companies that are expensive and have poor profitability characteristics enhances the potential of long-term returns. Indeed, removing companies with poor characteristics from the Defensive Equity index positively affects its long-term return potential, as displayed in Exhibit 2. This chart shows the negative impact on the return of an index that includes companies with undesirable characteristics (navy line) compared to the Defensive Equity Index (blue line).

EXHIBIT 2

Benefits of accounting for poor characteristics

Exhibit 2 shows cumulative returns based on monthly USD total returns from 30 June 1984 to 31 December 2023. The universe is the SciBeta Developed Cap-Weighted index. Indices used are the SciBeta Developed Defensive Equity index and the SciBeta Developed Defensive Equity index without removing companies with poor characteristics, their cumulative returns are displayed on the primary axis on the left-hand side of the chart. The outperformance corresponds to the excess returns of the SciBeta Developed Defensive Equity index relative to the SciBeta Developed Defensive Equity without removing companies with poor characteristics and is displayed on the secondary axis on the right-hand-side of the chart.



ACCOUNTING FOR SECTORS IN STOCK SELECTION

Traditional minimum volatility strategies are very often concentrated in a few typical defensive sectors such as Utilities or Non-Cyclical Consumer, while they underweight riskier sectors such as Technology. Such sector concentrations may come with risks investors may not be aware of and that can adversely impact the performance of defensive strategies.

For instance, in 1999, the Technology sector outperformed the cap-weighted benchmark by 84% driven by the dot com bubble. We show in Exhibit 3 below that not controlling for sectors in the stock selection would have resulted in an important relative loss for the strategy given a strong under allocation of -13.3% to the Technology sector, while the Defensive Equity index allocation was neutral and hence helped reducing relative losses and keeping defensive properties with an overall volatility reduction compared to the cap-weighted benchmark of 24.1%.

EXHIBIT 3

Absolute and relative performance and risk in 1999

Developed LTTR 1999 (RI/USD)	Cap-Weighted benchmark	Technology Sector	Defensive Equity without sector control	Defensive Equity
Ann. Returns	28.69%	112.74%	4.48%	17.62%
Ann. Volatility	13.61%	24.58%	8.75%	10.33%
Volatility reduction	-	-	35.7%	24.1%
Ann. Rel. Returns	-	84.05%	-24.21%	-11.07%
Ann. Tracking Error	-	14.94%	10.15%	7.10%
Allocation to Technology	16.7%	100.0%	3.4%	17.4%

Another example is the outperformance of the Energy sector in 2021, driven by the rise of energy prices following the invasion of Ukraine by Russia. We show in Exhibit 4 below that the Defensive Equity index without any sector control would have had no allocation to any energy stocks and that the index would have underperformed the cap-weighted benchmark. Conversely, accounting for sectors in the stock selection process enabled investors to benefit from the outperformance of energy stocks while keeping a defensive profile, as demonstrated by the volatility reduction of close to 20%.

EXHIBIT 4

Absolute and relative performance and risk in 2021

SciBeta Developed 2021 (RI/USD)	Cap-Weighted benchmark	Energy Sector	Defensive Equity without sector control	Defensive Equity
Ann. Returns	21.99%	39.81%	19.02%	23.11%
Ann. Volatility	11.08%	23.36%	8.33%	8.88%
Volatility reduction	-	-	24.8%	19.9%
Ann. Rel. Returns	-	17.82%	-2.97%	1.13%
Ann. Tracking Error	-	19.91%	6.09%	4.56%
Allocation to Technology	3.3%	100.0%	0.0%	2.4%

To promote sector diversity and avoid concentration in a few sectors, we apply the stock selection described above within 10 economic sectors[4], meaning that we select 30% of stocks then remove one-third of stocks with poor valuation or quality scores within each sector. The methodology, as depicted in Exhibit 5, eventually boils down to selecting 20% of companies from each sector with highly desirable low volatility characteristics that lack any of the above-mentioned negative attributes.

4
Scientific Beta uses the Thomson-Reuters Business Classification system to allocate every company into one of ten economic sectors. These sectors are Energy, Basic Materials, Industrials, Cyclical Consumer Goods and Services, Non-Cyclical Consumer Goods and Services, Financials, Healthcare, Technology, Telecommunications Services, Utilities. Company's membership to one of those sectors is maintained at quarterly intervals in March, June, September, and December.

EXHIBIT 5

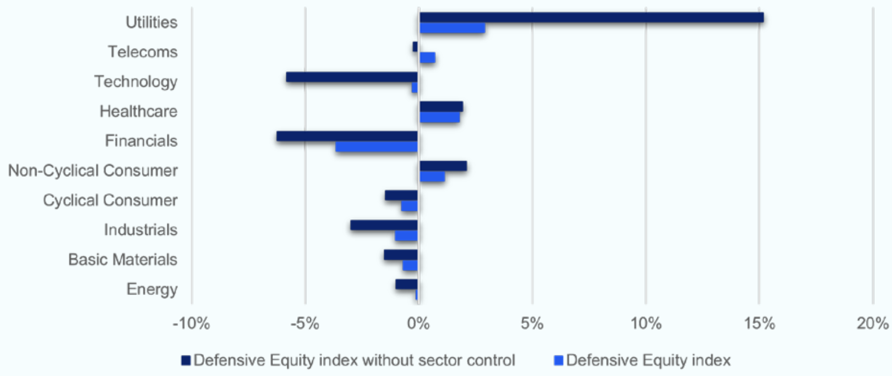
Choosing desirable low volatility companies

To conclude, accounting for sectors in the stock selection of the Defensive Equity index enables investors to reduce sector deviations relative to the cap-weighted benchmark, as shown in Exhibit 6 below. Eventually, the control of sectors mitigates potential unintended risks that may arise when deviating significantly from the benchmark.

EXHIBIT 6

Average sector weights

Exhibit 6 shows average sector weights for the SciBeta Developed Defensive Equity index and the SciBeta Developed Defensive Equity index without sector control, calculated on a quarterly basis from 30 June 1984 to 31 December 2023. Their universe is the SciBeta Developed Cap-Weighted index.



STATE-OF-THE-ART WEIGHTING APPROACH

There are two ways to build defensive strategies, as discussed in the introduction, namely pure selection and minimum volatility strategies. The pure selection strategies often weight stocks based on their market capitalisation or inverse volatility. Hence, they miss an important aspect of portfolio diversification, namely correlation between stocks. Indeed, by combining stocks with low correlation in the portfolio, it is possible to potentially offset losses in one company with gains in the other, which reduces the overall volatility of the portfolio. This diversification benefit arises from the fact that certain events that impact one company may not necessarily impact the other, thereby smoothing out the portfolio's returns over time.

This drawback is accounted by minimum volatility strategies which employs optimisation techniques to find the portfolio with the lowest volatility. These strategies usually do not apply stock selection but try to find optimal weights that correspond to the minimum volatility portfolio which lies on the efficient frontier. Indeed, the minimum volatility portfolio coincides with the optimal portfolio described by Modern Portfolio Theory, namely the tangency portfolio, if expected returns are identical across stocks.

However, this type of approaches suffers from two main drawbacks:

- First, the robustness of a minimum volatility portfolio is highly dependent on the quality of the covariance matrix estimation, namely the measurement of correlations and volatilities. Correlation estimation methods suffer from the curse of dimensionality which can lead to out-of-sample portfolios which are not stable, characterised by weights that can vary dramatically from one rebalancing to the other, and that can be far from the true minimum volatility portfolio. To address the difficulties in risk parameters estimation, Chan, Karceski, and Lakonishok, (1999) suggest using explicit factor models and stock weights constraints to tame potential noisy covariance estimates;

- Second, minimum volatility optimisation can be concentrated in a few low volatility stocks, which in turn can expose investors to stocks' idiosyncratic risks and potential for large losses. Again, a possible remedy to this problem of concentration in low volatility stocks is to introduce weight constraints (see Jagannathan and Ma, 2003).

Hence, most providers of minimum volatility strategies use the upper bounds of individual stocks' weights, which are combined with additional constraints such as sector or country deviations constraints to control for deviations relative to the cap-weighted benchmark as well as turnover constraints to limit weight changes from one rebalancing to the other. The problem with this approach is that the choice of parameters for these constraints is a purely ad-hoc exercise and can only be based on in-sample results. Moreover, the use of many constraints increases complexity and the lack of transparency of such solutions, since optimal weights will be more driven by constraints rather by the objective of minimising the volatility of the portfolio.

To address these issues, we employ the Efficient Minimum Volatility weighting scheme on the selected low volatility stocks with the objective to find optimal weights to minimise the volatility of the portfolio. Other objectives, such as turnover, limitation of sector or country deviations, are achieved via different steps of the index construction process to make sure the optimisation remains trackable and transparent. The problem of high concentration is avoided by imposing norm constraints (DeMiguel et al., 2009) to ensure that the portfolio is at least one-third as deconcentrated as an equally weighted portfolio on the underlying universe[5]. The advantage of using this approach is that it does not require any upper bounds on stock weights, since it only imposes that weights should be deconcentrated enough, and it has been shown to deliver better out-of-sample results than imposing fixed upper bounds. The problem of the quality of the estimation of the covariance matrix of stock returns is resolved by using an implicit factor model based on principal component analysis (PCA). Weekly stock returns over the past 104 weeks are used as inputs for the PCA.

The primary advantage of using the PCA is that it reduces the dimensionality of the problem. When dealing with a large number of stocks, the covariance matrix can become extremely large and difficult to estimate accurately. By identifying a smaller number of underlying factors that explain most of the variance in the returns, the model simplifies the covariance matrix estimation. High- dimensional covariance matrices often suffer from estimation errors due to limited data. By using PCA, we aim to mitigate these errors as the model emphasises the most important factors that drive stock returns, filtering out less significant and more noise-prone components. Finally, the Efficient Minimum Volatility weighting scheme is applied independently on each geographic block of our regional universe. This means that we estimate risk parameters for homogenous set of blocks such as the United States, the Eurozone or Japan. Hence, we avoid additional problematic that may arise when estimating risk parameters on regional universe such as asynchronous returns, namely the fact that some stocks are not traded during the same time periods, as US or Japanese stocks, which will tend to artificially reduce correlations.

The Efficient Minimum Volatility weighting scheme delivers improved out-of-sample risk management characteristics compared to a more naive approach that does not account for stock correlations, as shown in Exhibit 7. We can observe that the Defensive Index provided better volatility reduction relative to the cap-weighted benchmark as well as improvements in maximum drawdown and extreme absolute returns, showcasing the effectiveness of the Efficient Minimum Volatility weighting scheme.

5
The norm-constrained optimisation problem can be stated as follows:

$$w^* = \underset{w \in \mathbb{R}^N}{arg\,min} \sqrt{w'\Sigma w}$$

$$w'e = 1 \text{ where } e \in \mathbb{R}^n \text{ is a unit vector.}$$

And the norm constraint is given by the:

$$Deconcentration\ Ratio = \frac{1}{N \sum_{i=1}^{N} w_i^{\,2}} \geq \frac{1}{3} \Leftrightarrow \sum_{i=1}^{N} w_i^{\,2} \leq \frac{3}{N}$$

where $\sum$ is the covariance matrix of stock returns. $\sum$ is estimated using an implicit factor model based on principal component analysis (PCA).

EXHIBIT 7

Risk Profile

Exhibit 7 shows the statistics on the SciBeta Developed Index, the SciBeta Developed Defensive Equity index and the SciBeta Developed Defensive Equity index with simple inverse volatility weighting, computed on USD total returns from 30 June 1984 to 31 December 2023. Annualised Volatility is defined as the annualised standard deviation of the index' returns. The average three-year rolling volatility is the average standard deviation of returns calculated over rolling three-year periods. The three-year rolling returns are calculated on a rolling basis over the three-year period, with a one-week step size. The statistics are annualised. Maximum Drawdown measures the maximum loss experienced by an index between a peak and a valley over the period. Improvement is calculated as the percentage ratio of the SciBeta Developed Defensive Equity Index relative to the SciBeta Developed Defensive Equity Index with simple inverse volatility weighting.

Developed LTTR June 1984 to December 2023	Cap-Weighted	Defensive Equity	Defensive Equity index using Inverse Volatility	Risk reduction due to the Weighting scheme
Ann. Volatility	15.1%	12.3%	13.0%	5.6%
Average Three-Year Rolling Volatility	14.5%	11.9%	12.6%	5.5%
Three-Year Rolling Ret Worst 5%	-9.36%	-4.65%	-5.30%	12.3%
Max Drawdown	56.9%	45.7%	48.4%	5.6%

AVOIDING REGIONAL BIASES

Many defensive offerings are quite often exposed to regional biases, which favour stocks in markets with low volatility. Some countries can be often heavily over- or underweighted, relative to its starting cap weight, which expose investors to unrewarded risk. This is exactly what we illustrate in Exhibit 8. Indeed, we show that not accounting for regional biases can lead to severe over or under allocation to some countries. For instance, on average the United States was under-weighted by more than 20%, while Japan was overweighted by more than 8%. Unexpected shocks, positive or negative, related to these countries could easily lead to unintended losses in such defensive strategies.

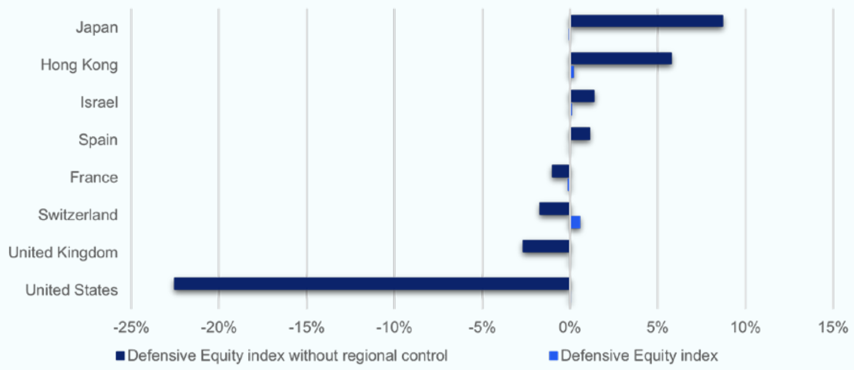
Hence, to mitigate regional biases, we first construct indices for each geographic basic block of the regional universe and then we combine them with weights that are neutral relative to the reference cap-weighted benchmark. Consequently, the SciBeta Developed Defensive Equity index is composed of 7 sub-indices, one for each geographic block as defined by SciBeta Universe Construction rules[6] and which are combined quarterly based on the weight of their corresponding block in the SciBeta Developed Cap-Weighted index. Our methodology enables to reduce significantly regional biases and prevent investors to be unexpectedly impacted by them.

6
Refer to the SciBeta Universe Ground Rules for the details at: https://www.scientificbeta.com/documentation/ground-rules/scientific-beta-universe-construction-rules

EXHIBIT 8

Average country weights

Exhibit 8 shows average country weights for the SciBeta Developed Defensive Equity index and the SciBeta Developed Defensive Equity index without regional control, calculated on a quarterly basis from 30 June 2002 to 30 June 2024. Their universe is the SciBeta Developed Cap-Weighted index.



ROBUST IMPLEMENTATION

Investability is an important element of Scientific Beta Defensive Equity indices. We apply implementation rules that embrace all three dimensions of investability, as explained below, and thus allow us to construct highly investable defensive indices.

- First, the liquidity of the universe needs to be ensured. We enforce strong liquidity requirements in the definition of our universe to make sure that the universe of investable stocks is highly liquid and guarantees sufficient investment capacity.
- Second, liquidity needs to be ensured at the defensive strategy level. We employ capping rules, which aim to strengthen the investability of the indices in reference to liquidity expressed in relation to the cap-weighting of the stocks. These liquidity rules facilitate the capacity of the defensive indices and avoid creating exposure to stocks with low levels of liquidity. Additional rules explicitly consider the available trading volume and allow the indices to respect bounds on the average days- to-trade that result from weight changes at the index rebalancing date.
- Third, investors expect defensive indices to maintain a reasonably low level of turnover. We use buffer rules to reduce fluctuation in the stock selection due to marginal shifts in the ranking of stocks, which have no material impact on the defensive features of those indices. In addition, we also use an optimal turnover control approach to limit index turnover. At each quarterly rebalancing date, new weights are effectively implemented only if weight changes surpass a specified threshold calibrated such that rebalancing occurs optimally once a year on average.

Our robust implementation process ensures the final index is investable, as depicted in Exhibit 9.

EXHIBIT 9

Liquidity and turnover

Exhibit 9 shows liquidity and turnover profile of the SciBeta Developed Defensive Index as well as the SciBeta Developed Cap-Weighted index. Analysis is based on data from 31 December 2003 to 31 December 2023. Liquidity is the average daily traded volume over 12 months in millions of USD. Annualised One-Way Turnover is the sum of the absolute deviations of individual weights between the end of a quarter and the beginning of the following quarter, which is then annualised and set to a one-way figure. Transaction costs represent the cost associated with the activity of buying and selling securities due to the rebalancing of the index over the defined period. We employ the closing quote bid-ask spread measure, because it has one of the highest cross-sectional and time-series correlations with the high frequency measures of effective spread as shown by Chung and Zhang (2014).

SciBeta Developed Dec 2003 - Dec 2023 (RI/USD)	SciBeta Developed Cap-Weighted	SciBeta Developed Defensive Equity
Average Liquidity	733.2	332.2
Avg. Effective Days-To-Trade	0.00	0.79
Annualised One-Way Turnover	3.3%	51.8%
Transaction costs	0.01%	0.07%

Benefits of our Defensive Equity Offering

CAPITAL PROTECTION IN BEAR MARKETS AND REDUCTION OF RISKS

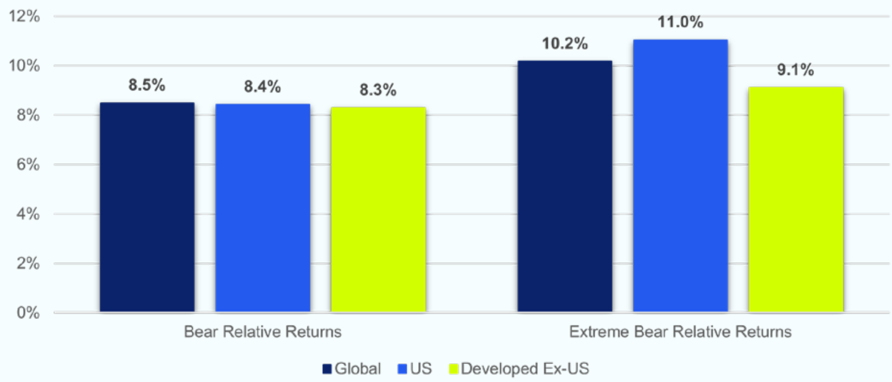
One of the primary advantages of our approach is the consistent capital protection it delivers across different markets. This consistency makes them a dependable choice for those looking to safeguard their investments against market volatility, regardless of geographic focus.

In bear markets, namely periods defined by negative cap-weighted benchmark returns, our Defensive Equity indices have shown resilience. Over the past 20 years, our Defensive Equity indices have delivered relative returns that are higher than those of traditional cap-weighted benchmarks during bear markets – i.e. 8.5% in the Global region, 8.4% in the US, and 8.3% the Developed Ex-US region. In extreme bear markets, which represent the worst-performing half of all bear market months, our indices have provided additional protection. During these periods, the relative returns of our indices were as follows: 10.2% for the Global Defensive Equity index, 11.0% for the US Defensive Equity index, 9.1% for the Developed Ex-US Defensive Equity index. These results demonstrate that our strategy can help mitigate losses during particularly severe downturns.

EXHIBIT 10

Relative performance of Scientific Beta Defensive Equity indices during bear and extreme bear markets

Statistics are computed based on daily USD total returns from 30 June 2005 to 30 June 2025. Performance is calculated relative to the Cap-Weighted benchmarks: the SciBeta USA Cap-Weighted, SciBeta Developed ex US Cap-Weighted and Global Cap-Weighted indices. Bear regimes are defined as months with negative cap-weighted benchmark performance. Extreme Bear months are the bottom 50% (worst market returns) of bear months (negative market returns). Bear and Extreme Bear relative returns are annualised. quarterly basis from 30 June 2005 to 30 June 2025. Their universe is the SciBeta Developed Cap-Weighted index.



As expected, the Scientific Beta Defensive Equity indices demonstrate a controlled risk profile with their lower volatility compared to cap-weighted benchmarks. Over the last 20 years, the volatility of the Global Defensive Equity index is notably lower at 12.6%, compared to 16.0% for the cap-weighted benchmark. Similarly, in the US, the Defensive Equity index shows a volatility of 15.7% versus 19.4% for the cap-weighted benchmark, and for Developed Ex-US markets, the Defensive Equity index had 13.7% volatility, compared to 17.0% for the cap-weighted benchmark. Overall, this translates to an improvement in volatility across these regions of more than 19%, highlighting the stability that the Scientific Beta Defensive Equity indices provide over cap-weighted benchmarks.

Additionally, the market beta of the Scientific Beta Defensive Equity indices underscores their lower risk profile. The Defensive Equity indices have a beta of 0.75 for the Global version, 0.77 for US, and 0.76 for Developed Ex-US. Lower market beta figures usually offer reduced exposure to market volatility, leading to a more stable strategy compared to cap-weighted benchmarks. Exhibit 11 below provides a detailed comparison of Scientific Beta Defensive Equity indices versus cap-weighted benchmarks across these different regions, highlighting the effectiveness and consistency of our approach.

EXHIBIT 11

Scientific Beta Defensive Equity indices volatility and market beta are reduced

Statistics are computed based on daily USD total returns from 30 June 2005 to 30 June 2025. The Cap-Weighted benchmarks are the SciBeta USA Cap-Weighted, SciBeta Developed ex US Cap-Weighted and Global Cap-Weighted indices. Market Beta is measured using daily returns.

From June 2005 to June 2025	Global		US		Developed ex-US	
	Cap-Weighted	Defensive Equity	Cap-Weighted	Defensive Equity	Cap-Weighted	Defensive Equity
Ann. Volatility	15.95%	12.56%	19.39%	15.66%	17.03%	13.69%
Improvement (%)	-	-21.25%	-	-19.24%	-	-19.61%
Market Beta	1.00	0.75	1.00	0.77	1.00	0.76
Improvement (%)	-	-25.00%	-	-23.00%	-	-24.00%

Scientific Beta Defensive Equity indices' protective design is further evidenced by the significantly lower maximum drawdowns experienced across all regions compared to cap-weighted benchmarks. For example, in the US, the maximum drawdown of our indices is reduced from 54.6% to 44.0%, offering investors a more stable investment experience during periods of heightened market stress.

When evaluating the resilience of investment strategies, it is important to consider the potential for extreme losses over a specific period, and which are not dependent on only a few data points as is the case with the maximum drawdown metric. For this objective, we also measure the extreme absolute loss an investor would occur over a one-year period, which is a normal period of evaluation for asset owners, and which provides insights into the potential downside risk of their investments over this period of time. For this reason, we look at the most 5% extreme one-year rolling returns of the Defensive Equity index.

Unlike other providers who may not use this specific metric, we believe that this measure offers a clearer picture of how resilient the indices are during periods of significant market stress, thus serving as a reliable indicator of strategy robustness (Amenc et al. 2015). The Scientific Beta Defensive Equity indices demonstrate notable robustness in this regard. By assessing absolute losses over a rolling one-year window, we observe that these indices have consistently outperformed their benchmark counterparts. Specifically, the Defensive Equity indices have reduced extreme one-year losses by an average of 10% to 25% across various regions.

● EXHIBIT 12

Extreme absolute losses of Scientific Beta Defensive Equity indices are improved

Statistics are computed based on daily USD total returns from 30 June 2005 to 30 June 2025. The Cap-Weighted benchmarks are the SciBeta USA Cap-Weighted, SciBeta Developed ex US Cap-Weighted and Global Cap-Weighted indices. Extreme rolling returns correspond to the worst 5% one- year rolling returns. One-year rolling returns are computed with weekly steps.

From June 2005 to June 2025	Global		US		Developed ex-US	
	Cap-Weighted	Defensive Equity	Cap-Weighted	Defensive Equity	Cap-Weighted	Defensive Equity
Max Drawdown	57.60%	46.60%	54.60%	44.00%	59.20%	49.00%
Improvement (%)	-	-19.10%	-	-19.41%	-	-17.23%
Extreme Rolling Return (worst 5%)	-19.64%	-15.56%	-18.69%	-14.00%	-21.71%	-19.55%
Improvement (%)	-	-20.74%	-	-25.09%	-	-9.99%

IMPROVED RISK-ADJUSTED PERFORMANCE

Scientific Beta Defensive Equity indices offer better risk-adjusted returns compared to their respective cap-weighted benchmarks as depicted in Exhibit 13. While the returns are comparable, they provide lower volatility, which contributes to the improved Sharpe ratios observed. Indeed, Sharpe ratios for our defensive indices are more than 18% higher in both the Global and Developed ex US regions. This suggests that investors may benefit from reduced risks without having to sacrifice return potential.

● EXHIBIT 13

Scientific Beta Defensive Equity indices improve risk-adjusted performance vs cap-weighted benchmarks

Statistics are computed based on daily USD total returns from 30 June 2005 to 30 June 2025. The Cap-Weighted benchmarks are the SciBeta USA Cap-Weighted, SciBeta Developed ex US Cap-Weighted and Global Cap-Weighted indices.steps.

From June 2005 to June 2025	Global		US		Developed ex-US	
	Cap-Weighted	Defensive Equity	Cap-Weighted	Defensive Equity	Cap-Weighted	Defensive Equity
Ann. Returns	8.84%	8.26%	10.81%	9.70%	6.65%	6.64%
Ann. Volatility	15.95%	12.56%	19.39%	15.66%	17.03%	13.69%
Sharpe Ratio	0.45	0.53	0.47	0.51	0.29	0.36
SR Improvement (%)	-	17.78%	-	8.51%	-	24.14%

In Exhibit 14, we provide an alternative illustration of the improvement of Sharpe ratio of our Defensive Equity indices. Indeed, we show their outperformance relative to a volatility-adjusted cap-weighted benchmark. To achieve this, we scale the returns of the cap-weighted benchmark such that it has the same level of volatility as the Defensive Equity index[7]. This approach enables for a one-to-one comparison of performance of both the Defensive Equity index and the cap-weighted benchmark, since their level of risk, as measured by the volatility, is identical. We observe that the level of outperformance is strong and consistent across the three regions.

The improved risk-adjusted performance of traditional defensive strategies is well-documented in the academic literature and is due to their exposure to the Low Volatility factor. Its existence and associated long-term premium are discussed in Black (1972), Frazzini and Pedersen (2014), Ang et al. (2006, 2009), and Blitz and van Vliet (2007). Rewarded risk factors are a source of superior risk-adjusted performance over the long-term compared to cap-weighted benchmarks. There is a limited set of consensus rewarded risk factors that are backed by academic research. Their long-term reward is justified by economic rationale. Investors

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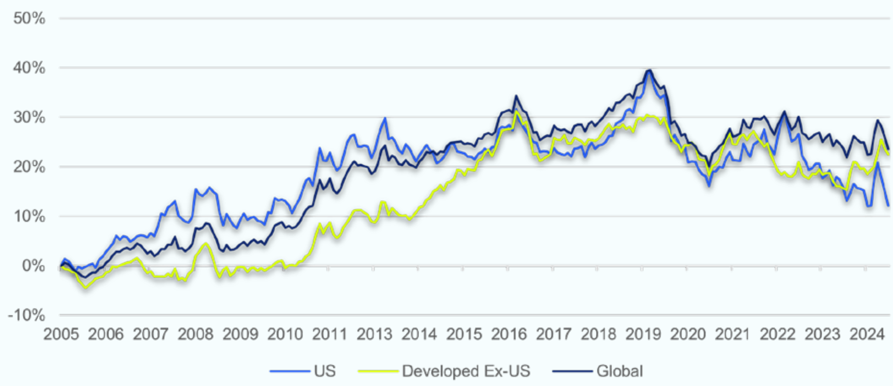
The adjustment is made ex-post over the full sample. The scaling factor is simply the volatility of Defensive Equity index divided by the volatility of the cap-weighted benchmark. Daily returns of the cap-weighted benchmark are divided by the scaling factor.

require compensation for additional risks brought by factor exposures in bad times when assets that correspond to a given factor tilt tend to provide poor payoffs (see Cochrane, 2005). Frazzini and Pedersen (2014) provided a risk-based explanation for the Low Volatility premium. The rationale is that leverage-constrained investors tend to overweight high-beta stocks and underweight low-beta stocks in their portfolios. Their actions lower future risk-adjusted returns on high-beta stocks and increase future risk-adjusted returns on low-beta stocks.

EXHIBIT 14

Risk-adjusted performance of Scientific Beta Defensive Equity indices in a volatility-adjusted Sharpe ratio context

Exhibit 14 shows the relative risk-adjusted performance of the Scientific Beta Defensive Equity Indices based on monthly USD total returns from 30 June 2005 to 30 June 2025, compared to their cap-weighted benchmarks. The Cap-Weighted indices used are the SciBeta Global Cap-Weighted index, SciBeta United States Cap-Weighted index, and SciBeta Developed ex USA Cap-Weighted index. All indices have been volatility-adjusted ex- post to ensure a comparable Sharpe ratio context.

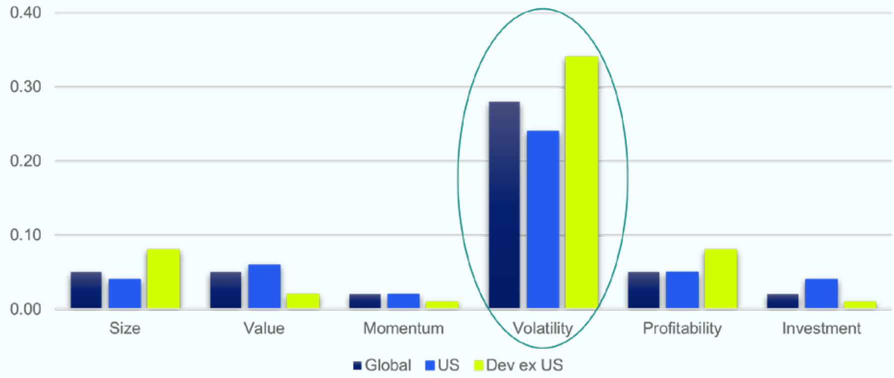


Our methodology is more robust than traditional defensive strategies given that the exposure to the Low Volatility factor is targeted explicitly with the stock selection process, while minimum volatility strategies does have an implicit exposure exclusively based on the weighting of the stocks and that can be less stable through time. Moreover, we avoid negative exposures to other rewarded factors by removing stocks with poor valuation or quality characteristics, which enables to improve the factor intensity or the sum of exposures to the six-consensus rewarded factors and help to deliver strong risk-adjusted performance. This is illustrated in Exhibit 15, where we show that the average low volatility exposure of our Defensive Equity index is strong across all three regions – Global, US, and Developed ex-US, while they display positive exposures to the other rewarded factors.

EXHIBIT 15

Strong exposure low volatility factor and strong factor intensity consistent across regions

Exhibit 15 shows exposures to Low Volatility as well as other factors. We use daily USD total returns from 30 June 2005 to 30 June 2025 to measure factor exposures. The yield on three-month secondary market US Treasury bills is used as a proxy for the risk-free rate. Exposure to desired factor is derived from a regression, which is based on daily total returns. Factors are equal-weighted daily rebalanced long/short factors obtained from Scien- tific Beta and are beta-adjusted every quarter with their realised CAPM beta. The cap-weighted indices are the SciBeta USA Cap-Weighted, SciBeta Developed ex US Cap-Weighted and Global Cap-Weighted indices. Factor tilts are displayed in following manner: Low-Size, High-Value, High-Mo- mentum, Low-Volatility, High-Profitability and Low-Investment.



Conclusion — A New Option for Defensive Investors

Investors who position their equity portfolios in defensive mode risk typically suffer from a variety of well-known biases of defensive equity strategies. The Scientific Beta Defensive Equity indices offer a new option for these investors, helping them to mitigate these biases.

Unlike discretionary defensive strategies, these indices are built on effective tools that are tractable and transparent to investors.

Selecting low volatility stocks within sectors addresses the problem of biases towards sectors such as Utilities and Consumer Staples. The regional neutrality avoids concentration in particular countries and the corresponding implicit risks. The avoidance of stocks with poor value or quality scores enables higher performance in bull markets to be captured. In addition to avoiding biases, these indices use an exhaustive assessment of stocks' contribution to portfolio risk, building both on transparent stock selection and a state-of-the art risk model to account for correlations.

The Scientific Beta Defensive Equity indices help investors to not only preserve capital during market downturns, but also to improve long-term risk-adjusted returns.

References

- Amenc, N., F. Goltz and S. Sivasubramanian (2015). Robustness of Smart Beta Strategies. *Journal of Index Investing* 6(1): 17–38.
- Ang, A., R.J Hodrick, Y. Xing and X. Zhang (2006). The Cross-Section of Volatility and Expected Returns. *The Journal of Finance* 61(1), 259-299.
- Ang, A., R.J Hodrick, Y. Xing and X. Zhang (2009). High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence. *Journal of Financial Economics* 91(1), 1-23.
- Black, F. (1972). Capital Market Equilibrium with Restricted Borrowing. *The Journal of Business* 45(3): 444-455.
- Black, F., M. Jensen and M. Scholes (1972). The Capital Asset Pricing Model: Some Empirical Tests. Studies in the Theory of Capital Markets. Praeger Publishers Inc.
- Blitz, D.C., and P. van Vliet (2007). The Volatility Effect: Lower Risk without Lower Return. *Journal of Portfolio Management* 34(1), 102-113.
- Chan, L.K.C., Y. Hamao and J. Lakonishok (1991). Fundamentals and Stock Returns in Japan. *Journal of Finance* 46(5): 1739-1764.
- Chung, K. H. and H. Zhang (2014). A Simple Approximation of Intraday Spreads with Daily Data. *Journal of Financial Markets* 17©: 94-120.
- Cochrane, J. H. (2005). Asset Pricing (Revised Edition). Princeton University Press.
- DeMiguel, V., L. Garlappi, F.J. Nogales and R. Uppal (2009). A Generalized Approach to Portfolio Optimization: Improving Performance by Constraining Portfolio Norms. *Management Science* 55: 798-812.
- Fama, E.F and K.R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1): 3-56.
- Friend, I. and M. Blume (1970). Measurement of Portfolio Performance under Uncertainty. *The American Economic Review* 60(4): 561-575.
- Frazzini, A. and L.H. Pedersen (2014). Betting Against Beta. *Journal of Financial Economics* 111(1): 1-25.
- Haugen, R.A. and A.J. Heins (1972). On the Evidence Supporting the Existence of Risk Premiums in the Capital Market. Available at SSRN: http://ssrn.com/abstract=1783797.
- Haugen, R.A. and A.J. Heins (1975). Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles. *The Journal of Financial and Quantitative Analysis* 10(5): 775-784.
- Hong, H. and D.A. Sraer (2016). Speculative Betas. *The Journal of Finance* 71(4): 2095-2144.
- Jagannathan, R. and T. Ma (2003). Risk Reduction in Large Portfolios: Why Imposing the Wrong Constraints Helps. *The Journal of Finance* 58(4): 1651-1683
- Liu J., R.F. Stambaugh and Y. Yuan (2018). Absolving beta of volatility's effects. *Journal of Financial Economics* 128(1): 1-15.
- Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance* 7(1): 77-91.
- Michaud, R.O. (1989). The Markowitz Optimization Enigma: Is 'Optimized' Optimal? *Financial Analyst Journal* 45(1): 31-42 (12 pages).
- Miller, M.H. and M. Scholes. (1972). Rates of Return in Relation to Risk: A Re-examination of Some Recent

Findings. In: Studies in the theory of capital markets. New York: Praeger Publishers Inc.

- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics* 108(1): 1-28.
- Petkova, R. and L. Zhang (2005). Is Value Riskier than Growth. *Journal of Financial Economics* 78(1): 187-202.
- Rosenberg, B., K. Reid and R. Lanstein (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management* 11(3): 9-16.
- Stambaugh, R.F., J. Yu and Y. Yuan (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *The Journal of Finance* 70(5): 1903-1948.

About Scientific Beta

Scientific Beta's aim is to encourage the entire investment industry to adopt the latest advances in smart factor and ESG/climate index design and implementation. Our institution was established in December 2012 by EDHEC-Risk Institute, one of the top academic institutions in the field of fundamental and applied research for the investment industry, as part of its mission to transfer academic know-how to the financial industry. Scientific Beta brings the same concern for scientific rigour and veracity to all the services that it provides to investors and asset managers. We offer the smart factor and ESG/Climate solutions that are most proven scientifically, with full transparency of both methods and associated risks.

On 31 January 2020, Singapore Exchange (SGX) acquired a majority stake in Scientific Beta. SGX continues to support our strong collaboration with EDHEC Business School, and the principles of independent, empirical-based academic research that have benefited our development to date.

Scientific Beta has developed two types of expertise over the years, responding to two of the major challenges that investors face:

- Smart Beta and, more particularly, factor investing.
- ESG, in particular climate investing.

To date, Scientific Beta has made offerings with two major types of climate objective available to investors:

Since 2015, we have offered products with financial objectives that respect ESG and carbon constraints. These correspond to the application of exclusion filters, the design of which allows the financial characteristics of the index to be conserved. This involves reconciling financial objectives and compliance with ESG norms and climate obligations. As such, our Core ESG, Extended ESG and Low Carbon filters can be integrated into smart beta or cap-weighted offerings in line with the financial objectives targeted by the investor.

Since 2021, Scientific Beta has also offered indices with pure climate objectives (Climate Impact Consistent Indices) that enable climate exclusions and weightings to be combined in order to translate companies' climate alignment engagement into portfolio decisions.

Since it was acquired by SGX in January 2020, Scientific Beta has accelerated its investments in the area of Climate Investing as part of the SGX Sustainable Exchange strategy, which is mobilising an investment of SGD20 million. In addition, EDHEC and Scientific Beta have set up a EUR1 million/year ESG Research Chair at EDHEC Business School.

With the aim of providing worldwide client servicing, Scientific Beta has a presence in Boston, London, Nice, Singapore and Tokyo. Scientific Beta has a dedicated team of 40 people who cover not only client support from Nice, Singapore and Boston, but also the development, production and promotion of our index offering. Scientific Beta signed the United Nations-supported Principles for Responsible Investment on 27 September 2016. We became an associate member of the Institutional Investor Group on Climate Change on 9 April 2021.

Today, Scientific Beta devotes more than 40% of its R&D investment to climate investing and more than 45% of its assets under replication refer to indices with an ESG or climate focus. As a complement to its own research, Scientific Beta supports an important research initiative developed by EDHEC on ESG and climate investing and cooperates with Moody's ESG and ISS ESG for the construction of its ESG and climate indices.

On 27 November 2018, Scientific Beta was presented with the Risk Award for Indexing Firm of the Year 2019 by the prestigious professional publication Risk Magazine. On 31 October 2019, Scientific Beta received the Professional Pensions Investment Award for "Equity Factor Index Provider of the Year 2019." On 2 February 2022, Scientific Beta was named "Best Specialist ESG Index Provider" at the ESG Investing Awards 2022. On 6 March 2025, Scientific Beta was named "Best ESG Index Provider" at the ESG Investing Awards 2025.

Scientific Beta Publications

2025 PUBLICATIONS

- Schneller, W, Crash-Tested: Rebuilding Momentum and Managing Crash Risk (September).
- Bruno, G., Goltz, F. and Naly, A., Does ESG Information Deliver Investment Value? A High-Dimensional Portfolio Perspective (June).
- Aguet, D., Schneller, W. and Sinaee, S., The Power of Completion: How Completion Portfolios Enhance Alignment, Efficiency, and Flexibility (June).
- Aguet, D., Goltz, F. , Is now the time to diversify across stocks? (May).
- Aguet, D. , V. Cady. Defensive Equity Investing Without the Implicit Bets (April).
- Aguet, D., Esakia, M., Goltz, F., Luyten, B. and Mirciov, I. Refining Value Investing: Benefits of Incorporating Intangible Capital and Stabilising Market Exposure (March).
- Aguet, D., Goltz, F. and Schneller, W. Understanding and Managing the Impact of Market Concentration on Factor Strategies (March).

2024 PUBLICATIONS

- Aguet, D. , Goltz, F.,and I. Mirciov. Improving Factor Exposure per Unit of Tracking Error: Managing Economic Risks to Improve Efficiency in Multi-Factor Equity Strategies (October).
- Aguet, D. , Goltz, F.,and B. Luyten. A New Approach to Quality Investing: Combining Risk Awareness and Robust Metrics (September).
- Christiansen, E. Can We Make ESG Scores Great Again? (April).
- Bruno, G., Goltz, F.,and B. Luyten.Trade Policy Risk Exposure in Equity Portfolios (February).
- Bruno, G., Goltz, F. From ESG Confusion to Return Dispersion: Fund Selection Risk is a Material Issue for ESG Investors (February).

2023 PUBLICATIONS

- Christiansen, E., D. Aguet and N. Amenc. Climate Impact Consistent Indices (September).
- Aguet, D. Why Diversification Still Matters for Investors? (September).
- Amenc, N., F. Goltz and A. Naly. Green Dilution: How ESG Scores Conflict with Climate Investing. (June).
- Bruno, G., Goltz, F.,and B. Luyten. Firm-Level Exposure to Trade Policy Shocks: A Multi-dimensional Measurement Approach. (June).
- Aked, M. The Three Principles of Climate Impact Investing. (May).
- Aked, M. Navigating the Factor Menu - The Role of Macroeconomic Factors. (February).

2022 PUBLICATIONS

- Christiansen, E. Scientific Beta welcomes the NZAOA’s Principles for Net-Zero-Aligned Benchmarks (December).
- Christiansen, E. Financing the Energy Transition: What is the Role of Fossil Fuels Divestment? (November).
- Mauguin, R. Scientific Beta Global Universe. (July).
- Christiansen, E., D. Aguet and N. Amenc. Climate Impact Consistent Indices. (March).

- Esakia, M and F. Goltz. Targeting Macroeconomic Exposures in Equity Portfolios: A Firm-Level Measurement Approach for Out-of-Sample Robustness. (February).

2021 PUBLICATIONS

- Amenc, N., G. Bruno and F. Goltz. Should ESG alpha Really be Positive? Assessing the Five Forces that Drive ESG Investment Returns. (December).
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- Bruno, G., M. Esakia and F. Goltz. "Honey, I Shrunk the ESG Alpha": Reactions of Investment Professionals (November).
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- Aguet, D. Protecting your Equity Portfolio Against Inflation. (July).
- Christiansen, E., D. Aguet and N. Amenc. Scientific Beta Core ESG Filter: A Consensus and Norms-Based ESG Investing Approach. (August).
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- Amenc, N., M. Esaki and F. Goltz. When Greenness is Mistaken for Alpha: Pitfalls in Constructing Low Carbon Equity Portfolios. (May).
- Bruno, G., M. Esakia and F. Goltz. "Honey, I Shrunk the ESG Alpha": Risk-Adjusting ESG Portfolio Returns. (April).
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