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Research for Institutional Money Management

EDHEC BUSINESS SCHOOL

INTRODUCTION

Introduction to Research for Institutional Money Management supplement in P&I, December 2020

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It is my pleasure to introduce the latest "Scientific Beta" special issue of the Research for Institutional Money Management supplement to Pensions & Investments.

We first discuss the question of why investors should stick with their factor strategies through periods of crisis. The main conclusion is that the importance of diversification across the six consensus risk factors remains intact.

We discuss crowding risk in smart beta strategies and find that assertions that the popularity of smart beta strategies will ultimately cancel out their benefits are not based on solid evidence.

We assess the robustness of a set of competitor and Scientific Beta indexes both from an index design point of view and through the lens of our robustness measurement protocol. We have developed a framework to assess robustness according to five different dimensions and assess whether or not the uncovered risks are acceptable given the objectives of a strategy.

Since the value factor proxy does not aim to capture the true value of a stock, including omitted intangible assets in the accounting book value is in line with the risk-based explanation for the value factor. We confirm in our article that an intangible-adjusted value factor adds investment value for multi-factor investors.

It is often argued that an investor who is dissatisfied with a company's ESG behavior, and who wishes to remedy the situation, should stay on as a shareholder and engage with it. We show that far from being incompatible with ESG engagement, ESG filtering sends a clear and consistent divestment message that allows an effective engagement policy to be implemented.

Traditional defensive solutions suffer from negative exposures to reward factors other than the low-volatility risk factor, as well as concentration and strong exposures to fixed-income risks. More importantly, they can suffer from huge peaks of volatility during market crises. Scientific Beta offers a new dynamic defensive solution that is really low volatility by combining a robust low-volatility index and a maximum volatility protection risk-control option.

Investors who want their factor strategy to remain defensive during episodes of severe market stress would benefit from the application of a volatility-control option. We present the historical volatility adjustment (HVA) risk-control option.

We hope you will find the articles in the supplement informative and useful. We extend our warmest thanks to P&I for their partnership on the supplement.

CONTENT

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Why Investors Should Keep Faith with their Factor Strategies

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- **The impact of the COVID-19 fallout on factor strategy performance has reignited questions over the reward of risk factors and the usefulness of multi-factor products.**
- **We warn that it is unhelpful to judge long-term rewarded factors on the basis of short-term performance.**
- **After analyzing the data, we show that the factor underperformance observed during the COVID-19 crisis is unusual but not totally abnormal.**
- **Our key takeaway is that the importance of diversification across the six consensus risk factors remains intact.**

INTRODUCTION

Over the first quarter of 2020, the performance of factor strategies has been heavily impacted by the turbulence generated by the COVID-19 pandemic. This has reignited questions over the reward of risk factors, in particular size and value, and consequently the usefulness of multi-factor products. Our view is that it is always paradoxical to judge the relevance of exposures to long-term rewarded factors on the basis of short-term assessments. This is especially the case when it comes to factor investing, because it is well documented in the academic and empirical literature that the expression of positive factor premia can only be judged over the long term and is highly variable. It is this variability that justifies the value of factor investing from a rational asset-pricing viewpoint. Within the context of the long-term horizon, the following analysis aims to put in perspective the factor performance during Q1 2020 when weighed against long-term data. We perform our analysis on the EDHEC-Risk Developed Long-Term Track Record universe that covers more than 35 years of data.

Our intention is to respond to investor queries on the usefulness of maintaining investment in factors. Hence we examine whether factor performance, especially in the case of extreme underperformance in recent months, has been in line with extreme quarterly performance over the long term. The idea here is firstly to ascertain whether the performance of each factor has been in line with, or worse than, extreme quarterly return distribution. This enables us to determine whether the performance observed over the short term, which might not have an equivalent, calls into question the long-term track records that justified the adoption of factor strategies as a superior risk-adjusted performance benchmark or investment vehicle. Secondly, we look at the factor performance in other market drawdowns to find out if the recent COVID-19 crisis was exceptional – or in line with past crises. Thirdly, we look more systematically at the factor performance in bear and extreme bear market regimes. This analysis is complementary to the second stage, in the sense that it does not rely on a specific market crisis and is therefore more robust to draw conclusions on the factor performance in extreme bear market regimes. These analyses of factor performance in crises aim to respond to investors' queries on the effectiveness of the defensive nature of defensive strategies. The fact is that most of them, on average over the long term, present lower volatility than cap-weighted indexes. They also tend to outperform cap-weighted indexes in bear markets. We conclude with an analysis of the expected time factors take to recover from extreme quarterly absolute losses.

The article is structured as follows: First, we look at recent quarterly factor performances and their long-term extreme distributions. Second, we examine factor performance during pre-defined periods of distinctive market drawdowns. Third, we analyze factor performance in bear and extreme bear market regimes. Fourth, we compute factors' expected recovery time from extreme absolute losses. Finally, we present our conclusions.

Factor performance over the first quarter versus long-term historical data

Factor performance over the first quarter of 2020

FIGURE 1

Recent quarterly factor performance versus extreme long-term distribution

We use daily USD total returns from 31-Dec-1984 to 31-Dec-2019 on the EDHEC-Risk Developed Long-Term Track Record universe. All statistics are calculated on a rolling basis over a one-quarter window size, with a one-week step size. Worst/Top 5% rolling return is the 5th/95th percentile of the quarterly rolling returns time-series of each factor. Conditional mean (< worst 5%) is the mean of quarterly rolling returns below the fifth percentile. Conditional mean (> top 5%) is the mean of quarterly rolling returns above the ninety-fifth percentile. The Size factor (SMB) is the return series of an equal-weighted portfolio that is long small market-cap stocks and short the top 30% stocks (large market-cap stocks) sorted on market capitalization in descending order. The Value factor (HML) is the return series of an equal-weighted portfolio that is long for the top 30% stocks (value stocks) and short for the bottom 30% stocks (growth stocks) sorted on book-to-market value in descending order. The Momentum factor (MOM) is the return series of an equal-weighted portfolio that is long the winner stocks and short the loser stocks. The winner stocks (inversely the loser stocks) are defined as the top 30% (inversely the bottom 30%) of stocks, sorted on the past 104 weeks' compounded returns excluding the most recent month, in descending order. The Low Volatility factor (LVOL) is the return series of an equal-weighted portfolio that is long the bottom 30% stocks (low volatility stocks) and short the top 30% stocks (high volatility stocks) sorted on past volatility in descending order. The High Profitability factor (HPRO) is the return series of an equal-weighted portfolio that is long the top 30% stocks (high profitability stocks) and short the bottom 30% stocks (low profitability stocks) sorted on gross profitability in descending order. The Low Investment factor (LINV) is the return series of an equal-weighted portfolio that is long the bottom 30% stocks (low investment stocks) and short the top 30% stocks (high investment stocks) sorted on two year asset growth in descending order. All factors considered are market beta neutralized quarterly using ex-post CAPM beta over the quarter.

Statistics	SMB	HML	MOM	LVOL	HPRO	LINV	Avg
Q1 2020	*-10.06%*	*-14.44%*	*15.86%*	*7.37%*	*6.83%*	*-5.89%*	*-0.06%*
Worst 5% rolling return	*-9.16%*	*-6.19%*	*-7.80%*	*-6.87%*	*-5.00%*	*-3.11%*	*-6.36%*
Conditional mean (< worst 5%)	*-13.34%*	*-10.46%*	*-16.93%*	*-12.89%*	*-7.21%*	*-5.27%*	*-11.02%*
Top 5% rolling return	*18.29%*	*6.97%*	*10.27%*	*11.65%*	*6.00%*	*6.47%*	*9.94%*
Conditional mean (> top 5%)	*27.77%*	*17.98%*	*17.55%*	*19.78%*	*7.13%*	*9.76%*	*16.66%*

was mixed and of very strong magnitude (see figure 1). Indeed, the size, value and low investment factors generated strong negative returns that were below their worst 5% level, while momentum, high profitability and low volatility posted strong positive returns, which were above their top 5% quarterly performance in the case of the first two factors. Despite this strong dispersion of returns, the average factor risk premium of the consensus six-factor long/short market-neutral factors was almost flat (–0.06%).

We highlight that the very negative performance observed for the size and low investment factors is not unprecedented, since the average extreme values (below worst 5%) for these factors are –13.34% and –5.27% when looking at more than 35 years of historical data. The performance of the value factor, however, is clearly extreme since it was below its average extreme value. However, it should be noted that the strong underperformance of the factors is inherent in the very existence of the premia that are associated with them. The premia are justified by the fact that, over the long term, investors are prepared to accept lower returns from stocks that are not exposed to these factors (such as, for example, growth and large-cap stocks, which dominate cap-weighted indexes). The reasoning is that, in extreme economic conditions when the marginal utility of savings is highest, these expensive – and therefore less profitable – stocks play the role of safer assets. As such, at a time when the economy is stalling, certain companies are going to be affected by the consequences of the increase in credit risk, such as mid-cap stocks, and by a risk of their activities being frozen (cost of reversibility) such as value stocks. It is logical that these companies are penalized because it is these same risks that justify their premium over the long run. Nothing in the abnormality of performance observed in recent months, therefore, draws us to call into question the long-term track record and distribution of those past which supported the purpose of investing in factors.

Finally, to conclude this section, we emphasize the benefit of diversification across factors since the strong negative performance of the size, value and low investment factors was almost offset by the performance of the other factors. This last point is very important when considering the choice of factor strategies. Indeed, a factor solution with well-balanced exposures to the six rewarded factors is less subject to the underperformance of specific factors. Over the long term, only good diversification of factor exposure can guarantee the robustness of outperformance.

FIGURE 2

Periods of drawdowns

Event Label	Start of Drawdown	End of Drawdown	Days	% Drawdown of Cap-Weighted Index
Black Monday	25-Aug-1987	4-Dec-1987	74	-24.19%
Gulf war	16-Jul-1990	11-Oct-1990	64	-17.26%
Asian crisis	17-Jul-1998	31-Aug-1998	32	-17.59%
Tech bubble burst	24-Mar-2000	9-Oct-2002	664	-50.46%
Financial crisis	9-Oct-2007	9-Mar-2009	370	-56.64%
Q4-2018	20-Sep-2018	24-Dec-2018	68	-17.61%
Covid-19	20-Feb-2020	23-Mar-2020	23	-33.40%

Factor performance during past market drawdowns

In this section, we compare factor performance during specific periods of market drawdowns to the COVID-19 crisis. More precisely, we analyze different periods of the EDHEC-Risk Developed Long-Term Track Record universe that correspond to extreme drawdowns of the cap-weighted index. We therefore consider drawdowns of more than 15% for the Developed LTTR Cap-Weighted index (see figure 2). We also add the recent COVID-19 crisis for comparison purposes, based on the SciBeta developed universe.

In figure 3 we show the performance for all factors as well as their average for each market drawdown. Performance figures are annualized when the period considered is greater than one year. Otherwise, the cumulative return is shown for the period considered.

First, we underline that the size factor mostly generates the lowest returns relative to the other factors. In addition, in all periods but the tech bubble burst, the factor delivered negative performance. By contrast, the low volatility and momentum factors generated positive returns during all the crises except during the financial crisis of 2008. However, during all crises, at least two factors out of the six performed positively, highlighting once again the benefit of diversification across factors in time of crisis.

Second, with few exceptions (notably the tech bubble burst, during which all factors delivered positive returns, especially the low volatility factor), the average cumulative return of the six factors is generally negative during market drawdowns. When considering the full sample period, however, the average performance of all factors is positive.

Lastly, we examine the most recent COVID-19 period more closely. In line with other crisis periods, the size factor posted the most significant losses. Moreover, the value and low investment factors experienced losses that were in line with those observed during other crises. The negative average performance of the factors was consistent with that observed during other crises (with the exception of the tech bubble burst).

One key takeaway of this analysis is that being diversified across factors reduces the risk of being exposed to the wrong factor and as such helps to mitigate losses in periods of market drawdown. There is ultimately nothing abnormal to be seen in the behavior of factors during the COVID-19 crisis when compared with other crises. There is also no evidence that the factors' average relative performance in bear markets is found in extreme situations, and indeed no reason that this should be the case. This is consistent with the observations that are often formulated on the fact that

FIGURE 3

Factor performance in different market drawdown periods

The table shows the factor performance over different periods as defined in Figure 2. Performance is annualized when the considered period is greater than one year (i.e., Tech bubble burst, Financial crisis, and the Full Sample period). Otherwise, the cumulative return is shown for the considered period. Factor performance is shown for the SMB, HML, MOM, LVOL, HPRO, LINV factors as well as the EW portfolio of the six L/S factors. The last row of this section shows the average return of the six L/S factors. L/S factors are constructed as defined in Figure 1.

Event	Black Monday	Gulf war	Asian crisis	Tech bubble	Financial crisis	Q4-2018	Covid-19
SMB	*-1.38%*	*-10.90%*	*-17.63%*	*2.52%*	*-8.10%*	*-8.24%*	*-6.83%*
HML	*3.84%*	*-3.21%*	*-5.56%*	*5.80%*	*2.27%*	*-5.69%*	*-6.62%*
MOM	*0.03%*	*5.85%*	*6.92%*	*3.10%*	*-5.97%*	*2.75%*	*5.92%*
LVOL	*4.40%*	*7.20%*	*2.06%*	*60.24%*	*-0.43%*	*2.82%*	*2.61%*
HPRO	*-6.22%*	*-0.23%*	*0.40%*	*14.02%*	*6.01%*	*3.12%*	*4.16%*
LINV	*4.44%*	*0.60%*	*1.41%*	*26.84%*	*-3.61%*	*-2.42%*	*-1.65%*
Avg	*0.85%*	*-0.12%*	*-2.07%*	*18.75%*	*-1.64%*	*-1.28%*	*-0.40%*

an average cannot represent extreme risks, and therefore extreme distributions of returns.

Despite the usefulness of this analysis, it only focused on very specific periods of market drawdowns. Therefore there are insufficient data points from which to draw statistical conclusions on the performance of factors in bear market regimes or during the COVID-19 crisis. This is exactly the objective of the next section.

Factor performance in bear and extreme bear market regimes

In this section, we analyze the distribution of factor performance in bear and extreme bear periods, based on the EDHEC-Risk Developed LTTR Cap-Weighted index. The analysis is performed from 31 December 1984 to 31 December 2019, using a rolling-quarter window with a one-week step. We classify periods as bear markets if the rolling quarterly performance of the cap-weighted index is negative. Half of these are then classified as extreme bear market regimes. Based on these two classifications and on the rolling analysis, we examine the performance of the long-short factors and compare them with what happened during the COVID-19 crisis (from 20 February to 23 March 2020).

- Figure 4 firstly shows that, on average, the size and value factors underperform in bear and extrem bear market regimes and that performance is worse in the latter. Indeed, the size factor return is –1.80% in bear and –2.78% in extreme bear market regimes, while the value factor return is –0.19% and –0.42% respectively. This observation confirms what we already observed in the specific market drawdowns analysis (figure 3).
- Second, we underscore that all the other factors tend to generate positive performance on average, which is higher in extreme bear market regimes.
- Third, the low volatility factor has the highest average performance among the six factors, which highlights its defensive bias.
- Fourth, the average performance across all the factors in these extreme periods tends to be positive. Even if when looking at the extreme of the distribution, in particular at the worst 5% level, the average performance can be negative by –7.61% in bear and –8.24% in extreme bear market regimes.

The negative performance of the size, value and low investment factors is lower than their respective average performance in bear or extreme bear market regimes. However, these negative performances are not exceptional, either in bear or extreme bear market regimes, since they were not worse than extreme levels (such as the worst 5%). We can draw the same conclusion for the average performance of factors. Indeed, the worst 5% observations, in bear or extreme bear market regimes, are far worse than the –0.43% performance observed during the COVID-19 crisis period.

We can therefore say that, even though the factor underperformance observed during the COVID-19 crisis is unusual, it is not totally abnormal. It is indeed well within the distribution observed over the long term. There is nothing in the observations made during the COVID-19 crisis that would bring into question the average positive performance of a multi-factor portfolio in bear markets.

Expected "time to recovery" from extreme drawdowns

In this section, we address the question that many investors have been raising since the strong underperformance of risk factors during the COVID-19 crisis, namely what is the expected time to recovery from extreme losses.

For this purpose, we compute the expected time to recovery from extreme absolute drawdown:

- First, we compute one-quarter rolling returns, with a step size of five days, over the whole period ranging from 31 December 1984 to 31 December 2019.
- Second, we extract the level of the worst 5% rolling returns, which corresponds to the fifth percentile of the distribution of rolling returns (see figure 5).
- Third, we look at all the periods for which the rolling return is below the worst 5% level and we compute the number of days it takes to recover from the loss.
- Lastly, we compute the median values (as well as worst and top 5% values).

Calculations are done on a working day basis (i.e. 260 days being equal to one year).

Figure 6 shows that the median days to recover range from 111 for the size factor to 405 for the high profitability factor. Interestingly, the equally-weighted portfolio of the six factors has a median of 97 days, which is lower than the minimum across the single factors. Median values are interesting because they provide a summary value that includes the largest number of recovery cases, but when we look at extreme values, the picture is slightly different. Indeed, the worst 5% days to recovery can be much higher.

For instance, the high profitability factor takes the equivalent of eight and a half years to recover from extreme losses. Despite its slow recovery, this risk factor is very popular among investors and index providers because of its recent performance, even if it can suffer large worst 5% one-quarter rolling returns (as seen in figure 5). Its popularity is aided by its very poor performances taking place during periods when it was much less popular than the three historical factors, value, size and momentum; consequently, most investors did not have to recover from the losses associated with it.

The value factor has the second highest number of days to recover, which is close to eight years. The lowest number of days to recover are seen in the low volatility and size factors with 506 and 509, or rather less than two years. When we look at the equally weighted portfolio, the worst 5% days to recover is slightly higher than two years. This highlights the benefits of diversification across the six rewarded factors, which make investors less dependent on the performance of any one specific rewarded factor.

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FIGURE 4

Factor performance distribution in bear and extreme bear market regimes

The table shows the distribution of L/S factor performance in bear and extreme bear market regimes. The analysis is made from 31-Dec-1984 to 31-Dec-2019 on the EDHEC-Risk Developed Long-Term Track Record universe. The bear and extreme bear market regimes are defined based on the performance of the EDHEC-Risk Developed LTTR Cap-Weighted index. Using a rolling quarter window with a one-week step, we classify the observations in bear/bull market regimes if the rolling quarterly performance of the cap-weighted index is negative/positive. Half of these observations that are below/above the median are classified in extreme bear/bull market regimes. Based on those two classifications we calculate different measures of factor performance. Worst/Top 5% rolling return is the 5th/95th percentile of the quarterly rolling returns time-series of each factor. Conditional mean (< worst 5%) is the mean of quarterly rolling returns below the fifth percentile. Conditional mean (> top 5%) is the mean of quarterly rolling returns above the ninety-fifth percentile. The last row shows the factor performance during the Covid-19 period (20-Feb-2020 to 23-Mar-2020). L/S factors are constructed as defined in Figure 1.

Factors	SMB	HML	MOM	LVOL	HPRO	LINV	Avg
Bear regimes							
Average	-1.80%	-0.19%	1.45%	4.70%	1.51%	1.27%	1.16%
Worst 5%	-14.26%	-6.72%	-12.62%	-5.69%	-3.36%	-2.98%	-7.61%
Conditional Mean (< Worst 5%)	-18.34%	-9.72%	-17.22%	-8.51%	-5.45%	-4.72%	-10.66%
Top 5%	8.72%	8.44%	12.83%	19.67%	6.54%	10.71%	11.15%
Conditional Mean (> Top 5%)	13.67%	17.13%	16.20%	32.58%	7.41%	12.28%	16.55%
Extreme bear regimes							
Average	-2.78%	-0.42%	1.55%	6.18%	2.03%	1.94%	1.42%
Worst 5%	-16.91%	-7.81%	-13.52%	-4.44%	-3.07%	-3.66%	-8.24%
Conditional Mean (< Worst 5%)	-20.82%	-10.29%	-16.81%	-9.02%	-5.42%	-5.96%	-11.39%
Top 5%	9.07%	12.64%	12.83%	25.76%	6.79%	11.01%	13.02%
Conditional Mean (> Top 5%)	12.42%	17.40%	16.13%	34.70%	7.62%	12.58%	16.81%
Covid-19	-6.83%	-6.62%	5.92%	2.61%	4.16%	-1.65%	-0.43%

FIGURE 5

Extreme absolute losses

We use daily USD total returns from 31-Dec-1984 to 31-Dec-2019 on the EDHEC-Risk Developed Long-Term Track Record universe. All statistics are calculated on a rolling basis over a one-quarter window size, with a one-week step size. Worst 5% rolling return is the 5th percentile of the quarterly rolling returns time-series of each factor. The L/S factors are constructed as detailed in Figure 1.

	SMB	HML	MOM	LVOL	HPRO	LINV	EW
Worst 5%	*-9.2%*	*-6.2%*	*-7.8%*	*-6.9%*	*-5.0%*	*-3.1%*	*-1.4%*

FIGURE 6

Distribution of days to recover from extreme absolute losses

The table shows the median and worst/top 5% days that it takes to recover from the worst 5% rolling returns over different periods. The analysis is conducted from 31-Dec-1984 to 31-Dec-2019 on the EDHEC-Risk Developed Long-Term Track Record. Rolling returns were calculated with a step size of five days over one-quarter and three-year return windows. The worst 5% percent rolling returns are extracted, and then it is calculated how many days it takes to recover the loss from the worst 5% percent rolling return. We include days to recovery when they are over the threshold of 1000 days in order to not neglect too many cases which would distort the calculations of statistics (this mostly pertains to the SML and HML factors for which many drawdown periods did not completed recovery until 31-Dec-2019). Calculations were done on a weekday basis. Calculations were done on a weekday basis. Calculations were done on a weekday basis. The L/S factors are constructed as detailed in Figure 1.

	SMB	HML	MOM	LVOL	HPRO	LINV	EW
Median	*111*	*210*	*318*	*172*	*405*	*125*	*97*
Worst 5%	*509*	*2008*	*981*	*506*	*2232*	*1012*	*546*
Top 5%	*17*	*17*	*75*	*16*	*136*	*22*	*23*

Figure 6 shows that the median days to recover range from 111 for the size factor to 405 for the high profitability factor.

values are interesting because they provide a summary value that includes the largest number of recovery cases, but when we look at extreme values, the picture is slightly different. Indeed, the worst 5% days to recovery can be much higher.

For instance, the high profitability factor takes the equivalent of eight and a half years to recover from extreme losses. Despite its slow recovery, this risk factor is very popular among investors and index providers because of its recent performance, even if it can suffer large worst 5% one-quarter rolling returns (as seen in figure 5). Its popularity is aided by its very poor performances taking place during periods when it was much less popular than the three historical factors, value, size and momentum; consequently, most investors did not have to recover from the losses associated with it.

The value factor has the second highest number of days to recover, which is close to eight years. The lowest number of days to recover are seen in the low volatility and size factors with 506 and 509, or rather less than two years. When we look at the equally weighted portfolio, the worst 5% days to recover is slightly higher than two years. This highlights the benefits of diversification across the six rewarded factors, which make investors less dependent on the performance of any one specific rewarded factor.

CONCLUSIONS

Factor performance during the COVID-19 crisis was strong both in terms of the magnitude of returns and also in the dispersion. Indeed, the size, value and low investment factors delivered strong negative returns, while the momentum, high profitability and low volatility factors posted strong positive returns. However, given our drawdown analysis, using more than 35 years of historical data, we can conclude that they were not unprecedented performances and do not call into question the usefulness of this type of strategy or benchmark over the long term. Moreover, whether we look at previous market crisis or bear and extreme bear market regimes, factor performance during the COVID-19 period was in line with historical observations. Here again there is nothing that would lead us to say that the behavior of factors during the COVID-19 crisis calls into question the risk reduction and bear market performance capabilities measured over the long term. It simply involves recognizing that, as is very often the case in finance, averages that are determined over a long period are not necessarily found in extreme and short-term return distributions.

Finally, the main conclusion from our analysis is that the importance of diversification across the six consensus risk factors remains intact. Even if some of them can generate strong negative returns during market drawdowns or bear market regimes, the only way to reduce this exposure to a factor specific underperformance is to be exposed to all of them. This is confirmed when looking at the expected days to recover from extreme losses; the equal-weight factor portfolio exhibits the lowest median number of days to recover. This result is consistent with the fact that combining factors over the long-term is robust from an absolute perspective since investors are less dependent on the negative performance of any one particular factor. From this point of view, good factor diversification measurement is a major challenge in analyzing the robustness of different factor strategies. In judging the quality of a factor strategy, investors would be better advised to analyze this diversification rather than relying on the in-sample returns of these same strategies, which may be the result of very poor, but lucky, diversification over the period.[1]

[1] *On this subject, please consult Amenc, N. and D. Korovilas (2020). Robustness of Smart Beta Strategies: A Competitor Overview, Scientific Beta white paper. Available at: www.scientificbeta.com/download/file/robustness-smart-beta-strats-competitor-overview.*

Smart Beta Strategies and the Crowding Effect

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- **Assertions that the popularity of smart beta strategies will ultimately cancel out their benefits are not based on solid evidence.**
- **Time variation in factor returns is expected, as factors are risky and vary with economic cycles.**
- **Evidence suggests that long-term premia have not disappeared after they have become widely known.**
- **Investors who seek novel exotic factors to avoid crowding will end up with heightened data-mining risks.**

A recurring criticism of smart beta strategies is the presumption of a risk of crowding. The idea is that, as the popularity of successful smart beta strategies grows, flows into these strategies will ultimately cancel out their benefits. However, as of today, there is no solid evidence of any significant negative effects of crowding on performance. This, of course, does not mean that such evidence may not be produced in the future, but it is important to ask what current claims about crowding are founded upon. The answer is often that we are in the sphere of unfounded assertions. Moreover, even when looking at the reasoning behind the supposed risk of crowding, one discovers several problems with the common wisdom.[2]

Crowding risk and economic explanations of factor premia

Whether or not we should expect crowding in smart beta strategies is closely related to the economic explanations of the premia we observe in the data. If a factor premium is explained rationally as risk premium, it is likely to persist, because some investors will rationally avoid a tilt despite the higher returns. If, on the contrary, factor premia are due to systematic errors that investors correct over time, factor premia may indeed narrow, unless limits to arbitrage exist that impede benefiting from these errors.

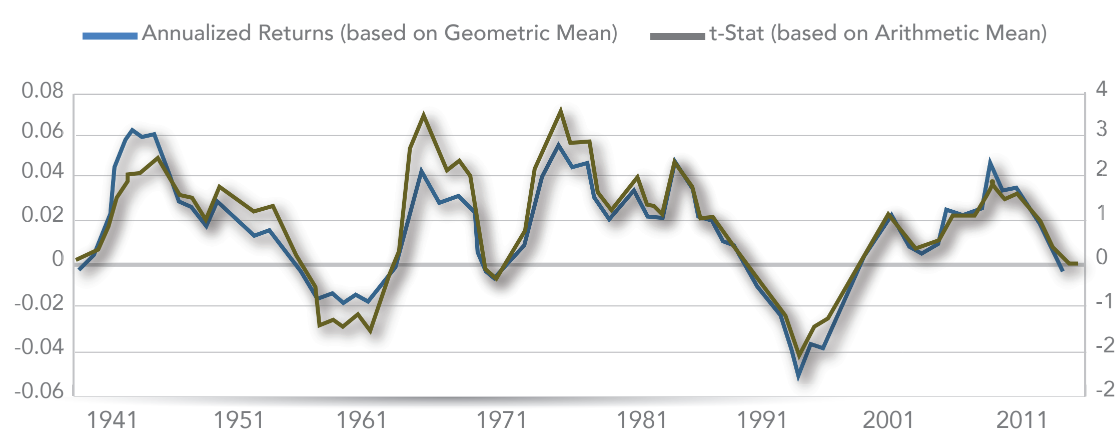
Some who theorize about the existence of crowding argue that the losses occurring in a particular factor at some point in time are evidence of crowding. However, claiming that there must be crowding in a factor because it suffers from losses completely ignores the nature of risk premia. All risk factors will have returns that vary substantially over time, and only an analysis of long-term data can lead to any meaningful conclusions on the average premium.

An example of the difficulties in concluding on changes in factor premia is the small-cap effect. The growing belief that the size effect has disappeared is often based on short-term analysis.[3] In figure 1 we show the size premium (annualized return) and its associated t-statistic over rolling periods of 15 years.

The results in figure 1 suggest that, at times, one will tend to conclude that the premium has disappeared when looking at such time periods of 15 years.[4] This shows that focusing on short-time windows is ill-suited to drawing inferences on the long-term behavior of factors. Losses in any factor strategy are not evidence of crowding; they may simply suggest that the reward for holding the factor comes with associated risk.

FIGURE 1

Rolling 15-year average annualized return premium of the Size Factor (SMB) in USA (1926-2019)
US Size Factor (SMB) returns are obtained from Kenneth R. French's data library http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The analysis is based on daily returns from 01/07/1926 to 31/12/2019. Starting from 1926, 15-year average annual returns are calculated by rolling each year forward until 2019 and the corresponding t-statistics are calculated.



Macroeconomic conditions contribute to factors' short-term variations

One of the rational explanations of the factor risk premia is the relationship between factor returns and the business cycle. Investors should care about how factors behave under different macroeconomic conditions because these will affect their marginal utility. The link between factors' expected returns and macroeconomic conditions is well documented in the financial literature.[5] Recent research by Scientific Beta[6] builds on previous empirical findings to select candidate macro variables and assesses the corresponding sensitivities across six consensus equity factors.

Figure 2 shows that factors indeed come with significant macroeconomic risks. Factor returns differ significantly across states of the macro-variables.[7] None of the factors is neutral with respect to all of the variables. The macro spreads are not only statistically significant but also important economically, in terms of magnitude. For example, the annualized return spread of the low investment factor and the value factor across states with different interest rate conditions (either short rate or term spread) exceeds 7% in absolute terms, which is about twice as large as the unconditional average return of these factors. Thus, an investor looking to harvest the premia of these factors is strongly exposed to changes in macroeconomic conditions.

This shows that short-term periods of factor underperformance due to variations in the macroeconomic environment are to be expected, and do not represent evidence of crowding.

Where is the evidence?

While there is no solid evidence on crowding effects in smart beta indexes, recent studies examine potential effects of wider use of well-documented factors. However, it should be emphasized that such recent studies do not provide clear evidence to suggest that factor premia are likely to disappear because of crowding. Below, we review recent evidence distinguishing between short-term and long-term effects:

- Short-term effects are due to many investors following a similar rebalancing schedule to invest in a factor. For example, even if the long-term value premium persists, implementing value exposure through a popular index could lead to a shortfall for investors.

2 In a recent white paper (Amenc, Bruno, and Goltz, 2020), Scientific Beta's researchers provide a comprehensive discussion on the evidence of crowding in smart beta indexes.
3 See, for example, Hirshleifer (2001), and Horowitz, Loughran and Savin (2000).
4 In particular, around the turn of the millennium, it was popular to state that the premium likely disappeared after it became widely known following its publication by Banz in 1981. Figure 1 shows indeed that the return to the size factor was clearly negative during the late 1990s. However, the size factor then showed strong positive returns up to the year 2013.
5 A summary of the evidence of this literature is reported in Amenc, Bruno, and Goltz (2020).
6 See Amenc et al. (2019).
7 States are defined by innovations in the seven macroeconomic variables.

- Long-term effects are independent of a particular implementation. If the long-term premium of a factor is driven to zero by popular demand, this would have a negative effect for all value strategies.

Short-term effects: Does crowding increase smart beta's cost of replication?

An unpublished working paper by Yost-Bremm (2014) examines short-term effects of crowding. Even though the paper finds evidence of abnormal trading volume for stocks that switch across thresholds of standard factor portfolios, the results do not imply that there is a burden for strategies following standard factors. In fact, the evidence presented is strong for effects on trading volume but much weaker for effects on stock returns.

Despite the absence of strong results, Yost-Bremm (2014) is sometimes referred to as support for the belief that smart beta strategies have severely limited capacity,[8] meaning that, as the assets under management grow, the price-impact costs generated at rebalancing will quickly erode their profits.

However, the crucial determinant of price impact is the liquidity of the strategies. Indeed, a common finding is that the application of proper investibility rules contributes to reduce the costs of replication and increases capacity.[9] For instance, Bregnard, Bruno and Goltz (2019) estimated the price impact generated by the rebalancing of two multi-factor smart beta indexes with stringent investibility rules, finding no evidence of significant price effects, as shown in Figure 3.[10] Indeed, that the performance drag is close to zero and even negative suggests that performance of the two smart beta indexes is not hurt by price effects during their rebalancing events. This shows that properly implemented smart beta strategies have not suffered because of price impact. Therefore, the effect of crowding on price-impact costs cannot be generalized.

Long-Term effects: Do factor's risk premia disappear after publication?

If investors automatically "crowd" into factors once they know about the documented reward, one would expect the premia to decline after publication of the respective paper. McLean and Pontiff (2016) address the question of whether the publication of results showing the existence of a factor premium destroys this premium going forward, comparing the pre- and post-publication returns of almost 100 different factor strategies. McLean and Pontiff (2016) attribute a 32% drop in returns to the publication effect. However, the authors also reject the hypothesis that post-publication anomaly returns decay entirely. The key conclusion is thus that while the publication of academic research tends to lower returns going forward, these premia do not disappear. It is noteworthy that this result is obtained when analyzing a large number of almost 100 factors, which include not only standard factors. Indeed, that the authors reject the hypothesis of disappearing rewards even for an extensive set of factors, which may include strategies that do not have a strong risk-based rationale, is strong evidence against the hypothesis that factors' premia are disappearing because of crowding.

More recently, Jacobs and Müller (2020) extended the analysis of post-publication returns to international data. They confirm the findings of McLean and Pontiff (2016) for U.S. equities — that there is some reduction in factor premia, but this reduction does not eliminate the premia. For international markets outside the U.S., they do not find any evidence that premia have shrunk at all following publication.

FIGURE 2

Sensitivity of premia to surprises in macroeconomic state variables

The first panel of the table reports unconditional annualized geometric mean returns of six equity risk factors. The second panel reports macro spreads, defined as the difference between the annualized geometric mean returns of equity factors when innovations in state variables were in the highest and lowest quartiles. Innovations come from VAR(1) model, and are orthogonalized to the market excess returns. Significance based on Welch's t-test at the 10%, 5% and 1% levels are indicated by *, ** and ***, respectively. The results are based on monthly data from July 1963 to December 2017. Data source: CRSP, K. French data library, AQR dataset, FED of St. Louis. (This table is from Amenc et al. 2019)

	Size	Value	Mom	Low Risk	High Prof	Low Inv
Unconditional Performance						
Annualized Return	2.5%**	3.7%***	7.0%***	9.3%***	2.7%***	3.2%***
Macro Spreads						
Short rate	3.8%	-8.4%*	1.4%	-10.5%**	-0.6%	-7.8%***
Term spread	1.2%	9.2%**	-13.5%**	5.4%	-5.6%*	7.8%***
Default spread	-5.3%	-0.1%	-2.0%	2.5%	6.8%**	-1.8%
Dividend yield	4.3%	-5.9%	-6.1%	-18.5%***	-14.8%***	-3.5%
Effective spread	11.1%**	0.1%	6.7%	4.5%	2.5%	-0.8%
Price impact	-3.0%	-0.3%	4.8%	0.1%	-1.9%	-2.6%
Systematic volatility	-9.9%**	-6.8%	-4.9%	-16.2%***	1.8%	-4.6%

FIGURE 3

Performance drag

The table reports the annualized average performance drag (PD) from December 2013 to March 2018 (live period) of the US Multi-beta multi-strategy 4 factors EW and the Dev. ex- US Multi-beta multi-strategy 4 factors EW. We report the PD obtained using the CAR estimated with the characteristics based methodology of Daniel et al. (1997) for two event windows AD:ED and ED. The demand pressure used for selecting the stocks is weight changes. This table is taken from Bregnard, Bruno and Goltz (2019).

Event Date	US MBMS 4-Factors EW	Dev. Ex-US MBMS 4-Factors EW
AD:ED	*-0.02%*	*-0.07%*
ED	*0.00%*	*-0.01%*

Figure 2 shows that factors indeed come with significant macroeconomic risks. Factor returns differ significantly across states of the macro-variables.

[8] See Blitz and Marchesini (2019).
[9] See for instance, Frazzini, Israel and Moskowitz (2015), Ratcliff, Miranda and Ang (2017), Novy-Marx and Velikov (2016, 2019), and DeMiguel et al. (2019).
[10] Note that the performance drag from any price effects would also be included in index performance, as long as it consists of a live track record during times when actual investments replicating the index took place.

Building on the extensive evidence in the literature that publication does not destroy factor premia, we provide a simple illustration using the six most consensus-based factors.[11] We construct a multi-factor portfolio that allocates equal weights each year only to factors (long-short portfolios) that had been published at that time. Starting with only one factor in 1972, the strategy adds an additional factor once it gets published. Figure 4 shows that the return of such a strategy would have been positive (the annualized return is 5.44%) and strongly statistically significant (the t-statistic is 5.53).

Both the extensive empirical evidence and this simple illustration suggest that the benefits of factor investing do not disappear when everybody knows about factors.

CONCLUSION — A PRACTICAL ANSWER TO CROWDING CONCERNS

It is striking that we have substantial talk in the industry about crowding while there is no evidence that it has occurred. In addition to there being no convincing supporting evidence, thinking about the economic rationale behind a specific premium should provide ample answers to allay any crowding concerns. If factor returns are explained by a risk-based rationale, there is no reason to expect these returns to disappear simply because a strategy becomes widely known or widely followed. Evidence in the financial literature shows that there is a significant link between factor returns and the business cycle, which is consistent with the intuition that factor risk premia represent compensation for exposure to macroeconomic risks. Moreover, precautions against crowding risks can be taken by careful implementation adopting proper investibility rules.

The confusion about factor crowding can have negative consequences for investors. It may lead them to invest in novel "exotic" factors, which in the end are not rewarded and expose them to heightened data-mining risks. In a recent paper, Amenc et al. (2020) extensively documented the risk of lack of robustness associated with over-fitted factors. Beside these negative consequences, one can only regret that many smart beta providers repeat assertions that are as little conceptually grounded as they are empirically verified.

FIGURE 4

Post-publication performance

The graph reports the cumulative monthly returns of a portfolio rebalanced at the end of each year that equal-weights across all the factors that are publicly known at that time. Initial portfolio consists of Low Beta factor. The markers on the graph indicate the date when corresponding factor was included in the portfolio (next rebalancing date after publication). We use monthly returns from Dec. 31, 1972, to Aug. 31, 2019, for US stocks. The data source for BAB (Low Beta) factor monthly returns is AQR, and for other factors - K. French library. We also report the annualized return of the portfolio and its t-stat. Under the graph, we report the seminal papers to which we attribute the discovery of the factor.

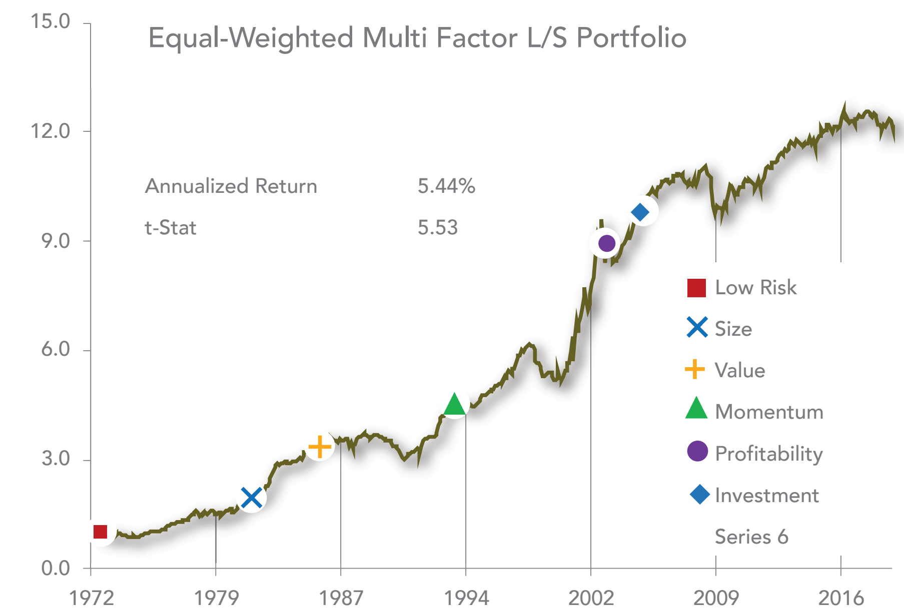


Figure 4 shows that the return of such a strategy would have been positive (the annualized return is 5.44%) and strongly statistically significant (the t-statistic is 5.53).

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[11] *See Amenc, Bruno and Goltz (2020) for a detailed discussion.*

Examining the Robustness of Various Smart Beta Strategies

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- **Popular smart multi-factor indexes suffer from a lack of robustness in the way they are constructed.**
- **Their index design process exposes them to risks such as factor fishing and factor redundancy, non-robust weighting schemes that introduce idiosyncratic unrewarded risks, and high factor dependencies.**
- **Scientific Beta smart beta indexes are designed with this issue in mind, and consequently benefit from good factor exposure quality, reducing conditional dependencies and increasing confidence in their expected out-of-sample outperformance.**
- **We discuss appropriate measurements of robustness and describe the robustness protocol that Scientific Beta employs to evaluate the robustness of strategies under scrutiny.**
- **As a last step, we employ our robustness protocol tests across the set of multi-factor strategies under consideration to quantitatively evaluate how their proposed objectives are being met in practice.**

1. Introduction

When it comes to making investment decisions, assessing the robustness of smart beta strategies should play a central role in every investor's due diligence process. It is essential to check that interesting in-sample results are complemented by a consistent construction framework as well as transparency on the methodology and implementation from the side of the strategy provider.

This article describes the sources of a lack of robustness in the design of smart beta strategies and explains the need for robustness checks in performance analysis of such strategies. We also outline the various methods by which Scientific Beta improves robustness. In particular, we outline the robustness issues present in a set of smart multi-factor indexes popular in the marketplace.

Investors should also be able to measure a strategy's robustness directly using appropriate tools and metrics in order to cross-check whether its behavior is consistent with its stated objective. However, assessing the robustness of a strategy based on historical simulations can be challenging due to sample dependence. For this reason, we discuss appropriate measurements of robustness and describe the robustness protocol that Scientific Beta employs to evaluate the robustness of strategies under scrutiny.

As a last step, we employ our robustness protocol tests across the set of multi-factor strategies under consideration. This allows us to quantitatively evaluate whether their proposed objectives are being met in practice, measure their overall robustness, and identify the issue of poor factor diversification and factor conditionality typically seen in these strategies. By contrast, we show how Scientific Beta's multi-factor indexes benefit from good factor exposure quality, which reduces the conditional dependencies of our strategies and increases confidence in the expected out-of-sample outperformance.

2. Robustness issues in index design and how to improve robustness

A lack of robustness in smart beta strategies is typically caused by exposure to three different risks in their construction process, namely factor fishing and factor redundancy, non-robust weighting schemes that introduce idiosyncratic unrewarded risks and high factor dependencies. Scientific Beta proposes solutions by which robustness of such strategies can be improved. As an illustration, we provide a list of multi-factor products offered by different providers and highlight flaws in the robustness of their design (see figure 1).

Factor fishing risks and factor redundancy: Harvey, Liu and Zhu (2016) document a total of 314 factors with positive historical risk premia, showing that the discovery of the premium could be a result of data mining. Alternative or new factor definitions may also be redundant with respect to consensus factors from the academic literature (Fama and French, 1996), e.g. dividend yield, leverage or sales growth. Among competitor strategies we see a proliferation of factor definitions (see figure 1) that often depart from the definition of factor risk premia as documented in academic studies and the economic rationale underpinning their existence, something that should be a key requirement for investors to accept factors as relevant in their investment process. In addition, a consistent index framework can prevent model mining by limiting the number of choices by which indexes can be constructed. Scientific Beta uses a consistent smart beta index design framework for the construction of its entire set of smart beta indexes, known as the Smart Beta 2.0 approach (Amenc, Goltz and Martellini, 2013).

Idiosyncratic unrewarded risks: The factor investing literature has documented broad relationships between factor exposures of diversified portfolios and their performance and warned against applying these relationships with high precision at the stock level (Fama and French. 2012). A strategy that is concentrated in few stocks runs counter to a factor investor's investment objective of seeking broad exposure to the equity asset class and leads to under-diversification and risk/reward inefficiency. In Scientific Beta's Smart Beta 2.0 approach, the weights for selected stocks target portfolio diversification using risk parameters (to reduce non-rewarded idiosyncratic risks). In addition, combining different weighting strategies — a concept called "diversifying the diversifiers"[12] — allows diversification of model risks which further reduces unrewarded risks.

Strong dependency on individual factor exposures: A common theme across competitor strategies is the use of factor scores as a measure of factor exposure in determining portfolios. Factor scores, however, suffer from "double counting" of exposures, which is due to their lack of regard for the correlation structure of factors. A factor strategy that optimizes allocation according to factor scores can easily end up with sizeable negative exposures to most of the other rewarded factors. This can lead to multi-factor allocations that can be detrimental to performance as factor dilution will prevail, cancelling out targeted exposures to rewarded factors.

In order to diversify the factor allocations well, Scientific Beta's high factor intensity (HFI) filter integrates the cross-sectional variability of factor intensity over time and across the six well-rewarded factors. It offers protection against negative exposure to other rewarded factors in the single-factor sleeve construction. The resulting highly efficient single smart factor indexes are then appropriate building blocks for a robust multi-smart factor allocation.

3. Measuring robustness

Measuring the robustness of smart beta strategies is important to gain a proper understanding of the stability of their performance and risks in different market environments or under changing assumptions. This ensures that investors can understand their performance and risks and have reasonable expectations for the strategies under different circumstances. For this purpose, Scientific Beta has developed its own robustness protocol covering five dimensions of robustness:

i. Factor Exposure: Well-balanced exposures are the key to robustness, and this part of the protocol gives a very good indicator of factor strength and factor diversification quality through the factor exposure quality metric. It is defined as the product of factor intensity and factor deconcentration. Factor intensity (the sum of non-market factor betas) measures the strength of factor exposures. Factor deconcentration (the inverse of the sum of squared relative betas) measures the diversification of factor exposures of a portfolio. Factor exposure quality reveals whether factor intensity goes hand-in-hand with a more balanced factor exposure.
ii. Conditional Performance: Conditional performance analysis allows investors to identify whether their portfolio is highly conditional on certain states of

[12] See Timmermann (2006), Kan and Zhou (2007), Tu and Zhou (2010) and Amenc et al. (2012) on the benefits of combining portfolio strategies.

EXHIBIT 1

Design of competitor multi-factor products

Index	Methodology	Factor Definitions	Weighting scheme
FTSE Russell 1000 Comprehensive Factor	*Bottom-up approach to multi-factor allocations, known to lead to concentrated portfolios.*	*Value and Quality definitions based on composite variables, known to increase degrees of freedom and introduce data mining risks.*	*Sequential multiplicative tilts, around cap weights known to lead to concentrated portfolios.*
FTSE JPMorgan Diversified Factor US Equity	*Sector balanced allocation by inverse sector volatility, while sector not a rewarded risk relative to the benchmark. Arbitrary choice of factors: targets three factors, while JPM offers five factors as individual products.*	*Two factors (dividend yield and low volatility) otherwise offered as separate products are sub-components of composite Value (1/4 variables) and Quality (1/10 variables) definitions. Further arbitrary choice to split Quality in three families of the 10 total variables.*	*Targets higher weight for stocks with higher multi-factor scores - stock level characteristics are noisy and expected returns not linear with factor exposure.*
MSCI USA Diversified Multi-Factor	*Arbitrary choice of factors: targets four factors, but excludes low volatility, which otherwise is offered as an individual product.'*	*Value and Quality definitions based on composite variables, known to increase degrees of freedom and introduce high data mining risks.*	*Bottom-up optimization to maximize portfolio alpha score (equal-weight factor score per stock) including multiple constraints. Leads to selection of "grey" stocks that are not exposed prominently to any factor but simply have high average factor exposure.*
MSCI USA Factor Mix	*Arbitrary choice of factors: targets three factors, with a mixed selection relative to their Diversified Multi-Factor product (Value, Quality included in both, but now Low Volatility is included instead of Momentum and Low Size)*	*Proprietary models used in MSCI Minimum Volatility which constitutes a part of this index.*	*Top-down equal factor allocation which is in contrast with the bottom-up optimization approach in their Diversified Multi-Factor product.*
S&P GIVI US	*No explicit factor selection, whereby high volatility stocks are excluded and the investible universe of stocks is weighted according to a composite model of Value and Profitability factors.*	*Proprietary model (Residual Income Model) used to define the intrinsic value for each company, which is then used to weight stocks. The model uses metrics of Value and Profitability factors.*	*Weighting scheme depends on stock-level factor metrics which are known to be noisy and makes the wrongful assumption that individual stock-level expected returns are proportional to stronger factor measurements.*
RAFI Multi-Factor U.S. Index	*Strong dependence on their fundamental weighting definition (based on four accounting measures related to the Value factor), which underpins universe construction, stock selection and individual factor sleeve weighting.*	*Value, Quality and Momentum definitions based on composite variables. Low Volatility based on a metric extracted from a multiple regression of stock returns against global, countries and industry groups. Size is not a standalone factor portfolio but rather a multi-factor portfolio of the four other factors in small size universe segment.*	*Value, Low Volatility, Quality are fundamentally weighted and carry a strong dependence on a proprietary definition to weight portfolios, while Momentum is cap-weighted, which is known to produce concentrated portfolios.*
RAFI Dynamic Multi-Factor U.S. Index	*Same as above, and additionally employs timing of factors based on momentum and reversal signals, while research shows inferiority of factor timing relative to well-balanced multi-factor portfolios.*		
AQR Large Cap Multi-Style Fund	*Arbitrary choice of three factors: value, momentum and profitability. It is not an index and therefore the methodology is not entirely transparent.*	*All factor definitions based on composite variables, known to increase degrees of freedom and introduce data mining risks.*	*Security weighting is discretionary/ proprietary with mentions of liquidity concerns.*
DFA US Core Equity	*Claims of exposure to three factors: Size, Profitability and Value. It is not an index and therefore the methodology is not entirely transparent.*	*Analysis of construction methodology shows that this is a single-factor index (Size index) that reduces negative interaction with other two well-rewarded factors.*	*No clear indication of stock weighting mechanism. Size factor is explicitly targeted through stock selection and then stocks with Low Profitability and Growth are eliminated.*

the economy, e.g. bull-bear market conditions or under different economic conditions. We look at the relative performance of smart beta indexes under bull and bear return or volatility periods relative to market, sectors, factors or macroeconomic variables.

iii. Stability of Performance: Rolling Statistics and Outperformance Probability: Long-run average statistics on risk measures can hide serious fluctuations over shorter periods. Therefore, we compute a set of rolling statistics that enables us to assess the stability and the extreme values of these measures. We also compute the probability of outperformance, defined as the empirical frequency of outperforming the cap-weighted reference index over a given investment horizon. Its objective is to assess the sensitivity of a strategy's performance to its entry point.

iv. Robust Inference: We also want to know how a strategy compares to a given benchmark. Simply comparing their risk-adjusted returns and concluding that the highest one is reliably better would ignore the fact that we work with only a sample of data and the potential for data mining in the design. To assess whether an observed difference is statistically significant, we conduct a hypothesis test as per Ledoit and Wolf (2008) to test for Sharpe ratio differences.

v. Out-of-sample Tests: We conduct out-of-sample tests to ensure that obtained results also hold in different datasets. We calculate and check that the key statistics of interest for a strategy align for a different and l onger data sample using our long-term U.S. dataset of more than 45 years.

4. Case study: comparison of the quality of factor exposures in popular factor strategies

Given the design limitations of the popular multi-factor strategies we pointed out in the second section above, it becomes important to gauge whether these strategies yield satisfactory results across the different dimensions of robustness. Therefore, we evaluate them, including the Scientific Beta High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW (SciBeta HFI Div MBMS 6F 4S EW) index and the version with the market beta adjusted risk control, under the lens of our robustness protocol. Figure 2 gives a concise overview of our robustness metrics over the past 10 years.[13] These numerical results highlight some of the robustness issues of popular multi-factor strategies that were evident in the design phase.

Our index, which benefits from the HFI filter, delivers much stronger factor exposure quality as a result of stronger factor intensity and factor deconcentration. The factor exposure quality of our standard multi-factor index (similar results for the MBA) is 118% higher (3.24 against 1.49) than that of competitors that mostly do not take account of cross-factor interactions but instead rely on scores and bottom-up construction approaches.

We underline that some competitors' strategies are concentrated with fewer than three effective factors. Well-balanced exposures across the six factors is key to the robustness of a strategy's outperformance, since it avoids the latter becoming too dependent on the underperformance of a specific factor. We emphasize that the factor performance contribution, which is a direct consequence of the strong factor exposure quality of our multi-factor index over the period, is well above (3.2×) the average measure for competitors, some of which even show negative factor contributions.

The table further reveals that the majority of competitor strategies fail the robust inference test for Sharpe ratio differences (p-values higher than the 1%, 5% or 10% confidence levels) and, therefore, show no statistically significant difference from the benchmark. Even the two indexes that pass the test are among the lowest in terms of factor exposure quality as a result of their low and concentrated factor exposure. Instead we see that the +0.17 Sharpe ratio differences for the Scientific Beta indexes are statistically significant, accompanied by healthy factor exposure quality metrics.

Many competitor strategies hit conditional dependencies of (or close to) 2.00, which is the upper limit for our conditional ratio metric. Clearly their performance is highly dependent on certain states of the economy and any outperformance is unlikely to be repeated should these conditions change in the out-of-sample period. Instead, we see that our market beta-adjusted index, which reduces the non-factor risk of market beta gap, shows very low conditional ratios.

We also see outperformance probabilities that decline over time for some competitor indexes, indicating that investors expecting long-term outperformance may face poor financial consequences. On the other hand, we see a healthy (strong and upward sloping) term structure of outperformance probabilities for the Scientific Beta indexes, highlighting their usefulness as long-term vehicles for outperformance.

The rolling statistics part of the protocol allows us to assess the distribution of risk measures such as the

EXHIBIT 2

Robustness synthesis of competitor and Scientific Beta indexes

10 years to Dec. 31, 2019, in USD	FTSE Russell 1000 Comprehensive Factor	FTSE JP Morgan Diversified Factor US Equity	MSCI USA Diversified Multi-Factor	MSCI USA Factor Mix	S&P GIVI US	RAFI Multi-Factor U.S. Index	RAFI Dynamic Multi-Factor U.S. Index	DFA US Core Equity	Average of Competitors	SciBeta HFI US MBMS 6F 4S EW	
										Standard	MBA Overlay
ROBUST INFERENCE: SHARPE RATIO TEST VS BENCHMARK											
Difference in Sharpe ratio	0.11	0.10	0.01	0.15	0.11	0.04	0.04	-0.08	0.06	0.17	0.17
P-value	21.50%	14.60%	90.85%	0.07%	2.85%	48.26%	57.69%	15.73%	NR	2.19%	1.04%
CONDITIONAL RATIOS											
Macro*	0.30	0.45	0.30	0.72	0.68	0.33	0.27	0.54	0.45	0.37	0.19
Market	1.61	1.98	0.99	1.94	1.99	1.98	1.92	2.00	1.80	1.90	0.49
Factors	1.24	1.96	1.35	1.81	1.91	1.91	2.00	2.00	1.77	1.70	0.57
Sectors	0.93	1.56	1.25	1.67	1.99	1.41	1.24	1.99	1.50	1.29	0.43
OUTPERFORMANCE PROBABILITY OVER BENCHMARK											
One year	60.6%	51.4%	60.6%	54.1%	53.2%	55.0%	56.0%	41.3%	54.0%	56.9%	81.7%
Three year	72.9%	68.2%	72.9%	76.5%	64.7%	55.3%	54.1%	38.8%	62.9%	71.8%	91.8%
Five year	73.8%	60.7%	73.8%	88.5%	50.8%	49.2%	52.5%	34.4%	60.5%	96.7%	100.0%
ROLLING STATISTICS (3Y ROLLING WINDOW)											
5% worst rolling Vol	18.1%	16.8%	18.7%	15.8%	16.1%	17.8%	18.3%	20.2%	17.7%	16.3%	18.9%
5% worst rolling tracking error	4.9%	3.5%	3.4%	2.8%	2.7%	3.0%	2.8%	3.2%	3.3%	3.5%	3.0%
FACTOR EXPOSURES											
Market	0.94	0.91	1.01	0.90	0.90	0.96	0.97	1.06	0.96	0.88	1.01
Factor Contribution	0.75%	1.22%	-0.11%	1.61%	1.40%	0.75%	0.56%	-1.14%	0.63%	2.04%	2.06%
Factor Intensity	0.65	0.34	0.54	0.20	0.31	0.50	0.52	0.37	0.43	0.63	0.63
Factor Deconcentration	3.84	2.24	4.65	2.00	2.59	3.96	4.35	1.96	3.20	5.14	5.11
Factor Exposure Quality	2.48	0.77	2.50	0.40	0.81	1.98	2.24	0.72	1.49	3.24	3.22

[13] *Sufficient data is not available for the AQR Large Cap Multi-Style Fund and thus it is not included in the 10-year numerical analysis of the robustness protocol.*

In this article, we have assessed the robustness of a set of competitor and Scientific Beta indexes both from an index design point of view and with the lens of our robustness measurement protocol.

volatility and the tracking error. Finally, the out-of-sample analysis part of the protocol requires availability of strategy data and methodology in order to simulate it over the long-term U.S. dataset, and this is not available for competitor strategies.

5. Conclusion

In this article, we have assessed the robustness of a set of competitor and Scientific Beta indexes both from an index design point of view and through the lens of our robustness measurement protocol.

Competitor multi-factor strategies remain at a deficit compared to the stronger factor exposure quality of Scientific Beta indexes thanks to the use of the high factor intensity filter mainly, and the avoidance of factor scores as a metric to define factor exposure. This weak factor exposure quality explains the lesser risk-adjusted outperformance potential of competitor strategies over the long term. Of course, over the short term, luck can help a multi-factor strategy with a weak factor exposure quality, if not exposed to the specific factor that underperforms. Scientific Beta indexes not only have strong factor intensity but also very good factor deconcentration, which makes them less sensitive to the underperformance of one specific factor and allows them to benefit from a higher potential of outperformance over the long term.

We believe that it is essential that smart beta strategy performance reporting is accompanied by a measurement of the robustness of that performance. We have developed a framework to assess robustness according to five different dimensions and assess whether the uncovered risks are acceptable given the objectives of a strategy or not. We have observed a lack of robustness across competitor strategies manifested in various forms. The Sharpe ratio test for statistically significant differences fails for most competitor strategies, indicating no difference from the benchmark they aim to outperform. Conditional dependence on different market and economic states remains high, and as such, any outperformance observed in one sample is unlikely to repeat itself unless the same conditions prevail in the out-of-sample period and over the long term.

Overall, we believe that our robustness protocol makes explicit certain risks that would have otherwise remained hidden. Better understanding of a strategy's performance in different environments enables investors to make investment choices that are well aligned with their objectives.

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Should Intangible Assets Be Included in the Definition of Value?

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- **The value factor proxy does not aim to capture the true value of a stock, but aims to capture exposure to the risk of costly reversibility of assets in place.**
- **Including omitted intangible assets in the accounting book value is in line with the risk-based explanation for the value factor.**
- **An intangible-adjusted value factor adds investment value for multifactor investors.**
- **Alternative valuation ratios, such as earnings-to-price, fail to add value due to a large overlap with other well-known factors.**

Index providers question whether book-to-price still provides a suitable definition of the value factor. They argue that intangible assets such as brand capital and technological know-how play an increasing role, but are not recognized in reported book values.

Many providers prefer combining several accounting ratios to define value. They argue that a composite of valuation measures using earnings, sales or cash flows will be better able to capture the true value of a stock. Such an approach builds on the insights found in Graham and Dodd (1934).[14] This prominent book on "security analysis" provides guidance to stock-pickers on how to identify securities that are underpriced relative to their intrinsic value. A common misunderstanding of the value factor is that its definition provides a measure of intrinsic value that can be used to identify underpriced stocks.

Of course, a combination of accounting metrics does not infallibly reveal the true value of a stock. We can derive from first principles that — even if they are valued fairly — different firms may have discrepant accounting ratios, depending on their growth prospects and risk. Likewise, undervalued and overvalued firms may have identical accounting ratios. Valuation needs to account for investors' growth expectations and risk perceptions. Financial accounts, and even analyst forecasts, do not provide sufficient information. More generally, if true value could be extracted from financial and market data, there would not be an armada of active managers working hard to identify underpriced stocks.

Identifying true value is more an art than a science and best left to active managers. The value factor was never meant to provide a view on securities valuation and does not require true values as an input. Instead, factor investing builds on insights from asset pricing that have identified patterns in the cross section of expected returns. Exposure to the value factor captures differences in expected returns across stocks that reflect compensation for risk.

While they may not have higher volatility or higher market beta, value stocks tend to produce losses in bad times, when marginal utility of consumption is high. Investors need to be compensated for holding such risk. Academic research has identified a detailed economic mechanism that leads value firms to suffer in bad economic times. Such firms' value is mainly made up of assets in place, rather than growth options. If assets in place are costly to reverse, such firms cannot adapt easily to reduced output in bad economic times. The value of growth firms, on the other hand, mainly consists of growth options. Such firms can delay their growth options flexibly without incurring high costs. This leads value firms to suffer more in bad economic times. Investment patterns observed for listed firms confirm that downward adjustments of a firm's capital stock are indeed more difficult than upward adjustments, and such differences help explain the value premium.

Importantly, this theory does not imply that the book value should exclude intangibles. Instead, it considers that the book value captures capital investments, irrespective of whether conservative accounting rules also allow firms to report these values as investments instead of expenses. Empirical research has shown that investments into intangible capital increase systematic risk and are costly to reverse. Hence, we can apply the economic mechanism described above to both physical and intangible capital. Holding a large stock of either form of capital should lead to compensation for stockholders.

Intangible capital also exposes firms to shocks in financing conditions in the economy. For example, firms that rely on specialized know-how are exposed to a risk of key talent leaving the firm. Such talent dependency increases the risk exposure of firms to financing constraints, as key talent will tend to leave financially constrained firms when financing conditions deteriorate. Similarly, highly innovative firms may have to abandon research and development (R&D) projects under financial stress, leading to additional losses in bad times. More generally, firms cannot use intangible assets as collateral, exposing them to a risk of tighter financing constraints in bad economic times.

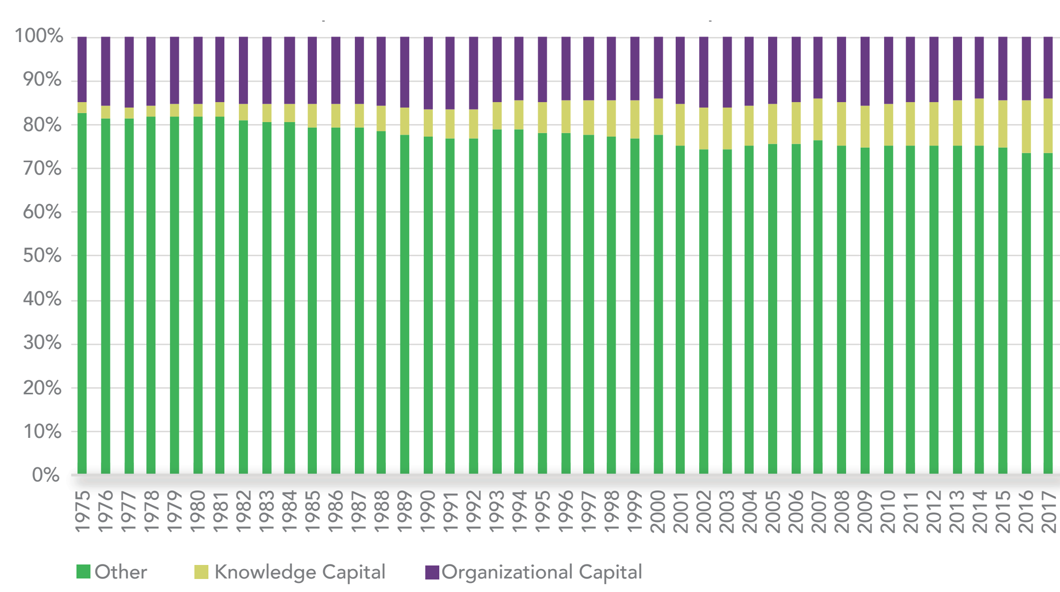
There is a simple answer to the problem that reported book value excludes intangible assets: we can adjust book values to include unrecorded intangibles. The academic literature has established measures of intangible capital. Rather than dismissing book-to-price as outdated, we can update how it is measured by including intangible capital in the book value.

Economists recognized early on that intangible capital is a crucial part of firms' capital stock. In addition to physical capital (property, plant and equipment), firms invest

FIGURE 1

Proportion of omitted intangible capital

The graph shows the average percentage of knowledge and organization capital in total capital across firms in the broad Compustat universe. The data is based on accounting statements for fiscal years ending between January 1975 and December 2017. Data source: Compustat.



14 *Graham, B., and D. Dodd (1934). Security Analysis, McGraw-Hill.*

in knowledge capital and organization capital. Knowledge capital is created through R&D that leads to know-how in the form of patents, improved processes and better product quality. Organization capital is created through investment in training, advertising and organizational design, and leads to a skilled workforce, brand recognition and customer relationships.

It follows that a standard approach to measuring intangible capital uses data on reported expenses that represent investments in this capital. In particular, R&D expenses can be reinterpreted as investment into knowledge capital, advertising expense as investment into brand capital, and part of overheads (selling, general and administrative expenses) as investment into organization capital.

Intangible capital represents a significant portion of firms' total capital. Figure 1 shows the average size of knowledge and organization capital relative to total capital across the broad U.S. stock market. These intangible assets represent on average around 20% of total capital. Consequently, omitting them might have a material impact. There is also some support for the increasing importance of intangible assets in recent years. This is driven by a strong rise in the proportion of knowledge capital, from 3% in 1975 to 12% in 2017. The proportion of organization capital has fluctuated around 15% throughout the past decades.

Recent research[15] conducted by Scientific Beta assesses an intangible-adjusted book-to-price factor, drawing on the definitions that academic research offers, and compares it to using other valuation ratios. Figure 2 shows the various alternative value proxies compared in the study. In light of the previous discussion on the discrepancy between security valuation and the concept of the value factor, a clear dichotomy arises. On the one hand, the use of the book-to-price or the intangible-adjusted book-to-price ratios is supported by the rationale of costly reversibility of assets in place. On the other hand, valuation ratios such as earnings- or cashflows-to-price do not have a clearly identified link with the risk of value stocks. Instead, the use of these proxies is grounded in the ideas of securities valuation.

Figure 3 gives a brief overview of the performance of these alternative value factors. We find that the intangible-adjusted book-to-price factor produces a particularly strong premium of 4.8%, compared with 2.2% for the standard value factor. However, most of the alternative proxies lead to higher value premia compared with the standard book-to-price definition.

It is important to look beyond standalone performance. The premium that remains unexplained by other rewarded factors is a better measure of the added value to a multi-factor investor's portfolio, since standalone performance ignores potential correlation between factors. The strong premium for the intangible-adjusted book-to-price factor remains significant when accounting for exposures to other factors, at 2.1% per year. The intangible adjustment thus improves investment outcomes for multi-factor investors. For an investor who held exposure to six factors, including the intangibles in the book-to-price factor increased the Sharpe ratio by more than 10% historically.

The intangible-adjusted book-to-price factor also aligns closely with the risks of the standard book-to-price factor. This alignment with a risk-based explanation is important for investors who are trying to capture a premium that will likely persist, even when it becomes widely known. The intangible-adjusted value factor leads to cyclical variation in market betas and earnings. Value stocks with high book-to-price also have higher operating leverage than growth stocks with low book-to-price when we adjust for intangibles. These observations all show that value stocks are riskier than growth stocks.

FIGURE 2

Overview of the alternative value proxies tested

Alternative value proxy	Adjustment
Book-to-price (B/P)	*The book-to-price ratio as proposed by Fama and French (2018)[16]*
Adjusting the book value for intangibles	
Book-to-price (B/P)	*The book-to-price ratio as proposed by Fama and French (2018)*
Using other valuation ratios	
Sales-to-price (S/P)	*Replace book value by sales*
Earnings-to-price (E/P)	*Replace book value by earnings*
Dividend yield (D/P)	*Replace book value by dividends*
Cash flow-to-price (CF/P)	*Replace book value by cash flows*
Composites	
Composite of S/P, E/P, D/P and CF/P	*Average of the z-scores of the individual metrics*
Composite of B/P, S/P, E/P, D/P and CF/P	*Average of the z-scores of the individual metrics*

Using alternative valuation ratios does increase returns compared to book-to-price. However, this improvement is explained by implicit exposures to other factors, such as quality and low risk. When adjusting for multiple exposures, the premium of a composite value factor is not distinguishable from zero, at –0.4% per year.

It is not a surprise that some of the alternative valuation ratios result in a tilt to other factors. In particular, using earnings or cash flows results in a strong tilt toward the profitability factor. Highly profitable firms generate high earnings and will also tend to have high cash flows. Consequently, these alternative value factors lead to increased overlap with the profitability factor.

Changing from book-to-price to other valuation ratios or composites reduces the Sharpe ratio of multi-factor portfolios due to this factor overlap. Figure 4 illustrates this point. The red bars show the Sharpe ratio of a portfolio containing the value, low risk and profitability factors. The blue bars show the correlation of the value factor with the other two factors. Switching to other valuation ratios such as earnings- or cash flows-to-price increases correlation with the other factors in the portfolio and reduces the Sharpe ratio. The opposite is true for the intangible adjustment, which results in a decreased correlation and an increased portfolio Sharpe ratio.

While the research we published on this topic focuses on U.S. data, we also confirmed that the key results are consistent across the various Scientific Beta universes, covering global geographic regions.

Combining various valuation metrics is an old recipe from the 1990s. Back then, investors did not have access to other factors, such as quality and low risk. However, investment practices have changed. Many investors now hold portfolios that combine multiple factors. Therefore, picking up implicit exposure to other factors in a composite value definition does not improve investment outcomes.

Such composite value definitions may indeed be approaching their expiration date. Book-to-price, on the other hand, is still looking fresh, especially when unreported intangible capital is included.

Figure 2 shows the various alternative value proxies compared in the study. In light of the previous discussion on the discrepancy between security valuation and the concept of the value factor, a clear dichotomy arises.

[15] See Amenc, N., F. Goltz, and B. Luyten (2020) Intangible Capital and the Value Factor: Has Your Value Definition Just Expired? Scientific Beta White Paper (February). Available at: https://bit.ly/39xO3tK

[16] Fama, E. F., and K. R. French (2018). Choosing Factors, Journal of Financial Economics (128)2: 234-252.

FIGURE 3

Factor performance

The top row of the table shows the standalone performance for alternative value factors. The remaining rows show the unexplained returns and the exposure to the high profitability factor based on a factor regression of the alternative value factors on the market, size, momentum, low volatility, high profitability and low investment factors. The value factors are based on the value scores described in Figure 2. The time period of the analysis is July 1976 to December 2018 and all measures are annualized. * indicates statistical significance at the 5% level. Data source: CRSP, Compustat, K. French database, AQR.

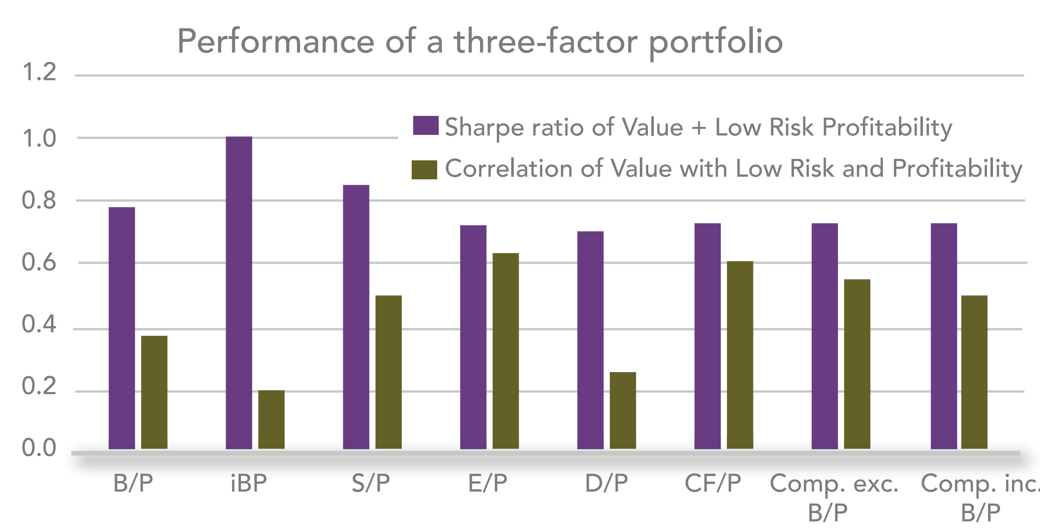
Factor performance	B/P	iB/P	S/P	E/P	D/P	CF/P	Comp. exc. B/P	Comp. inc. B/P
Median	111	210	318	172	405	125	97	
Standalone Return	*2.21%*	*4.82%**	*4.20%**	*2.95%**	*-0.28%*	*2.77%**	*2.66%*	*2.50%*
Unexplained Return	*-0.72%*	*2.09%**	*-1.24%*	*-0.27%*	*1.77%*	*-0.11%*	*-0.08%*	*-0.41%*
Profitability Exposure	*0.09**	*-0.01*	*0.44**	*0.57**	*-0.11**	*0.49**	*0.39**	*0.32**

Figure 3 gives a brief overview of the performance of these alternative value factors. We find that the intangible-adjusted book-to-price factor produces a particularly strong premium of 4.8%, compared with 2.2% for the standard value factor.

FIGURE 4

Performance of a three-factor portfolio

The graph shows the Sharpe ratio of a portfolio consisting of the value, low risk and profitability factors and the correlation of the value factor with the other two factors. The value factors are based on the value scores described in Figure 2. The time period of the analysis is July 1976 to December 2018 and all measures are annualized.



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- **Holding an ESG portfolio does not change the real economy in itself. It is the portfolio decisions that send strong and consistent signals on the attractiveness of stocks and the cost of capital to business directors, which allow them to change their practices.**
- **In this article we contend that, far from being incompatible with ESG engagement, ESG filtering sends a clear and consistent divestment message that allows an effective engagement policy to be implemented.**
- **Divestment is thus not a passive bystander approach to ESG challenges, or an investor capitulation. On the contrary, it is an effective form of action.**
- **We also demonstrate that such a top-down approach, which places ESG engagement in prime position in the portfolio construction process, avoids the mixed and inconsistent messages of score-based optimization and reweighting approaches.**

Introduction

It is often argued that an investor who is dissatisfied with a company's ESG behavior, and who wishes to remedy the situation, should stay on as a shareholder and engage with it. The reasoning is that when an investor divests, its influence over the company ceases. Moreover, the act of divesting is often presented as a passive approach that has no bearing on the company's management, a capitulation rather than a form of action.

On the contrary, we contend that divestment and engagement are both actions that promote change. Divestment is a force of change when it directly and indirectly contributes to raising the cost of capital for divested companies — this limits their ability to invest in projects the investor deems harmful and gives their management an incentive to improve their ESG performance. Lower share prices also reduce the value of management's share-based remuneration, thereby giving top executives an incentive to integrate ESG considerations. There is some uncertainty on what proportion of equity investors need to divest for the cost of capital to increase, and some researchers have pointed to a proportion of more than 20%, which would set a high bar for effective divestment campaigns. Note, however, that the proportion of assets invested according to at least one type of ESG strategy has, by 2018, topped the 20% bar in all developed equity markets except Japan (Global Sustainable Investment Review, 2018). As two thirds of these ESG-invested assets follow an ESG strategy that includes normative or negative/exclusionary screening, it appears plausible that at least some industries have seen their cost of capital increase due to the implementation of large-scale divestment policies. There is also some empirical evidence that the announcement of ESG-related divestments may negatively affect stock prices, both through direct impacts on share prices and indirect reputational impacts that participate in creating new norms. The effectiveness of divestment campaigns, such as the fossil-free divestment movement, could be reinforced by a strong non-linear relationship between the proportion of investors that divest and the effect on share prices/cost of capital, through tipping points that suddenly break any linear relationship.

Properly managed and executed engagement can also contribute to improvement in the ESG performance of investee companies. The empirical results of academic studies thus indicate that both engagement and divestment approaches can be effective in achieving the desired ESG outcomes. We also argue that these two strategies are entirely compatible — in particular, the rise of collaborative engagement campaigns, in which current and potential shareholders combine their forces, is testimony to the fact that divestment does not put an end to an investor's ability to engage with a company. Divestment and engagement, therefore, are not mutually exclusive. And a shareholder who engages with a company without signaling a willingness to draw a red line — by exit in case engagement fails — will enter the negotiation in a weak position; the possibility of divestment is in that sense a prerequisite for effective engagement. Conversely, engagement can make divestment campaigns more effective — noisy exits can be more impactful than silent ones. Therefore, far from being mutually exclusive, both engagement and divestment are mutually reinforcing.

Divestment is often wrongly reduced to two ESG filtering-based strategies, namely norms-based screening and negative/exclusionary screening. Proponents of ESG mixing strategies — i.e. so-called ESG integration strategies whereby ESG data and analysis are mixed with traditional financial inputs in the portfolio construction process — often claim that ESG mixing is more compatible with engagement than ESG filtering, on the ground that ESG mixing does not lead to divesting. However, contrary to common perception, ESG mixing strategies — such as over/underweighting based on ESG scores or using portfolio-average ESG scores as a constraint or objective in an optimizer — also lead to divesting based on ESG scores. This is apparent in the two practical examples of investment processes that mix ESG data with market capitalization weights and/or traditional factors (value, profitability, etc.), which we will now study. And while ESG filtering sends unambiguous and predictable — and therefore actionable — signals to all companies, we will show that ESG mixing strategies send blurred — and therefore less effective — signals.

Compared with ESG filtering, ESG reweighting techniques lead to the divestment of companies with better ESG credentials and send blurred signals

One simple example of an ESG mixing strategy consists of applying an ESG tilt to index constituent weights. In the simple case where an ESG metric is used to tilt market capitalization weights, ESG reweighting leads to greater divesting from companies with better ESG performances than filtering would, to reach the same ESG target. In the context of low carbon strategies, for example, reweighting leads to divesting from companies that are less carbon intensive than filtering would, for the same reduction in portfolio weighted average carbon intensity. To illustrate this point, in figure 1 we have ranked the companies in the Scientific Beta Developed equity universe at end 2019 in terms of carbon intensity (as per the definition recommended by the Financial Stability Board's Taskforce on Climate-related Financial Disclosures, i.e., the ratio of a company's Scope 1 and 2 emissions to its revenues). We then compare which proportion of companies needs to be impacted by the decarbonization divesting scheme to reach the same decarbonization target: all strategies achieve the same level of weighted average carbon intensity as the filtering out of the 5% most carbon-intensive companies, i.e., the same as a reweighting strategy where a 100% weight reduction of the 5% most carbon intensive companies is permitted. The X axis thus represents the severity of the reweighting allowed, while the Y axis plots the proportion of stocks affected by the partial divestment strategy in order to achieve the same carbon exposure reduction as the full divestment strategy. We also show the one-way turnover that the decarbonization scheme entails to reach its target.

While the filtering strategy by construction leads to divesting the 5% of stocks with the worst carbon intensities, the reweighting strategy needs to divest from 43% of the stocks if a 60% weight reduction is allowed for, for example, in order to achieve the same level of weighted average carbon-intensity reduction.

By spreading out the divestment more thinly across more stocks, the price impact through which divestment is meant to influence companies' behavior will be less significant for the worst ESG performers. Moreover, contrary to a common perception that reweighting is a less intrusive portfolio construction technique than filtering, reweighting may induce a larger turnover to reach the same weighted average decarbonization target — while the filtering strategy creates a 3% turnover, the reweighting strategy with a 60% weight reduction, for example, creates 19% turnover.

Another problem with such an approach is that, while divesting from high carbon emitters on average, the weight of a stock in a portfolio can increase over time if the stock is performing well relative to the others, irrespective of the carbon-intensity levels or change in carbon intensity. To illustrate this point, we construct a portfolio that weights securities based on the product of market cap and a carbon-intensity score. Figure 2 provides the analysis that highlights the signaling problems with this score-weighting approach. Firstly, while the weighted average carbon intensity of this portfolio is reduced by 84% relative to the cap-weighted index, on average over the five-year period we consider, the portfolio leads to problematic positions in individual stocks. Indeed, it increases the weight over time toward more than 30% of the stocks that fall into the category of the "worst emitters," that is, 10% of the stocks with the highest carbon intensity.

Moreover, while score-weighting clearly sends wrong signals to the worst emitters, it also happens to be the case when it comes to firms that increase their carbon intensities. We extend the previous analysis by focusing on firms that had significantly increased their carbon intensity relative to the equity universe. If a firm moves from one decile of carbon intensity to a higher decile, we refer to such firms as "deteriorators." Here, again, the score-weighted portfolio would increase allocation to more than 40% of the deteriorators. These illustrations indicate that using firm-level scores to tilt toward low carbon-intensity stocks leads to a blurred message to firms.

Yet another way to send mixed signals: incorporating low-carbon and factor exposure objectives using optimized weighting schemes

The problem with score-based approaches is only magnified when multiple stock-level information is mixed, in particular when using portfolio-optimization techniques to respect both ESG/low carbon and factor exposure objectives. Such approaches can lead to even greater increases in weights among the worst emitters. This is intuitive even without looking at the results, since optimization will only care about the average carbon intensity across the portfolio. Moreover, such mixing approaches also consider other stock-level characteristics, such as factor scores or contribution to tracking error. Pursuing the low carbon objective and other objectives simultaneously can lead to increasing weights to a firm even if its carbon emissions have become much worse over time.

To illustrate the point, we construct a stylized multi-factor portfolio that minimizes the tracking error with respect to the broad cap-weighted index, while achieving a similar level of factor score intensity (sum of individual factor scores) and carbon intensity to a low carbon smart beta strategy that simply excludes the 10% worst emitters. In this illustration, this reference strategy is a low carbon HFI multi-beta six-factor equal-weighted portfolio, constructed in a top-down manner on a decarbonized universe (excluding the worst 10% emitters).

Unsurprisingly, the optimization-based portfolio leads to a substantial reduction in weighted average carbon intensity compared to the cap-weighted index. During the period we consider, this reduction amounts to 74% on average. Despite this reduction on average, the strategy leads to problematic weights in the worst-offending stocks. The results in figure 3 confirm that the optimization-based portfolio would increase the weight of the worst emitters quite often. For example, each year between 2016 and 2018, the optimization-based portfolio allocated higher weight to more than 60% of the stocks that were among the worst emitters in the universe. We also observe that, in certain years, allocation across more than 10% of the worst emitters is higher than that of the cap-weighted index.

FIGURE 1

Scientific Beta Developed universe at end 2019

Proportion of stocks affected by divestment (%) and induced turnover (%), as a function of the weight reduction (%) allowed for carbon intensive companies.

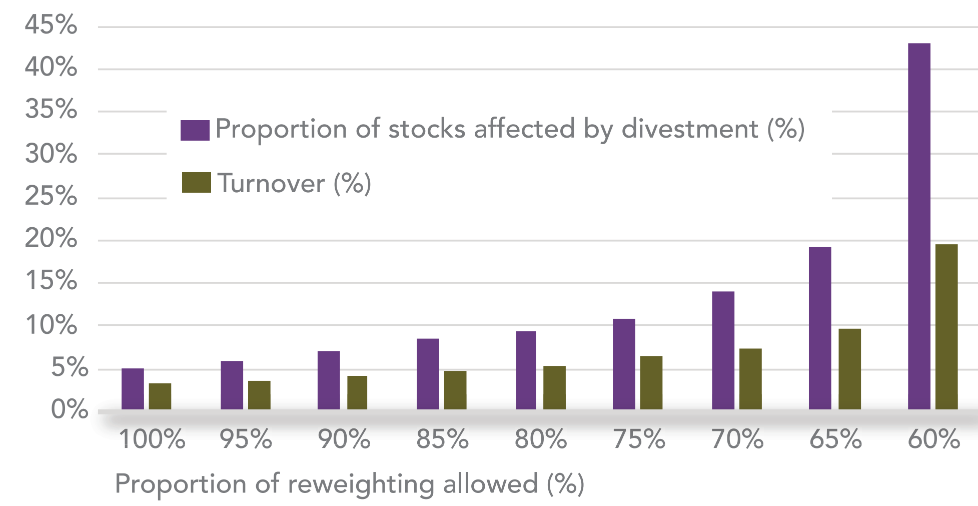

FIGURE 2

Percentage of deteriorators and worst emitters receiving higher weights in score-weighted portfolio

Percentage of deteriorators and worst emitters receiving higher weights in score-weighted portfolio. The analysis is based on the Scientific Beta United States universe, from June 2014 to June 2019. Each June, we exclude coal stocks and classify the remaining stocks into deciles according to their carbon intensity over the previous year. Carbon intensity is the sum of Scope 1 and Scope 2 emissions divided by total revenue. Coal stocks are the ones that (1) belong to the coal industry or derive turnover of at least 30% from thermal coal mining, (2) belong to the utilities industry, which makes significant use of coal in its power generation fuel mix (30%), and (3) own coal reserves, except those in the iron and steel industry. The worst emitters are those classified within the highest decile, i.e., top 10% after exclusion of coal companies. The reported figures correspond to the weighted average carbon intensity (in tons/USDm), percentage of stocks among deteriorators that have higher weight in a score-weighted portfolio than in the previous year and the percentage of worst emitters that have higher weight in a score-weighted portfolio than in the previous year. The score-weighted portfolio weights securities based on their score times the market-capitalization. Scores are transformed into cumulative distribution function of the normalized (truncated z-Score at 3 and -3) Carbon Intensity measures.

Scientific Beta United States Carbon intensity market cap weighted portfolio	Percentage of deteriorators with increasing weight	Percentage of the worst emitters (10%) with increasing weight
2015	47%	41%
2016	41%	61%
2017	48%	44%
2018	40%	40%
2019	48%	33%

Figure 2 illustrations indicate that using firm-level scores to tilt toward low carbon-intensity stocks leads to a blurred message to firms.

We have shown that, far from being incompatible with ESG engagement, ESG filtering sends a clear and consistent divestment message that allows an effective engagement policy to be implemented.

CONCLUSIONS

We have shown that, far from being incompatible with ESG engagement, ESG filtering sends a clear and consistent divestment message that allows an effective engagement policy to be implemented. Divestment is therefore not a passive bystander approach to ESG challenges, but is an effective form of action that has the power to change the real economy by sending strong and consistent signals on the attractiveness of stocks and the cost of capital to business directors.

This effective signaling of ESG filtering strategies is in stark contrast with score-based reweighting and optimization approaches, which mix-up ESG and financial considerations. We have illustrated how such mixing strategies lead to blurred and inconsistent messages, where the companies with the worst — or worsening — carbon performances can receive high — and even higher — weights in portfolios over time, thus hindering effective investor engagement with companies. It is clear that for strategies that mix up financial and ESG objectives without prioritizing the latter, which a top-down approach can do, there is a major risk of the good scores at portfolio level corresponding to inconsistent decisions at stock level.

FIGURE 3

Percentage of worst emitters receiving higher weights in optimization-based portfolio

The analysis is based on Scientific Beta United States universe, from June 2014 to June 2019. Each June, we exclude coal stocks and classify the remaining stocks into deciles according to their carbon intensity over the previous year. Carbon intensity is the sum of Scope 1 and Scope 2 emissions divided by total revenue. Carbon stocks are the ones that (1) belong to the coal industry or derive turnover of at least 30% from thermal coal mining, (2) belong to utility industry that make significant use of coal in their power generation fuel mix (30%), and (3) own coal reserves, except those in iron and steel industry. The worst emitters are those classified within the highest decile, i.e., top 10% after exclusion of coal companies. The reported figures correspond to the percentage allocation across the worst emitters and the percentage of stocks among the worst emitters that have a higher weight in an optimization-based portfolio than in the cap-weighted market portfolio.

Scientific Beta United States Low Carbon/multi-factor optimization-based portfolio	Percentage of worst emitters (10%) with increasing weight	Percentage of the worst (10%) with higher weight than the Broad Cap-Weighted Index
2015	18%	2%
2016	61%	0%
2017	69%	4%
2018	69%	12%
2019	17%	10%

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Limitations of Traditional Defensive Strategies

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- **Traditional defensive solutions suffer from negative exposures to reward factors other than the low volatility risk factor, as well as concentration and strong exposures to fixed income risks.**
- **More importantly, they are not always low volatility and can suffer from huge peaks of volatility during market crises.**
- **Scientific Beta offers a new dynamic defensive solution that is really low volatility by combining a robust low volatility index and a maximum volatility protection risk control option.**
- **Moreover, with the application of the narrow high-factor intensity filter, the diversification of idiosyncratic risks and the reduction of sector and regional risks, this solution benefits from a strong factor intensity, a superior long-term risk-adjusted performance and reduced fixed income risks.**
- **A decarbonized version of this new solution is available for investors who care about having an impact on climate change.**

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 typically leads to equity investors investing in low volatility factor solutions whose main objectives are to offer defensive payoff profiles and a superior risk-adjusted performance relative to cap-weighted indexes.

Traditional defensive strategies offered to investors, however, suffer from five common drawbacks:

(i) They deliver negative exposures to other rewarded factors since most competitors do not account for negative factor interactions. This often translates to defensive portfolios having negative exposures to rewarded risk factors such as value, momentum, high profitability and low investment that have a negative impact on their long-term risk-adjusted performance.

(ii) They are very often concentrated portfolios and lack diversification since stocks are either weighted using the inverse volatility or determined through optimization under ad hoc constraints. Minimum volatility optimizations are known to produce highly concentrated portfolios without the use of proper constraints; similarly, using market capitalization or the inverse of volatility as weight can also produce concentrated portfolios.

(iii) They are often exposed to macroeconomic risks since they tend to have persistent sector and/or regional exposures.

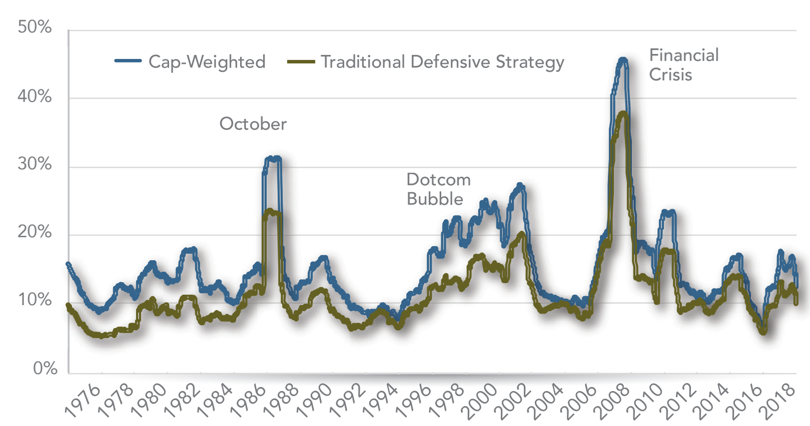
(iv) They tend to overweight low-risk sectors such as utilities that include companies with a strong carbon intensity, and as a result their weighted average carbon intensity (WACI) is much higher compared to the cap-weighted index.

(v) They are not always low volatility. In reality, traditional defensive indexes, despite delivering on average lower volatility than their reference cap-weighted indexes, still suffer from periods of significant volatility such as in October 1987, during the dotcom bubble or during the financial crisis of 2008 (see Exhibit 1). These peaks might be undesirable for investors seeking to be defensive, not only on average, but in periods when they need it the most — namely, in bad times.

EXHIBIT 1

One-year rolling volatility of a traditional defensive strategy

The figure plots the one-year rolling volatility of the EDHEC-Risk Long-Term United States Cap-Weighted index and the EDHEC-Risk Long-Term US Traditional Defensive Strategy index (Traditional Defensive Strategy). This index is constructed by rebalancing monthly 30% of the lowest volatility stocks, weighted by the inverse of the volatility. Data is from Dec. 31, 1974, to Dec. 31, 2019, using daily total returns in USD.



How to do better?

First and foremost, a defensive solution should properly and efficiently capture the low-volatility factor reward. At Scientific Beta, we employ the Smart Beta 2.0 framework[17] to harvest consensus-based rewarded risk factors. For the low-volatility factor, we first select stocks with the lowest volatility, then apply a high factor intensity (HFI) filter to tackle negative factor interactions by removing stocks with the lowest multi-factor scores, and finally diversify away idiosyncratic risks with a diversified weighting scheme. Our approach favors a clear separation of the stock selection and weighting phases. The stock selection objective is to expose the portfolio toward a desired and rewarded factor tilt, such as the low volatility factor, and the weighting objective is to diversify away from idiosyncratic risks in order to obtain a well-diversified portfolio. The latter is key when it comes to capturing factor rewards efficiently and to achieving a strong risk-adjusted performance over the long term.[18]

The Narrow iHFI Low Volatility Diversified Multi-Strategy index offered by Scientific Beta is based on the Smart Beta 2.0 framework. The narrow HFI filter is designed to obtain a strong exposure to the desired factor tilt. The process selects only 30% of the stocks in the entire universe and filters out one-third of those based on the multi-factor score; only 20% of stocks remain compared to the starting universe. The index offers four main benefits over the common drawbacks of traditional defensive solutions[19]:

First, the strong exposure to the low-volatility factor permits investors to benefit from this factor's rewards and defensiveness.

The HFI filter implemented in the index reduces negative exposures to other long-term rewarded factors, often present in traditional low volatility or minimum volatility indexes. It thereby improves the long-term risk-adjusted return and robustness of the outperformance of the index, especially when the low-volatility factor is underperforming. Exhibit 2a shows that compared with the MSCI Minimum Volatility index, our Narrow iHFI Low Volatility index retains strong exposure to the low-volatility factor while achieving strong factor intensity overall.

Due to the application of the HFI filter, Scientific Beta indexes result in good dissymmetric conditionality to

[17] The original approach termed Smart Beta 2.0 was introduced by Amenc and Goltz (2013).
[18] Amenc, et al. (2012) shows that this approach is more robust for achieving well-diversified defensive portfolios that produce a similar level of outperformance with higher risk reduction than portfolios based solely on Modern Portfolio Theory.
[19] For more details on the construction of Scientific Beta single smart factor indexes, we refer the reader to Aguet and Amenc (2019).

low-volatility factor regimes. This means that when the low-volatility factor underperforms, our low-volatility index benefits from positive exposure to the other well-rewarded factors that tend to be uncorrelated to the low-volatility factor in the long term. This results in stronger performance compared with the traditional defensive strategies during low-volatility regimes (see Exhibit 2b). On the other hand, the strong exposure to the low-volatility factor allows investors to benefit from the premium during high-volatility periods. Therefore, our low-volatility index benefits overall from better conditionality, and therefore better robustness with respect to expected performance going forward. Consequently, our Narrow iHFI Low Volatility index offers a strong cumulative return across both regimes, 3% higher compared than the MSCI Minimum Volatility index.

Second, the diversification of idiosyncratic risks helps to efficiently capture risk factor rewards.

Scientific Beta eschews the concentration attached to capitalization and factor score weighting. Instead, it employs a robust diversified multi-strategy weighting scheme to diversify non-rewarded idiosyncratic risks in order to efficiently capture the long-term risk premium associated with the low volatility factor. The benefit with respect to traditional weighting approaches is shown in Exhibit 3. Cap-weighting increases concentration from the relevant measures and therefore resulting performance metrics, such as the Sharpe and information ratios, remain much lower relative to our diversified multi-strategy scheme.

Third, regional block neutrality and mega-sector selection embedded in the construction steps of the Narrow iHFI Low Volatility index protect against undesired implicit non-factor risks, such as macroeconomic and interest rate risks.

Our indexes are constructed at the geographic basic level, which is defined by separate economically integrated regions.[20] Furthermore, a central part of our index construction is that stocks are selected within three mega-sectors,[21] which improves sector diversity and helps reduce sector deviations. These embedded index construction steps enable better management of the implicit macroeconomic risks encountered in traditional defensive solutions, which often have interest rate risk dependencies. Investors interested in mitigating these risks will benefit from lower interest rate risk exposure relative to traditional defensive indexes, as depicted in Exhibit 4.

Fourth, we provide a low-carbon version of the Narrow iHFI Low Volatility index to reconcile defensive strategies and climate change and support the transition toward a low carbon economy while materially reducing index exposure to the potential risks of this transition.

The low-carbon filter also includes filters that screen out companies that fall short of global standards of responsible business conduct and corporate governance or that are involved in activities that conflict with global environmental, social and governance (ESG) norms or their objectives globally, the pursuit of decarbonization and financial performance does not harm the respect of ESG norms.[22] Exhibit 5 shows that the decarbonized version of the Narrow iHFI Low Volatility index allows carbon exposure metrics to be significantly reduced; the decarbonized version has a WACI (Scope 1+2) reduction of 24% compared with the cap-weight index and 65% compared with the MSCI Minimum Volatility.

EXHIBIT 2a

Factor exposures of SciBeta Developed Narrow iHFI Low Volatility DMS and MSCI World Minimum Volatility

Based on weekly total returns in USD from June 21, 2002, to June 30, 2020. The SciBeta Developed Cap-Weighted index is used as the benchmark. The three-month US Treasury bill rate is used as the proxy for the risk-free rate. Factor exposures are based on a seven-factor model. The Market factor is the excess return series of the cap-weighted index of all stocks that constitute the index portfolio over the risk-free rate. The other six factors are equal-weighted daily rebalanced factors obtained from Scientific Beta and beta-adjusted every quarter with their realized CAPM beta. The factors are market beta neutralized ex-post on a quarterly basis. Factor intensity is the sum of non-market beta exposures. The regression is based on weekly total returns. Coefficients significant at 5% p-value are highlighted in bold. Indexes used are the Narrow iHFI Low Volatility DMS and MSCI World Minimum Volatility index.

SciBeta Developed	Narrow iHFI Low Volatility DMS	MSCI World Minimum Volatility
Size (SMB) factor	**0.11**	**0.11**
Value (HML) factor	**0.08**	**-0.12**
Momentum (MOM) factor	**0.03**	-0.03
Low volatility factor	**0.40**	**0.42**
Profitability factor	**0.06**	-0.03
Investment factor	-0.04	-0.06
Factor intensity	0.65	0.29

EXHIBIT 2b

Conditional dissymmetry of SciBeta Developed Narrow iHFI Low Volatility DMS and MSCI World Min Vol

Based on total returns in USD from June 21, 2002, to June 30, 2020. All statistics are annualized. Bull regimes are defined as months with positive performance of the low volatility factor. Bear regimes are defined as months with negative performance of the low volatility factor. The Conditional Ratio is the absolute value of the relative bull/bear spread divided by the sum of the bull and bear relative returns and subject to a smoothing function so that the ratio falls between 0 and 2. Indexes used are the Narrow iHFI Low Volatility DMS and MSCI World Minimum Volatility index.

SciBeta Developed	Narrow iHFI Low Volatility DMS	MSCI World Minimum Volatility
Bull low volatility return	13.98%	13.39%
Bear low volatility return	3.50%	0.90%
Cumulative return	17.47%	14.28%
Conditional ratio	0.58	0.82

Exhibit 2a shows that compared with the MSCI Minimum Volatility index, our Narrow iHFI Low Volatility index retains strong exposure to the low-volatility factor while achieving strong factor intensity overall.

20 If the universe contains different geographic basic blocks, they are aggregated proportionally to their free-float market capitalisation weight in the Scientific Beta Cap-Weighted Reference index.
21 Financials, Technology and Non-Financial Non-Technology firms.
22 To see more on our low-carbon filter, we refer to Ducoulombier and Liu (2020).

In addition, in order to control the volatility fluctuations of the Narrow iHFI Low Volatility index, Scientific Beta offers a Maximum Volatility Protection (MVP) risk-control option.

Its objective is to cap volatility at the historical volatility of underlying index. Therefore, the solution is not only defensive relative to the cap-weighted index but also in an absolute way and investors can benefit from a solution that is defensive all the time. To ensure this good protection against volatility risk, Scientific Beta uses a robust volatility forecasting model, which provides good forecasting accuracy. This model captures stylized facts of financial returns such as volatility clustering, leverage effect and fat-tails. Moreover, we tackle structural breaks by using two forecasts based on an expanding window and a five-year rolling window.

The risk-control option is easily implemented via a CW overlay, which means that there is no additional rebalancing in the Narrow iHFI Low Volatility index but only in futures. The allocation to the CW overlay is reviewed every week but is implemented only if the change in the allocation is above a buffer. The buffer control allows the number of effective rebalancing to be limited and is set to 20%. This rebalancing approach is not based on a fixed calendar maturity but on a signal triggered by a significant change in the forecasted volatility, which is estimated by a robust method capturing volatility dynamics. The MVP risk control option is state of the art in terms of risk management and is offered by Scientific Beta in a transparent and robust framework.[23]

A dynamic defensive solution

Scientific Beta's dynamic defensive solution combines the Narrow iHFI Low Volatility index with the MVP risk control option. The solution limits volatility spikes as shown in Exhibit 6. The dynamic defensive solution provides much more stable volatility and significant reduction of volatility peaks during market-distressed regimes, such as the financial crisis of 2008 or the recent COVID-19 crisis. Indeed, we observe that the level of volatility at the end of June 2020 was 28% for the cap-weighted index, 23% for the MSCI Minimum Volatility index and 16% for the dynamic defensive solution.

The success of the dynamic defensive solution finds its roots in the dissymmetry of market betas in low and high volatility market regimes as observed in Exhibit 7. We underscore that the market beta of the solution is higher in low-volatility market regimes than in high-volatility market regimes, whereas the MSCI Minimum Volatility index displays the opposite behavior with a stronger market beta in high-volatility market regimes. This is exactly what investors want to avoid with a defensive solution.

Overall, this dissymmetry reduces downside risks such as maximum drawdown and worst 5% one- or three-year rolling returns, and also provides a strong average volatility reduction and Sharpe ratio improvement compared not only to the cap-weighted index but also to the MSCI Minimum Volatility index. Indeed, we

EXHIBIT 3

Diversification matters

The table shows the average index concentration level. The Change in Specific Volatility is calculated as the difference in volatility of the strategy and its Multi-factor Benchmark, a synthetic portfolio levered to match returns of the respective strategy that contains the same magnitude of systematic risk. Indexes used are the Narrow iHFI Low Volatility DMS and the SciBeta Developed Narrow iHFI Low-Volatility Cap-Weighted (Narrow HFI Low-Volatility Cap-Weighted). Data is from June 21, 2002, to June 30, 2020 (RI/USD).

SciBeta Developed	Narrow iHFI Low Volatility Cap-Weighted	Narrow iHFI Low Volatility DMS
Sharpe ratio	0.51	0.66
Information ratio	0.14	0.38
Effective number of stocks	75	218.1
Change in specific volatility	0.22%	-4.02%

EXHIBIT 4

Mega-sector selection and regional neutrality reduce macro risks

Based on weekly total returns in USD from June 21, 2002, to June 30, 2020. Coefficients significant at 5% p-value are highlighted in bold. Indexes used are the Narrow iHFI Low Volatility DMS and MSCI World Minimum Volatility index.

SciBeta Developed	Narrow iHFI Low Volatility DMS	MSCI World Minimum Volatility
Unexplained	**0.1%**	**0.0%**
Equity Beta	**0.78**	**0.73**
T-Bill	**-0.37**	**-0.68**
Term Spread	**-1.83**	**-2.53**
Credit Spread	0.59	**0.87**

EXHIBIT 5

Weighted average carbon intensity

WACI: Average exposure of portfolio to carbon-intensive companies expressed in tons of CO2e per (USD) million of revenues including scope 1+2. Data is computed as of June 30, 2020. Indexes used are the SciBeta Developed Cap-Weighted, the SciBeta Developed Narrow iHFI Low-Volatility Diversified Multi-Strategy and the MSCI World Minimum Volatility.

SciBeta Developed	CW Index	Low Carbon Narrow iHFI Low Volatility DMS	Narrow iHFI Low Volatility DMS	MSCI World Minimum Volatility
WACI (S1+2, t/USDm	156	118	354	339
Reduction vs CW	-	-24%	127%	117%

The benefit with respect to traditional weighting approaches is shown in Exhibit 3.

see in Exhibit 7 that maximum drawdown and worst 5% one-year rolling returns for our dynamic defensive solutions are reduced respectively by 25% and 35% compared with the MSCI Minimum Volatility index, and 38% and 52% compared with the cap-weighted index. Furthermore, the volatility reduction compared with the cap-weighted index is close to 40%; this is much stronger than the MSCI Minimum Volatility index. This reduction in average volatility is not offset on a one-to-one basis by a reduction in returns — this means that the Shape ratio is strongly improved, by 85% compared with the cap-weighted index. Finally, relative to the MSCI Minimum Volatility, the Sharpe ratio and volatility of our dynamic defensive solution are improved by 27% and 19%.

The Scientific Beta Dynamic Defensive solution is state of the art in terms of risk management and is offered in a transparent and robust framework. It should be considered by institutional investors who want to be protected not only on average but when it matters most.

Scientific Beta's dynamic defensive solution combines the Narrow iHFI Low Volatility index with the MVP risk control option. The solution limits volatility spikes as shown in Exhibit 6.

EXHIBIT 6

One-year rolling volatility of Scientific Beta's Dynamic Defensive Solution

The figure plots the one-year rolling volatility of the SciBeta Developed Cap-Weighted index, the SciBeta Developed Dynamic Defensive Narrow iHFI Low-Volatility Diversified Multi-Strategy Max-Vol Protected index (Dynamic Defensive), the SciBeta Developed Dynamic Defensive Low-Carbon iHFI Low-Volatility Diversified Multi-Strategy Max-Vol Protected index (Dynamic Defensive Low Carbon), and the MSCI World Minimum Volatility index. Data are from June 17, 2005, to June 30, 2020, using daily total returns in USD.

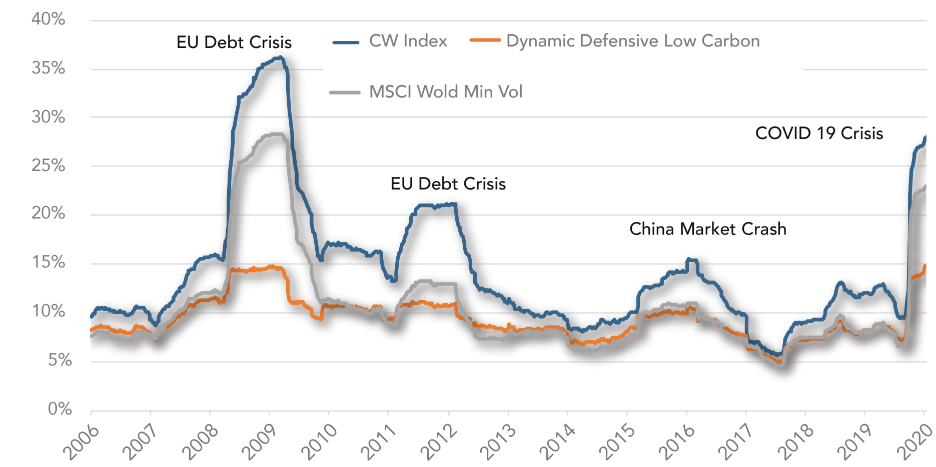


EXHIBIT 7

Benefits of Scientific Beta's dynamic defensive solution

The top panel of the table shows the conditional market beta in low/high volatility market regimes. Low (High) volatility market regimes are defined as the 50% of months with lowest (highest) market volatility. The mid-panel shows absolute statistics. The bottom panel shows the maximum drawdown, the worst 5% one- and three-year rolling returns. We use a weekly step-size for rolling statistics. Indexes used are the SciBeta Developed Cap-Weighted, the SciBeta Developed Dynamic Defensive Narrow iHFI Low-Volatility Diversified Multi-Strategy Max-Vol Protected (Dynamic Defensive), the SciBeta Developed Dynamic Defensive Low Carbon Narrow iHFI Low-Volatility Diversified Multi-Strategy Max-Vol Protected (Dynamic Defensive Low Carbon) and the MSCI World Minimum Volatility. Data are from June 17, 2005, to June 30, 2020, using daily total returns in USD.

SciBeta Developed	CW Index	Dynamic Defensive	MSCI Minimum Volatility
Conditional statistics			
Low Vol Mkt - Mkt Beta	1.00	0.74	0.65
High Vol Mkt - Mkt Beta	1.00	0.52	0.72
Absolute Statistics			
Ann. Returns	7.11%	7.93%	7.69%
Ann. Volatility	16.76%	10.31%	12.68%
Vol reduction		-39%	-24%
Sharpe Ratio	0.35	0.65	0.51
Sharpe Improvement		85%	45%
Downside Risks			
Max Drawdown	57.1%	35.6%	47.7%
1Y Rolling Return worst 5%	-29.90%	-14.25%	-22.16%
3Y Rolling Return worst 5%	-8.50%	-1.22%	-5.65%

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[23] *Concerning its implementation, we recognize that many institutional investors may face leverage constraints that hinder them from using a CW overlay. For these investors, we offer a physical implementation that requires a dynamic allocation between the Scientific Beta Narrow iHFI Low Volatility index and cash.*

Benefits of a Historical Volatility Adjustment Risk-Control Option

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- **Managing volatility strategies leads to a considerable reduction in downside risk, and can deliver improved risk-adjusted performance and improves conditionality.**
- **It also bolsters the positive return asymmetries, something that is greatly appreciated by investors who are always concerned about benefiting fully from equity risk premia while limiting their exposures to these risks in times of market stress.**
- **Scientific Beta's historical volatility adjustment (HVA) risk control option helps to manage and smooth the volatility of its flagship multi-factor strategies.**
- **Using the HVA risk control option has a considerable impact on risk management.**
- **Investors who want their factor strategy to remain defensive during episodes of severe market stress, notably to keep its volatility lower than that of the market, would benefit from the application of a volatility-control option, such as the one offered by Scientific Beta.**

Managing volatility strategies offers three major advantages to factor investors. First, it leads to a considerable reduction in downside risks.[24] Second, it can deliver improved risk-adjusted performance[25] — the Sharpe ratio gains from managed volatility strategies are usually associated with reduced overall strategy risk, while returns are unchanged or in some cases higher. Third, it improves conditionality and bolsters positive return asymmetries, something that is greatly appreciated by investors, who are always concerned about benefiting fully from equity risk premia while limiting their exposures to these risks in periods of market stress. Indeed, the market beta of managed volatility strategies is lower in high-volatility market regimes and higher in low-volatility market regimes because of the reduction/increase of exposure to the unmanaged index. Similarly, the volatility of managed volatility strategies is higher in low-volatility market regimes and lower in high-volatility market regimes compared with unmanaged strategies.

These advantages can be explained by a mean-variance trade-off — in periods of low volatility, returns and Sharpe ratios are highly positive on average, while in periods of high volatility, returns are negative on average and Sharpe ratios are undefined. Investors who could perfectly switch allocation to the unmanaged strategy could benefit fully from the mean-variance trade-off. Of course, this would imply knowing the volatility in advance, which is impossible. Still, it highlights the importance of the accuracy of the volatility forecast. Indeed, the latter is critical for the success of managed volatility strategies and poor forecasts could reduce or even erase their benefits. For example, if the volatility forecast is below the realized volatility of the unmanaged index, the allocation to the latter will be too high. Therefore, if returns are strongly negative during this period, it will adversely impact the performance and risks of the managed strategy.

Scientific Beta's historical volatility adjustment (HVA) risk control option presents the opportunity to manage and smooth the volatility of its flagship multi-factor strategies. It is available on our multi-beta multi-strategy indexes, including both sector-neutral risk control options and low-carbon and ESG options. It targets the long-term historical volatility of the multi-factor strategy to guarantee that its average volatility is a fair representation of the volatility risk. We use a cap-weighted overlay to increase or reduce the risk of the solution, instead of leveraging/deleveraging the index itself. The overlay position is reviewed weekly and is modified only if the change in allocation is above a 20% buffer. The allocation is reset every month on the third Friday. The size of the overlay position is calculated based on the index market beta and the ratio of the volatility target and the volatility forecast of the index, subject to a cap of 30% on borrowing. The use of a CW overlay has three advantages. First, there is almost no additional turnover associated with the multi-factor index. Second, there is no need to borrow or lend cash to change exposures to the index. Third, there is no counterparty risk. Moreover, the CW overlay can be replicated using futures that are highly liquid and generates very low transaction costs.

We use an asymmetric GARCH model to forecast volatility with student-t innovations. This model captures financial returns stylized facts such as volatility clustering, leverage effect, non-normality. Moreover, we tackle structural breaks by using two forecasts based on an expanding window and a five-year rolling window as suggested by Rapach et al. (2007). In figure 1, we show that our model delivers very good accuracy compared with more traditional methods used, since it delivers the lowest root mean squared errors (RMSE) and extreme 5% squared errors.

The main benefits of the HVA risk-control option

We now take a closer look at the main benefits of the HVA risk control option and how it mitigates volatility fluctuations and seeks to maintain the index's volatility near its long-term volatility level. We base our analysis on the EDHEC-Risk Long-Term United States (US LTTR) historical data universe. This spans 45 years of data from December 1974 to December 2019 over the U.S., including major crisis periods such as the dot-com bubble and the global financial crisis. In our analysis, the HVA risk control option is applied to US LTTR iHFI Diversified Multi-Beta Multi-Strategy 6-Factor EW index.

First, we highlight the HVA strategies' ability to control volatility more effectively than the underlying multi-factor index in both high- and low-volatility periods. The one-year rolling volatilities in figure 2 show that the HVA is very effective in smoothing volatility through time. During the 1999 dot-com bubble, the 2008 financial crisis, or the 2011 European Union debt crisis, the HVA index one-year rolling volatility was clearly reduced. In periods of lower volatility, meanwhile, its rolling volatility was slightly higher, to benefit from the higher risk-adjusted performance that characterizes these periods.

Second, we emphasize that the HVA risk control option improves the conditionality of the underlying multi-factor index. The asymmetric conditionality is the key element in explaining the benefits of managed volatility strategies. The conditional market betas in figure 3 show that during adverse market conditions, defined by high volatility or bear market regimes, the HVA leads to a strong reduction in the market beta. This is confirmed by the reduction of the market beta for the HVA strategy, from 0.84 during a bull market regime to 0.59 in a bear market regime. The HVA strategy has a similar impact on the market beta conditioning on different volatility regimes. In low-volatility periods, there is a marked increase in market beta to 1.05, whereas it reduces the market beta to 0.63 in high-volatility periods.

The HVA leads to a strong reduction in the conditional volatility of the strategy as reported in figure 3; during adverse market conditions defined by high-volatility periods (or bear market regimes), volatility is reduced to 15.03% (15.12%) which compares with a level of 18.79% (19.90%) for the standard multi-factor index. Consistently, HVA conditional volatility increases during favorable market conditions characterized by low-volatility period (or bull market regimes), when volatility increase to 11.14% (12.31%) against a level of 9.38% (12.20%) for the index without HVA.

24 Studies such as Barroso and Santa Clara (2015), Hocquard, Ng, and Papageorgiou (2013) demonstrate that managed volatility strategies allow maximum drawdowns and extreme risks to be reduced.
25 Higher Sharpe ratios from managed volatility strategies have been documented by Moreira and Muir (2017), Fleming, Kirby, and Ostdiek (2001, 2003), Barroso and Santa Clara (2015), Perchet et al. (2014) and Harvey et al. (2018).

The benefits of managing volatility by achieving better market beta conditionality lowers downside risks such as extreme negative returns. In figure 4 we show maximum drawdown and the worst 5% returns over one, three- and 10-year rolling windows. The results suggest that the HVA risk control option is more effective in reducing negative extreme returns. We observe that both worst extreme rolling returns and maximum drawdowns are considerably reduced, the latter by 60% compared with the standard multi-factor index, reflecting the downside risk control benefits of targeting volatility.

In figure 5, we find that the HVA index produces the greatest Sharpe ratio improvement due to both higher returns and a stronger volatility reduction compared with the CW index. Furthermore, the reduction of volatility peaks produces a stronger average volatility reduction and Sharpe ratio improvement compared with the index without the HVA risk control option. The HVA achieves a volatility reduction of 21% versus the CW index, while the index without HVA reduces the volatility only by 11%. Moreover, the reduction in average volatility is not offset on a one-to-one basis by a reduction in returns. This implies that the Sharpe ratio, compared with the CW index, is improved by 77% for the HVA index and 64% for the standard multi-factor index. In particular, the Sharpe ratio improvement for our managed volatility approach arises primarily from a reduction in risk, while returns are only slightly lower than that of the standard index (14.77% versus 15.17%). Therefore, we reiterate that the HVA strategy serves primarily to improve portfolio risk controls, and it should not be viewed as a mean to boost returns.

As discussed above, the HVA risk control option reduces downside risks and improve risk-adjusted performance over the long-term. At the same time, it retains the advantages of our multi-factor index while benefiting from an established and controlled defensive profile. In fact, the factor exposures reported in figure 6 demonstrate that our multi-factor index using the HVA option still manages to provide investors with strong exposures to the six consensus-based well-rewarded risk factors. As such, investors need not sacrifice factor exposures in exchange for the risk control benefits. The main noticeable change in exposure is a lower overall market beta of 0.76 for the multi-factor index with the HVA option, which compares with a beta of 0.88 for the standard multi-factor index. The lower market beta is expected due to the periods when the solution downscales exposures to the standard multifactor index. The HVA's exposures to the others risk factors are highly similar to that of the standard index, while the factor intensity is slightly improved from 0.56 to 0.63.

> The HVA leads to a strong reduction in the conditional volatility of the strategy as reported in figure 3.

FIGURE 1

Forecasting accuracy of different models

We compare our model to the usual well-known measures used for forecasting volatility. We use the historical volatility with 1 year of daily data, the Exponentially Weighted Moving Average (EWMA) with one year of daily data and VIX-implied volatility based on options on the S&P 500. We forecast the one-week ahead volatility of the S&P 500 and compare it to realized weekly volatility. The analysis is conducted over the period February 1995 to December 2019. Root Mean Squared Errors or RMSE is our proxy to measure the quality of the forecast. The lower the RMSE, the better the quality of the forecast.

1995-2019 – S&P 500	Historical	EWMA	VIX	GJR-GARCH
RMSE	1.38%	1.08%	1.26%	1.04%
Worst 5% Errors	2.54%	2.02%	2.27%	1.91%

FIGURE 2

One-year rolling volatilities

The figure plots the one-year rolling volatility of the US LTTR Cap-Weighted (CW) Index, the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW (HFI MBMS), the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW Hist-Vol Adjusted (HVA) and the target volatility for the HFI MBMS index (Target Vol). The analysis is conducted over the period Dec. 31, 1974, to Dec. 31, 2019, using daily total returns in USD. Rolling statistics are computed using a weekly step.

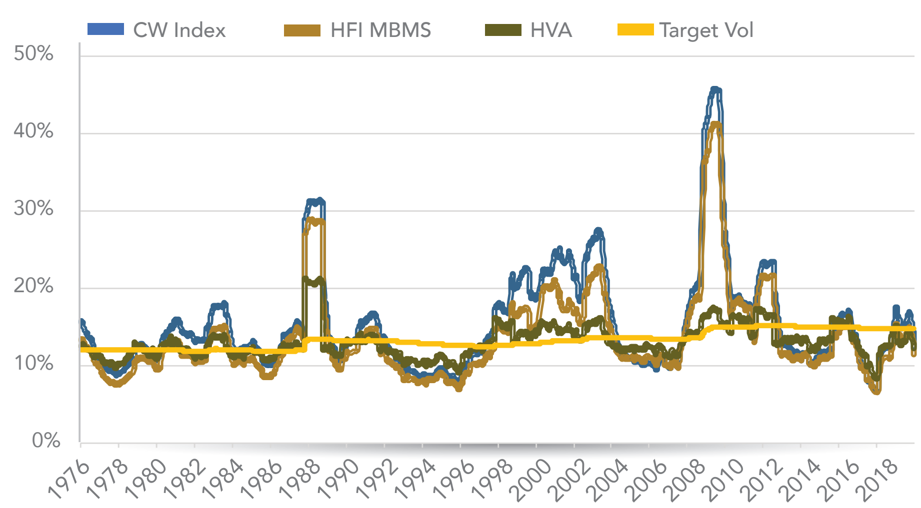

FIGURE 3

Conditional market betas and conditional volatilities

Conditional market betas are estimated from a CAPM regression for periods in each condition. Bull/bear periods: quarters with positive/negative CW index returns. Low/High volatility periods: quarters in the bottom/top 50 percentile of volatility for the CW index. Indexes used are the US LTTR Cap-Weighted index (Cap-Weighted), the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW (iHFI MBMS 6F EW) and the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW HVA. The analysis is conducted over the period Dec. 31, 1974, to Dec. 31, 2019, using daily total returns in USD.

LTTR: Dec. 31, 1974, to Dec. 31, 2019 (RI/USD)	Cap-Weighted	iHFI MBMS 6F EW	iHFI MBMS 6F EW HVA
Conditional Market Betas			
Bull market beta	1.00	0.86	0.84
Bear market beta	1.00	0.86	0.59
LVol market beta	1.00	0.88	1.05
HVol market beta	1.00	0.86	0.63
Conditional Volatilities			
Bull vol	13.72%	12.20%	12.31%
Bear vol	22.49%	19.90%	15.12%
LVol vol	10.24%	9.38%	11.14%
HVol vol	21.35%	18.79%	15.03%

In figure 5, we find that the HVA index produces the greatest Sharpe ratio improvement due to both higher returns and a stronger volatility reduction compared with the CW index. Furthermore, the reduction of volatility peaks produces a stronger average volatility reduction and Sharpe ratio improvement compared with the index without the HVA risk control option.

FIGURE 4

Downside risks

The table shows max drawdown and the worst 5% (5th percentile) return over one, three and 10-year rolling window. We use a weekly step-size for rolling statistics. Indexes used are the US LTTR Cap-Weighted index (Cap-Weighted), the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW (iHFI MBMS 6F EW) and the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW HVA. The analysis is conducted over the period Dec. 31, 1974, to Dec. 31, 2019, using daily total returns in USD.

LTTR: Dec. 31, 1974, to Dec. 31, 2019 (RI/USD)	Cap-Weighted	iHFI MBMS 6F EW	iHFI MBMS 6F EW HVA
Max Drawdown	55.50%	50.88%	30.92%
1Y rolling return worst 5%	-17.47%	-9.20%	-9.09%
3Y rolling return worst 5%	-8.35%	-2.72%	0.38%
10Y rolling return worst 5%	-0.36%	5.99%	6.88%

FIGURE 5

Absolute performance

The table shows absolute statistics. Indexes used are the US LTTR Cap-Weighted index (Cap-Weighted), the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW (iHFI MBMS 6F EW) and the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW HVA. The analysis is conducted over the period Dec. 31, 1974, to Dec. 31, 2019, using daily total returns in USD.

LTTR: Dec. 31, 1974, to Dec. 31, 2019 (RI/USD)	Cap-Weighted	iHFI MBMS 6F EW	iHFI MBMS 6F EW HVA
Absolute Performance			
Ann. Returns	11.89%	15.17%	14.77%
Ann. Volatility	16.75%	14.85%	13.23%
Volatility Reduction	-	-11%	-21%
Sharpe Ratio	0.43	0.71	0.76
Sharpe Ratio Improvement	-	64%	77%

FIGURE 6

Factor exposures

Indexes used are the US LTTR Cap-Weighted index, the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW (iHFI MBMS 6F EW) and the US LTTR iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW HVA (iHFI MBMS 6F EW HVA). The analysis is conducted over the period Dec. 31, 1974, to Dec. 31, 2019, using daily total returns in USD. Factor exposures are calculated from regressions on Long/Short Market-Neutral Factor regressors using weekly returns. Coefficients significant at 5% p-value are highlighted in bold.

LTTR: Dec. 31, 1974, to Dec. 31, 2019 (RI/USD)	iHFI MBMS 6F EW	iHFI MBMS 6F EW HVA
Unexplained	**1.04%**	1.05%
Market Factor	**0.88**	**0.76**
Size (SMB) Factor	**0.09**	**0.11**
Value (HML) Factor	**0.12**	**0.12**
Momentum (MOM) Factor	**0.07**	**0.09**
Volatility Factor	**0.09**	**0.13**
Profitability Factor	**0.11**	**0.12**
Investment Factor	**0.09**	**0.06**
R Squared	96.6%	85.8%
Factor Intensity	0.56	0.63
Factor Deconcentration	5.81	5.71
Factor Exposure Quality	3.28	3.57

An explicit risk-control option to protect against variations in volatility.

We focus now on the performances our multi-factor index with the HVA risk-control option during the first half of 2020 using the SciBeta Developed iHFI Diversified Multi-Beta Multi-Strategy Six-Factor EW (iHFI MBMS 6F EW) index.

Figure 7 shows the one-year rolling volatilities of the standard and HVA multi-factor indexes. As was the case with the long-term results, we find that the HVA strategy is very effective in maintaining volatility near its target compared with the underlying multi-factor index. The impact of the HVA is remarkably evident toward the end of Q1 2020. During this period, the HVA index was highly responsive in mitigating the sharp spike in market volatility triggered by the COVID-19 outbreak, whereas the standard multi-factor index and the CW index produced large upswings in volatility3. Indeed, we observe that the level of volatility at the end of June 2020 was 28% for the cap-weighted index, 28.2% for the standard multi-factor index and only 17% for the HVA strategy. This is in line with other episodes of severe stress in recent decades, such as the financial crisis that began in late 2007 or the European sovereign debt crisis in 2011.

Figure 8 focuses on the average and extreme risks of the different versions of the multi-factor index during the first half of 2020. We find that the HVA index leads to a sharp 44% reduction in volatility compared with its underlying index (21.79% vs 38.84%). Furthermore, it was able to deliver a maximum drawdown reduction of 24% versus the standard index as well as a reduction in the maximum loss of 26%. Overall, the HVA risk control option offered a very strong reduction in risk and a very effective downside protection during the COVID-19 crisis.

We conclude by observing that the choice of using the HVA risk-control option has a considerable impact on risk management. Investors who would like their factor strategy to remain defensive during episodes of severe market stress, notably because its volatility is lower than that of the market, would be better off ensuring this with the application of a volatility-control option, such as the one we offer.

FIGURE 7

One-year rolling volatilities

The figure plots the one-year rolling volatility of the SciBeta Developed Cap-Weighted (CW) Index, the iHFI MBMS 6F EW (HFI MBMS) and the iHFI MBMS 6F EW HVA (HVA). The analysis is conducted over the period June 17, 2005, to June 30, 2020, using daily total returns in USD.

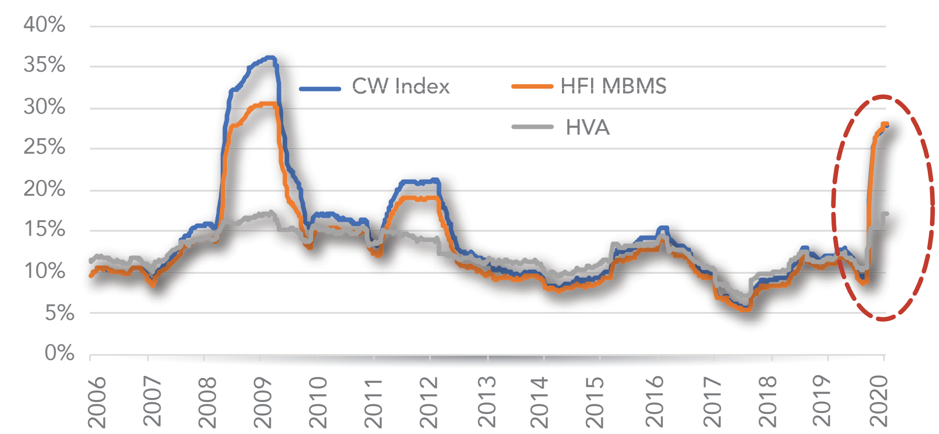

FIGURE 8

Risk analysis

Results computed on SciBeta Developed (Dec. 31, 2019, to June 30, 2020) and daily total returns in USD. Indexes used are the SciBeta Developed Cap-Weighted index, the iHFI MBMS 6F EW and the iHFI MBMS 6F EW HVA.

SciBeta Developed: S1-2020 (RI/USD)	Cap-Weighted	iHFI MBMS 6F EW	iHFI MBMS 6F EW HVA
Ann. Volatility	38.38%	38.84%	21.79%
Max Drawdown	33.77%	35.70%	27.19%
Max Loss	-31.55%	-34.37%	-25.29%
Market Beta	1.00	1.00	0.47

Figure 8 focuses on the average and extreme risks of the different versions of the multi-factor index during the first half of 2020.

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