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When Greenness is Mistaken for Alpha: Pitfalls in Constructing Low Carbon Equity Portfolios

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Executive Summary

Low carbon investing products are typically built on the assumption that green stocks produce positive alpha. Economic theory contradicts this assumption: all else being equal, green firms should earn lower returns than brown firms because they provide non-pecuniary benefits and risk-hedging benefits to investors. The empirical literature does not support the claim of positive alpha for low emission firms either. This paper analyses how low carbon strategies can be mistaken for alpha and what the consequences are for investors.

First, we show that low carbon strategies can easily be mistaken for alpha when ignoring exposure to well-known equity factors and estimation error. Analysing US equity and carbon emissions data, we show that there is apparent alpha due to a long-short low carbon factor, which delivers positive returns over our sample period with 1.74% per year. However, this alpha becomes negative at -0.32% per year when adjusting for equity style factors, and it disappears entirely when accounting for estimation error. The profitability factor plays a central role in bringing down the alpha of the low carbon factor: 85% of average return is explained by exposure to the profitability factor. Moreover, returns of low carbon strategies display a negative relation with fossil fuel prices. Performance during periods of declining fossil fuel prices is thus inflated.

Second, we document the costs borne by investors who build portfolios with a mistaken belief in a positive low carbon alpha. This cost is substantial. Multi-factor portfolios that impose positive weights on the low carbon factor have an inferior risk-return profile: A low carbon allocation of 40% leads to giving up 100bp of annualised returns on a risk-adjusted basis. Note that this result occurs despite the positive returns of the low carbon factor. Increasing investment in the low carbon factor leads to a reduction in factor diversification due to overlap with the profitability factor and thus to low returns per unit of volatility within a multi-factor portfolio. Mistaking positive returns for positive (multi-factor) alpha is indeed costly for investors.

Third, we analyse the shortcomings of portfolio construction approaches used in low carbon investment products. Such approaches exploit highly granular information in stock-level scores to combine carbon objectives with equity style factors. We assess the incremental performance benefits from exploiting stock-level scores. On the one hand, allowing strategies to use scores more aggressively, by tolerating higher tracking error, does not improve performance. Annualised returns increase marginally until annualised tracking error reaches 2% to 3%, and then decrease if tracking error is allowed to increase further. This finding reflects the fact that carbon scores are not informative about expected returns, and scores for equity style factors are not reliable at the individual stock level. On the other hand, using scores more intensely increases portfolio concentration and impedes investability.

Our results suggest that using low carbon strategies as a source of alpha is costly to investors. This does not imply that investors cannot benefit from low carbon investing. Investors should analyse whether low carbon strategies can help them hedge climate risks or make a positive impact on corporate behaviour.

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Introduction

Introduction

Greenhouse gas emissions of firms produce a negative externality because they contribute to climate change. Nordhaus (2019) emphasises that "climate change threatens, in the most extreme scenarios, to return us economically whence we came". Institutional investors have tried to incorporate climate considerations in their equity portfolios through low carbon strategies. An example of an investor initiative that aims to reduce holdings in shares of carbon intensive companies is the Portfolio Decarbonization Coalition (PDC) that was created in 2016 and now represents more than USD800bn in assets with a low carbon objective.

There are different motivations that drive investors to consider low carbon strategies. First, some investors want to align investments with their values and avoid firms that pollute a lot. A second motivation is to influence firms to change their practices by reducing the aggregate supply of capital to heavy polluters. Thirdly, avoiding exposure to high emitters should reduce exposure to transition risk, the risk of rising costs of carbon. A fourth motivation is that low carbon investing may provide positive alpha and thus boost performance.

Alpha appears to be the dominant motivation emphasised by product marketers. For example, one major fund management firm states that "*low carbon investing can help improve alpha over time*".[1] Another well-known asset manager states: "*Investors need to pay attention to climate change in their strategies. It can drive alpha*".[2] Alpha is also a widespread motivation for investors. Krueger, Sautner and Starks (2020) conduct a survey and report that more than 25% of institutional investors stated performance benefits as one of the main motivations for incorporating climate risk in their investment strategies.

However, there is no sound support for positive alpha from low carbon strategies in the financial literature. Economic theory (see Pástor, Stambaugh & Taylor, 2020) predicts that firms that emit less (green firms) should earn lower returns in the long term than the high emitters (brown firms). This is because some investors are willing to give up performance to receive the non-pecuniary benefits of holding green firms that correspond to their social values. Moreover, investing in more sustainable firms could allow investors to hedge against climate risks. Risk-averse investors are willing to give up some of the expected return for this risk reduction, leading again to lower returns for green firms. Empirical evidence of investor behaviour supports the theory. Fund flows and investor behaviour show that investors are indeed willing to give up performance for holding green investments (Riedl and Smeets, 2017, and Hartzmark & Sussmann, 2019). Evidence on stock returns also contradicts the notion of a positive alpha for holding green firms. Bolton and Kacperczyk (2020) analyse carbon emissions data and show that brown firms earn higher returns than green firms when using total emissions, while there are no significant return differences when using emissions standardised by revenues. Evidence is also available for more involved measures of carbon risk that go beyond emissions. Görgen, Jacob and Erlinger (2021) use a combination of 55 ESG metrics to proxy for carbon risks of stocks and do not find any support for positive alpha. Alessi, Ossola & Panzica (2020) combine emissions data and emission disclosure quality and find that brown stocks outperform green stocks. Overall, economic theory and empirical evidence contradicts the claim of positive alpha for low carbon strategies that is popular in the industry[3].

1 - Available at: <https://www.alliancebernstein.com/library/Low-Carbon-Investing-Doesnt-Have-to-Mean-Low-Return.htm#>. Accessed on 22 April 2021.
2 - Available at: <https://www.refinitiv.com/perspectives/future-of-investing-trading/decarbonization-investment-strategies/>. Accessed on 22 April 2021.
3 - Another strand of research assesses timing strategies that move in and out of brown and green firms. For example, Cheema-Fox et al. (2019) show that a strategy that chases institutional fund flows into green stocks generates alpha.

Introduction

This paper examines the consequences of viewing low carbon strategies as a source of positive alpha (as is popular in the industry) when they actually are not (as shown in the academic literature). We first analyse how industry participants may conclude positive alpha exists when analysing returns, despite its absence. We then analyse the cost of wrongly assuming positive green alpha for an investor who has access to a well-diversified set of equity factors. Finally, we draw on portfolio construction approaches that are popular in the industry for exploiting carbon scores, and that closely mimic portfolio construction for exploiting alpha signals. We show the consequence of using carbon scores as an alpha signal in such approaches.

Analysing US equity and carbon emissions data, we show that there is apparent alpha to a long-short low carbon factor, but that this alpha becomes negative when adjusting for equity-style factors and in fact disappears when accounting for estimation error. Multi-factor portfolios that impose positive weights on the low carbon factor have an inferior risk-return profile: a low carbon allocation of 40% leads to giving up 100bp points of annualised returns on a risk-adjusted basis. Constructing portfolios using low carbon scores like any other alpha score does not improve performance and leads to problems with concentration and investability.

The remainder of this paper is organised as follows. We first introduce the long-short low carbon strategy and show how alpha changes when conducting adjustments for equity style exposures. We then analyse optimal portfolios of long-short factors that impose positive holdings of the low carbon factor. Finally, we analyse long-only strategies constructed from carbon scores that follow popular portfolio construction methods used in the industry to tilt to factors.

1. How Low Carbon Returns are Mistaken for Alpha

1.How Low Carbon Returns are Mistaken for Alpha

We illustrate how investors can easily mistake returns of low carbon strategies with positive alpha even when there is none. The key to understanding the performance that is due to low carbon investing is to adjust returns for exposures to other sources of performance, such as equity style factors and business sectors. It is easy to misinterpret returns as alpha when proper adjustments are omitted from performance analysis. We illustrate this point using low carbon strategies in a US equity universe.

We construct the low carbon factor using the carbon intensity[4] measures of the largest 500 stocks across US. The carbon intensity is defined as the sum of scope 1 and scope 2 emissions divided by the revenue of a firm over the recent year. We choose this particular measure for our illustration as it is popular in the industry and avoids problems associated with alternative measures (see Ducoulombier and Liu, 2021). The carbon intensity of a stock s at time *t* is defined as:

$$CI_{s,t} = \frac{Carbon\ Emmision_{s,t}}{Revenue_{s,t}}$$

That carbon intensity does not lead to positive alpha has been shown in part of the analysis of Bolton and Kacperczyk (2020). As discussed in the introduction, using more involved measures or other emissions-based measures has not been shown to lead to positive alpha either[5].

We construct a long-short portfolio that buys 30% of the stocks with the lowest carbon intensity (green stocks) and sells 30% of the stocks with the lowest carbon intensity (brown stocks). The resulting factor is a green minus brown factor, that we refer to as GMB factor. We analyse four version of GMB factor for robustness purposes. The first version assigns weights to the selected stocks proportional to their market capitalisation. The second version uses the same stock selection approach, but equally weights each security. The last two versions follow the same stock-selection rule within each sector[6], and cap-weights or equal-weights are attributed to the selected stocks. Each sector is weighted based on the respective market capitalisation. Hence, the third and the fourth versions account for sector effects that will eliminate the performance impact on GMB factor that might come from sector biases. Considering different weighting schemes and sector adjustments should allow for robust conclusions.

The GMB factor is a useful addition to an investor's portfolio if it contains information about average returns that is not contained in existing factors. For example, Carhart (1997) proposed the addition of the momentum factor to Fama-French 3-Factor model because the existing factors in the model – the market, size and value factors – could not explain the positive average returns generated by the momentum factor. In other words, momentum generated alpha relative to a 3-Factor model. On the other hand, Fama and French (1996) showed that factors such as dividend yields and earnings-to-price do not generate alpha in a 3-Factor model. Their returns are fully explained by exposures to the market, value and size factors.

For investors, it is crucial to assess whether a GMB strategy does offer additional returns that cannot be explained by other factors (like momentum) or whether they are already fully captured by exposures

4 - Carbon emissions data is only available since 2012. We backfill carbon emissions for each stock based on its first available data.
5 - We also report the results when including scope 3 emissions in the supplement. The results are similar and do not alter the conclusions of our analysis.
6 - We use Thomson Reuters Sector Classification.

1.How Low Carbon Returns are Mistaken for Alpha

to other factors and do not generate alpha (like the dividend yield). It is crucial that exposures to well-known factors are taken into account before concluding that there is a new characteristic that can add to the performance of a portfolio. The most relevant question for an investor who has easy access to existing equity factors is whether low carbon factor generates non-zero returns after we adjust for its exposure to other equity factors. We adjust GMB returns for the exposure to well-documented and widely used factors. These are the Market, Size, Value, Momentum, Profitability, Investment and Low Volatility. In addition to adjusting for factors, we obviously need to consider the statistical significance of the GMB alpha to account for estimation error.

Exhibit 1 below reports the annualised performance measures of the GMB factors. The t-statistics for all four versions of GMB factor are indicated in brackets. The final column reports average results across all four specifications. In the first row, we can see that the returns of all four versions of GMB is positive in our sample that spans for 15 years. However, returns of GMB factors are statistically weak, i.e., far from significant. Next, we adjust for the market exposure of the GMB factors. Once we account for the market exposure of GMB factor, we see a reduction of average returns from 1.74% to 1.38% on average. The last row of Exhibit 1 corresponds to a measure that is the most relevant for investors. The multi-factor alpha indicates whether there is an information in average returns of a GMB factor unexplained by other factors in the model. The results indicate that once accounting for exposures to all well-known factors, the estimated premium becomes negative on average. Note the large reduction from simple returns of the GMB factor to the multi-factor alpha. The estimated premium goes from 1.74% to -0.32% once factor exposures are accounted for.

Exhibit 1: Performance of Green minus Brown Factor.

United States 31/12/2004 - 31/12/2019	Green Minus Brown factor				
	Equal-Weighted	Cap-Weighted	Equal-Weighted Sector-Neutral	Cap-Weighted Sector-Neutral	Average
Ann. Return	1.64%	2.11%	1.13%	2.08%	1.74%
	(0.86)	(0.94)	(0.75)	(1.23)	
Ann. Volatility	9.23%	11.17%	7.15%	7.34%	8.72%
Sharpe Ratio	0.18	0.19	0.16	0.28	0.20
Max Drawdown	32.85%	45.55%	17.49%	17.12%	28.25%
CAPM Alpha	1.22%	1.25%	1.19%	1.87%	1.38%
	(0.55)	(0.47)	(0.66)	(0.99)	
Multi-Factor Alpha	-1.47%	-0.58%	-0.40%	1.17%	-0.32%
	(-0.90)	(-0.28)	(-0.24)	(0.63)	

The analysis is based on the Scientific Beta United States universe. It uses daily data except for the CAPM and Multi-Factor analysis, which uses weekly data. The multi-factor model includes the market factor and the Scientific Beta long-short equal-weighted factors, namely the Size, Value, Momentum, Low Volatility, Profitability and Investment. Numbers in parentheses indicate the t-statistic associated with the parameter shown just above (return or alpha).

Point estimates of average returns of GMB factor may look attractive to investors. When adjusting for exposure to well-known factors, the point estimates of value added become negative. Therefore, investors who consider these point estimates would conclude on positive alpha when omitting

1.How Low Carbon Returns are Mistaken for Alpha

adjustments. However, when considering adjustments for factor exposures, they would conclude on negative alpha. When considering the uncertainty around these point estimates, GMB performance is indistinguishable from zero.

It is also interesting to identify the factor exposures of the GMB factor that drive the reduction point estimates of performance. The Exhibit 2 below reports factor exposures of GMB factor from a seven-factor model. The results in the top panel suggest that the GMB factors are highly exposed to the profitability factor. We also observe high exposure to the low investment factor for non-sector-neutral portfolios. Moreover, all GMB portfolios are positively exposed to the market factor.

The second panel of the table shows how much of the average return does exposure to each factor explain. As expected, market and the profitability factors stand out in that they drive a significant amount of total returns generated by GMB factors. On average, 1.48% of annualised GMB returns are generated by the exposure to the profitability factor. Recall that the total return of GMB factors was 1.74% on average (see Exhibit 1). This means that 85% of the average return is explained by the exposure to the profitability factor.

Exhibit 2: Factor exposures of Green minus Brown Factor

United States 31/12/2004 - 31/12/2019	Equal-Weighted	Cap-Weighted	Equal-Weighted Sector-Neutral	Cap-Weighted Sector-Neutral	Average
Factor Exposures					
Market	**0.10**	**0.13**	**0.07**	**0.06**	0.09
Size	-0.04	0.02	**-0.14**	**-0.12**	-0.07
Value	-0.07	**-0.33**	**0.18**	0.07	-0.04
Momentum	**-0.19**	**-0.30**	-0.04	**-0.06**	-0.15
Low Volatility	**-0.15**	**-0.20**	-0.03	**-0.07**	-0.11
High Profitability	**0.79**	**0.68**	**0.42**	**0.30**	0.55
Low Investment	**0.28**	**0.28**	0.02	-0.07	0.13
Return explained by factor exposures					
Market	0.77%	0.97%	0.57%	0.49%	0.70%
Size	-0.02%	0.01%	-0.06%	-0.05%	-0.03%
Value	-0.05%	-0.27%	0.15%	0.05%	-0.03%
Momentum	0.31%	0.49%	0.06%	0.10%	0.24%
Low Volatility	0.16%	0.21%	0.03%	0.08%	0.12%
High Profitability	2.15%	1.84%	1.14%	0.80%	1.48%
Low Investment	0.32%	0.31%	-0.02%	-0.08%	0.13%
R-squared	**47.70%**	**44.00%**	**14.80%**	**10.50%**	**29.25%**

The analysis is based on the Scientific Beta United States universe. it was done using weekly returns. The independent variables are the market factor and the Scientific Beta long-short equal-weighted factors. Long-short factors are not neutralised to the market. Factor exposures that are statistically significant at 5% level are indicate with bold format. The performance attributed to each factor is computed as a product of factor exposure and average factor return (geometric) over the given period.

1.How Low Carbon Returns are Mistaken for Alpha

Our findings are in-line with the existing evidence in the literature. A positive relation between corporate social performance (CSP), of which climate consideration are a particular aspect, and profitability of a firm is well-established. Waddock and Graves (1997) found that CSP is positively associated with financial performance. They argue that a possible explanation is that more profitable firms have higher capacity to do good, which in our case means to reduce their emissions. Alternatively, consumers might prefer products of green firms rather than brown firms, which plays out in favour of green firms. Bruno, Esakia and Goltz (2021) find a similar relation between ESG and profitability factors.

The analysis also indicates that more than 40% of the return variation in non-sector-neutral versions of the GMB factor is explained by our multi-factor model. When looking at sector-neutral versions of GMB factor, standard equity factors explain up to 15% of return variation only. Put differently, more than 85% of return variation of GMB factor is unexplained by common equity factors. However, we have seen above that return variations left unexplained do not lead to a positive return on average. Instead, the exposures to equity factors explain most of the average return generated by the GMB factor.

In addition to considering time periods of a decade or more, such as our sample, investors frequently draw conclusions from much shorter time periods. In this case, conclusions on alpha may be driven by the particular market conditions that favour green strategies. To illustrate this point, we analyse performance dependency to oil prices. If green strategies omit or short fossil fuel related stocks, they will post strong performance in times of declining oil prices when energy stocks have low returns. In Exhibit 3, we compare the returns of the low carbon factor in different conditions of oil price returns. The table reports annualised average returns during the calendar months when the return on an oil price was low (bottom 25%), stable (middle 50%), or high (top 25%).

We observe that the returns of the GMB factors without sector-adjustments is highly influenced by movements in the oil price. GMB factors without sector-neutrality have strong performance during times of decreasing oil prices. For example, the equal-weighted GMB factor (without sector neutrality) yielded an annualised return of 8.6% during times of low oil returns, compared to an unconditional return of only 1.64% per year. Investors may get a biased picture of performance of low carbon strategies when evaluating periods that are influenced by particular conditions, such as movements of the oil price. As an aside, when promoters of low carbon strategies emphasise their positive performance, they should perhaps also point to the fact that this performance is driven by conditions which hamper the energy transition. Low oil prices are not only associated with high performance of green strategies but also mean low incentives for firms to move away from fossil fuels as an energy source.

1.How Low Carbon Returns are Mistaken for Alpha

Exhibit 3: Conditional performance of GMB factor on oil prices

United States 31.12.2004 - 31.12.2019	Equal-Weighted	Cap-Weighted	Equal-Weighted Sector-Neutral	Cap-Weighted Sector-Neutral	Average
			GMB Factor Annualised Return		
Low Oil Returns	**8.6%***	5.1%	3.7%	0.1%	**4.4%**
Stable Oil Returns	2.9%	**7.1%***	0.8%	2.5%	**3.3%**
High Oil Returns	-6.7%	-9.2%	0.0%	3.8%	**-3.0%**
High - Low	**-15.2%****	**-14.3%***	-3.7%	3.7%	**-7.4%**
Unconditional	1.64%	2.11%	1.13%	2.08%	1.74%

*The table shows average (geometric) annualised returns of GMB factors in different conditions of oil price returns. We classify three conditions that consists of calendar months when returns on oil is in bottom 25% (low), middle 50% (stable) and top 25% (high) over the full period of the analysis. We used crude oil WTI prices for our analysis (Datastream code: CRUDWTC). Statistical significance at 10%, 5% and 1% are indicated by *, ** and ***.*

Overall, we show that there is clearly no evidence of alpha in our GMB factors over the sample period. However, our results do not allow for a complete conclusion on the low carbon premium. We analyse a particular definition of greenness over a short sample. In addition, the sample period is likely influenced by upward attention shifts to low carbon investing which bias estimates of alpha upwards over the period and also reduce future expected returns[7]. The absence of positive alpha however aligns well with findings in the literature cited in the introduction. A more interesting aspect of our results is that they show how investors can end up with a belief of positive alpha when looking at past performance. When omitting adjustments for standard equity factors and ignoring statistical uncertainty, investors could mistakenly conclude that alpha of the GMB strategies is positive. We now turn to an analysis of the consequences of a mistaken belief in positive low carbon alpha when it is translated into portfolio decisions.

7 - See Bruno, Esakia and Goltz (2021) for empirical evidence of attention shifts and inflated performance of ESG strategies during high attention periods.

2. The Cost of a Mistaken Belief in a Positive Low Carbon Alpha

2. The Cost of a Mistaken Belief in a Positive Low Carbon Alpha

The implications for investors who follow the idea of "doing well by doing good" with low carbon strategies can be substantial. We show in this section that maintaining a belief in positive alpha to the GMB factor is detrimental to portfolio performance.

We have shown above that point estimates of simple returns of the GMB strategy are positive but point estimates of multi factor alpha are negative. In this section, we develop the portfolio implications of the negative multi factor alpha. We assume the case of an investor who has access not only to the GMB factor, but also to the market factor and equity style factors. In this setting, simple returns (or volatility-adjusted returns such as the Sharpe Ratio) are not relevant for investors because they ignore the interaction of the GMB strategy with other components of the investor's portfolio.

The multi-factor alphas above have direct implications for portfolio performance. Only strategies with significant alpha increase the Sharpe ratio of the total portfolio of investors who have access to standard factors (Fama 1998). Gibbons, Ross & Shanken (1989) show that the difference in squared Sharpe ratio between the total portfolio that includes a candidate strategy and the squared Sharpe ratio of the portfolio without this strategy is a function of the multi-factor alpha.

Taking the GMB strategy as the candidate strategy, we can write:

$$\left(\frac{\alpha_{GMB}^2}{\sigma_\varepsilon^2}\right) = SR^2(Factors\ and\ GMB) - SR^2(Factors\ without\ GMB)$$

where SR denotes the Sharpe ratio, α_{GMB} is the intercept from a time series regression for strategy returns onto the returns of standard factors, and σ_ε is the idiosyncratic volatility of the GMB strategy, i.e. the variation of returns that is not explained by the standard factors.

The equation shows that an GMB strategy with a multi-factor alpha of zero does not support increasing the Sharpe ratio for the investor, relative to the case where he ignores the GMB strategy. A GMB strategy with a positive alpha will help investors improve the Sharpe ratio of their overall portfolio through a long position in this strategy. A GMB strategy with a negative alpha will also help investors improve the Sharpe ratio but through a short position, i.e., a brown investing strategy.

Given the negative multi factor alpha for the GMB strategy, we know that investors could increase their Sharpe ratio by allocating a negative weight to the strategy. Alternatively, investors could attribute a zero weight to the GMB strategy if they completely ignore it. But investors who mistakenly believe in a positive alpha, perhaps based on looking at simple returns that are unadjusted for factors, would allocate a positive weight to this strategy. We examine the cost of such a positive allocation.

To represent different choices for the GMB factor allocation, we consider a mean-variance efficient portfolio that we calibrate over the full sample. The resulting portfolio corresponds to a static allocation to equity factors that leads to the highest Sharpe ratio in our sample. The factors considered are the

2. The Cost of a Mistaken Belief in a Positive Low Carbon Alpha

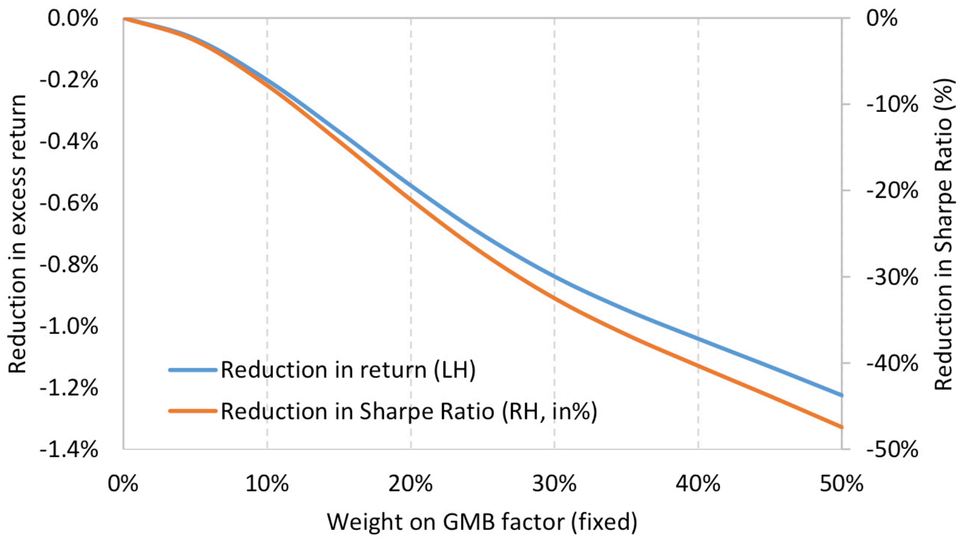
Market, Size, Value, Momentum, Low Volatility, High Profitability, Low Investment and the equally weighted GMB factor without sector-neutrality.

$$\max_{w}\left\{\frac{w'E(r)}{\sqrt{w'\Sigma w}}\right\}$$

$$\text{s.t. } w'I = 1;\ w_{GMB} = \overline{w_{GMB}}$$

The analysis allows us to assess the impact on an optimal portfolio when including the GMB factor and fixing its allocation at different levels. We take the case of zero allocation to the GMB factor as our base case. When fixing the weight of the GMB factor to zero, the investor ignores the investment opportunities represented by the GMB strategy, and he optimally chooses the allocation to the seven equity factors. We then fix the weight of the GMB factor at increasing levels, up to 50%. This increase in a fixed GMB weight reflects an investors' belief that GMB is an attractive strategy due to its supposed alpha. Exhibit 4 traces the reduction in excess returns and the percentage reduction in Sharpe ratio. Excess returns are for leveraged strategies that match the volatility of an unconstrained mean variance portfolio. Thus reduction in excess returns are directly interpretable as reductions in performance, since the volatility levels are set to be equal. These performance reductions are the direct consequence of increasing weight in a strategy that has positive return but negative multi-factor alpha.

Exhibit 4: Losses by including GMB factor in allocation



The plot shows the reduction in annualised excess return (in percentage points) and Sharpe Ratio (in percentage) of an ex-post tangency portfolio when optimisation is forced to allocate a fixed weight to GMB factor. The base case portfolio with the GMB weight fixed at zero delivers an excess return of 2.58% and a Sharpe ratio of 1.06. The factors considered are the Market, the GMB (EW), and six equal-weighted Scientific Beta factors without market-beta adjustment. To make returns comparable, portfolios are leveraged so that they match the volatility of an unconstrained (GMB factor weight not fixed) Max Sharpe Ratio portfolio.

The loss for investors due to a positive allocation to GMB factor is clearly visible from the downward sloping curves. In terms of (volatility-matched) excess returns, a 10% weight in the GMB factor reduces portfolio returns by about 20 basis points per year. This is a large reduction from a small weight in

2. The Cost of a Mistaken Belief in a Positive Low Carbon Alpha

the GMB factor. At a weight of 40%, the GMB factor allocation leads to a return reduction of almost 100 basis points. In terms of Sharpe ratio, allocating 10% of a portfolio to GMB factor would lead to roughly 8% reduction in the Sharpe ratio, and allocating 40% to the GMB factor reduces the Sharpe ratio by 40%.

Note that this result occurs despite the positive returns of the GMB factor. In fact, adding weight to the GMB factor leads to a reduction in factor diversification due to its overlap with the profitability factor and thus to low returns per unit of volatility within the multi-factor portfolio. Mistaking positive returns for positive (multi-factor) alpha is indeed costly for investors.

While this analysis shows the implications in principle of assuming a positive GMB alpha when there is none, actual investment decisions do not fit with the framework we employed. We now turn to analysing portfolios that resemble industry practice on low carbon strategies.

3. Using Carbon Scores as an Alpha Signal in Portfolio Construction

3. Using Carbon Scores as an Alpha Signal in Portfolio Construction

We have shown that investors do not get any benefit from investing in the low carbon factor. This means that a good carbon score does not signal high alpha. Given this finding, constructing portfolios that target reduction in overall carbon intensity, all else equal, should not lead to substantial improvements in the performance.

However, industry approaches to low carbon investing precisely follow such approaches. Starting with firm-level scores, portfolios tilt to green firms and away from brown firms. This approach is identical to portfolios that are constructed to tilt to the value and momentum factors for example. The difference is that value and momentum have returns that are not captured by other factors; they do deliver multi-factor alpha. Using such portfolio construction approaches to tilt to characteristics that do not deliver alpha is not likely to lead to success.

We illustrate this problem using long-only low carbon portfolios that use different approaches to gain exposure to equity style factors while reducing carbon intensity. These approaches reflect different schools of thought of how low carbon investing can be combined with factor tilts.

The first school of thought relies on filtering out high emitters. The rationale for such an approach is that the carbon objectives should be addressed separately from financial objectives. Our first approach simply excludes the worst polluters (10%) from the initial universe[8], and then follows a standard methodology for factor indices which first selects stocks by factor score and then weights them to improve diversification. Factor-based stock selection and diversification-based weighting target financial performance and are separated from the filtering step which targets carbon objectives. In detail, we select 30% of stocks based on factor objectives. We get to this 30% selection by first selecting 50% of the stocks from the filtered universe with the highest factor characteristic for the target factor. Then we remove 20% of stocks in the initial universe that have the worst multi-factor score among selected stocks. Selected stocks are weighted using the Scientific Beta diversified multi-strategy scheme, which is the average of four weighting schemes: Maximum Deconcentration, Maximum Decorrelation, Maximum Sharpe Ratio and Diversified Risk-Weighted[9].

The second school of thought is score-based weighting. This school of thought is dominant in the industry. It simply treats the carbon score like any other factor score and does not separate carbon objectives from financial objectives. Instead, such approaches mix the stock-level factor scores and carbon measures to come up with a single metric that directly determines the weight of each stock. Weights that directly depend on a mixed score at the stock level can be obtained either by tilting or by optimisation.

Tilting approaches employ score-weighting, using the product of market-capitalisation and a composite score. The composite score is itself a product of a normalised carbon intensity and a normalised factor score. Such an approach is a popular way of designing indices that integrate carbon and factor scores. For comparability of our test strategies with the filtering approach, we apply a power to the composite score that leads to matching the ex-ante tracking error of score-weighted and filtering strategies[10].

8 - To reflect a common constraint in low carbon investment practice, all portfolios analysed in this section exclude coal companies from the investable equity universe. Coal companies are those classified in the Coal Industry (TRBC 50101010 in the Thomson Reuters Business Classification) as per their dominant involvement in coal mining or beneficiating, coal mining support (e.g. testing, tunneling, blasting, training and other contract-based coal-related services) and wholesaling. These are companies deriving significant turnover from thermal coal mining, utilities that make significant use of coal in their power generation fuel mix, and companies that own coal reserves.
9 - For more details about the methodology, refer to index methodology of Scientific Beta.
10 - We use robust estimates of ex-ante tracking error. The covariance matrix of stock returns is estimated using weekly returns over the most recent two years. We use principal component analysis to extract the common statistical factors in stock returns. The covariance matrix uses N common factors that explain most of the return variation of stocks, wherethe Nth principal component has eigenvalue greater or equal to the Marcenko-Pastur edge.

3. Using Carbon Scores as an Alpha Signal in Portfolio Construction

The second score-based approach uses optimisation to maximise the composite score, which is again the product of the normalised factor score and the normalised carbon intensity measure. To ensure comparability again, we constrain the optimiser to respect a level of tracking error smaller or equal to that of the corresponding filtering strategy[11].

We build strategies targeting either the value, size, momentum, low volatility, profitability or investment factor. For each factor, we build a filtering strategy, a score-weighted strategy and an optimised strategy. To conduct comparisons across the three approaches, below we report the average result across the six factors.

Exhibit 5 reports performance analysis of stylised portfolios following three approaches. The results indicate that none of the score-based approaches outperform the simple filtering approach that focuses on diversification. The filtering approaches achieves Sharpe ratio of 1.04 on average across six factors, while the corresponding numbers for score-weighted and optimisation-based portfolios are 0.93 and 0.98. The score-based portfolios reduce weighted-average carbon intensity by a larger amount. Nevertheless, they fail to improve the performance, as expected based on our analysis in the previous sections. The filtering approach leads to a solid reduction of weighed average carbon intensity (WACI) by 55%, while score-based approaches reduce WACI more aggressively, by around 80% on average.

Exhibit 5: Performance of Long-only Low Carbon Equity Portfolios

US Equity Universe Dec-2009 to Dec-2019	Cap-Weighted	Filtered iHFI Multi Strategy: Average across 6 Factors	Score*Cap-Weighted: Average across 6 Factors	Optimised: Average across 6 Factors
Ann. Return	13.55%	15.16%	14.45%	15.23%
Ann. Volatility	14.69%	14.15%	15.01%	15.00%
Sharpe Ratio	0.88	1.04	0.93	0.98
Max Drawdown	19.37%	19.02%	20.66%	21.47%
Ann. Rel. Return	-	1.61%	0.92%	1.71%
Ann. Tracking Error	-	3.58%	3.48%	5.01%
Information Ratio	-	0.46	0.24	0.31
Max Rel. Drawdown	-	8.25%	9.03%	10.58%
Turnover	3.98%	39.1%	49.4%	107.0%
Avg. Effective Number of Stocks	135.0	110	95	28
Avg. WACI ($M/tons)	244.5	110.1	36.5	59.5
Reduction in WACI	-	-55%	-85%	-76%

The analysis is based on the Scientific Beta United States universe. The analysis was done using daily total returns in USD, from 31-12-2009 to 31-12-2019. All figures are annualised. Effective number of stocks (inverse of Herfindal index) and portfolios' weighted average carbon intensity (WACI) are computed each quarter, at the rebalancing date, and average across time are reported. Results are also averaged across each of the six individual standard factor-targeting portfolios for both Filtered iHFI Portfolios and Low Carbon Optimised portfolios. Carbon Intensity at the stock level is computed as an aggregate measure of Scope 1 and Scope 2 emission normalised by revenue. Stocks with more than 10 consecutive zero returns and stocks with missing carbon Intensity data have been excluded from the analysis.

11 - More details on optimised strategy can be found in the supplement.

3. Downside Risk

Despite failing to deliver performance benefits, score-based approaches come with more concentration and higher turnover than the filtering approach. The optimised strategies have turnover above 100% on average, and effective number of stocks of around 28. Score-weighted approaches lead to turnover of 49% on average and an effective number of stocks of 95. The filtering approach leads to lower turnover and higher effective number of stocks. Overall, despite additional implementation hurdles, score-weighted strategies do not outperform a simple filtering approach.

All three approaches to constructing factor portfolios that integrate low carbon objectives reduce carbon intensity, and all of them outperform the market index due to their positive exposure to the rewarded equity style factors. However, the difference between the filtering approach and the score-based approaches suggest that exploiting scores more aggressively does not necessarily improve the performance.

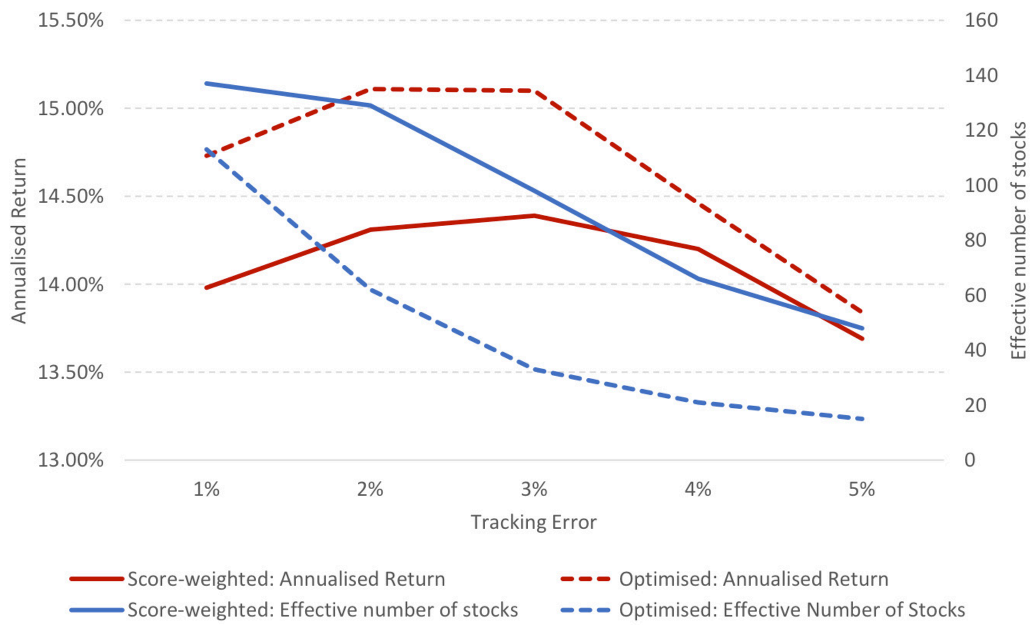
To further assess the consequences of exploiting scores more aggressively, we compare score-weighted strategies with different levels of aggressiveness, and optimised strategies with different levels of aggressiveness. The comparison across different approaches above does not allow to control the level of aggressiveness in a precise manner. Comparing strategies that use the same approach, but vary the intensity with which scores are translated into weights, should give a sharper view on the impact of exploiting scores more aggressively.

To conduct this analysis, we construct score-weighted strategies that obtain different levels of tracking error. To vary the level of tracking error, we vary the power score applied to scores. This allows us to obtain score-weighted strategies with tracking error ranging from 1% to 5%. For optimised strategies, we simply vary tracking error target specified in the constraint. Relaxing the level of tracking error allows the strategies to exploit scores more aggressively. Our question is whether this possibility to exploit scores more aggressively leads to any increase in performance.

The results in Exhibit 6 show that the more aggressive use of scores does not improve performance. The annualised returns tend to mildly increase until the tracking error reaches around 2-3%, and then decrease as the tracking error increases further. Clearly, higher tracking error is not compensated with higher performance overall.

3. Downside Risk

Exhibit 6: Performance and concentration as a function of tracking error



There are two reasons why exploiting scores more aggressively does not improve performance.

• First, we have seen above that carbon scores do not carry incremental information for expected returns. Thus using these scores aggressively at the stock level does not improve performance.
• Second, even when using factor scores that contain useful information on average returns, there is no deterministic link between returns and scores at individual stock level (see e.g. Cederburg and O'Doherty, 2016). Factor scores can be used to design well-diversified portfolios that have higher returns. They cannot be used to reliably identify stock-by-stock differences of returns.

On the other hand, tilting more heavily to few stocks with desired characteristics means giving up on the benefits of diversification. Exhibit 6 shows that aggressively exploiting scores leads to high levels of concentration. Concentration is more pronounced for the optimised portfolios than for score-weighted portfolios. At 3% tracking error, the optimised portfolio has an average effective number of stocks of less than 40 in a universe of 500 stocks, a rather extreme bet on highly scored stocks.

In sum, using stock-level scores to achieve high factor exposures and carbon intensity reduction does not improve performance over a simple filtering approach, but comes with higher implementation hurdles, and foregoes diversification benefits. An additional shortcoming of score-based approaches is that they may lead to signals to companies that are inconsistent with positive social impact. We refer to Amenc et al. (2020) for the analysis of inconsistencies that score-based approaches may lead to.

Conclusion

Conclusion

We have shown that using low carbon strategies as a source of alpha, when this is not the case, is costly to investors. What may appear as positive alpha disappears when adjusting for factors and accounting for estimation risk. We find that the performance of low carbon factors decreases from 1.74% to -0.32% once factor exposures are accounted for. Mistakenly using low carbon strategies as a source of alpha reduces portfolio performance for investors who have access to standard equity factors. Constructing portfolios using low carbon scores like any other alpha score does not improve performance and leads to problems with concentration and investability.

Using low carbon as an alpha signal is not only ineffective financially, it also does not do justice to investors' important nonfinancial objectives. An important motivation for investors is to push companies to act on climate change. There are both empirical and theoretical reasons why focusing on alpha will curtail the impact of green strategies on firms' climate action. Empirically, it has been shown that portfolios using low carbon scores as an alpha signal generate inconsistent signals to firms. Firms with deteriorating climate performance may see increases in their portfolio weights, implying increasing capital allocation to firms that worsen their climate impact (see Amenc et al. 2020). Theoretically, if investors can generate higher long-term returns from green investments, this implies that the cost of capital of green firms is high, preventing them from expanding their scale. As emphasised in the literature on sustainable investing[12], driving down the cost of capital is a channel of positive impact. This channel implies that investors who want to have impact cannot expect higher returns at the same time.

Investors need to reconsider how to design low carbon strategies in order to maximise their impact. The pressing issue faced by society is tackling climate change, not generating alpha. And while low carbon alpha appears to be fake, the damage from climate change unfortunately is real.

12 - See Oehmke & Opp (2020), Pástor, Stambaugh & Taylor (2020), and Hong, Wand & Yang (2021).

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About Scientific Beta

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EDHEC-Risk Institute set up Scientific Beta in December 2012 as part of its policy of transferring know-how to the industry. In January 2020, Singapore Exchange (SGX) acquired a majority stake in Scientific Beta and is maintaining the strong collaboration with EDHEC Business School and principles of independent, empirical-based academic research that have benefited Scientific Beta's development to date. Scientific Beta is an original initiative which aims to favour the adoption of the latest advances in "smart beta" design and implementation by the whole investment industry. Its academic origin provides the foundation for its strategy: offer, in the best economic conditions possible, the smart beta solutions that are most proven scientifically with full transparency of both the methods and the associated risks. Smart beta is an approach that deviates from the default solution for indexing or benchmarking of using market capitalisation as the sole criterion for weighting and constituent selection.

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