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Contents

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Introduction

It is a great pleasure to introduce the latest Scientific Beta special issue of the Research Insights supplement to IPE.

Our first findings question a widespread practice of using ESG as an alpha signal. While many of the ESG strategies analysed have positive returns, adjusting these returns for risk shrinks 'alpha' (or excess risk-adjusted return) to zero. Investors should ask how ESG strategies can help them to achieve objectives other than alpha, such as aligning investments with their values and norms, making a positive social impact, and reducing climate or litigation risk.

We then identify greenwashing risks in the construction of portfolios that represent popular climate strategies, especially those that correspond to net zero alignment strategies. Across strategies focusing on climate, the climate scores only account for 12% of differences in weights across stocks. In contrast, market capitalisation accounts for 88% of the differences in weights in these strategies.

Greenwashing is also detrimental to the efficacy of engagement. While climate investing sets out to make an impact by pushing firms to take urgent action to address the climate emergency, there is a danger that investors end up paying for 'feel good' products that induce complacency. Likewise, engagement strategies that are not combined with consistent portfolio decisions could lead to a false sense of investor action, without leading to a real effect.

We look at Scientific Beta's new series of inflation-friendly equity indices, which protect investors' portfolios against rising inflation and deliver an equity market risk premium over the long term. These indices are ideal candidates to replace cap-weighted indices for investors with inflation fears and as equity components of a multi-asset portfolio that needs insulation against inflation shocks.

We propose a methodology to estimate stock-level exposures to macroeconomic risks. The success of our methodology relies on the use of appropriate proxies for a relevant macroeconomic variable and robust measurement tools from statistics as well as textual analysis. Portfolios constructed with a target of high or low exposure to our forward-looking macro variables achieve significant exposures out of sample, which is not the case when using naïve estimation techniques or backward-looking economic variables, such as realised inflation or growth.

We present research results that 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 or not low carbon strategies can help them hedge climate risks or make a positive impact on corporate behaviour.

We introduce the Climate Impact Consistent (CIC) indices, which have a unique design that creates consistency between investors' engagement activities and investment decisions to maximise the potential for real-world impact. Indeed, the real impact of investment decisions from a climate alignment perspective comes from the consistency between these decisions and the climate performance of the companies that make up the portfolio. This is what is achieved by the CIC indices, which weight each stock according to its intra-sector climate performance and alignment trajectory.

Following the rise in trade tensions across the globe in recent years, it has become more relevant than ever to have access to effective tools to manage exposure to the risk of shifts in trade policies. We have shown that it is possible to capture heterogeneity in exposure to trade policy risk among stocks to construct effective risk management tools. Our methodology allows us to consider several dimensions of exposure, which improves the robustness of the resulting trade policy sensitivity.

We hope you will find the articles in the supplement useful and informative. We extend warm thanks to IPE for their partnership on the supplement.

Noël Amenc, Associate Professor of Finance, EDHEC Business School, CEO, Scientific Beta

‘Honey, I shrunk the ESG alpha’

Giovanni Bruno, Senior Quantitative Analyst, Scientific Beta;
Mikheil Esakia, Quantitative Research Analyst, Scientific Beta;
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In a new research paper, Honey, I Shrunk the ESG Alpha: Risk-Adjusting ESG Portfolio Returns, we examine equity strategies that exploit information in ESG ratings, following several papers that suggest that these strategies lead to outperformance.

While many of the ESG strategies have positive returns, adjusting these returns for risk shrinks ‘alpha’ (or excess risk-adjusted return) to zero. Sector biases and exposures to equity style factors capture the returns of ESG strategies. In addition, the analysis suggests that returns are inflated when investor attention to ESG rises.

The findings do not question that ESG strategies can offer substantial value to investors. Instead, they suggest that investors who look for added value through outperformance are looking in the wrong place.

The research has important implications for investors. As a general matter, the analysis provides an example of how one can document outperformance where there is none: it is sufficient to omit necessary risk adjustments. Concerning ESG strategies, the findings question a widespread practice of using ESG as an alpha signal. They do not question the added value of such strategies on other dimensions, especially on the financial materialisation of extreme risk reduction, which still requires serious studies that are forthcoming.

Popular papers document positive alpha for equity strategies that favour ESG leaders[1], and asset managers readily adopt the idea of positive ESG alpha. For example, one asset manager “views ESG as a source of alpha that could lead to positive portfolio performance over time. [...] This premise rests on the thesis that value creation (or destruction) is influenced by more than financial capital alone, especially longer term.”[2]

In recent research conducted by Scientific Beta,[3] we construct ESG strategies that have been shown to outperform in popular papers. We construct six different strategies in US equity markets and in developed markets outside the US. Each strategy goes long ESG leaders and short ESG laggards, using a different type of ESG score.[4] The scores we use are the aggregate ESG rating, each of the three component ratings, the rating trend, and finally, a combination of ESG rating level and trend.

Our main contribution is that we conduct a thorough risk adjustment when analysing the performance of these strategies. We assess performance benefits for investors when accounting for sector and factor exposures, downside risk, and attention shifts. These adjustments to performance are necessary to get a fair view of potential performance benefits to investors. The effect of these adjustments is clear-cut. They shrink the apparent alpha of ESG strategies to a level where none of the strategies delivers positive alpha.

1 See, eg, Giese, Nagy and Lee (2020), Giese, Lee, Melas, Nagy and Nishikawa (2019), Nagy, Kassam and Lee (2016), Giese and Nagy (2018), Verheyden, Eccles and Feiner (2016).

2 State Street (2018).

3 See Bruno, Esakia and Goltz (2021).

4 We use MSCI IVA (Intangible Value Assessment) ratings data.

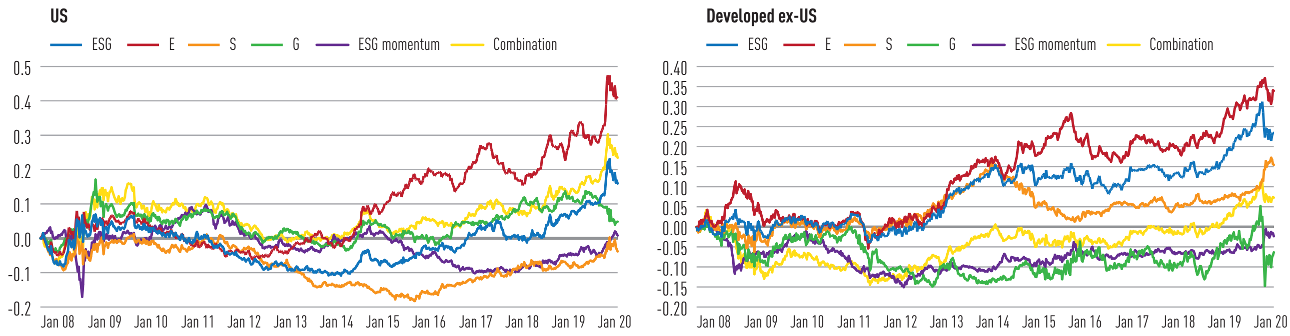
Risk-adjusting the performance of ESG strategies

We first confirm that simple returns of ESG strategies may indeed look attractive, with annualised returns of up to almost 3% per year. Figure 1 shows cumulative returns of several strategies that go long in ESG leaders and short in laggards. The plot on the left-hand side shows US returns, and the plot on the right-hand side shows developed markets outside the US. Cumulative returns for the best performing strategies are substantial: above 30% in both universes.

While such return plots are commonly shown in papers on ESG investing, they do not allow for sensible conclusions on the investment merits of a strategy. Even if ESG strategies have high returns, investors do not gain if these returns are due to sector biases or exposure to standard factors. The relevant question for investors is whether non-financial information in ESG scores offers *additional* performance benefits. Therefore, our analysis adjusts returns for sector biases and subtracts the effects that stem from exposure to standard equity style factors such as size, value, momentum, low risk and quality (high profitability and low investment).

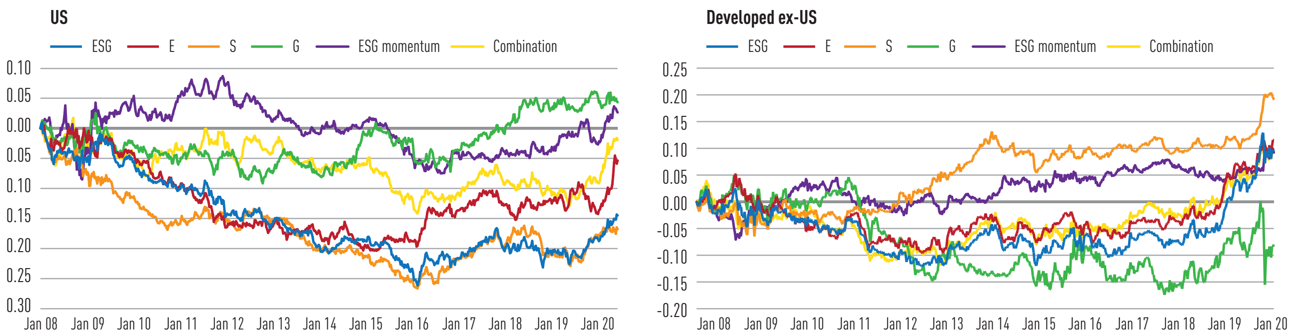
When accounting for sector biases and exposure to standard factors, none of the strategies we construct to tilt to ESG leaders adds significant outperformance, whether in the US or in developed markets outside the US. We show in the paper that 75% of outperformance of ESG strategies is due to quality factors that are mechanically constructed from balance sheet information. In addition, ESG strategies in the US equity market have a heavy tilt to the technology sector. After adjusting for such exposures, none of the strategies shows significant alpha. This finding implies that ESG ratings do not

1. Cumulative returns of ESG strategies



The plots show the time series of cumulative returns of the strategies, calculated at daily frequency. The sample period ranges from 1 January 2008 to 30 June 2020.

2. Cumulative returns net of sector and factor effects



The plots show the daily time series of cumulative seven-factor alphas of the strategies (sector neutral version). The cumulative alpha is computed as the difference between the cumulative absolute returns of a strategy and the cumulative factor returns times the factor betas (estimated over the full sample). The sample period ranges from 1 January 2008 to 30 June 2020.

add value over information contained in sector classifications and factor attributes. Despite relying on analysis of non-financial information by hundreds of ESG analysts, ESG strategies perform like simple quality strategies constructed from accounting ratios.

Figure 2 plots cumulative alphas after adjusting for sector biases and factor exposure. Cumulative alpha is the difference between the return of sector-neutral ESG strategies and the return component that is explained by their factor exposures.

The graphs in figure 2 show that ESG strategies consistently fail to deliver positive alpha when accounting for sector neutrality and exposure to standard factors. The flat lines in figure 2 provide relevant information for investors on the performance benefits of ESG strategies because the results fully account for risks related to sector biases and factor exposures. In contrast, the upward-sloping lines in figure 1 are not directly relevant because they ignore such risks.

Accounting for sector biases and factor exposures is crucial to conclude on value-added to investors. However, our simple multi-factor model with constant exposure parameters does not capture potential benefits of ESG strategies from reduced downside risk. Downside risk is reflected in asymmetric exposure. Investors are more averse to losses that occur in bad times than to losses that occur in good times. We extended the analysis in our paper to account for possible benefits in terms of downside risk reduction. The results reported in our paper show that ESG strategies do not offer significant downside risk protection.[5] Accounting for exposure of the strategies to a downside risk factor does not alter the conclusion that there is no value-added beyond implicit exposure to standard factors such as quality.

Rising attention to ESG

Our analysis exploits a sample from January 2008 to June 2020. We have shown that, over this period, ESG strategies did not deliver value-added to investors in terms of financial performance. Even if ESG strategies do not provide outperformance over an extended period, they may outperform in the short term. In particular, if attention to ESG shifts upwards, ESG strategies have positive short-term performance. but their long-term expected returns decline (Pastor, Stambaugh and Taylor [2020]; Cornell [2020]).

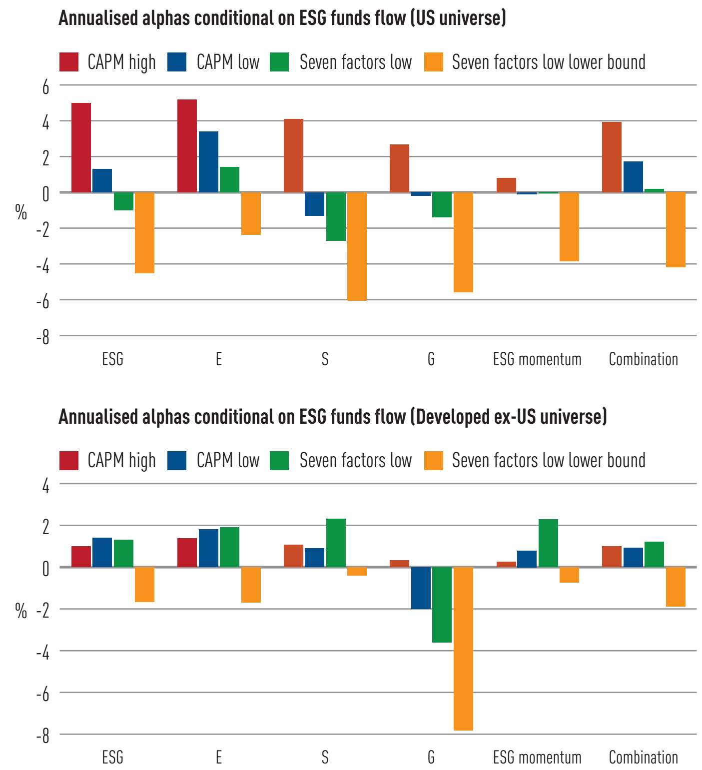
For investors, it is crucial to disentangle long-term returns from the effects of attention shifts. If upward attention shifts drive ESG returns over the recent period, investors need to conduct two adjustments to observed returns to form realistic expectations. First, returns of ESG strategies over periods with upward

5 Of course, ESG strategies may avoid other types of risk exposures that are not captured by our downside risk factor, such as climate risk. Analysing climate risk exposure and assessing how far commonly used ESG strategies effectively capture such risks is an interesting question for further research.

3. Attention shifts

	Before attention shifts	During period when attention shifts upward	After attention shifts
Return of ESG strategies (after removing random error)	Initial long-term average	Initial long-term average *+ tailwind*	Initial long-term average *– drag*

4. Shrinking ESG alphas when adjusting for attention shifts



The chart shows annualised alphas conditional on realisations of the ESG attention shift proxy for six ESG strategies constructed using the Scientific Beta US universe (top chart) and the Ddeveloped ex-US universe (bottom chart). The attention shift proxy used is net flows in US ESG funds (ESG_FF). For each strategy we report the average CAPM alpha conditional on ESG_FF being above the median, the average CAPM alpha conditional on ESG_FF being below the median, the average seven factors alpha conditional on ESG_FF being below the median, and the 95% lower bound of the seven factors alpha conditional on ESG_FF being below the median. The time sample is from January 2008 to June 2020.

attention shifts are inflated. Increasing attention raises demand for a firm's shares, leading to higher prices. Investors need to deflate returns by subtracting the tailwind from rising attention. These deflated returns will of course look less attractive than the returns that were observed over the period. Second, following upward attention shifts, long-term expected returns will be even lower than they were before the attention shifts occurred. This is because increasing attention drives up prices and thus drives down expected returns. Investors thus need to adjust the deflated returns and subtract the drag imposed by rising valuations that occurred because of rising attention. In other words, not only will ESG strategy returns go back to their initial long-term average after a period of tailwind from upward attention shifts, but they will now deliver a lower long-term average return.

Figure 3 illustrates this principle.[6]

We assess the impact of attention shifts on ESG performance by distinguishing high and low attention states. We proxy for shifts of investor attention to ESG with flows into sustainable funds. We divide the sample into quarters with high and low attention, using the median value of fund flows into sustainable funds as the cut-off point to classify quarters.

We summarise our results on attention shifts in figure 4. Outperformance during high attention periods, and when adjusting only for market exposure, is spectacular. The US strategies based on overall ESG ratings or on either of the three components all show substantial positive performance often exceeding 4% per year. However, outperformance shrinks and sometimes becomes negative when considering the low attention states. When adjusting for additional factors, outperformance shrinks further. Finally, accounting for parameter uncertainty does not lead to a single positive result for any of the strategies.

These results show that alpha estimated during low attention periods is up to four times lower than alpha during high attention periods. Further analysis reveals that the attention shifts occurred over the later part of the sample period with a strong rise in attention from 2013 onwards. For this reason, studies that focus on the recent period tend to overestimate ESG returns. Investors need to be wary of analysis of ESG alpha that is limited to short periods which coincide with rising attention to ESG.[7]

Conclusion

Our study delivers important insights for investors. As a general matter, our analysis provides an example of how one can document outperformance where there is none: it suffices to omit necessary risk adjustments. Concerning ESG strategies, our findings question a widespread practice of using ESG as an alpha signal. They do not question the value-added of such strategies on other dimensions. Investors should ask how ESG strategies can help them to achieve

6 This table builds on the model insights of Pastor, Stambaugh and Taylor (2020), who assume that a single preference shift occurs at a discrete point in time. The table indicates what happens during the period of attention shifts and afterwards. In real life, attention shifts are likely to occur continuously and repeatedly. After a period of upward attention shift, the attention level does not stay constant. Even after an upward shift there may be further upward shifts, boosting returns with more tailwind. On the other hand, attention may also decline, creating a headwind. Betting on the direction of attention shifts that are not expected by the market could be another motivation for ESG investing (when predicting positive shocks to attention) or anti-ESG investing (when expecting negative shocks), for investors who believe they have unique insights to predict changes in attention shifts.

7 Our sample starts in 2008. Starting from 2013 as in Giese, Nagy and Lee (2020) increases ESG returns by more than 1% per year for our strategy using the overall ESG score.

objectives other than alpha, such as aligning investments with their values and norms, making a positive social impact, and reducing climate or litigation risk. Investors would benefit from further research on these important questions.

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Doing good or feeling good?

Detecting greenwashing in climate investing

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Even though investors and managers communicate extensively on the use of climate data to construct their portfolios, this data represents at most 12% of the determinants of portfolio stock weights on average. This low percentage very clearly means that the construction of climate indices remains essentially guided by purely financial considerations.

To tackle this inconsistency between the stated climate objective and the reality of their investments, we suggest that when climate considerations represent less than 50% of the determinants of the weight of the stocks in a portfolio, then this portfolio should be considered to be at significant risk of greenwashing and should not be permitted to claim that it is climate-friendly or aligned with net-zero ambitions.

The lack of consistency between the evolution of companies' climate performance and their weights in green portfolios has very negative consequences for the impact of investor engagement on these same companies, and especially on their positive response to the request for a climate alignment plan. As such, we observe that the stylised strategies that represent the vast majority of transition or alignment benchmark offerings see the weight of a highly significant percentage (35% on average) of climate deteriorators (ie, companies whose climate performance deteriorates) increase over time. This inconsistency between companies' climate performance and weights in investors' portfolios removes any credibility from the engagement actions that investors conduct with these same companies.

It must be recognised that portfolio decarbonisation objectives are often achieved by implementing sector greenwashing. Climate strategies and benchmarks may exhibit strong sector deviations by organising their decarbonisation through a reduction in the capital allocation to sectors with strong climate intensity. An under-representation of sectors that are key not only for growth but also for energy transition would be particularly problematic. Since considerable investment is necessary to ensure electrification of the economy and decarbonisation of electricity, underfunding of this sector in climate-aligned benchmarks, which can correspond to a reduction in capital allocation of up to 91%, would constitute a form of greenwashing

In a new study conducted as part of the EDHEC-Scientific Beta Advanced ESG and Climate Investing Research Chair,[1] we identify greenwashing risks in the

1 Amenc, N., F. Goltz and V. Liu (September 2021). Doing Good or Feeling Good? Detecting Greenwashing in Climate Investing. EDHEC-Scientific Beta Advanced ESG & Climate Investing Research Chair publication.

construction of portfolios that represent popular climate strategies, especially those that correspond to net zero alignment strategies.

To carry out this analysis, we define key requirements for strategies to be consistent with influencing firms to reduce greenhouse gas emissions. Based on stylised equity strategies constructed using firm-level emissions data, we show that commonly-used portfolio construction mechanisms fail to deliver consistency with impact objectives. As a result, the vast majority of institutional funds and mandates that assert themselves as having a positive impact on the climate, because they exhibit attractive climate metrics at portfolio level through implementation of these strategies, are exposed to large and obvious greenwashing risks. De facto, the investment industry, in spite of its promises, does little to reallocate capital in a direction and in a manner that may incentivise companies to contribute to the climate transition.

Key indicators of greenwashing risks

We differentiate between two types of greenwashing. The first, which is the better known, is corporate greenwashing, whereby firms advertise to the public environmental credentials for their products and practices (or otherwise seek to shape perceptions) that are materially inflated or even in contradiction to their performance. This type of greenwashing receives considerable attention from all stakeholders (investors, NGOs, regulators) and is widely criticised. Besides corporate greenwashing, there is portfolio greenwashing by the finance industry. Investment managers may represent to investors that their funds (help) produce a positive impact on the environment when they are not managed in a manner that is consistent with promoting such an impact.

A key feature of popular climate strategies is that they improve portfolio greenness scores, such as weighted average emissions. While portfolio greenness scores are displayed extensively to lure investors, increasing the portfolio's score does not suffice to influence firms to reduce emissions, either through direct impact of allocation on cost of capital or a signalling channel. Instead, three main problems[2] may occur when focussing solely on a portfolio greenness score.

First, if emissions are concentrated in few stocks, strategies may achieve large improvements in a portfolio greenness score despite staying very close to cap-weighted indices.

We assess whether climate strategies can correspond to 'closet business-as-usual investing', that does not differ to a large extent from cap-weighted benchmarks, despite displaying higher greenness scores. In particular, we assess what the key determinants of portfolio weights are, and how climate scores impact portfolio weights in relation to other characteristics, such as market capitalisation or general ESG scores. As such, we observe that even though investors and managers communicate extensively on the use of climate data to construct their portfolio, these data represent at most 12%[3] of the determinants of portfolio stock weights on average.

Second, it is easy to display greenness by down-weighting high emissions sectors. However, the outputs of these sectors, notably the energy sector, are essential to the functioning of the economy. The key issue is not how to restrict investment in these industries, but rather, how to make sure that these industries invest in technology that allows them to produce needed goods and services with minimum release of greenhouse gases. This alignment of key sectors requires highly selective intra-sector capital allocation favouring climate change leaders and incentivising progress across and within sectors. To characterise this second dimension of portfolio greenwashing, we assess whether climate strategies simply underweight such key economic sectors which would be inconsistent with the promotion of transition. We look at changes in sector allocation over market indices, the contribution of sector weighting decisions to reductions in portfolio climate scores, as well as the weighting decisions of key economic sectors, like electricity, for which financing of carbon efficiency is key to achieving energy transition for the whole economy.

Third, a portfolio's green score does not account for individual firm dynamics. Firm-level weighting decisions need to send clear signals to firms' management to motivate them to improve their climate performance. Such clear signals are also important for engagement strategies to be effective. There needs to be a synergistic relationship between portfolio construction and engagement. For example, if an investor dialogues with a company to try and convince it to increase its efforts to mitigate its emissions, it would be counterproductive for the effectiveness of such of an engagement for the investor to increase the weight of the company's stock in the portfolio without strings being attached.

To detect how portfolio decisions in climate strategies suffer from blurred signals, we analyse stocks with deteriorating climate scores, and report to what extent climate strategies increase the weight in such deteriorators. We also analyse the extent to which changes in climate scores influence changes in stock weights in climate strategies.

A taxonomy of climate strategies

To carry out our analysis, we have represented the impact and alignment investment strategies with a taxonomy that takes account of the various portfolio construction methods that underlie the asset management and climate index offerings. Like any taxonomy, the one proposed in this research allows the multiple climate investing approaches and offerings to be reduced to stylised facts that are representative of key features, and to draw conclusions that are not only relevant but also robust in order to respond to a question that concerns the investment industry as a whole rather than a particular asset manager or index provider.

Although products come in various flavours when it comes to climate metrics, security screenings or input data, we can clearly distinguish two main approaches to stock weighting: a tilting approach and an optimisation-based approach.

The tilting approach consists of taking the market capitalisation weight of a stock and multiplying it by an adjustment factor. In the case of climate strategies, the adjustment factor would be based on one or more climate scores representing climate performance, which results in post-normalisation portfolio weights that are tilted toward climate friendly companies and tilted away from high polluting companies. That is a typical way of constructing portfolios, with the possibility of incorporating multiple objectives simultaneously using multiplicative adjustment factors representing each objective.

The second approach is optimisation-based, usually targeting a minimum level of improvement in climate metrics while portfolio weights are optimised to minimise deviation from a market cap-weighted reference universe. The deviation from the reference universe can be measured as the sum of stock-level active weights or the ex-ante tracking error of the portfolio. This approach

2 An additional issue which we do not pursue in our empirical analysis is that overly ambitious emissions data may lack robustness (see Ducoulombier [2021]).

3 According to our regression-based Weight Determinant Analysis, on average across 10 years ending in 2020. The impact of climate scores in percentage ranges from 6% to 12%.

would typically achieve portfolio-level metric improvement at low 'cost' in a market capitalisation-anchored framework, with obvious appeal for investors with tracking error budgets.

The other dimension of interest is the distinction between strategies that are concerned solely with climate and strategies that mix climate considerations with general ESG considerations. If investors wish to prioritise climate change mitigation, integrating general ESG considerations could potentially lead to mixed signals when climate performance and general ESG performance diverge. Our taxonomy thus includes four strategy types: climate tilting strategies, mixed climate and ESG tilting strategies, climate optimised strategies and mixed climate and ESG optimised strategies.

We construct stylised strategies in developed equity markets to reflect these strategies, drawing on firm-level greenhouse gas emissions data. Stylised strategies reflect the main weighting mechanisms used in commercial climate strategies, not the commercial products themselves. The advantage of stylised strategies lies in the replicability and tractability of our results. To ensure robustness of our conclusions independent of a particular emissions metric, we consider eight different metrics, using different emissions scopes and different normalisations of emissions by firm size.

Popular weighting mechanisms in climate strategies do not align with impact objectives

We test whether the stylised climate strategies fulfil the three impact criteria mentioned above. Across 32 specifications of stylised strategies that build on commonly-used weighting schemes and greenhouse gas emissions data, we found that climate strategies are inconsistent with the objective of influencing firms to reduce their emissions.

First, we find that climate scores only have a marginal impact on weights. Conducting a regression-based analysis of determinants of stock weights in the strategies, we find that weights are driven mainly by other aspects, such as market capitalisation. Across strategies focusing on climate, the climate scores only account for 12% of differences in weights across stocks. In contrast, market capitalisation accounts for 88% of the differences in weights in these strategies. Thus, the impact of market capitalisation overwhelms any climate consideration. Mixing in ESG scores makes climate scores even less impactful. In mixed objective strategies, the main driver remains market capitalisation, with 73% on average, followed by the ESG score, with 21% on average, leaving a mere 6% to the climate score. Indeed, climate strategies, just like business-as-usual strategies, are mostly influenced by the market capitalisation of stocks. The climate score plays second fiddle at best.

Second, strategies are relatively insensitive in their allocation decisions to the dynamics of corporate climate performance. Climate strategies display significant weight increases in stocks with deteriorating climate score over time ('deteriorators'). We observe that on average around 35% of deteriorators are rewarded with an increase in weight across the strategies we analyse. This percentage increases to 41% when using popular emissions metrics that do not normalise by firm value, such as carbon intensity. We find an even starker conflict with consistent signalling from a regression-based analysis. The analysis indeed shows that weight changes do not have any statistically significant dependence on climate score changes. This suggests that strategies are basically indifferent to the evolution of climate performance and thus fail to send clear signals to companies. When assessing methodologies from commercial index providers, we do not find any rule that would explicitly address the problem of increasing weights of deteriorators.

Third, a key mechanism creating the optical effect of improved portfolio green scores of climate strategies is simple underweighting of essential sectors with high emissions. We find that climate strategies underweight an essential sector like electricity in a drastic way, by up to 91%. While this allows good portfolio green scores to be displayed, it will be less easy to greenify the economy by doing away with electricity. We also find that sector constraints in climate indices are too loose to safeguard against underfunding of the electricity sector.

We conduct extensive robustness checks and confirm that introducing additional elements of investment practice does not alter our diagnosis. Incorporating emissions trajectories and constraints on high climate impact sectors, as required by the EU regulation for Paris-Aligned Benchmarks, does not address any of the problems we document. Using commercial ratings for environmental or climate scores, we find that the main problems emphasised in stylised strategies prevail, even though at a more moderate level.

Ultimately, we can conclude from the analyses carried out that, for want of an appropriate strategy and despite considerable investment (that justifies higher fees) in producing and qualifying climate performance data, the investment industry fails to deliver portfolios that are consistent with affirmed ambitions to promote real-world climate change mitigation.

Our analysis is easily replicable for any investor who has access to the portfolio weights of a climate strategy and firm-level data for their preferred climate score. When conducting due diligence, institutional investors and their consultants need to pay attention to these greenwashing risks.

As part of this consideration and to favour the fight against portfolio greenwashing, we suggest that when climate considerations represent less than 50% of the determinants of the weight of the stocks in the portfolio that is presented as promoting the transition to a low carbon or net-zero economy, then the portfolio should be considered to be at a significant risk of greenwashing and it should not be possible to label it as climate-friendly or aligned with net-zero ambitions.

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When you do not put your money where your mouth is

How portfolio greenwashing compromises investors' climate engagement

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Investors' engagement strategies will only work if companies respond to dialogue with action. Therefore, investors need to provide incentives for firms to improve their climate performance.

Widely used climate strategies do not provide such incentives, because they may reward worsening climate performance with increased holdings in stocks of deteriorating companies.

Investors need to create a feedback loop between engagement and portfolio construction to ensure that portfolio weights are aligned with their engagement strategy.

Portfolio greenwashing

Corporate greenwashing, where firms inflate the environmental credentials of their products and practices, is widely criticised. In this article, we focus on a different type of greenwashing, which has received considerably less attention. With the advent of sustainable and climate investing, investment managers may claim that their funds produce a positive impact on the environment when in fact they are not managed in a manner that is consistent with promoting such an impact. We refer to such practices as portfolio greenwashing.

In the area of climate investing, investors seek to contribute to a reduction of corporate greenhouse gas emission through their investments. A key feature of popular climate strategies is that they improve portfolio greenness scores, such as weighted average emissions. While portfolio greenness scores are displayed extensively to attract investors, increasing a portfolio's score does not necessarily encourage firms to reduce emissions. Therefore, such strategies bear a risk of portfolio greenwashing. Another key feature of practices in climate investing is that investors and asset managers rely heavily on maintaining an active dialogue with companies on environmental issues to achieve a real world impact. We argue that such engagement with companies is likely to be futile if investment managers continue simply to improve portfolio greenness scores, without thinking more carefully about how to use portfolio construction to contribute to the success of engagement.

How can investors have an impact on real world emissions?

Investors do not directly control how much greenhouse gas firms emit. Investor impact on emissions in the real economy is necessarily indirect and works through different transmission channels. Among these channels, we can clearly differentiate between engagement and capital allocation.

Figure 1 provides an overview of these two channels. First, investors provide capital to firms, which allows firms to develop their activities at scale. Green investors may provide additional capital or require lower compensation for providing capital to greener firms. This allows greener firms to increase their scale and it incites brown firms to become greener to lower their cost of capital. The second channel is engagement. Any investor can hold dialogue with management to express a concern for firms to become more climate friendly. For example, a firm might have incentives to go greener if investors who do not currently hold its shares express that they might start buying shares in the company if it embraces greener practices. Another form of engagement is that shareholders can make proposals and vote and thus may force companies to become greener.

The table shows engagement and capital allocation as two distinct channels of investor impact on corporate greenhouse gas emissions. However, the two channels are tightly linked. If engagement consists of mere dialogue with companies without any consequence in terms of portfolio decisions, investors fail to set

1. Channels for investor impact

Channel	Impact
Capital supply	Upscaling of green firms
	Incite companies to become greener
Engagement	Dialogue with management (any investor)
	Shareholder voting

Note: the illustration does not consider impact via advocacy to influence political decisions, which is an additional possibility).

relevant incentives for corporate managers to actually act based on such dialogue. Dawkins (2018)[1] emphasises that "engagement as a negotiating posture is hollow without the explicit threat of withdrawal".

Why consistency between engagement and portfolio decisions matters

When asset managers change the weight of a stock in their portfolio, this decision needs to send clear signals to firms' management to incite them to improve their climate performance. Such clear signals are important for engagement strategies to be effective. For this reason, institutional investor initiatives on climate change recommend that investors maintain a feedback loop from their portfolio decisions to their engagement strategy. For example, the Paris-Aligned Investment Initiative states in its implementation guide[2] that an engagement strategy should have "clear milestones and an escalation process with a feedback loop to investment, weighting, and divestment decisions".

Such a feedback loop from portfolio construction to engagement immediately appears sensible: For example, if an investor pressures a company to reduce its carbon intensity, it would be counterproductive for effective engagement if the investor increases the weight of this stock in the portfolio at the same time as telling management that they are on the wrong track concerning carbon emissions.

Beside engagement endeavours, investment decisions are how investors can express their views and influence corporate strategies. In that sense, portfolio weights are the practical reflection of investors' preferences, which in aggregate are one of the drivers that dictate the supply of capital. It is then crucial that in a climate strategy the portfolio weights remain consistent with the overall message investors wish to convey to companies.

Blurred signals in climate investing

To detect portfolio greenwashing, it is useful to look at weighting schemes used in climate strategies and how they shape the signals sent to corporations. Such an analysis is conducted in a recent EDHEC Business School study.[3] In particular, the study analyses stocks with deteriorating climate scores, and reports to what extent climate strategies increase the weight in such deteriorators.

The findings reveal that the methods of portfolio construction in use for climate strategies lead to pronounced inconsistencies. Climate strategies are relatively insensitive in their allocation decisions to deteriorating climate performance of firms. The study shows that climate strategies display weight increases in deteriorators (stocks with deteriorating climate score over time). On average, around 35% of deteriorators are rewarded with an increase in weight across the different climate strategies. This percentage increases to 41% when using popular emissions metrics that do not normalise by firm value, such as carbon intensity. These results are reproduced in figure 2.

2. Percentage of deteriorators that have increasing weights in different types of climate strategies

Stock weighting scheme used in the portfolio	Tilted portfolio	Optimised portfolio	Tilted portfolio	Optimised portfolio
Investment objective	Objective is to increase a climate score		Objective is to increase a combined score with climate and other ESG objectives	
Percentage of deteriorators with increased weight	33.5%	36.5%	40.9%	29.2%

Results are for different types of climate strategies, averaging across eight different climate scores used in the analysis. Impact consistency is measured once a year in June from 2011 to 2020 and the table reports the average value. It thus provides a view on impact consistency observed on average over one decade. Each strategy is assessed on the specific carbon metric used in the score tilting or optimisation to ensure they have improved in 'greenness' at the portfolio level.

The study finds an even starker conflict with consistent signalling from a regression-based analysis. Regression analysis allows us to assess whether changes in a stock's weight in climate strategies depend on changes in climate scores. The results show that weight changes do not have any statistically significant dependence on climate score changes. This suggests that strategies are basically indifferent to the evolution of climate performance and thus fail to send a clear signal to companies.

When assessing methodologies from commercial index providers, the study does not find any rules that would explicitly address the problem of increasing weights of deteriorators. Thus, such strategies are prone to sending highly blurred signals that will be inconsistent with the engagement objectives of climate investors. Corporate managers, who see that there is no clear link between their firm's climate performance and weights in climate strategies will not perceive any incentive to make the firm greener.

Conclusion: investors need to assess impact consistency

Greenwashing is detrimental to the efficacy of engagement. While climate investing sets out to make an impact by pushing firms to take urgent action to address the climate emergency, there is a danger that investors end up paying for 'feel good' products that induce complacency. Likewise, engagement strategies that are not combined with consistent portfolio decisions could lead to a false sense of investor action, without leading to a real effect.

Our recommendation for climate conscious investors who seek impact on corporate behaviour is to look beyond the display effects of portfolio-level metrics. Instead, they should exploit the synergistic action of engagement efforts and consistent capital allocation decisions. Investors need to make sure that they combine both channels in a consistent manner.

There are also clear implications for selecting climate investing products: when investors select green products, they need to give special attention to how greenness is achieved. Impact consistency involves making sure that firms that are deteriorating in carbon performance are not rewarded.

1 Dawkins, Cedric E. (2018). Elevating the Role of Divestment in Socially Responsible Investing. Journal of Business Ethics 153: 465–478.

2 IIGCC (Institutional Investor Group on Climate Change – 2021). Net-Zero Investment Framework Implementation Guide. Available at https://www.iigcc.org/download/net-zero-investment-framework-implementation-guide/?wpdmdl=4425).

3 Amenc, N., F. Goltz and V. Liu (September 2021). Doing Good or Feeling Good? Detecting Greenwashing in Climate Investing. EDHEC-Scientific Beta Advanced ESG & Climate Investing Research Chair publication.

Inflation-friendly equity indices

How to protect against rising inflation in equity portfolios

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The continued economic recovery and the unprecedented economic stimulus observed in recent months has led to fears of inflation re-emerging.

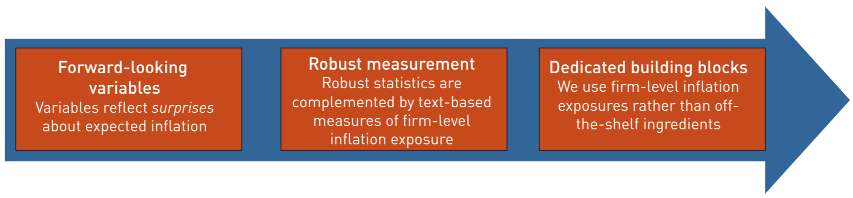
Using TIPS to fully hedge inflation risk has a high opportunity cost, especially when interest rates are negative.

Instead, investors can turn to their equity portfolio to provide some protection against inflation surprises. Equities are a natural candidate to provide some protection and, unlike commodities, equities also offer a positive long-term risk premium.

Scientific Beta's new series of inflation-friendly equity indices protects investors' portfolios against rising inflation and deliver an equity market risk premium over the long term.

These indices are ideal candidates for cap-weighted index replacement for investors with inflation fears and as equity components of a multi-asset portfolio that needs insulation against inflation shocks.

1. Scientific Beta inflation indices' methodology relies on three pillars



The way to control for inflation can be quite different depending on whether it is the hedging portfolio or the performance-seeking portfolio (PSP) of an investor's asset allocation.[1] In the PSP, investors seek high risk-adjusted returns so will allocate to asset classes or sectors that benefit from a rise in inflation (such as commodities, REITs or equities, etc).

However, choosing an alternative asset class over equities, such as commodities, is counterproductive as commodities are not a good candidate for long-term allocation due to the lack of a long-term premium. Instead, investors would be better off designing an equity portfolio that will benefit from a rise in inflation.

The question that immediately arises is whether it is possible to know which securities will react positively or negatively to a rise in inflation. Ang, Briere and Signori (2012) show that stocks that have provided a hedge against inflation in the past fail going forward. This problem arises because asset prices move much faster than backward-looking macroeconomic fundamentals, making it hard to establish a robust relationship between the two (Fama [1990]). Scientific Beta overcomes these challenges in three ways.

Using forward-looking measures of inflation surprises

Similar to central banks, we base our measure of expected inflation on observable market prices defined as the difference between the yield of nominal treasury bonds and 10-year TIPS (breakeven inflation). Following Amenc et al (2019), surprises of breakeven inflation are used. We do not use the level of expected inflation because this reflects an equilibrium view about future inflation already accounted for in asset prices; what really matters are surprises or unexpected changes around this equilibrium.

Measuring sensitivity of stocks to inflation surprises reliably using robust statistics

We use a robust statistical approach that embeds four important elements:

- Controlling for a stock's market exposure as our objective is to exploit differences in stock-level inflation exposure without altering access to the market premium;[2]
- Using weekly frequency to improve the accuracy of stock-level estimates;
- Using a long sample to estimate exposure while accounting for possible

1 Investors optimally divide their allocation into a performance-seeking portfolio (PSP) and hedging portfolios for relevant state variables (Merton [1971]). An example of hedging assets for inflation are inflation-linked bonds: they provide a reliable offset to realised inflation; however, opportunity cost is high.

2 The estimation model is based on a bivariate regression which includes the market excess return and changes in inflation expectations where the latter are defined as weekly changes in breakeven inflation.

2. Robust estimation on fast-moving variables

US 31 March 2008 to 31 December 2019

	Realised macro exposure	T-statistic
Breakeven inflation surprises (Robust measurement)	**4.24**	2.31
Breakeven inflation surprises (Naive measurement)	2.46	0.95
Breakeven inflation level (Robust measurement)	−0.22	−1.58

The realised macro exposures are estimated in a bivariate regression that includes the market factor and innovations in corresponding macro variable. The realised exposures are estimated to the variable that was used during estimation. Levels refer to absolute value of breakeven inflation, surprises refer to innovations over a lag of one period. Robust measurement uses weekly frequency, weighted least squares, 20 years' calibration window, Bayesian shrinkage, and complements this with textual analysis. Naïve measurement uses monthly data, ordinary least squares, and a five-year calibration window.

time variation in exposure via a weighted least squares (WLS) approach; and

- Accounting for differences in estimation uncertainty across stocks via a Bayesian shrinkage approach.

Finally, we complement the statistical estimate of macro exposures with a text-based measure which allows additional information on exposures beyond what is contained in data on past returns to be used.[3] The reliability of our estimation methodology is evaluated by constructing inflation-mimicking portfolios[4] and comparing our approach to a naïve approach that estimates exposures using a five-year monthly OLS regression out-of-sample. Figure 2 shows that our robust estimation approach, using both statistical and text analysis, produces high and statistically significant out-of-sample exposures to inflation surprises, whereas the naïve approach delivers exposures that are not statistically significant; additionally, using levels instead of surprises in inflation leads to unreliable exposures.

Build dedicated blocks instead of a sector or factor allocation

Building dedicated inflation-sensitive portfolios using stock-level exposures is more reliable than building portfolios that make an allocation to factors or sectors, as stock level inflation exposures lead to more reliable out-of-sample inflation betas. Figure 3 shows that stock-based allocation portfolios have the desired out-of-sample exposures, whereas factor or sector allocation approaches struggle to obtain the desired exposures.

3. Realised inflation exposures – dedicated portfolio vs factor/sector allocation

US 31 March 2008 to 31 December 2019

	Stock allocation	Factor allocation	Sector allocation
Breakeven inflation exposure+	0.86	1.57	2.70
Breakeven inflation exposure−	−1.04	2.04	2.70
Difference in macro exposures	**1.90**	**−0.47**	**0.00**

The realised macro exposures are estimated in a bivariate regression that includes the market factor and innovations in corresponding macro variable (breakeven inflation). Breakeven inflation exposure+ and breakeven inflation exposure− for stock allocation select 30% of stocks respectively. Factor allocation selects two of six equity style factors. Sector allocation selects three of 10 sector indices (TRBC sectors). Red signifies that macro exposure or the macro spread is of the wrong sign. In case of reliable out-of-sample exposures, figures for the Inflation exposure row would be negative, and macro spreads strong and positive, as is the case for the first column.

Using this robust framework, Scientific Beta has built a US Inflation+ index that tilts stock weights in the reference cap-weighted index towards stocks that have a positive exposure to surprises in expected inflation and conversely, a US Inflation− index that tilts stock weights in the reference cap-weighted index towards stocks sensitive to negative inflation surprises. These indices are designed with a market beta close to one to deliver full exposure to the equity market risk premium over the long term and with a moderate level of tracking error to provide the desired conditionality to inflation over the short term.

Figure 4 shows that the Inflation+ (Inflation−) index has a positive (negative) and statistically significant exposure which means that returns are driven by upwards (downwards) inflation shocks. Figure 5 shows that the indices also display the expected conditional outperformance during the respective inflation surprise regimes. The Inflation+ (Inflation−) index has an annualised relative performance of 14.77% (2.84%) during periods with positive (negative) inflation surprises.

4. Strong exposure to inflation surprises

SciBeta US 31 December 2008 to 30 June 2021

	Inflation+	Inflation−
Inflation	**1.24**	**−1.02**
T-stat	4.03	−3.62

The analysis is based on weekly US dollar total returns from 31 December 2008 to 30 June 2021. The realised macro exposures are estimated in a bivariate regression that includes the market factor and weekly inflation innovations defined as changes of the 10-year breakeven inflation rate. Statistics in bold are statistically significant at a 95% level. The indices used are the SciBeta US Inflation+ and SciBeta Inflation−.

Figure 6 shows that the Scientific Beta inflation indices also deliver risk-adjusted performance in line with the cap-weighted index over longer time horizons. The Sharpe ratio for the Inflation+ and Inflation− indices is 0.85 and 0.80 respectively, very close to the metric of 0.83 for the broad cap-weighted

5. Scientific Beta US inflation indices' conditional performance

SciBeta US 31 December 2008 to 30 June 2021

	% of regimes (weeks)	Inflation+	Inflation−
Negative inflation surprises	157	−3.41%	2.84%
Stable inflation	331	0.66%	−0.86%
Positive inflation surprises	163	14.77%	−12.36%
Macro spread	–	18.18%	−15.20%

The analysis is based on daily US dollar total returns from 31 December 2008 to 30 June 2021. Outperformance figures are computed as annualised relative performance of inflation indices compared to the CW index in top (positive surprise) and bottom (negative surprise) quartiles of weekly inflation innovations defined as changes of the 10-year breakeven inflation rate. Macro spread is the difference of returns between positive and negative inflation surprise regimes. The indices used are the SciBeta US Inflation+ and SciBeta Inflation− as well as the SciBeta US Cap-Weighted index.

3 We count keywords related to inflation in the 'risk factors' sections of firms' annual reports (form 10-K filings with the SEC).

4 Mimicking portfolios go long 20% of the stocks with the highest ex-ante exposure to inflation surprises and go short 20% with the lowest ex-ante exposure; mimicking portfolios are equal-weighted and rebalanced quarterly.

benchmark. Furthermore, the two inflation indices are able to provide the desired conditionality with respect to expected inflation while maintaining a reasonable tracking error with the cap-weighted benchmark (2.7% and 2.3% respectively for the Inflation+ and Inflation– indices).

Figure 7 shows that the Scientific Beta US Inflation+ index provides better protection from inflation compared to other assets such as commodities or REITS. Although all assets depict the desired conditionality with respect to inflation in absolute terms, both commodities and REITS underperformed the cap-weighted benchmark during periods with positive surprises. Instead, the Scientific Beta US Inflation+ index outperformed the cap-weighted benchmark consistently during these regimes.

We also confirm that the US Inflation+ index offers better access to a long-term premium compared to these assets. Over the same sample period, commodities and REITS underperformed the equity market (–3.4% and 13.6% annualised returns respectively versus 15.7% for the cap-weighted benchmark; the REITS Sharpe ratio is about half that of the benchmark) while the Inflation+ index matched the broad equity market performance (0.9% relative outperformance with a similar Sharpe ratio).

The Scientific Beta inflation indices benefit from a reliable measurement of firm-level inflation exposure to deliver 'market-like' characteristics while providing the desired conditionality to inflation. In particular, the Inflation+ index improves inflation protection compared to traditional cap-weighted indices, allowing long-term investors to improve excess returns in the event of high inflation. It also allows for compensating losses in bond portfolios, which are often used to hedge liabilities that are explicitly or implicitly linked to inflation and for which hedging through TIPS is often prohibitively expensive. Investors can use the Scientific Beta inflation indices to replace the cap-weighted index and position for inflation shocks or as equity components of a multi-asset portfolio that needs insulation against inflation shocks.

6. Scientific Beta US inflation indices' risk-adjusted performance

SciBeta US 31 December 2008 to 30 June 2021	CW	Inflation+	Inflation–
Annualised returns	15.69%	16.58%	14.59%
Annualised volatility	18.22%	19.00%	17.67%
Sharpe ratio	0.83	0.85	0.80
Maximum drawdown	33.77%	36.24	31.99%
Annualised relative returns	–	0.89%	–1.11%
Annualised tracking error	–	2.74%	2.35%
Information ratio	–	0.32	nr

The analysis is based on daily US dollar total returns from 31 December 2008 to 30 June 2021. The indices used are the SciBeta US Inflation+ and SciBeta Inflation– as well as the SciBeta US Cap-Weighted index.

7. Conditional performance across alternative asset classes

31 December 2008 to 30 June 2021	Scientific Beta US CW	Commodities	REITS	Scientific Beta Inflation+
Absolute performance in different conditions (inflation surprises)				
Negative inflation surprises	–41.63%	–55.94%	–31.84%	–45.04%
Stable inflation	27.58%	4.31%	25.57%	28.24%
Positive inflation surprises	**81.43%**	**74.00%**	**53.69%**	**96.19%**
Relative performance to cap-weighted index in different conditions (inflation surprises)				
Negative inflation surprises	–	–14.31%	9.79%	–3.41%
Stable inflation	–	–23.27%	–2.01%	0.66%
Positive inflation surprises	**–**	**–7.43%**	**–27.74%**	**14.77%**

The analysis was conducted using weekly returns in US dollars. The indices used are the Scientific Beta US Cap-Weighted, S&P GSCI Commodities index (GSCITOT), FTSE USA REITS index (F3USRN$), and Scientific Beta US Inflation+. Negative/positive inflation surprises are defined as weeks (Friday to Friday) when changes in 10-year breakeven inflation were in the bottom/top 25%. The remaining 50% of the sample is defined as stable inflation conditions. Data sources: Scientific Beta, Datastream, Federal Reserve Bank of St Louis.

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Targeting macroeconomic risks in equity portfolios

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We propose a methodology to estimate stock-level exposures to macroeconomic risks in a way that remains reliable out of sample.

The key to the success of our approach is that we detect how individual stocks react to economic surprises using robust measurement tools.

We build equity portfolios that allow exposures to macroeconomic risks to be targeted more efficiently than through sector or factor allocation strategies.

Investors benefit from managing the exposures of their equity portfolios to different macroeconomic risks. For example, investors have recently been worried about rising inflation. Measuring how different stocks are exposed to changes in expected inflation would allow portfolios to be designed that fare well during times of increasing inflation. Similarly, investors may care about how their portfolios fare in different conditions for interest rates or credit risk in the economy.

We show that it is possible to create portfolios that capture the long-term equity premium while protecting against undesired macro-outcomes in terms of inflation, interest rates and credit risk. Importantly, building dedicated equity portfolios using firm-level information generates more robust macroeconomic exposures as opposed to allocating to pre-existing equity portfolios, such as sector portfolios or factor strategies.

How to measure macro exposures reliably

Measuring macro exposures reliably out of sample is not easy. For example, Ang, Briere and Signori (2012) find that a portfolio of stocks with the highest in-sample exposure to inflation did not provide any protection against inflation when going out of sample. We follow several important steps to ensure that our measures of exposure are reliable.

Surprises in forward-looking variables

Realised quantities of fundamental economic measures are not suitable when analysing movements in asset prices. In liquid markets, information is quickly reflected in prices. Financial assets that are claims for future cash-flows depend on investors' expectations going forward. Therefore, we rely on macro state variables that are forward-looking. These are: (1) short-term interest rates, (2) term spread, (3) credit spread and (4) expected inflation.[1] These variables provide a good reflection of investors' expectations about economic conditions.[2]

Another important aspect of our methodology is to use surprises, or innovations, in macro variables instead of levels. The current value of assets already reflects information that is known to investors today. As new information arrives, asset prices, including stocks, will adjust accordingly. This is why we are interested in surprises, since the levels of macroeconomic variable that were fully anticipated by investors will not lead to different price reactions across stocks.

When it comes to estimating anticipated changes in a macroeconomic variable, there are various methods available. The standard approach followed in literature is to use a vector auto-regressive model (VAR). In our case, we can simply use the change in macro variables as it delivers similar results to more complex models, such as using a VAR model.[3]

Statistical estimates of macro exposures

We now describe the necessary ingredients for robust estimates of macro exposures. Our objective is to exploit differences in stock-level macro exposures without altering investors' access to the market premium. Therefore, we control for the market exposure when we estimate stock-level macro exposures. In addition, we take several important steps to ensure that exposures estimated on past data remain reliable out of sample.

First, we use weekly[4] frequency of observations. Levi and Welch (2017) show that using such higher frequency data provides substantial improvements in accuracy of estimated betas over using monthly returns data. Having higher frequency leads to more observations, which helps to reduce estimation error.

Second, we manage to account for recent dynamics in macro betas while maintaining deep historical samples for estimation. Estimation problems face a basic trade-off between sample size and reactivity to changes in exposures. We overcome this trade-off by using a long-term history of stock returns (20 years, if available) and by attributing decreasing importance to observations as we go further back into history. Our methodology differs from commonly used rolling-window approaches in investment

1 Short-term interest rates are defined as the yield on three-month US Treasury bills. Term spread is defined as the difference between yields on 10-year and one-year US Treasury bonds. Credit spread is defined as the difference between yields on Moody's Corporate Aaa and Baa bonds. Expected inflation is defined as the difference between 10-year Treasury inflation protected securities and nominal 10-year Treasury bonds.
2 Amenc et al (2019) provide a protocol for selecting relevant state variables, and among various criteria, they show that these variables are useful in predicting future economic growth.
3 We have also tested innovations from a VAR model and our findings are unaffected by this change.
4 Note that the data that we use is also available at a daily frequency, but we use weekly observations to avoid problems due to differences in closing times between bond and equity markets.

practice because we fit the model using a weighted-least squares method.[5]

Third, we explicitly account for estimation risk at the firm level. Treating betas of identical magnitude for two stocks as equal would ignore estimation risk. Even if the macro betas for two stocks are estimated to be identical in magnitude, they may differ in terms of the uncertainty around the point estimate. Therefore, we also account for the differences in uncertainty across stock-level estimates and adjust macro betas that are estimated imprecisely, using the Bayesian shrinkage proposed by Vasicek (1973).

Text-based measure of macro exposures
To use a richer set of information beyond past returns, we complement our statistical estimates of macro exposures with firm's risk disclosures. We rely on the 'risk factors' section of firms' annual 10-K filings with the SEC. This text mentions key risk factors that may affect the firm's profitability. The more often a given risk is discussed in this section, the more likely it is that a given firm is exposed to this risk.[6] We combine this text-based measure of exposure with the statistical measures to rank stocks in our equity universe.

1. Out-of-sample exposures when using different macro variables

US 31 December 1979 to 31 December 2019

	Realised macro exposure	T-stat
Mimicking portfolios based on a naive estimation approach		
Short rates	0.38	1.04
Term spread	−0.05	−0.10
Credit spread	**3.03**	**2.37**
Breakeven inflation	2.46	0.95
Mimicking portfolios based on a robust estimation approach		
Short rates	**1.24**	**4.78**
Term spread	**1.95**	**4.43**
Credit spread	**2.76**	**3.64**
Inflation	**4.24**	**2.31**

The realised macro exposures are estimated in a bivariate regression that includes the market factor and surprises in the respective macro variable. The analysis of inflation-mimicking portfolios is done over a shorter time period, from 31 March 2008 to 31 December 2019. Figures in bold are statistically significant 5% level.

Assessing the reliability of macro exposure estimates
We evaluate the reliability of macro exposure estimates by creating a high exposure minus low exposure portfolio. We buy 20% of the stocks with the highest estimated exposures and sell those with the lowest exposures.[7] We refer to such strategies as mimicking portfolios since they try to track surprises in a given macro variable. If macro exposure estimates are reliable, the mimicking portfolio should have a positive exposure after it is formed – ie, out of sample.[8]

Figure 1 reports the realised exposures of mimicking portfolios for different macro variables, as well as the corresponding t-statistics. We start by looking at mimicking portfolios that rely on a naïve estimation technique in the top panel. Naïve estimation follows widespread industry practice and does not build in the improved estimation technology we described above.[9] We observe that mimicking portfolios based on naïve estimation come with weak out-of-sample exposures. The realised exposure to the term spread is close to zero, and exposures to short rates and breakeven inflation are statistically insignificant. The only portfolio that has significant and positive exposure is the credit-spread-mimicking portfolio.

The bottom panel reports results when using the robust estimation technique that we propose. It is clear that, when using proper measurement tools, the mimicking portfolios come with positive and highly significant exposures out of sample. This holds for all four macro variables. The improvements are substantial compared to using naïve estimation techniques.

Protecting equity portfolios against macro risks
Measuring macro exposures reliably allows us to construct long-only equity portfolios that will perform well relative to the market in desired economic conditions. If an investor is concerned with increasing inflation expectations in the future, he/she can invest in an equity portfolio that has high exposure to expected inflation surprises (Inflation+). Similarly, if an investor wants to protect their total portfolio from raising interest rates, Short rates (+) will provide strong performance during those periods.

We create long-only cap-weighted portfolios that select 30% of the stocks out of the equity universe with the desired exposure to a given macro variable. Our universe consists of the 500 largest stocks in the US. We refer to such strategies as macro-dedicated portfolios.

Figure 2 shows that macro-dedicated portfolios perform as expected in different conditions of the target variable. Short rates (+) outperforms the market by 3% annually when innovations in short rates are high, while short rates (–) outperforms the market by around 2.5% when innovations are low. We find a similar pattern for portfolios targeting the other variables.

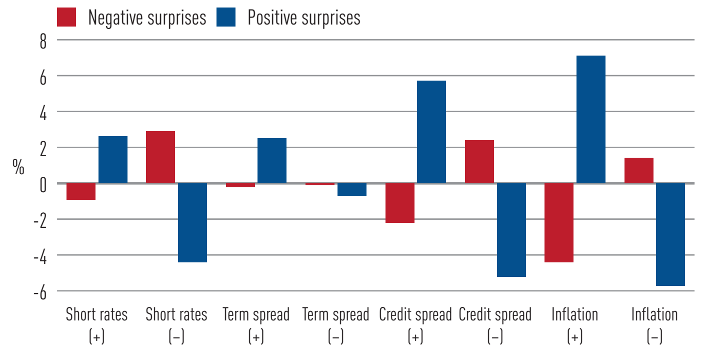
We also find in unreported results that the long-term average returns and multi-factor alphas of these strategies are not different from each other, suggesting that one can target positive or negative macro exposure without giving up access to the long-term performance of the equity market.

We also assess how building macro-dedicated portfolios at the stock level compares to simply allocating to sectors or factors to achieve target exposures. We build strategies using our robust measures but operating at a broad sector or factor level rather than the firm level.[10]

Figure 3 presents the out-of-sample exposures of macro-dedicated portfolios

5 The weights of the first five years are close to half of total weights attributed to all observations.
6 Number of counts gives us a score that indicates how important the given macro risk is for a given firm.
7 The stocks are selected each quarter and equal weights are assigned to all stocks in both long and short branches.
8 The out-of-sample macro exposures are computed in a bivariate linear regression (OLS) that includes the market factor and surprise in the respective macro variable.
9 Naïve approach estimates macro exposures using the OLS on monthly returns over the most recent five years. Levi and Welch (2017) find that roughly two-thirds of the papers from top academic journals between 2013 and 2015 estimate betas using monthly frequency over the past one to five years. The incomplete list includes Novy-Marx (2013), Bali, Brown and Caglayan (2014) and Ferson and Lin (2014).
10 Each quarter, we select three sectors out of 10, or two equity factors out of six, to form sector and factor allocations. The sectors are classified following the Thomson Reuters Business Classification, while equity factor portfolios select 30% of the stocks based on the cross-sectional rank score of size, value, momentum, low volatility, high profitability and low investment. All portfolios are cap weighted.

2. Average returns in different macro conditions



The reported figures correspond to average annualised returns relative to the broad market index during the times (calendar months) of high (25%) and low (25%) realisations of surprises in a respective macroeconomic variable. The analysis of inflation-mimicking portfolios is done over a shorter time period, from 31 March 2008 to 31 December 2019, due to data limitations.

3. Out-of-sample exposures of macro-dedicated portfolios and allocation approaches

US 31 December 1979 to 31 December 2019	Short rates	Term spread	Credit spread	Inflation
Macro-dedicated portfolios				
Macro exposure +	**0.38**	**0.92**	**1.35**	0.86
Macro exposure –	**–0.60**	**–0.43**	**–0.73**	–1.04
Difference in macro exposures	**0.98**	**1.35**	**2.08**	1.90
Factor allocation				
Macro exposure +	0.14	**0.57**	0.21	1.57
Macro exposure –	–0.26	**0.05**	**–1.30**	**2.04**
Difference in macro exposures	**0.40**	**0.53**	**1.52**	–0.47
Sector allocation				
Macro exposure +	**0.35**	**0.64**	0.83	**2.70**
Macro exposure –	**–0.51**	–0.05	**–1.78**	**2.70**
Difference in macro exposures	**0.86**	**0.69**	**2.61**	0.00

The realised macro exposures are estimated in a bivariate regression that includes the market factor and innovations in the corresponding macro variable. The analysis of inflation-mimicking portfolios is done over a shorter time period, from 31 March 2008 to 31 December 2019, due to data limitations. Figures in bold are statistically significant 5% level.

as well as the sector and factor allocations in separate panels. The results suggest that building dedicated portfolios by stock selection leads to stronger and more reliable out-of-sample macro exposures than sector or factor allocation strategies.

Conclusion

We have proposed a methodology to estimate stock-level exposures to macroeconomic risks. The success of our methodology relies on the use of appropriate proxies for a relevant macroeconomic variable and robust measurement tools from statistics as well as textual analysis.

Portfolios constructed with a target of high or low exposure to our forward-looking macro variables achieve significant exposures out of sample, which is not the case when using naïve estimation techniques or backward-looking economic variables, such as realised inflation or growth.

Our estimation approach can be used to construct long-only equity portfolios using stock-level exposure estimates. Dedicated macro portfolios provide more reliable out-of-sample exposures than factor or sector allocation strategies. Investors who want to target macroeconomic risk exposures can use our approach to construct portfolios that provide performance in line with the broad equity premium as well as dependence on macro conditions in line with their target.

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When greenness is mistaken for alpha

Pitfalls in constructing low carbon equity portfolios

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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.

Scientific Beta has analysed how low carbon strategies can be mistaken for alpha and what the consequences are for investors.

Motivations for low carbon investing

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's initiative that aims to reduce holdings in shares of carbon intensive companies is the Portfolio Decarbonization Coalition (PDC), which was created in 2016 and now represents more than $800bn in assets with a low carbon objective.

There are different motivations for investors to consider low carbon strategies. First, some investors pursue non-pecuniary motivations, either wanting to align investments with their values and avoid firms that pollute a lot or wishing to influence firms to change their practices by reducing the aggregate supply of capital to heavy polluters. Second, low carbon investing may address pecuniary motivations. Avoiding exposure to high emitters should tend to reduce exposure to transition risk, the risk of rising costs of carbon. In addition, low carbon investing may provide positive alpha and thus boost performance, especially if such risks are underpriced by the market.

Alpha appears to be the dominant motivation emphasised by product marketers and is a widespread motivation for investors. Krueger, Sautner and Starks (2020) conducted 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.

Low carbon investing products commonly build on the assumption that green stocks produce positive alpha. However, a review of the literature reveals that both theory and empirical evidence contradict the case for positive low carbon alpha. Economic theory contradicts this assumption. All else 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. In a recent Scientific Beta publication (Amenc et al (2021), we analyse how low carbon strategies can be mistaken for alpha and what the consequences are for investors.

When green alpha is just an illusion

Our paper shows 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 to a long-short low carbon factor, which delivers positive returns over our sample period with 1.74% per year. However, alpha becomes negative at −0.32% per year when adjusting for equity style factors, and it disappears when accounting for estimation error.

Figure 1 reports the annualised performance measures of different specifications of low carbon or green minus brown (GMB) factors, using different weighting schemes and different rules on sector neutrality. 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 are positive in our sample, which spans 15 years. However, when we account for the market exposure of the GMB factor, we see a reduction of average returns from 1.74% to 1.38% on average. The last row of figure 1 corresponds to a measure that is the most relevant for investors. The multi-factor alpha indicates whether there is an information in the average returns of a GMB factor unexplained by other equity style factors in the model. The results indicate that once accounting for exposures to all well-known factors, the estimated premium becomes negative on

1. Performance of green minus brown factor

US 31 December 2004 to 31 December 2019					
	Green minus brown factor				
	Equal-weighted	Cap-weighted	Equal-weighted sector neutral	Cap-weighted sector neutral	Average
Annualised return	1.64%	2.11%	1.13%	2.08%	1.74%
	(0.86)	(0.94)	(0.75)	(1.23)	
Annualised volatility	9.23%	11.17%	7.15%	7.34%	8.72%
Sharpe ratio	0.18	0.19	0.16	0.28	0.20
Maximum 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 US universe. The analysis was conducted using daily data except for the CAPM and multi-factor analyses, which use weekly data. The multi-factor model includes the market factor and the Scientific Beta long-short equal-weighted factors, namely 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).

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.

Point estimates of average returns of the 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 adjustments. 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.

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.

The cost of a mistaken belief in green alpha

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 100 basis points of annualised returns on a risk-adjusted basis.

In particular, we assess the impact on an optimal portfolio when including a long-short factor that tilts to low carbon stocks (green minus brown factor, or GMB). We take the case of zero allocation to the ESG 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 commonly-used equity style 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 investor's belief that GMB is an attractive strategy due to its supposed alpha. Figure 2 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, reductions 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 a positive return but negative multi-factor alpha.

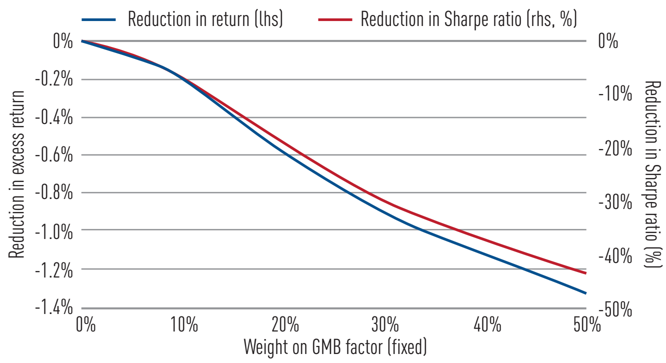
The loss for investors due to a positive allocation to the GMB factor is clearly visible from the downward sloping curves. In terms of (volatility-matched) excess returns, a 10% weight in the GMB factor reduces portfolio returns by about 20 basis points per year. This is a large reduction from a small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

Pitfalls of industry approaches to constructing low carbon portfolios

Industry approaches to the construction of low carbon strategies tend to treat carbon scores just like any other alpha signal. We analyse the shortcomings of

2. Losses from including GMB factor in allocation



The plot shows the reduction in annualised 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 the 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 market, 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) maximum Sharpe ratio portfolio.

such 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.

Setting realistic expectations for low carbon investing

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 if low carbon strategies can help them hedge climate risks or make a positive impact on corporate behaviour. Addressing such objectives requires further research, careful thinking, and dedicated methodologies. The pressing issue faced by society is tackling climate change and managing the related risks, not generating alpha. And while low carbon alpha appears to be fake, the damage from climate change and the risk to investors unfortunately are real.

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Scientific Beta Climate Impact Consistent indices

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The Climate Impact Consistent (CIC) indices are part of the new pure climate indices launched by Scientific Beta.

They are offered in two versions, one of which is compliant with the EU Paris Aligned Benchmark (EU PAB) regulation.

Their design is unique as it creates consistency between investors' engagement activities and investment decisions to maximise the potential for real-world impact and avoid greenwashing risks.

It would be a dangerous self-delusion for investors to believe that simply holding a low carbon or even net zero equity portfolio can effectively reduce emissions in the real economy. The real impact of investment decisions from a climate alignment perspective comes from the consistency between these decisions and the climate performance of the companies that make up the portfolio. This is what is achieved by the Climate Impact Consistent (CIC) indices, which weight each stock according to their intra-sector climate performance and their alignment trajectory. As such, attractive climate metrics at the portfolio level are neither achieved by divestment of sectors that are central to the transition nor by algorithms that condition climate action to financial characteristics.

As a representation of a pure climate investing strategy, CIC indices organise weighting decisions that directly affect companies' cost of capital and send strong and consistent signals to the management of the companies on the relevance of improving climate practices. Thus, portfolio construction contributes to funding conditions and sends clear signals to the affected companies and other stakeholders. Since investors' main impact channels correspond to the financing and engagement of the companies themselves, the consistency between investors' climate engagement objectives and company-level investment decisions guarantees that the investment strategy maximises potential climate impact. Indeed, aligning the objectives of capital allocation with those of the engagement activity brings credibility to the latter by demonstrating the investor's commitment to climate-consistent investing and is in line with net zero investment coalitions such as the Paris Aligned Investment Initiatives (PAII).

The CIC indices promote climate alignment of each sector of the economy since their weight is anchored to its broad cap-weighted weight.[1] Hence, the financing of key sectors of the climate transition such as the electricity production sector, which requires extremely significant investment in the coming

1 The only exception is the fossil fuel sector, which can be under-represented. Indeed, the Intergovernmental Panel on Climate Change (IPCC) acknowledges that a significant reduction in fossil fuel use is required to limit global warming to 1.5°C in 2050, which is also in line with the EU PAB requirement to drastically reduce the financing of this sector.

decades to achieve the 1.5°C objective, is protected.

To achieve this alignment ambition, the CIC indices were designed around five principal methodological objectives that address the main risks of greenwashing that are common in most alignment benchmarks:

- Ensuring that decarbonisation at the global level is consistent right down to stock level and avoiding the global portfolio displaying greenwashing risk.
- Real sustainable growth ensuring real representation of all sectors in the economy and avoiding the risk of sector greenwashing.
- Ensuring that climate performance and engagements are really taken into account in the evolution in issuers' weights.
- Appropriate use of data and metrics in portfolio construction to guarantee the climate robustness of the portfolio and avoid data greenwashing risks.
- Ensuring that the index has a very good level of investability, even though it is not anchored on cap weights.

These objectives result in an index construction process that is itself organised into five steps (figure 1). Each step contributes to the overall index objective of enabling investors to send strong consistent signals to companies on their carbon activities while avoiding greenwashing risks which may arise when stock-level investment decisions result in poor or confused signalling to companies.

We emphasise that the EU PAB-compliant version differs from the standard version through:

- A greater number of exclusions, leading notably to the elimination of nearly all stocks from the fossil fuel sector.
- The implementation of a carbon intensity reduction constraint that is more than 50% compared to the cap-weighted reference from the start of the index.

The two features may be seen as excessive for some investors, or indeed counterproductive for fossil fuel sector engagement. Therefore Scientific Beta offers a standard version that allows investors to avoid having to conform with the European regulation in order to implement their alignment strategy.

1. CIC indices: construction steps

<table>
<tr><th>Step</th><th>CIC</th><th>CIC EU PAB-compliant</th></tr>
<tr><td>1</td><td colspan="2">Exclusions</td></tr>
<tr><td></td><td colspan="2">Core ESG filter</td></tr>
<tr><td></td><td colspan="2">Non-reporting emissions (high emitting companies)</td></tr>
<tr><td></td><td></td><td>PAB normative and activity exclusions</td></tr>
<tr><td>2</td><td colspan="2">Intra-sector carbon intensity parity weighting</td></tr>
<tr><td></td><td colspan="2">Weighting as per Scope 1 + 2/revenues within carbon-oriented sectors</td></tr>
<tr><td></td><td colspan="2">Adjustments for disclosure, science-based targets and climate mitigation revenues</td></tr>
<tr><td>3</td><td colspan="2">Sector neutrality assurance</td></tr>
<tr><td></td><td colspan="2">Broad capitalisation-weighting anchoring (ex-fossil fuel sector)</td></tr>
<tr><td>4</td><td colspan="2">Liquidity and signal consistency constraints</td></tr>
<tr><td></td><td colspan="2">2-5-9 capping of CW-relative weights per regional liquidity (ATV) tercile</td></tr>
<tr><td></td><td colspan="2">Cap on issuers with deteriorating performance at previous rebalancing weights</td></tr>
<tr><td>5</td><td colspan="2">Conditional mechanism (sector-weight adjustment)</td></tr>
<tr><td></td><td colspan="2">7% carbon intensity annual self-reduction</td></tr>
<tr><td></td><td>Carbon intensity lower than CW</td><td>Carbon intensity 50% lower than CW</td></tr>
<tr><td></td><td colspan="2">Minimum cumulative exposure to 'high climate impact' sectors</td></tr>
</table>

2. Mixing climate and financial strategies sends contradictory signals

Weighting scheme	Score-tilted	Optimised	Score-tilted	Optimised
	No ESG score		Include ESG score	
Impact of ESG and climate scores	12.00%	13.00%	27.00%	28.00%
Percentage of deteriorators with increased weight	40.28%	38.04%	44.72%	31.24%
Electricity sector deviation (percentage under- or overweight relative to cap-weighted index)	−87.28%	−95.59%	−46.59%	−59.98%

The analysis is based on the Scientific Beta Developed universe, from June 2013 to June 2020. We show the percentage of deteriorators and with increasing weights for two stylised strategies, namely score-tilted and optimised. We implement weighting schemes that reflect those used in the main industry offerings for climate indices. Score-tilted: Stock weight is set to free float market cap weight times the standardised score. The score is defined as a climate score. Optimised: Stock weight is based on a minimisation of tracking error with regard to the CW reference index while matching the portfolio level weighted average score of the corresponding score-tilted strategy.

CIC indices reflect pure climate objectives without mixing financial considerations

Non-financial objectives such as the incorporation of a climate policy should not be mixed with financial objectives. Indeed, there is no academic consensus on a long-term reward associated with an ESG or low carbon factor. Mixing ESG and financial characteristics therefore makes no sense, and it is more appropriate to manage these two dimensions separately. The CIC indices therefore clearly prioritise climate change mitigation. This objective is achieved through the weighting of companies. The CIC indices' constituent weights are determined solely based on companies' carbon characteristics. Companies with a poor climate impact receive lower weights relative to their sector peers as defined by Scientific Beta's carbon-orientated sector classification. In contrast, alternative stock weighting methods may attempt to simultaneously consider financial characteristics and climate impacts. For example, cap-weight-tilted weighting or tracking error-optimisation weighting methods are commonly adopted. Such weighting strategies may pose considerable greenwashing risks if a company's strong financial characteristics overshadow its poor climate record, leading to a higher weight and an inconsistent stock-level investment decision.

The CIC indices are truly consistent as their stock-level decisions do not conflict with portfolio outcomes

Besides the CIC indices' pure climate stock-weighting, additional guarantees are in place in their design to ensure consistency between their stock-level decisions and portfolio outcomes. In particular, a signal consistency constraint is applied to stock weights to ensure that companies with increasing carbon intensity do not have increasing weights. As such, they explicitly avoid the greenwashing risk which arises when companies with deteriorating climate performance receive higher portfolio weights. This guarantee against climate deteriorators with increasing weights is a unique feature of Scientific Beta's CIC indices. Alternative climate investing indices which do not provide such a guarantee could result in the opposite signalling effect on companies regarding their climate impacts. The CIC indices' signal consistency constraint is applied together with a liquidity constraint to support their investability.

It is not just stock-level decisions that are consistent in the design of the CIC indices. Sector allocation also seeks to avoid greenwashing in the form of underweighting sectors with high carbon intensity. By anchoring sector weights to the broad cap-weighted benchmark, the CIC indices can reflect the real economy and ensure that each sector participates in the climate transition. This is aligned with the recommendations of the net zero framework.

Finally, the CIC indices' strong carbon metrics reduction can be clearly attributed to consistent stock-level investment decisions as demonstrated in figure 5, where we note that WACI reduction at portfolio level can be attributed mainly to a stock effect rather than a sector effect. This highlights the consistency between stock-level and portfolio-level climate objectives.

The CIC indices incorporate forward-looking data and adjustments to reflect the quality of emissions data

Throughout the CIC index construction process, careful checks and adjustments are performed so that forward-looking data on companies' climate impacts can be appropriately used while the scope and estimation of emissions data is properly addressed. In particular, the carbon intensity metric used for weighting stocks is Scope 1 and 2 emissions normalised by revenues. Scope 1 and 2 emissions are favoured for stock weighting because they are reported by individual companies, and they provide a clear metric for engagement since they relate directly to companies' activities. Revenues are used to normalise emissions as they reflect companies' activity without financial market performance, unlike alternatives such as market capitalisation or enterprise value including cash.

The stocks' carbon intensities undergo adjustments to enhance their robustness and incorporate forward-looking data before they are used for weighting. Each stock is assigned the median carbon intensity of its sector's carbon intensity decile in the global universe to avoid over-reliance on individual company data. Thereafter, the carbon intensities are revised downwards as a reward for green revenues or pledges in the Science-Based Target (SBT) initiatives and revised upwards as a penalty for not self-reporting emissions. A final shrinkage method is applied to the adjusted carbon intensities to recognise the improving data quality of self-reported emissions. Collectively, these adjustments capture forward-look-

3. The CIC indices avoid greenwashing risks

SciBeta Developed	Percentage of deteriorators with increasing weights at index level			Worst 10% emitters at index level that are deteriorators with increasing weights		
	CW	CIC	CIC PAB	CW	CIC	CIC PAB
2014	46.4%	0.0%	0.0%	14.6%	0.0%	0.0%
2015	58.6%	0.0%	0.0%	12.1%	0.0%	0.0%
2016	54.8%	0.0%	0.0%	7.5%	0.0%	0.0%
2017	53.8%	0.0%	0.0%	10.1%	0.0%	0.0%
2018	50.6%	0.0%	0.0%	15.1%	0.0%	0.0%
2019	41.8%	0.0%	0.0%	18.5%	0.0%	0.0%
2020	31.9%	0.0%	0.0%	6.1%	0.0%	0.0%
2021	43.9%	0.0%	0.0%	9.5%	0.0%	0.0%

Results are computed on the SciBeta Developed universe (2014–21) on June review dates. Deteriorators are defined as stocks included in the index with a higher carbon intensity decile compared to the previous year, where carbon intensity deciles are estimated on the global universe, using Scope 1+2 emissions normalised by revenues with adjustments for disclosure, science-based targets and climate mitigation revenues. A deteriorator with increasing weight is a stock classified as a deteriorator which also has a weight increase compared to its previous year weight. The table shows the number of deteriorators with increasing weights as a percentage of the number of deteriorators. Worst emitters at index level refer to stocks with the highest 10% Scope 1+2 carbon to revenues in the universe. A deteriorator with increasing weight is a stock classified as a deteriorator which also has a weight increase compared to its previous year's weight. The indices used are the Scientific Beta Developed Cap-Weighted index and the standard and EU PAB-compliant versions of the Scientific Beta Developed Climate Impact Consistent index (CIC and CIC PAB).

4. The CIC indices' sector allocation reflects the real economy

SciBeta Developed 30 June 2013 to 30 June 2021	Absolute weights			Deviations	
	CW	CIC	CIC PAB	CIC	CIC PAB
Building materials, basic metals, aluminium	0.6%	0.7%	0.7%	0.1%	0.1%
Other materials	4.6%	4.8%	5.4%	0.3%	0.8%
Electricity	2.6%	2.9%	2.7%	0.2%	0.0%
Fossil fuels	6.1%	5.6%	0.0%	−0.4%	−6.1%
Utilities and infrastructure	3.1%	2.8%	3.1%	−0.3%	0.0%
Agriculture, food, beverage	4.2%	4.3%	4.7%	0.1%	0.6%
Building	3.6%	4.0%	4.3%	0.4%	0.8%
Electronics manufacturing	9.5%	9.9%	10.9%	0.3%	1.4%
Other manufacturing	21.3%	22.2%	24.3%	0.8%	3.0%
Sales	7.1%	7.5%	8.3%	0.4%	1.2%
Services	18.7%	17.9%	18.0%	−0.8%	−0.7%
Financial and insurance activities	18.6%	17.4%	17.6%	−1.2%	−1.1%

The analysis is based on yearly data. Sector data are averaged across all the years in the sample. Deviations are the sector weight of the CIC indices minus the sector weight of the Broad Cap-Weighted index. The indices used are the Scientific Beta Developed Cap-Weighted index and the standard and EU PAB-compliant versions of the Scientific Beta Developed Climate Impact Consistent index (CIC and CIC PAB).

5. Excess weighted average carbon intensity (WACI) decomposition

SciBeta Developed June 2021	CIC				CIC EU PAB-compliant			
	Excess	Stock	Sector	Inter	Excess	Stock	Sector	Inter
Building materials, basic metals, aluminium	−1.2	−3.2	3.0	−1.1	−1.5	−3.6	3.6	−1.4
Other materials	−8.2	−10.2	3.7	−1.7	−7.8	−10.1	4.3	−1.9
Electricity	−35.7	−34.3	−4.1	2.7	−39.7	−33.6	−17.6	11.4
Fossil fuels	−5.1	−4.5	−0.8	0.2	−16.5	0.0	−16.5	0.0
Utilities and infrastructure	−5.7	−5.2	−1.2	0.6	−6.5	−5.9	−1.4	0.8
Agriculture, food, beverage	−0.1	−0.2	0.1	0.0	0.2	0.0	0.2	0.0
Building	−1.7	−1.8	0.3	−0.2	−1.5	−1.7	0.4	−0.2
Electronics manufacturing	−1.4	−1.4	0.1	0.0	−1.3	−1.5	0.4	−0.2
Other manufacturing	−0.9	−1.3	0.5	−0.1	−0.6	−1.3	1.0	−0.2
Sales	−1.3	−1.1	−0.3	0.1	−1.2	−1.1	−0.2	0.1
Services	−1.2	−1.1	−0.1	0.0	−1.2	−1.1	−0.1	0.0
Financial and insurance activities	−2.3	−2.3	−0.2	0.2	−2.3	−2.3	−0.2	0.1
Total	**−64.8**	**−66.7**	**1.0**	**0.8**	**−79.9**	**−62.3**	**−26.1**	**8.5**

The table shows the sector WACI (weighted average carbon intensity) contribution for each Scientific Beta sector. The excess WACI is the difference in sector WACI contributions between the CIC and CW indices. The excess WACI is decomposed into stock, sector and interaction components. WACI is based on Scope 1+2 emissions divided by revenue (t/$m). The indices used are the Scientific Beta Developed Cap-Weighted index and the standard and EU PAB-compliant versions of the Scientific Beta Developed Climate Impact Consistent index (CIC and CIC PAB).

ing data on green revenues and SBT pledges and result in a robust and meaningful carbon intensity metric for investors to engage companies on their environmental impact.

The CIC indices reduce climate transition risks

While the primary objective of CIC indices is to support investors' impact on tackling climate change through consistent signalling, the indices are also effective in mitigating climate transition risks. Climate transition risks cover both financial risks in the transition to a low-carbon economy and asset stranding risks. The CIC indices strongly reduce climate transition risks via three channels:

- First, negative screening removes assets most exposed to stranding risks. The core ESG filter includes screens on coal and tar sands activities which are incompatible with the Paris Agreement. In the PAB-compliant CIC index, additional regulatory screens remove almost all fossil fuel companies, thus strongly reducing exposure to companies facing high risks of asset stranding.
- Second, by overweighting firms with good carbon performance within sectors, the CIC pure climate weighting strategy reduces transition risk exposure across all sectors, proxied by carbon intensity. Transition risk exposure is further improved by overweighting companies with positive net contributions to climate solutions or approved science-based targets. Companies that fail to self-report emissions are underweighted or even excluded in high transition risk sectors.
- Thirdly, the CIC indices' 7% self-decarbonisation trajectory reflects 1.5°C ambitions and includes Scope 3 emissions. Aligning with the trajectory thus promotes emissions reductions among unlisted parts of the economy and reduces transition risks associated with value-chain emissions. At the same time, the sector adjustment used to adhere to the trajectory preserves the signalling effect of the CIC intra-sector weights, and the indices remain representative of the real economy.

The CIC indices maximise the impact of climate investing in the real economy through consistency

At a time when all investors are mobilising in the fight against climate change and when this mobilisation mostly involves strong engagement practices, CIC indices correspond to a choice of benchmark that is consistent with this engagement. It avoids the inconsistency of the vast majority of optimised or CW-tilted climate benchmarks and means that investors, at the same time as they are engaging with companies whose climate practices and metrics need to be improved urgently, are not sending a contradictory signal to these same companies by increasing their investments in them even though they have not made an alignment commitment and their current carbon intensity is worsening. By allowing investors to put their money where their mouth is, the CIC indices bring the strength of consistency to investors' climate commitments.

War and peace

Positioning equity portfolios for trade policy shifts

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Trade policy risk is relevant for investors, but investors lack dedicated financial products to manage their exposure.

We measure a stock's exposure to trade policy risk using information on the intensity of trade in its industry and corporate risk disclosures.

We design dedicated indices that benefit from falling or rising trade tensions. We show how these indices react to a series of US-China tariff announcements.

The indices deliver more efficient exposure than simple sector strategies that ignore the more granular information we use.

In a world where international trade accounts for more than 50% of total output,[1] trade policy matters. More protectionist or liberal trade policies affect firms' playing fields and create winners and losers. The profitability of some firms may suffer due to increased costs of production and reduced export possibilities, while the profitability of more domestic firms may remain unscathed and for some, it may even improve due to reduced foreign competition.[2]

These effects matter for investors. Besides any impact on aggregate asset prices,[3] investors' financial portfolios may differ in their exposure to the impact of trade policy. In addition, for many

1 Trade as a percentage of GDP has been above 50% since 2003 on a global basis, based on data from the World Bank and the OECD. See https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS

2 Bernard et al (2003) and Melitz (2003) argue that trade liberalisations tend to favour the most productive firms because they can absorb the costs required to participate in international trade.

3 Political uncertainty may be priced as shown in Pastor and Veronesi (2013).

investors a significant proportion of their wealth is represented by their future labour income, which may be concentrated in exposed sectors. Finally, investors also care that purchasing power can be significantly affected by shifts in trade policy.[4] These mechanisms will have an overall impact that differs across investors. They generate hedging demand from investors who feel particularly exposed. Other investors may have views on future shifts in trade policy that they want to take advantage of.

Unfortunately, investors are at a loss to control such exposures when it comes to risk management tools. There are no dedicated financial assets, such as derivatives, on tariffs. Sometimes, allocation strategies across different asset classes are proposed as a solution. However, these are too imprecise and based on weak intuitions such as using gold as a hedge, which are not backed by solid empirical evidence.[5] Alternatively, investment managers also propose stock-picking approaches, but these are purely ad hoc and can expose investors to excessive idiosyncratic risk.[6]

To fill this gap, we developed dedicated equity indices to target exposure to trade policy risk. We first measure firms' exposures to trade policy shifts using fundamental data on trade intensity in a firm's industry and the firm's risk disclosures in regulatory filings. This combination allows us to consider different dimensions of exposure. We use our measure of exposure to form portfolios with opposite exposures to trade policy risk. We construct a war index whose objective is to protect investors from shifts towards protectionist policies and a peace index that can instead help investors to take advantage of shifts towards liberalisation. We show that our war and peace indices behave as expected during heightening trade tensions. Our dedicated indices that use firm-level measures of exposure to trade policy risk are a useful new tool for investors because heterogeneity in exposure cannot be captured as accurately by simple sector bets.

Measuring firms' exposure to trade policy risk

Characterising exposure to global trade is a complex task because there are several factors to take into consideration. For instance, firms can be led to trade internationally by the low cost of transportation for their products,[7] specialised knowledge (product uniqueness) that reduces competition and helps to penetrate foreign markets, or economies of scale of their production processes that creates incentives for geographical concentration of production. On the contrary, high costs of transportation or the existence of a high barrier to entry (eg, in the case of a politically established domestic monopoly) reduce the incentives for firms to trade. This complexity means that it is impossible to capture exposure by looking at a single dimension.

To capture this complexity, we leverage the insights from different academic papers and focus on three measures:

- Tradability of goods;[8]
- Export share;[9]
- Corporate risk disclosures.[10]

The first two are obtained at industry level,[11] using fine-grain industry classifications, as opposed to broad sector classifications.[12] The last measure is obtained at firm level. These three measures capture different dimensions of exposure to trade policy risk. Tradability is measured as the shipping cost of goods, relative to the total value of the goods, where we can obtain data for all the firms in manufacturing industries.[13] The cost of transportation is a structural feature of an industry that represents a natural barrier to international trade. Therefore, it affects the potential of firms to do international trade. The export share is measured as the share of an industry's output that is exported. It captures an economic outcome, ie, realised levels of international trade. This makes it a good complement to tradability, which captures the potential for international trade. Finally, we obtain our third measure via natural language processing[14] of the risk disclosures in firms' annual reports (10-K filings with the SEC). The risk disclosure data allows us to capture firm-specific exposure to trade policy risks. Concerns for tariffs and other regulatory changes, including those that affect the firm indirectly through the supply chain, can potentially be captured from the management's discussion of such risks in mandatory disclosure.

Each of the three measures comes with data limitations in terms of either granularity or coverage. We overcome these issues by augmenting the characteristics as described above with covariances between the stocks' returns and long/short portfolios that are constructed from characteristics.

Then we combine the three dimensions of exposure by averaging among the augmented scores.

By combining these measures, we use the information provided by each dimension and overcome the limitations of each individual measure to obtain a more robust measure, rather than trying to pick the best in-sample measure.

Based on the final combined scores, we then select the 30% stocks with the lowest exposure as constituents of the war index and the 30% stocks with the highest exposure as constituents of the peace index.[15]

Returns in time of war

To manage trade policy risks, investors need indices whose returns respond consistently to shifts in trade policy. We test whether our measure captures differences in stocks' price responses to trade policy shocks by conducting an event study.[16]

4 Handley and Limão (2017) show that the reduction in the threat of trade tensions following the accession of China to the WTO lowered goods prices and increased consumers' purchasing power in the US.

5 Gold has a reputation of a 'safe haven' (see Baur and McDermott [2010]). Among other industry publications, one could cite Schroders (2019), in which the authors advise being 'long gold' as a hedge against the prospect of weaker growth outcomes due in part to the intensification of the trade tensions between the US and China.

6 See for example https://www.cnbc.com/2019/05/16/these-stocks-are-poised-to-win-big-from-the-trade-war-two-experts-say.html

7 In particular, the academic literature (eg, Hummels [2007]) on international trade shows that the cost of shipping goods is the main driver of global trade.

8 This measure has been proposed by Barrot, Loualiche and Sauvagnat (2019).

9 As in Lombardo and Ravenna (2014) and Tian (2018).

10 Several papers have used textual analysis to obtain measures of exposure to trade policy risk, such as Caldara et al (2020), and Baker, Bloom and Davis (2016).

11 By industry-level we mean that the data is obtained for the industries given the industry classification associated with the dataset. Then we assign to each firm the score of its industry.

12 By broad sector classifications we mean those that aggregate stocks in only a few industries, like the least granular classification of Thomson Reuters that has only 10 distinct sectors. The fine-grain industry classifications further divide the broad sectors, to obtain classifications consisting of around 30 to 80 sub-sectors.

13 We obtain data from the US Census Bureau that does not provide data on cost of international trade for service sectors.

14 The score is defined as the fraction of the words in the risk disclosure section that occurs in a pre-specified trade tensions dictionary (based on Baker, Bloom and Davis [2016] and Caldara et al [2020]).

15 Ranks are updated each year, and portfolios are rebalanced with the updated ranks in June and cap-weighted.

16 Several papers have studied the impact of policy shifts on prices using an event study approach, for instance, Amiti, Kong and Weinstein (2020), Bianconi, Esposito, and Sammon (2020), Breinlich (2014), and Wagner, Zeckhauser and Ziegler (2018).

We follow Amiti, Kong and Weinstein (2020) who identify events in the US-China trade war between 2018 and 2019. The events are tariff announcements, and their relevance is confirmed by corresponding peaks in Google searches of trade war-related terms.[17]

For each event date, we estimate the average cumulative abnormal return (CAR) of the constituents of the war and peace indices. The CAR of a stock is the sum of the daily abnormal returns, which are given by the difference between realised and normal returns during the event period. The CAR represents the impact of the event on prices that cannot be explained by factor exposures.[18] We expect stocks with high exposure to trade policy shocks (peace index constituents) to suffer when international trade conditions deteriorate and have a negative average CAR. In contrast, since we expect the war index to provide protection during these turbulent periods, the average CAR of its constituents should be positive.

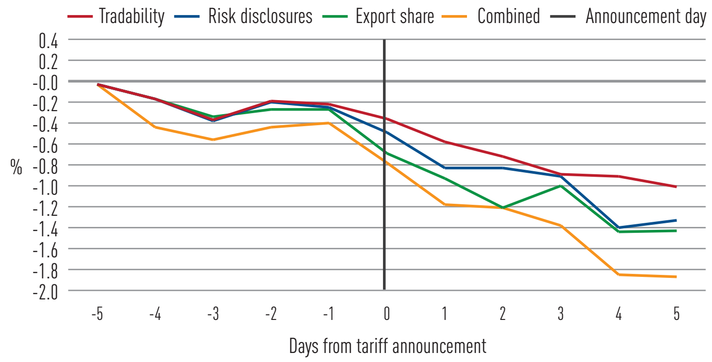
We also expect the combined measure to enhance robustness relative to the individual measures, because we are looking at different events that may affect different dimensions of exposure to trade policy risk.

The results of the tests support our expectations. Figure 1 shows the average CAR[19] of the peace index constituents minus the average CAR of the war index constituents from five days before an event day to five days after. Focusing on the results of the combined measure, we observe that the peace stocks suffer more relative to the war stocks around a trade war announcement. Indeed, the average difference in CAR is about –1.8% after five days from an announcement.

We observe similar effects when we construct indices with the three individual measures; however, we see that combining them adds robustness to the measurement. Indeed, the average difference in CAR is larger for the stocks selected with the combined measure.

Figure 2 allows us to look at the impact on the war and peace indices separately.

1. Differential price impact of trade tensions on US stocks



This plot shows the average cumulative difference in daily abnormal returns (from day –5 to day +5 around the events) between US stocks with high and low exposure to trade tensions. High and low exposure stocks are selected among the US stocks using augmented risk disclosures, tradability, the export share measures and a measure combining these three. The results are obtained by pooling all the observations around seven events related to the US-China trade war. Normal returns are obtained using the Fama-French five-factor model.

2. Cumulative abnormal returns of the constituents of the war and peace indices

Average cumulative abnormal return after US-China trade war announcements

Index	Statistics	Risk disclosures	Tradability	Export share	Combined
US trade war	Average CAR	0.55%	0.36%	0.72%	**0.76%**
	t-stat	2.29	1.75	2.33	**2.46**
US trade peace	Average CAR	–0.53%	–0.43%	–0.45%	**–0.72%**
	t-stat	–2.72	–2.07	–2.13	**–3.36**

The table reports the average cumulative abnormal returns (ACAR) from event day (included) to +5 working days, and the t-stat adjusted for event-induced variance and for cross-correlation (Kolari and Pynnonen [2010]) for stocks in the war and in the peace indices. The normal returns are computed using the Fama-French five-factor model. US war (peace) indices are constructed by selecting at the rebalancing day stocks having a score below (above) or equal the 30th (70th) percentile. We report in bold the highest statistics in absolute value among the three scores.

We report the average CAR[20] from announcement day (day 0) to five days after for stocks in the war and peace indices. We see that all the average CARs have the expected sign, positive for the war indices and negative for the peace indices, and they are mostly statistically significant. Furthermore, combining the measures improves both the magnitude and the t-stat of the CAR for both types of exposures.

These results show that our measures capture the differences across stocks in price responses to changes in trade policy. Furthermore, combining the information contained in our three individual measures of exposure provides additional robustness. This means that the war and peace indices represent effective tools that investors can use to manage the risk of trade policy shifts.[21]

It's not just about broad sector exposures

The indices are affected by differences in trade policy risk exposure across sectors. For instance, the war index is skewed towards financial firms, which are protected from foreign competition by domestic regulation. Similarly, the peace index is skewed towards technology and industrials, which include many manufacturing firms that are more likely to export. However, as figure 3 shows, there is also significant intra-sector heterogeneity in exposure. When we use the broadly defined sectors employed for sector allocation decisions by equity investors,

17 In total this gives seven events between the years 2018 and 2019.

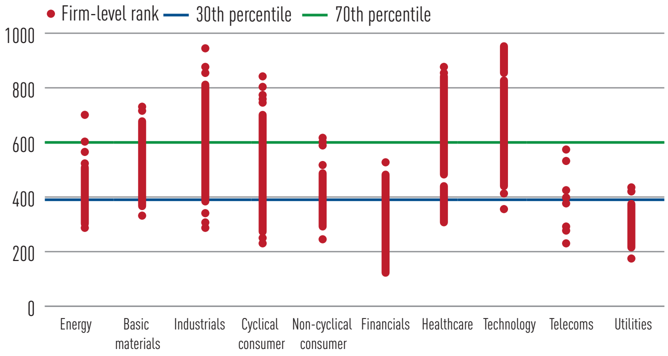
18 We obtain factor exposures using three different models whose parameters are estimated using one year of daily returns observations preceding the event period. The event period is composed of six days, it goes from the announcement day (day 0) to +5 days. The models used to obtain the normal returns are the CAPM, CAPM plus intercept, and the Fama-French five-factor model. When we compute the t-stat of the average CAR we correct standard errors for event-induced volatility and for cross-sectional correlation across stocks following Kolari and Pynnonen (2010).

19 The graph reports the results obtained using the Fama-French five-factor model for the normal returns, but similar results are observed using the CAPM and the CAPM plus intercept.

20 The model for the normal returns of the CAR reported in figure 2 is the Fama-French five-factor model. However, using the CAPM and the CAPM plus intercept we obtain similar results.

21 Furthermore, standard statistical tests did not detect significant underperformance of the war index over its multi-factor benchmark despite its protection against trade policy shifts; we do not report these results here for brevity.

3. Intra-sector exposure dispersion – US universe as of June 2019



The graph shows the combined scores of all stocks in the universe categorised per Scientific Beta sector. The y-axis shows the value of the combined score, the different sectors are spread out over the x-axis and each red dot represents a firm. The analysis is based on data at the June 2019 rebalancing date.

most of the 10 sectors contain both stocks included in the peace index (with an exposure above the 70th percentile) and stocks included in the war index (with an exposure below the 30th percentile).[22] These broad sectors tend to group firms that have very different exposures to trade policy risk. For instance, the healthcare sector includes both hospitals, whose business is inherently domestic, and pharmaceutical companies, which sell their products across the globe. Clearly, shipping doctors is not as easy as shipping drugs.

Our indices capture such important intra-sector differences in exposure to trade policy risk. In contrast, simple sector tilts diminish investors' ability to manage such risk.

22 We use the Thomson Reuters Business Classification (TRBC).

Conclusions

Following the rise in trade tensions across the globe in recent years, it has become more relevant than ever to have access to effective tools to manage exposure to the risk of shifts in trade policies. We have shown that it is possible to capture heterogeneity in exposure to trade policy risk among stocks to construct effective risk management tools. Our methodology allows us to consider several dimensions of exposure, which improves the robustness of the resulting trade policy sensitivity. Finally, we show that our methodology cannot be replicated with simple broad sector bets.

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