EDHEC BUSINESS SCHOOL

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RESEARCH INSIGHTS EDHEC

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EDHEC CLIMATE + FINANCE SPECIAL

EDHEC-Risk Climate Impact Institute
Professor Rebonato receives PMR Quant of the Year Award

Very few names in finance command as much respect as Riccardo Rebonato's. Riccardo is an exceptionally prolific author who has made numerous influential contributions to our field, particularly in the context of interest-rate modelling, asset pricing, and risk management. This year's Quant Researcher of the Year Award pays tribute to a colleague to whom the field of quantitative finance owes much.

Dr Marcos López de Prado,
Global Head - Quantitative Research and Development, ADIA,
Professor of Practice, College of Engineering, Cornell University

About the Award

Established by Portfolio Management Research, the leading provider of thought-leadership for the investment-industry, the "PMR Quant Researcher of the Year" award, distinguishes individuals responsible for major advances in academic knowledge, and specifically researchers with a history of outstanding contributions to the field of quantitative portfolio theory.

Past Winners of the Award:
2021 – Petter N. Kolm,
Clinical Full Professor of Mathematics,
Courant Institute, New York University
2020 - Campbell R. Harvey,
Professor of Finance,
Fuqua School of Business, Duke University
2019 - Marcos López de Prado,
Global Head - Quantitative Research and Development, ADIA,
Professor of Practice, College of Engineering, Cornell University

About the Laureate

Riccardo Rebonato is Professor of Finance at EDHEC Business School and Scientific Director of the EDHEC-Risk Climate Impact Institute, where he also heads the research programme on "The Impact of Climate Change on Asset Prices And Investment Management".

He was previously Global Head of Rates and FX Analytics at PIMCO.

Professor Rebonato is recognised as having pioneered the application of Bayesian networks to stress testing and asset allocation.

He has served on the boards of ISDA and GARP.

He holds a doctorate in Nuclear Engineering and a PhD in Materials Science and Solid State Physics.

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EDHEC-RISK Climate Impact INSTITUTE

Contents

Introduction

I am delighted to introduce the first EDHEC Climate + Finance special issue of the EDHEC Research Insights supplement to Investment & Pensions Europe.

Since 2001, EDHEC Business School has been implementing an ambitious research policy combining academic excellence with practical relevance. This includes furthering scientific research in those areas where the school excels in terms of expertise and research results, and highlighting practical implications and applications to decision makers. This is complemented by business ventures, backed by the EDHEC Foundation, which are designed to accelerate the transfer of innovation to the industry.

This policy was spearheaded by risk and investment management research centre EDHEC-Risk Institute, which has now become EDHEC-Risk Climate Impact Institute. Its transition demonstrates the school's commitment to helping organisations integrate sustainability risk and impact considerations.

Fittingly, four of the six contributions in this special issue were penned by EDHEC-Risk Climate researchers. The others were prepared by researchers from EDHEC*infra*, the research institute at the origin of the leading provider of index data, benchmarks and analytics in the unlisted infrastructure universe, and Scientific Portfolio, an early-stage technology initiative designed to help institutional investors integrate financial and non-financial information to analyse and design equity portfolios in a cost-efficient manner.

This issue opens with a contribution by EDHEC-Risk Climate Scientific Director Professor Riccardo Rebonato. It describes how the oft-criticised models linking the economy and the planet's climate can be upgraded to include the latest advances of science. Professor Rebonato presents original simulation work showing that targeting 1.5–2°C of warming can be justified as an optimal goal from an economic standpoint. He also shows that while the emissions abatement pace implied by such an objective is technically possible, it is improbable and should not be considered a 'central' scenario.

In the second article, the core team of Scientific Portfolio describe how they developed a factor that captures both the sectoral and intra-sectoral dimensions of transition risks. Head of Research Benoit Vaucher, PhD, CFA, ESG Director Vincent Bouchet, PhD, and Director Benjamin Herzog find that, while their factor is forward looking, it efficiently identifies funds considered as 'green' or 'brown'. The authors also discuss how their approach enables the management of transition risks to be seamlessly integrated into portfolio construction.

In the third article EDHEC-Risk Climate Affiliate Member Professor Noël Amenc and EDHEC*infra* Director Frédéric Blanc-Brude, PhD, analyse the outperformance of low-carbon energy infrastructure investments over the past decade and find that it is largely explained by excess demand. After controlling for risk factors, they find no persistent 'green' risk factor, but instead a 'green price premium' that investors have been willing to pay.

In the fourth article, EDHEC-Risk Climate Research Engineer Emanuele Chini uses advanced econometric methods to explore the relationship between stock returns and proxies for environmental footprint. He identifies a latent environmental factor with significant explanatory power in the energy sector and finds that emissions-related metrics are the main drivers of stocks' exposure to this factor.

In the penultimate article of this special issue, EDHEC-Risk Climate Research Director Professor Dominic O'Kane and Senior Research Engineer Jean-Michel Maeso, PhD, use a variety of language models to construct climate news indices. The authors find that returns of high carbon intensity portfolios show a strongly statistically significant negative association with a climate-news index constructed from the aggregation of sources. This research benefits from the support of Amundi.

Corporates and investors are increasingly expected, if not legally required, to assess their climate-related financial risks using climate scenarios. Our closing article is by EDHEC-Risk Climate Research Programme Director and climate-stress testing pioneer Professor Irene Monasterolo. Professor Monasterolo introduces and discusses the characteristics of these climate scenarios, their operationalisation for climate-financial risk assessment, their current limitations and their potential for further development.

We wish you an enjoyable read and extend our warmest thanks to IPE for their collaboration on the supplement.

Emmanuel Métais, PhD, Dean, EDHEC Business School

What integrated assessment models can tell us about asset prices

Riccardo Rebonato, Scientific Director, EDHEC-Risk Climate Impact Institute; Professor of Finance, EDHEC Business School

This paper explains what integrated assessment models (IAMs) are, why they are useful to analyse the impact of climate change, and how the criticisms levelled at the early versions have largely been addressed.

With the new-generation IAMs, the Paris Agreement 1.5–2°C target emerges as an optimal, rather than 'aspirational', goal.

The paper also shows that following this optimal path requires an unprecedented change in emission trajectory. As a consequence, there is ample scope for negative surprises, which may currently be only imperfectly reflected in asset prices.

Integrated assessment models (IAMs) are ambitious descriptions of the whole economy and of the Earth's climate, designed to give policy recommendations about the most cost-efficient course of action to counter the effects of climate change. After enjoying an initial popularity, they have been severely criticised for being of little use – and perhaps even dangerous. The criticisms levelled at the early incarnations of IAMs, and in particular at the (first version of) the dynamic integrated climate-economy (DICE) model of Nordhaus (1993), were justified, as their 'optimal' policy suggestions – such as recommending an 'optimal' temperature increase by the end of the century of 3°C or more – seemed to fly in the face of common sense.

I intend to argue that, if made fit for purpose, IAMs *can* provide extremely useful policy guidance. In particular, their modern versions show that the target of 1.5–2°C warming by the end of the century can be justified as an optimal, not just an 'aspirational', goal. They also show how ambitious the optimal policy would be: abatement would have to accelerate at an unprecedented rate and buck all existing trends. By highlighting how radical our commitment to abatement (and removal) would have to be for these optimal temperature targets to be met, IAMs draw our attention to the essential distinction between what is theoretically and what is practically (read, politically) possible.

These findings are of relevance not only to policymakers, but also to strategic investors. If markets currently price in a 'soft climate landing' in which a close-to-optimal climate policy will somehow be followed, it is important to understand how aggressive (and hence unlikely to be implemented) such an optimal policy actually is. And it is just as important to understand what the repercussions on asset prices may be if we do *not* engage in this unprecedented reduction in emissions.

Fortune and misfortune of IAMs

The DICE model has enjoyed very different fortunes on either side of the Atlantic: in the US, it has been used (together with two other models) by the Environmental Protection Agency to inform government policy. In Europe, policymakers have turned their backs on IAMs in general, and on the DICE model in particular, and have instead endorsed the Paris Agreement 1.5–2°C target. In the European approach, optimisation tools are still used, but only to minimise the cost of attaining the 'exogenous' 1.5–2°C target. The reason for these different responses to the DICE model is probably to be found in the very gradual pace of emission abatement and the low social cost of carbon (the optimal 'carbon tax') it recommends. These policy recommendations have chimed better with the US political environment of recent decades (which has, on average, been less than enthusiastic in its pursuit of climate action), but have jarred with the more 'progressive' European institutions.

The situation is far from ideal, because economic and climate-physics models have become political tools rather than conceptual aids to make sense of what is already an extremely complex problem. In the US, a frankly outdated version of the DICE model is still used, despite the fact that (or perhaps because) it recommends very gradual abatement efforts and a low social cost of carbon. In Europe, the 1.5–2°C target has acquired totemic value, despite the fact that climate science cannot pinpoint with the degree of accuracy implied by the Paris target a 'safe' or 'dangerous' temperature range. Indeed, the best estimates of the climate sensitivity (which is a key quantity in the calibration of climate models) span as wide a range as shown in figure 1, which displays the fit by Roe and Baker (2007)[1] to the best climate sensitivity values reported in the literature.[2] As the figure shows, there is a 10% chance that the true sensitivity may be below 1.7 or above 4.7. As the director of the Harvard University Center for the Environment, Professor Daniel Schrag, points out, as far as we currently know there is no cliff either side of the 1.5–2°C interval. In his words, "1.5°C is not safe and 2.2°C is not the end of the world".[3]

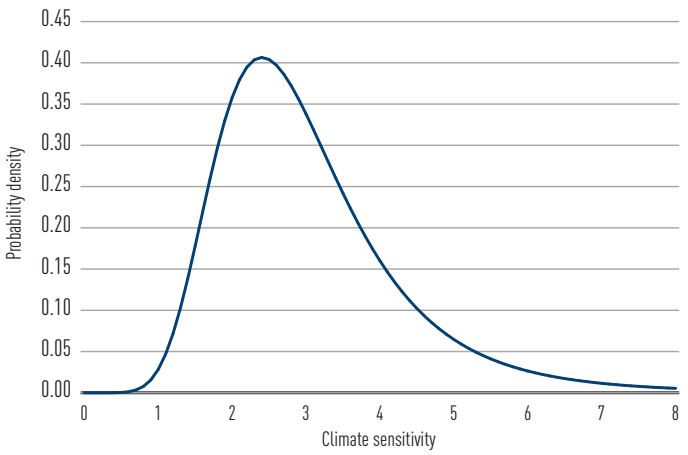
All of this may well be true, and an uncompromising rationalist may conclude

1 For a good discussion, see Pindyck (2022).

2 Climate sensitivity is the rise in global temperature in response to a doubling of CO_2 concentration with respect to pre-industrial levels. It is a key input to all climate models.

3 Professor Daniel Schrag quoted in *The Economist*, November 2022. Available at: https://www.economist.com/interactive/briefing/2022/11/05/the-world-is-going-to-miss-the-totemic-1-5c-climate-target

1. A fit to the dispersion of the climate sensitivity, a key input for all climate models: probability density of climate sensitivity



Source: Author's calculations using references in Pindyk (2022)

that obsessing on this round-number target as if it were the be-all-and-end-all of climate control does not make a lot of sense. The fact remains, however, that the 1.5–2°C target *has* become a universally recognised policy reference point, and that it *has* become part of the political discourse. This has value in itself. Clear and simple targets, especially if expressible in numbers (and even more especially, in *round* numbers) *do* serve a useful role.

This raises questions. Can the 'totemic' (read, aspirational) 1.5–2°C target be reconciled with the recommendations of state-of-the-art IAMs? Can policymakers on both sides of the Atlantic re-engage with DICE-like models, or are we doomed to have differing American and European versions of climate truth?

How IAMs work

To answer these questions, we must understand why the original DICE model produced such a gradual abatement schedule. As in all IAMs, there are in DICE two connected blocks. This first makes up a module that describes the world economy following the well-trodden path of dynamic stochastic general equilibrium models: capital, labour and the total factor of production combine via a Cobb-Douglas function to give gross economic output. To produce this output, greenhouse gases are emitted – the more so, the less the economy is 'decarbonised'. This is where the economic module feeds into the physics module: the industrial emissions increase the concentration of CO_2 in the atmosphere, and this causes an increase in global temperature. The higher the temperature, the greater the damage inflicted on the economic output. The standard capital allocation choice (how much of the output should be saved rather than consumed) is made more complex than usual by the existence of this feedback loop from production to temperature and to reduction in production. It is because of this feedback loop that it is rational to divert some of the productive resources to abatement initiatives. The key question is: how much?

To answer this question, IAMs associate a utility with consumption, all the way from now to centuries in the future. The goal of the policymaker is then to fine-tune 'control variables' (how much to save and how much to abate) so as to maximise some function of the discounted values of all these utilities.

Every single step of this procedure is fraught with uncertainties. However, some particularly deep trenches have been dug in the climate wars along a handful of key modelling points. It pays to understand why the debate is so heated, and what these bones of contention are.

The first observation is that the bulk of climate damage will be suffered by generations in the future – and, sometimes, in the very distant future. The problem therefore arises of how to 'present value' the utility enjoyed by future generations. Some economists (and many philosophers) have argued that we should accord to 'future people' exactly the same importance as we do to our contemporaries.[4] In the context of climate change, Stern (2006a, 2006b) is the best-known representative in this camp, but the 'altruistic' tradition goes all the way back to Ramsey (1928). Most economists (Nobel laureate Nordhaus among them) favour a 'low' but non-zero discount rate. The difference between Stern's 0.1% discount rate and Nordhaus's 1.5% may seem small but, given the extremely long horizons (centuries) of the climate change problem, such small differences matter a lot. From Nordhaus's perspective, the welfare of our great-great-grandchildren has little bearing on the climate decision of a current policymaker; using Stern's choice, future generations remain almost exactly as important as the present one. Because of this telescoping effect, the Nordhaus optimal solution envisages 'optimal' temperatures (and damages) for the end of the century and beyond well above the values recommended by Stern-approaches. Stern's best abatement action is fast and on a large scale; Nordhaus's is gradual and limited in its initial scope.

Since economists and philosophers have been debating for decades (if not for centuries) the merits and blemishes of unlimited altruism, there is unfortunately little hope that this disagreement will be resolved any time soon. This is one of the two main reason why IAMs have been distrusted by policymakers.

The other main determinant of the optimal abatement policy about which there is huge disagreement is the so-called 'damage function'.[5] For a given level of CO_2 concentration, this is the function that transforms the temperature increases predicted by the climate models into damages to economic output. As figure 1 shows, climate models may suffer from a high degree of uncertainty. However, their predictions have pin-point accuracy compared with what we can extrapolate about economic damages in response to temperature changes never experienced by human civilisation. The problem is that we have no scientific or economic theory to estimate this function, and, by and large, we have to use rather crude extrapolations. And *extra*polations they must be because (fortunately) we have, so far, only observed damages for increases in global temperature of little more than 1°C, while we would like to know what might happen due to an increase of, say,

4 See, eg, Sidgwick (1907), Harrod (1948), Solow (1974), Dasgupta (2020).

5 The rate of growth of the economy also has a very large effect on the optimal solution. There is, however, much less disagreement among economists about this quantity. If we are sure that our grandchildren will be much richer than we are, engaging in large and costly abatement today would be akin to imposing a tax on the poor (us) to benefit the rich (our grandchildren). How much we dislike uneven consumption plays an important role in determining how important this consideration is.

3°C or 6°C. A variety of methods have been used,[6] but there are huge variations not only across methods, but also within each method. So, for instance, for a probably very severe degree of warming of 5°C, the estimated impact on output ranges from *positive* 5% to negative 16%. Climate scientists have criticised economists for projecting damage values that are too low – and, indeed, in figure 2, the red dots obtained by elicitation (mainly from climate scientists) are below the green dots estimated by econometricians for all levels of warming. However, it is not *a priori* clear why climate physicists should be better placed to estimate economic damage than economists. Having said this, some economists have not done themselves any credibility favours by predicting that a 5°C warming would be greatly beneficial for the planet.[7] (Should a clarification be needed, Nordhaus is *not* one of these overoptimistic economists.)

Now, the damage function used in the original DICE model belongs to the econometric class, and has been roundly criticised for being too tame. In particular, the 'damage exponent', ie, the quantity a_3 in the equation that links temperature (T) to damages (Ω):

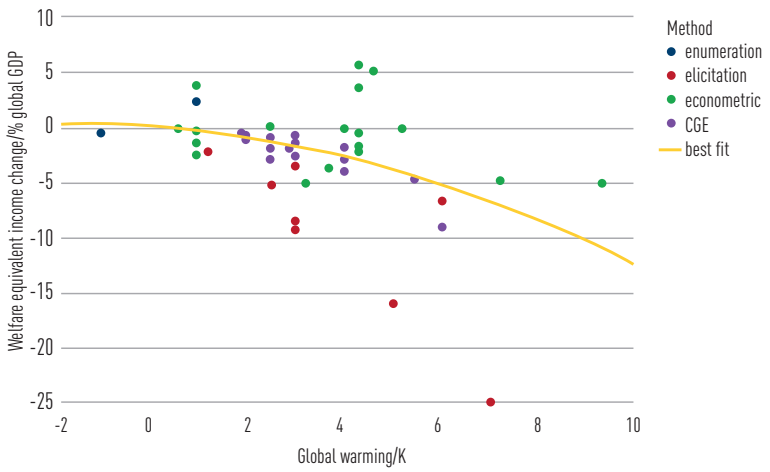
$$\Omega = a_2 T^{a_3}$$

was estimated to be equal to 2, giving rise to a relatively mild quadratic dependence of damages on temperature.[8]

As figure 2 shows, many different functional dependences could be estimated depending on which method is used. When used as input to an IAM, each of these different and difficult-to-justify assumptions produces very different optimal abatement schedules and carbon tax. Understandably, this has given powerful ammunition to the critics of IAMs in general, and of the DICE model in particular.

Since neither of these two sources of uncertainty is likely to be resolved any time soon, does this sound the death knell for the use of DICE-like IAMs as 'serious' policy applications? Are these models destined to produce nice academic papers, or, if used in earnest, to be hijacked for political purposes? This need not be the case, because a suitably enriched version of the DICE model *can* provide useful guidance in navigating the stormy waters of climate policy.

2. The effect of temperature on global annual output



The climate damage (welfare equivalent income change as % of global GDP), as estimated by the enumeration, elicitation, econometric and CGE methods. The yellow curve shows an equal-weight polynomial fit to all the estimates. Source: Tol (2022).

Making IAMs fit for purpose

Most of the lines of criticism that have been levelled against the DICE model often use the straw man of its early incarnation, the Nordhaus (1993) version. Huge modelling strides have been made in the intervening decades. Once the DICE model is suitably enhanced, both the fundamental critiques discussed above (about the lack of agreement regarding the correct discount rate and about the damage function) lose much of their bite. Given the strength and, apparently, 'existential' nature of these objections, how can a perhaps better model that still rests on such shaky foundations be of much use? How can it escape the garbage in, garbage out curse? To explain how this modelling miracle is possible, we have to understand what is *really* wrong with the early IAMs.

The original DICE model described a world with no uncertainty: the rate of growth of the population and of the economy, the damage function, the future cost of abatement with yet to be discovered technologies – everything was perfectly known to the policymaker. It was not difficult to add uncertainty and stochasticity to this or that model variable. However, when this was done, the first results were surprisingly similar to the optimal policies obtained with the deterministic version of DICE. Did the huge degree of uncertainty really not matter?

The problem was that, for computational reasons, the early IAMs invariably used what are described as constant relative risk aversion, time-separable utility functions. Functions, that is, that have two features: the first is that a poor and a rich agent will suffer the same pain (loss of utility) for the same *percentage* (not absolute) loss of wealth; the second is that today's total welfare can be simply computed as the sum of the discounted utilities experienced at different times.

Neither of these features in isolation seems particularly unpalatable (the first may not be empirically correct, but is certainly a big improvement over assuming *absolute* risk aversion). However, put together, they produce a toxic result. The problem is that these utility functions force dislike for static risk (for taking a gamble today) and dislike for uneven consumption (which have nothing to do with each other, as the latter can arise even in a deterministic setting) to be identical. This is a big problem: if we say that we are very risk averse, we are forced to say that we strongly dislike uneven consumption. Couple this feature with the (mainstream) assumption that we shall be much richer in the future, and all of a sudden investing a lot in climate abatement becomes akin to imposing a tax on the poor (us) to benefit the rich (our

6 Kainth (2022) distinguishes the enumeration, elicitation, econometric and computational general equilibrium approach, and discusses the strengths (few) and weaknesses (many) of each.

7 Among the 'optimistic' results, the work by UCSB Professor Olivier Deschenes (2007, 2011) should be mentioned. One of the arguments of those economists who predict a net benefit from global warming is that the increase of CO_2 in the atmosphere will enhance the growth of agricultural foodstuffs (the so-called 'CO_2 fertilisation effect').

8 A damage exponent of approximately 2°C (1.98) was independently estimated by Rudik (2020). In theory, there is a linear term in a_1 but, when a quadratic term is present, this coefficient is usually estimated to be zero.

great-grandchildren). The more we dislike uneven consumption, the more this 'regressive taxation' seems unacceptable, and the more we want to push the greatest burden of the abatement effort on to future generations. This leads inescapably to a paradoxical result for early DICE-like models: even in the presence of huge uncertainty (say, about damages and economic growth), *a high aversion to static risk causes the optimal abatement policy to be one of procrastination, not of decisive action*. This is because, with the original modelling framework, the high aversion to static risk implies an equally high dislike for uneven consumption, and the two effects at best cancel each other out. At worst, they cause the optimal abatement policy to be even slower (and the carbon tax lower).

Is there really no way out of the impasse? There certainly is: if we use so-called recursive utility functions (eg, of the Epstein and Zinn [1989] class), we can assign independently a coefficient of aversion to static risk, and a coefficient of aversion to uneven consumption. With a realistically strong dislike for static risk,[9] the great uncertainty about climate outcome can now have the expected effect of making the abatement strategy prompter and more decisive, *without the dislike for uneven consumption* (that can be parametrised independently) *working in the opposite direction*.

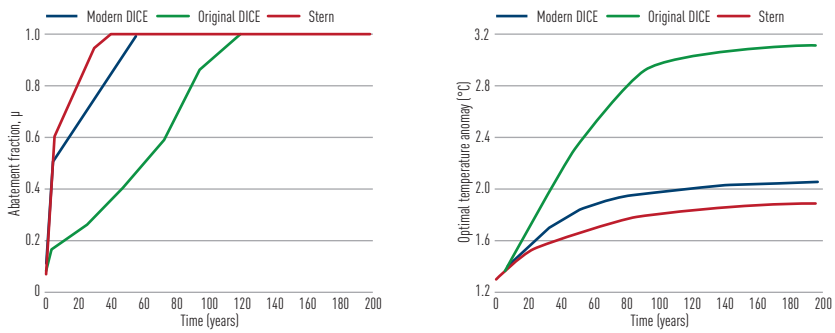
Seen in this light, the extremely high uncertainty about climate damages (and, to a lesser extent, about the physics of the problem) no longer render IAMs useless: knowing that we do not know, *and knowing how ignorant we are*, immediately makes the optimal policy more prudent, the abatement effort more urgent, and the carbon tax higher.

Why did the early IAMs make use of the time-separable power utility functions? Why weren't aversion to static risk and to uneven consumption decoupled from the start? Because recursive utility functions, which allow the independent parameterisation of these different 'preferences', are indeed much more palatable (every economist agrees on this), but come at a high (and, until recently, exorbitant) computational cost. Luckily, more powerful computers, but, above all, smart computational techniques – including some spearheaded by EDHEC-Risk Climate Impact Institute – have turned a near-impossible task into a reasonably manageable one.

What about the 'philosophical' debate about how altruistic we should be towards future generations – about, that is, the rate of utility discounting? No degree of computational wizardry can solve what is in essence an ethical problem. However, when the aversion to static risk and to uneven consumption are disentangled, and a realistic degree of uncertainty is injected into the problem, the optimal abatement schedule produced by the new and improved DICE model *with the same degree of impatience posited by the original DICE model* is already so ambitious and aggressive (and the carbon tax so high), that it is already at the limit of what is practically and politically achievable. In practical terms, once we disentangle aversion to static risk and uneven consumption with recursive utility functions, we no longer need to be infinitely (and, arguably, unrealistically) altruistic to obtain an optimal solution close to Stern's extremely aggressive recommendations. See in this respect the left panel of figure 3, which also shows in the right panel the similarity of the optimal temperature profile recommended by the Stern and 'modern DICE' approach, and the much higher optimal temperature obtained by the original DICE model.

It is also important to stress that the modern DICE optimal temperature remains within the Paris accord 1.5–2°C target by the end of the century. It is in this sense that staying within the target can be justified as an optimal policy, and not just an 'aspiration'. For the reasons discussed in the opening paragraphs, the importance of this result should not be underestimated.[10]

3. The abatement fraction and the temperature anomaly



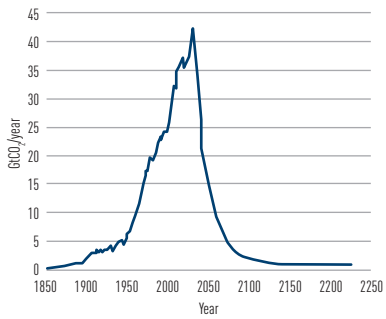
The abatement function, μ (left panel) and the temperature anomaly (right panel) obtained by the Stern model, by the original DICE model and by the modern version of the DICE model described in the text.

From optimality to implementation

Knowing what would be optimal to do is clearly important, and it is good to know that an abatement schedule that keeps the temperature between 1.5°C and 2°C by the end of the century is, *in principle*, technologically achievable, especially if carbon removal is allowed (see in this respect the discussion in footnote 10). The magnitude of the task, however, should not be underestimated. Figure 4 shows the historical CO_2 emissions from 1850 to date in the left part of the graph, and, in its right portion, the optimal emission path obtained by the modern DICE approach – a path that, let's remember, *just* keeps us inside the Paris Agreement target.

Clearly, an unprecedented change in

4. Historical and projected emissions



Historical CO_2 emissions (left portion of the graph up to 2022) and projected emissions along the future optimal path (right portion of the graph after 2022).

9 I say 'realistically' because all estimates of the coefficient of relative risk aversion from observed asset prices point to values much higher than the 1.45 posited in the DICE model. In their seminal paper, Bansal and Yaron (2004) estimate a coefficient of aversion to static risk above 10.

10 Research carried out at ERCII (Rebonato, Kainth, Melin and O'Kane [2023]) extends this analysis to the case when negative emission technologies are available alongside traditional abatement tools. A detailed discussion would take too long a detour, but the qualitative results are not changed. If anything, the optimal temperature path is a bit lower than shown in the second panel of figure 3.

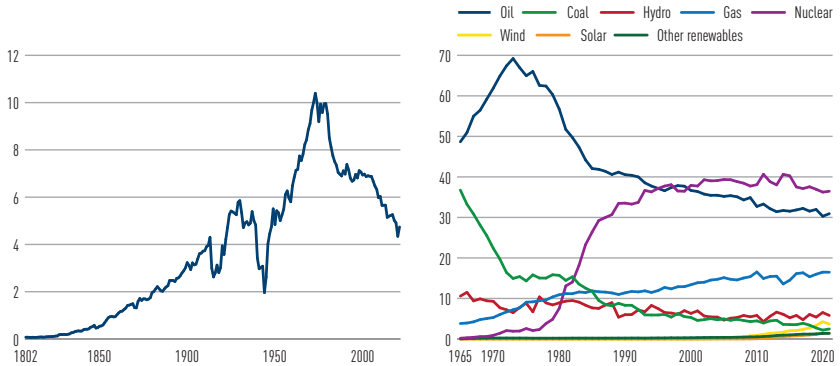
global emission policy must take place, and the required change of abatement pace is, literally, breathtaking. Has anything similar so far been observed?[11] Yes and no. Figure 5 (left panel) shows per capita CO_2 emissions in France since the start of the nineteenth century. If we ignore the dips associated with the two world wars (this is not how we want to curb emissions), we note a remarkably sharp fall in emissions starting in the late 1970s.

The drop is clearly attributable to the peculiarly French choice of adopting nuclear energy as the dominant energy source: notice (right panel), the parallel drop in oil consumption, brusquely reversing what had been a steady increase until the late 1970s.

The most pronounced falls in CO_2 emissions per capita to date have occurred in the Western world and, as far as we have been able to ascertain, in no major country has the drop been faster than in France.[12] Since few countries share France's enthusiasm for nuclear energy, it is difficult to see this pace of abatement repeated elsewhere.[13] In Germany, for instance, despite the enthusiastic embrace of sources of renewable energy, the pace of abatement has been 50% slower than in France. In any case, even looking at how quickly the 'best in class' have managed to abate can be seriously misleading. As figure 6 shows, all European countries have 'exported' a significant part of their emissions (by having parts of the goods they consume manufactured elsewhere – often in parts of the world with lower emission standards). When imported emissions are taken into account, China has grown emissions some 10% less than its headline figure, but, depending on the country, European emission figures should be increased by up to 68% (for Sweden).

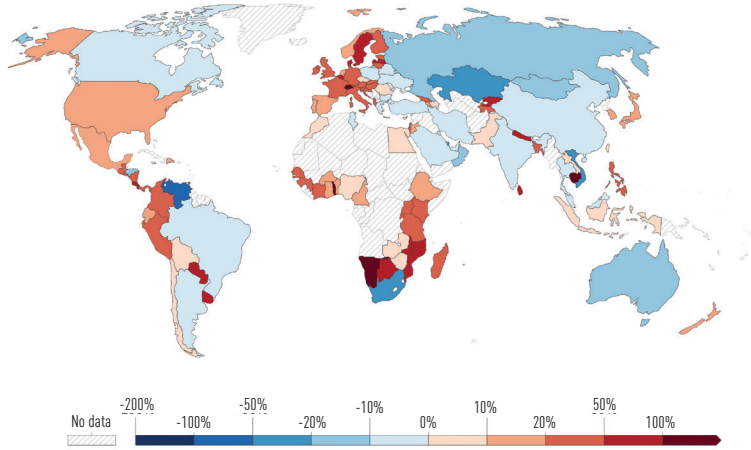
The realised declines in emissions are shown in figure 7 for a handful of countries, each representative of different approaches to apparently successful abatement: the right-hand panel shows the CO_2 emissions normalised by their level at the beginning of the 20th century; the left-hand panel gives an idea how quickly the economy has decarbonised, by plotting the ratio of the emissions in the year shown on the x axis to the maximum level of emissions (whenever these occur). We note first that for all countries the maximum emissions are reached around the mid to late 1970s. We have discussed the case of France and Germany. Sweden seems to have achieved a relatively impressive feat of emission reduction. However, for Sweden, imported emissions have grown steadily from 48.6% in 1990 to 68.5% in 2020. When this figure is factored

5. CO_2 emissions in France



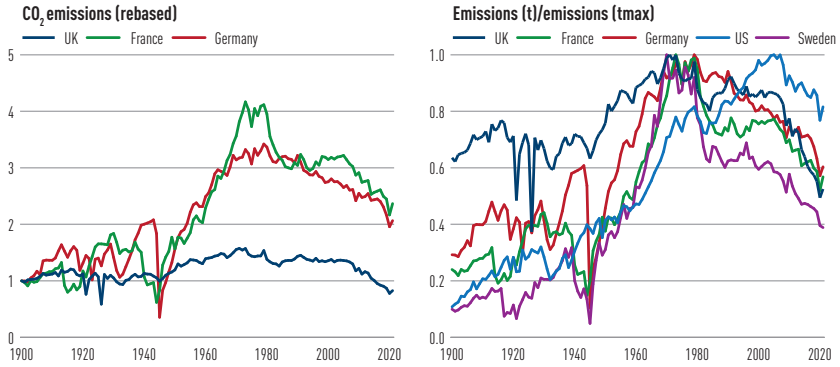
The graphs show per capita CO_2 emissions (tonnes) from 1800 to date (left panel) and the percentage share of energy consumption by source from 1965 to date (right panel). Source: Our World in Data.

6. CO_2 emissions embedded in trade, 2020



Expressed as emissions exported or imported as percentage of domestic production emissions. Positive values (red) represent net importers. Negative values (blue) net exporters.
Source: Our World in Data using data from the Global Carbon Project.

7. Realised cuts in emissions



The right-hand panel shows CO_2 emissions normalised by their level at the beginning of the 20th century; the left-hand panel gives an idea of how quickly the economy has decarbonised, by plotting the ratio of the emission in the year shown on the x axis to the maximum level of emissions (whenever these occur).
Source: Author's calculations using data from Our World in Data.

11 The analysis that follows is based on data made available by the excellent resource Our World in Data.

12 This is after adjusting for 'exported emissions' – see the discussion to follow.

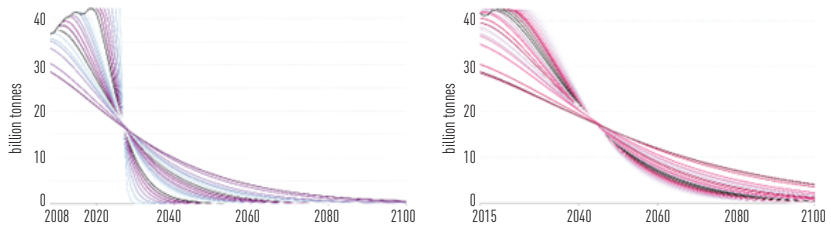
13 Higher safety standards and a loss of engineering expertise due to reduced building activities in recent decades may also limit the speed at which one can develop the share of nuclear power in the next decade.

back in, Swedish emission decreases from the peak are much less impressive. The UK also seems to have achieved a very significant reduction in emissions from the peak, but the left-hand panel shows a very atypical pattern for Western countries because in the 1960s and1970s the increase in emissions was much more muted. And, in any case, the 'hidden' emissions coming from trade have steadily grown for the UK from 11% in 1990 to 42% in 2020 (the same figures are 13% to 20% for Germany, with the initial low figures distorted by German reunification).

This is what the best in class have managed to achieve in terms of the pace of decarbonisation. In the light of this, how difficult is it to meet the Paris Agreement temperature ambitions? Figure 8, which displays the pace of abatement required to remain within 1.5°C (left panel) and 2°C (right panel) suggests an answer. Without negative emissions, the more ambitious goal is essentially unattainable. The 2°C target requires sustained reductions in (trade-adjusted) emissions, the like of which have not been seen anywhere in the world – and, when it has been approximated, the feat has been achieved only thanks to a massive switch to nuclear energy. To put things in perspective, the unique, nuclear energy-led fall in emissions experienced in France has seen a reduction of 53% in 28 years; the required global fall in emissions to remain within the less ambitious target of 2°C by the end of the century requires approximately the same percentage reduction in 22 years – and this is before correcting for trade-embedded emissions.

Of great concern is also the fact that, although the production of energy from renewables has doubled in the past decade, global emissions have also increased. This is mainly due to emission-intensive sources (such as the production of cement or steel), for which there are currently very few large-scale non-fossil-fuel alternatives.[14] The key problem is that the appetite for cement and steel seems insatiable: Smil (2022) reports that in the two pre-COVID years China alone produced roughly as much cement (4.4bn tonnes) as the US during the whole of the 20th century. Unfortunately currently "there are no large-scale, proven ways of producing these four material pillars [cement, steel, plastic and ammonia] of modern civilisation with electric energy alone (green or otherwise)" (Rebonato [2023]).

8. The pace of abatement required



The pace of abatement required to keep global temperatures from rising above 1.5°C (left panel) or 2°C (right panel). The black line represents the abatement pace required if the required abatement policy is started immediately. Every year of delay (curves to the right of the black line) makes the abatement pattern steeper. Source: Ritchie, Roser and Rosado (2020).

What does this mean for investors?

This paper has described in very broad terms what the latest-generation IAMs tell us about the optimal course of climate action, and how achievable this target may be. A lot more could be said on the topic – the most glaring omission being the important role that negative emissions must play in any realistic 1.5–2°C strategy.[15] A few key messages stand out:

- When updated to reflect the latest advances in physics and economics modelling, IAMs can give very useful policy advice;
- The recommendations they provide point to a much faster and steeper abatement policy than the original DICE model indicated – a policy consistent with the 1.5–2°C Paris target;
- This fast abatement pace is *technically* possible, but (apart from what has been observed during world wars) it would be unprecedented: technologically not impossible, but by no means a 'central scenario'.

What does this mean for investors? Which abatement scenarios are current asset prices reflecting? Are substantial price adjustments to be expected?

Answering these questions is far from easy, because it has proved difficult to establish to what extent asset prices have moved so far in response to climate news. The very fact that detecting the impact of climate risk on prices has proven so difficult, however, points to the fact that the price sensitivity so far cannot have been very pronounced. Let us assume that this is true – that asset prices have to date changed relatively little because of our climate predicament. This could mean three things:

- That the market believes that, whatever the climate outcome, the impact on asset prices will be very limited;
- That the market believes that 'this time is different' and all the major emitters will stick to their pledges, and actually increase them, and the temperature increases will be contained (possibly within the Paris Agreement target);
- That the market is 'asleep at the wheel'.

The first option (the irrelevance of a poorly controlled climate outcome for asset prices) is difficult to believe. Perhaps it is true that the economic (certainly not the human!) cost, as such cost is currently measured, will be limited, but clearly, we cannot be sure of this. See Pindyck (2022) in this respect. And, in any case, as we have seen, just our uncertainty about the economic effects should affect asset prices. As we hear after every election with an unclear outcome, 'Markets hate uncertainty'. If the first explanation is true, this time they seem, if not to love it, at least to ignore it.

The second possibility requires a very high degree of confidence in an unprecedented change in *actual* climate action (without cosmetic adjustments behind the smoke screens of exported emissions). As Pyndick (2022) points out, every major climate pledge to date has been broken or 'massaged to hit the numbers'. And even if the current pledged reductions were enacted, they would still fall somewhat short of the 2°C (let alone a 1.5°C) target.

The third possibility (that the market is wearing climate blinkers) is in my view the most likely, but clearly flies in the face of any notion of market efficiency. If markets were to adjust their expectations of the impact of climate change on cashflows and profitability in a sudden and disorderly fashion, this could create sudden asset repricing and heightened volatility.

14 Source: McKinsey Report, The Energy Transition: A Region-by-Region Agenda for Near-Term Action, December 2022. See also Smil (2021).

15 See, in this respect, the EDHEC-Risk Climate Impact Institute paper by Rebonato, Kainth, Melin and O'Kane (2023).

It is difficult at the moment to state with confidence which of the three possibilities is the correct one. All of this, however, points clearly to two topics for further investigation: first, measuring what the impact on asset prices of different climate outcomes can be (see in this respect preliminary work by Rebonato, Kainth and Melin [2023]); and, second, assessing to what extent this information is reflected in prices. Both these pieces of information are necessary to establish a connection between economic modelling, actual climate policy, and the impact of this on asset prices. Research in both these directions is under way at EDHEC-Risk Climate Impact Institute.

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Look up!

A market measure of the long-term transition risks in equity portfolios

Vincent Bouchet, ESG Director, Scientific Portfolio (EDHEC venture); **Benoit Vaucher**, Head of Research, Scientific Portfolio; **Benjamin Herzog**, Director, Scientific Portfolio

We propose a transition factor that captures both the sectoral and intra-sectoral dimension of the transition to a low-carbon economy by relying on the climate-policy relevant sector classification and on GHG emissions intensity.

We present an approach that enables us to disentangle the risk attributed to financial risk from those stemming from climate transition risks.

Over the recent period (2017–20), this risk associated with the climate transition factor already represents a significant part of the active risk of some funds.

Through the Paris Agreement, the international community has committed to keep global average warming below 2°C, along with a more ambitious objective of 1.5°C. In addition to the physical effects of climate change, the economic transformations required to reach this objective will affect (positively or negatively) certain business sectors more than others (IPCC [2022]). These transformations will generate new transition risks. From an investor perspective, it is therefore essential to identify the companies that have best anticipated the regulatory, technological

and market developments to avoid financial and reputational risks linked to drops in revenue, increases in costs or depreciation of (stranded) assets.

Transition risks are difficult to estimate using fundamental approaches. First, despite reinforced regulatory requirements[1] and recommendations[2], persistent gaps in climate-related data remain (NGFS [2022]). Secondly, the radical uncertainties associated with transition scenarios are difficult to incorporate into fundamental valuation models (Bolton et al [2020]). As a result, transition risk metrics display a significant degree of diversity (Bingler, Senni and Monnin [2021]).

Against this backdrop, academics have sought to measure transition risks directly from market prices. This approach relies on the ability of markets to process information in real time, which reduces the data and model barriers mentioned above. So far, the effort has focused on building climate transition (CT) factors. These factors are designed on the same principle as traditional factors (eg, size, value): they are portfolios constructed in such a way that their price changes are representative of the dynamics of the stocks affected by the transition risks.

The methodology we present aims to contribute to this literature on price-based analysis of transition risks by addressing two main conceptual issues. The first is related to the design of a CT factor. While some papers rely solely on carbon intensity – ie, the greenhouse gas (GHG) emissions of a company divided by its revenues – others use up to 10 metrics to build their representative portfolio (Görgen et al [2020]). The type and number of metrics raise questions regarding their current availability, quality, and their relevance to assess *long-term* transition risks. Our approach departs from previous attempts at producing a CT factor based solely on individual company characteristics. Instead, we utilise what is likely to be the most robust information regarding a company's exposure to transition risks: its industrial sector. We introduce a new CT factor that relies on i) the climate-policy relevant industrial sectors (CPRS) classification developed by Battiston et al (2017), and ii) the carbon intensity to differentiate companies within these CPRS sectors.

The second issue of price-based analysis of transition risks is related to the use of a CT factor in a risk model. Investors have started considering transition risks relatively recently: 2015 was a pivotal year with the Paris Agreement and the warning by Bank of England governor Mark Carney (Carney [2015]). Because the traditional tests to validate the relevance of a factor rely on long timeframes, CT factors usually do not pass these tests and are therefore not qualified as 'proper' risk factors (Amenc, Esakia and Goltz [2021]; Görgen et al [2020]). We propose a different approach, one that focuses on the practical management of transition risks by disentangling the links between a portfolio's exposure to the CT factor and the traditional ones.

Our goal is to give priority to the long-term robustness and to avoid the 'Don't Look Up' syndrome. In this movie, the discovery of a world-killing comet serves as a metaphor for the (lack of) reaction of our society to climate change. What if this comet was not going to destroy the world, but just a single city? How would you design a 'comet' factor? As in the first part of the movie, while the comet's trajectory is known only to scientists, the effect on market prices will be negligible. However, this effect will increase dramatically once the public becomes aware of the comet's trajectory and believes it to be true. The risk is therefore real, but its impact on prices is not observable for a long time; testing the validity of such a comet factor on historical prices is not relevant. In this case, the factor validation should focus on the inclusion of the most robust information about the comet: where it will crash. Therefore, we believe that the use of industrial sectors in the construction of a CT factor is crucial.

From a fundamental to a market measure of transition risks

Since 2015, several articles have investigated how transition risks are already reflected in asset prices (Giese, Nagy and Rauis [2021]). Early studies focused on firms' fundamental data as indicators of transition risks, but poor data quality as well as short analysis timeframes have limited their conclusiveness. For example, Bolton and Kacperczyk (2021) analyse 3,421 US firms over the period 2015–17. They show that firms with higher GHG emissions and changes in GHG emissions are valued at a discount, suggesting that investors demand compensation for their exposure to transition risks (consistent with Görgen et al [2020]). Engle et al (2020) also note that stocks of firms with lower E-scores – which the authors argue capture higher exposure to transition risks – generate lower returns during periods with negative news about the future path of climate change, suggesting that investors reassess the compensation required to hold 'brown' stocks when new information related to climate change is released.

The limitations of the fundamental measures of transition risks encouraged academics to turn to the price signal from companies with similar transition risk profiles (market measure). The main advantage of prices over characteristics is that they integrate information that has been processed by market participants. Whereas scores and characteristics are based on sub-optimal data and ad hoc models, prices reflect the opinion of market participants who process information from a wide variety of sources. Prices thus have a richer informational content that is, moreover, updated in real time.

However, studies based on a market measure of transition risks are also inconclusive with respect to the existence of 'green' or 'brown' premiums. For example, In, Park and Monk (2017) build a carbon efficient-minus-inefficient (EMI) portfolio based on GHG emissions intensity within each of the 11 GICS sectors. They find positive alphas for the EMI portfolio that cannot be explained by the Fama-French five factor model (between 2010 and 2015, alpha amounts to 3.5–5.4% for EMI on the US market). Gurvich and Creamer (2022) find similar results on a broader sample (MSCI ACWI). On the other hand, the existence of this 'green' premium is disputed by Alessi et al (2021) and Amenc, Esakia and Goltz (2021) who find that the 'green' premium disappears entirely when accounting for estimation error. These results are consistent with Görgen et al (2020), who do not find a significant contribution of a CT factor.

Just like Roncalli et al (2021), our approach is less concerned with the existence of a premium than the impact of the CT factor on risk. A price-based approach is therefore the most appropriate, as risk estimates based on prices allow a direct comparison with traditional factors.

A sector-based climate transition factor

A CT factor is meant to capture the exposure of a portfolio to the energy transition by constructing a signal that is positively correlated to companies that might suffer from an abrupt transition, and negatively correlated to companies that might benefit from this transition.

The energy transition has both a sectoral and a company-specific dimension. First, the extent of the transforma-

1 For example, with the EU corporate sustainability reporting directive or taxonomy regulation.

2 For example, from the Task force on Climate-related Financial Disclosures (TCFD).

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tions brought by the transition depends on the sectors, as the abatement cost of GHG emissions is directly related to the sector technologies (IPCC [2022]). Sector treatment in the construction of the CT factor is therefore a major concern. On the one hand, energy transition cannot be expected to wipe out entire branches of the economy, which argues in favour of a sector-neutral approach. On the other hand, some sectors will be affected more than others by the energy transition. In order to address both concerns, we design our factor as follows.

First, we narrow down the investment universe[3] to climate-policy relevant sectors (CPRS) as defined by Battiston et al (2017). This classification identifies sectors whose primary economic activities "could be affected, either positively or negatively in a disorderly low-carbon transition [...] considering (i) the direct and indirect contribution to GHG emissions; (ii) their relevance for climate policy implementation [...] (iii) their role in the energy value chain" and has been used by several financial regulators to assess the exposure of financial institutions to transition risks (ECB [2021]; EIOPA [2018]). This first source of information for the design of our CT factor is both robust (the sectoral affiliation is easily accessible) and forward-looking (the classification is established on the basis of disorderly transition scenarios).

The second step is to identify companies within these sectors that may benefit (or suffer) from a disorderly transition in the long run. Ideally, this step would be carried out on the basis of multiple company climate-related data. For example, Görgen et al (2020) compute a 'brown green score' from 10 variables containing company-specific information related to value chain, adaptability and public perception. However, these data remain scarce and are not available for all sectors (NGFS [2022]). Moreover, Roncalli et al (2020) showed that the composite indicator built by Görgen et al (2020) is well captured by a factor based on the GHG-emissions intensity only. We therefore consider GHG emissions intensity as a robust and still relevant metric for identifying companies exposed to transition risks *within* the climate-policy relevant sectors.

This brings up the question of the scope of the emissions to be considered. The objective of our factor is to capture a market signal that is expected to evolve as new information becomes available, in particular when companies' greenhouse gas emissions are updated. It is therefore important that the granular design of the CT factor is based on consistent data, regardless of the data provider used by market participants. By comparing seven data providers, Busch, Johnson and Pioch (2020) highlighted strong inconsistencies in indirect (Scope 3) data, whether reported by companies or estimated by external parties. To be as robust as possible, our CT is therefore only built on the GHG emissions intensity on the direct (Scope 1) and energy consumption (Scope 2) perimeters, for which there are higher levels of data consistency. Not explicitly taking into account Scope 3 emissions is also consistent with our sectoral approach. As pointed out by Ducoulombier (2021), reporting standards are not intended to support comparisons between firms, and estimates take insufficient consideration of firm-level circumstances to support intra-sector comparisons. Therefore, a company's Scope 3 emissions data (currently available) is essentially linked to its sector. This information is already taken into account in our factor by the CPRS classification.

Finally, our CT factor is constructed as follows: the long ('brown') leg is built as an equally weighted (EW) portfolio of the 50% most GHG emissions-intensive stocks selected within each of the six CPRS sectors. Similarly, the short ('green') leg is built as an EW portfolio of the 50% least GHG emissions-intensive stocks selected within each of the six CPRS sectors. Then, the weight of each leg is set so that the factor is market neutral. In this way, we assume that the CT factor should not contain any market risk. This approach is consistent in the context of asset management, where the market serves as a benchmark for risk.

Climate transition factor consistency

Identifying the ability of a factor to capture the sensitivity of a portfolio to the energy transition is difficult because we have not experienced energy transition episodes of sufficient magnitude in the past to test such a factor. For example, the maximum carbon price observed on the EU ETS market before 2020 was €30, while the average global carbon price associated with ambitious decarbonisation scenarios reaches several hundred dollars. The robustness of the CT factor should therefore be assessed on its design more than on its statistical power. To do so, we compare three candidate factors: the CT factor described above, a sector-relative intensity factor based on a traditional sectoral classification (IOS), and an intensity-only factor (IO). The IOS factor is based on the GHG emissions intensity relative to its Refinitiv Business Classification (TRBC) sector (at the first level, ie, 10 sectors) while the IO factor is built on a long-short strategy based on the GHG emissions intensity only.

A first test to assess the robustness of these factors is to compare their composition. Since the objective is to construct a signal centred on transition risks, it is important that this composition be representative of companies sensitive to the transition: the various sectors concerned should be represented, and both 'green' and 'brown' activities should be included. The composition of each factor shows that considering only carbon intensity leads to large weights outside of climate-sensitive sectors (figure 1).

Indeed, in the considered universe (US), 49% of the stocks are not considered to be climate policy relevant according to the CPRS classification. In the IO factor, while the long leg contains mostly CPRS stocks, the short leg contains less than 20% of CPRS stocks (26% for the short leg of the IOS factor). In the future, the signal from these factors will therefore be driven mainly by companies with little concern for transition risks while companies that might benefit from the transition (best in class within the CPRS sectors) will remain

1. Weights of different CT factors in climate sensitive sectors

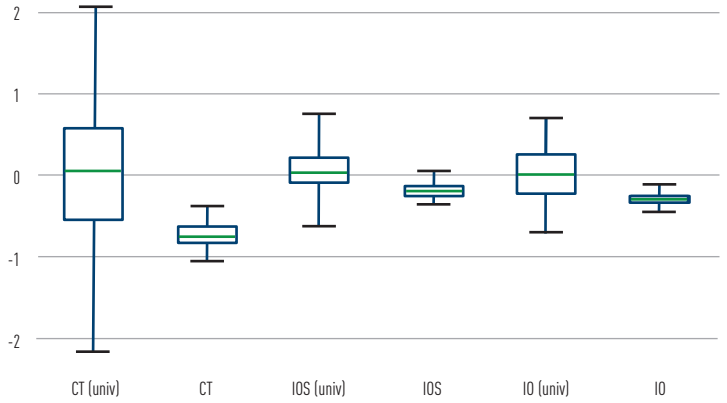
CPRS clean	Universe	IO short	IO long	IOS short	IOS long	CT short	CT long
1 Fossil fuel	6%	0%	20%	3%	4%	9%	9%
2 Utility	3%	0%	25%	5%	7%	10%	11%
3 Energy-intensive	31%	8%	20%	8%	31%	51%	51%
4 Buildings	3%	5%	12%	5%	22%	15%	15%
5 Transportation	7%	1%	9%	2%	12%	15%	14%
6 Agriculture	0%	0%	0%	0%	0%	0%	0%
7 Other	1%	3%	2%	3%	2%	0%	0%
No CPRS	**49%**	**83%**	**12%**	**74%**	**21%**	0%	0%

3 Our universe consists of the 500 largest companies in the US market.

2. Main sectors represented in the short leg of the intensity-only (IO) factor

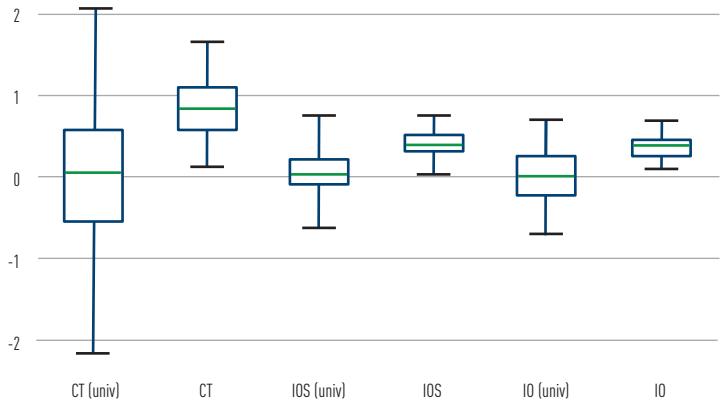
NACE sector	IO short
Non-life insurance	19%
Other software publishing	10%
Other activities auxiliary to financial services, except insurance and pension funding	6%
Other monetary intermediation	6%
Other credit granting	4%
Total	45%

3. Beta distribution of 'green' funds to different transition factors



The distribution of betas is done on a universe of 615 funds (univ) and on a selection of the 10% of funds with the highest share involved in climate action, according to Morningstar (representing 62 'green' funds).

4. Beta distribution of 'brown' funds to different transition factors



The distribution of betas is done on a universe of 615 funds (univ) and on a selection of the 10% of funds with the highest 'carbon risk score', according to Morningstar (representing 53 'brown' funds).

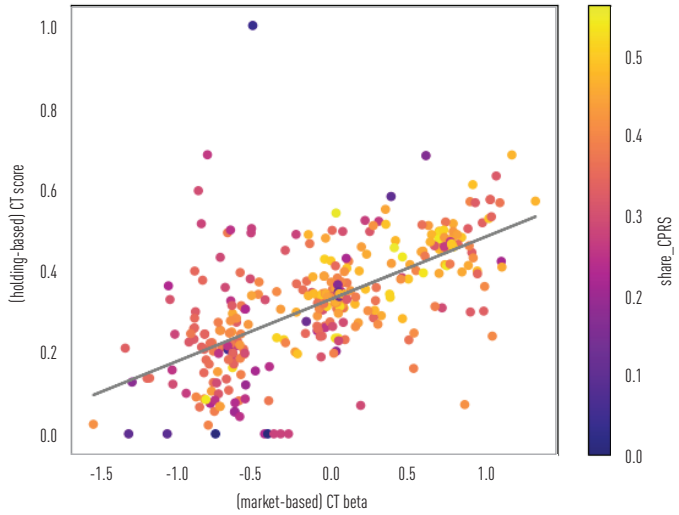
out of scope. For example, the five NACE[4] sectors most represented in the short leg of the IO factor are financial and IT sectors, which are not directly concerned by the energy transition (figure 2). This holding-based analysis thus shows the importance of restricting the construction of factors to the CPRS universe to target where the transition risks are likely to occur.

While the first goal of the CT factor is to capture sensitivity to the long-term transition, such a factor should already allow the identification of funds considered as 'green' or 'brown'. A second test then consists of measuring the extent to which the sensitivity of a fund to the various factors is consistent with its current 'green' or 'brown' characteristic (estimated by a third party). Since there is no homogeneous definition of such funds, we consider a sample of 'green' funds as the top decile of funds of our universe[5] based on the average share of corporate revenues that contribute positively to the climate mitigation (data from Morningstar). Conversely, we define a sample of 'brown' funds as those with the highest transition risk score (as defined by Morningstar). We show that the betas of the 'green' (respectively 'brown') funds to the CT factor are significantly lower (respectively higher) than the average betas of the funds of our universe (figures 3 and 4). This confirms the ability of the CT factor to identify 'green' and 'brown' funds from their prices. When considering correlation instead of betas, we find that the CT factor has higher correlations to green funds than the IO and IOS factors.

A final test is to check the consistency between our market-based approach and a holding-based approach built on the same metrics as those used to design the CT factor. On the one hand, it is important to ensure consistency between these two approaches, which have the same ultimate objective: to measure the sensitivity of a portfolio to the energy transition. On the other hand, the use of a price signal is motivated by the fact that it can indirectly integrate more information than a holding-based score, which can therefore explain the different results between the two approaches. To do this, we regress a holding-based risk metric constructed for each fund as the weighted share of constituents with carbon intensity above the median carbon intensity of their related CPRS main sector (only considering CPRS weights) against the beta of the fund to the CT factor. The coefficient is positive and significant, which confirms the consistency of the market-based approach. Several reasons can explain the remaining different results between the two approaches. First, we observe that the outliers are essentially funds where the share of securities belonging to the CPRS sectors is low (figure 5) and where transition risks are therefore not a priority concern. Moreover, the market-based approach is based on prices, which represent a large amount of information 'digested' by market participants and can therefore capture more information than sector and carbon intensity. Two companies with the same carbon intensity and belonging to the same sector may indeed be impacted differently by the energy transition, for example if the regulations applicable in their respective countries of activity differ (presence or absence of carbon taxes) or if one of them has been the subject of climate change controversy. A market-based approach captures these kinds of differences, whereas a holding-based approach only focuses on a small number of transition-related metrics.

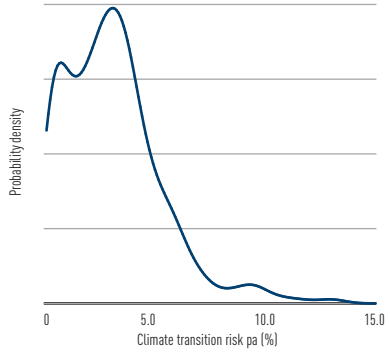
4 The Statistical Classification of Economic Activities in the European Community (see https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-ra-07-015).
5 Our fund universe consists of 600 funds and ETFs offered in the US market.

5. Consistency between holding-based and market-based measure of transition exposure



The (holding-based) CT score is constructed for each fund with the same metrics used to design the transition factor. The coefficient of the regression line (0.15) is significant (t-stat 15.23).

6. Distribution of annualised CT risk between 2017 and 2022 within a universe of active funds



Disentangling climate transition risks from traditional risks

In its simplest form, the price-based transition risks correspond to the volatility that is due to an exposure to the CT factor:

$$Active\ CT\ risk: \sqrt{\beta_{i,CT}^2 Var\left(F_{CT}\right)}$$

Here $\beta_{(i,CT)}$ corresponds to the exposure of an instrument to the CT factor. Because the CT factor is market neutral, this risk does not include any market risk, hence the 'active' denomination. As detailed in Vaucher, Bouchet and Herzog (forthcoming), this definition enables the management of climate-transition risks via portfolio optimisation. The (absolute) annualised contribution of the CT factor of our sample of 1,361 active US funds and ETFs is shown in figure 6. On average, this contribution represents 30% of the total active risk in these funds.

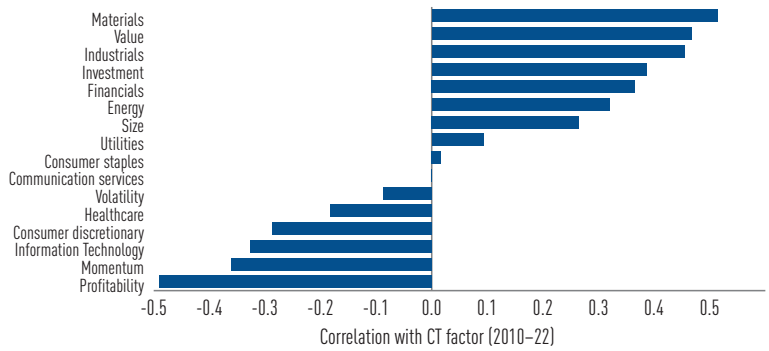
Much of the contribution of the CT factor can be traced back to the correlations between the CT and traditional factors (figure 7). Notably, the CT factor exhibits important correlations to the industrials and materials sectoral factors, and to the value and investment factors. Although our factor is designed as a long-short factor within transition sensitive sectors, the two sectoral biases, industrials and materials, can be explained by the fact that these two sectors (GICS) are grouped within the same energy-intensive sector in the CPRS classification. This relationship suggests that a portfolio optimisation aiming at reducing the CT factor exposure will also tend to reduce the exposure of the portfolio to these factors if it is performed without controlling for factor exposures.

However, Vaucher, Bouchet and Herzog (forthcoming) show that the portfolios obtained by seeking to reduce the portfolio exposure to the IO factor will differ from the portfolios seeking to reduce the exposure to the CT factor. Because the carbon intensity is heavily correlated to the oil and coal sectors, reducing exposure to the IO factor will lead to divestments concentrated in these sectors, as well as investments in the retail and IT sectors. On the other hand, reducing exposure to the CT factor is obtained by performing divestments in a more diverse set of sectors including mining, steel production, shipping and agriculture, while moving relatively less capital to the IT sector.

Conclusion

To overcome the climate-related data gaps and to take advantage of the ability of market participants to integrate broader information in asset valuation, we propose a market-based measure of transition risks. In order to avoid the 'Don't look up' effect associated with validating a factor only from a historical perspective, we focus on the design of a

7. Correlation between the CT factor and traditional factors



The long (short) leg of each factor corresponds to an equally weighted portfolio of stocks with the 20% highest (lowest) performance expectations with respect to a given fundamental characteristic (size: free-float adjusted market cap; value: book-to-market ratio; investment: total asset growth over the last two years; profitability: gross profit to total asset ratios; volatility: weekly volatility estimated over the last two years; momentum: price momentum over the past 12 months without the last month). The relative weight of each leg in the final portfolio is calculated so as to cancel the exposure of the factor to the market factor. The long leg of the factors associated with industrial sectors simply corresponds to the cap-weighted stocks belonging to this sector, while the short leg is the market factor whose weight is adjusted to make the factor market neutral. More details are provided in Vaucher, Bouchet and Herzog (forthcoming).

relevant and robust climate transition factor sensitive to the long-term energy transition shocks.

We propose a CT factor that captures both the sectoral and intra-sectoral dimensions of transition risks by relying on the climate-policy relevant sectors classification (Battiston et al [2017]) and on GHG emissions intensity. By construction, this leads to a reduction in the eligible universe of 50%, and thus avoids the factor signal being disrupted by companies little affected (negatively or positively) by transition risks, as opposed to a factor based solely on the GHG emissions intensity. While the main goal of our CT factor is to be forward-looking, we show that this factor is already able to efficiently identify funds considered as 'green' or 'brown'.

We also highlight that exposure to certain traditional factors such as value and investment is associated with greater transition risk. Without control, reducing exposure to transition risks may therefore lead to undesirable biases on other factors.

Our market-based approach to transition risks allows the practical management of transition risks via portfolio optimisation. As detailed in Vaucher, Bouchet and Herzog (forthcoming), these techniques are straightforward to implement as they only require already existing sets of financial factors. Climate transition risks are not only measurable, but they are also manageable with the same tools as those used to manage financial risks.

One of the major avenues for future research would be transposing this methodology to other complex environmental issues such as biodiversity, where important data gaps remain but where the recent development of specific indicators would permit such a factor to be built.

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Is there a 'green' risk factor in infrastructure investment?

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In recent research, we examined the impact on realised performance of the permanent shift in investor preferences for low carbon energy investments, and how it relates to the expected returns of green power investments.

While green infrastructure has outperformed the 'core' infrastructure market over the past decade, this is largely the result of excess demand for such assets that has pushed asset prices up and discount rates down.

After controlling for a number of risk factors present in the returns of unlisted infrastructure equity investment, there is no persistent 'green' risk factor, but instead a 'green price premium' that investors have been willing to pay to increase their holdings of such assets.

We showed the impact of excess demand for green power investments on yield compression by building a measure of the liquidity of the market for green power investment. When too few green infrastructure investments are available in the market, asset prices increase and yields compress. Controlling for this effect, any outperformance of the green power sector over the considered period disappears.

This phenomenon peaked in 2019 and the expected returns of green power investments are now much lower than they used to be. As a result, realised returns should not be used directly as a proxy of the future performance of green power investments.

It is often argued that more sustainable investments should coincide with better financial performance. This raises two distinct questions:

- Firstly, is there any empirical evidence of superior performance by more sustainable or greener investments? And, if so, what might explain such outperformance, and can it be expected to persist in the future?
- Alternatively, is any superior performance the result of an identifiable transition in investor preferences resulting in a positive shift in asset prices (higher realised returns) but not in higher expected returns?

In recent research (see Amenc and Blanc-Brude [2022]), we show that there is indeed empirical evidence of historical outperformance of *green infrastructure investments* (defined narrowly as wind and solar power projects). We then consider whether this finding implies continued future outperformance. In line with the literature, we argue that more sustainable infrastructure investments should *in fine* have lower expected returns than less sustainable ones, but that the recent shift in investor preferences in favour of greener power investments temporarily created excess demand, explaining realised performance over the past decade.

The existence of a systematic difference in pricing and expected returns between sustainable and less sustainable investments is examined in recent academic research (see Pastor, Stambaugh and Taylor [2022]; Alessi, Ossola and Panzica [2021]). Pastor, Stambaugh and Taylor summarise the reason why greener investments should have low expected returns: either investors bid up asset prices because they have increasing preferences for them, or the customers of greener businesses shift their demand towards their services, increasing their revenues and profits, and consequently their market value. As asset prices rise in response to greater demand, their cost of capital falls. In other words, the premise that greener companies and services – and the positive externalities they create – are increasingly valuable to investors and desirable to consumers (and the reverse for less green companies) implies that the market price of their equity must be higher, their cost of capital lower and their expected return (which, in equilibrium, must equal their cost of capital) also lower. As long as we accept the hypothesis of weakly efficient financial markets, in equilibrium risk must be adequately priced, which leaves little hope for the continued strong performance of green infrastructure investments in the near to long term.

Of course, in this context, it is still possible for greener investment to outperform during a period of persistent changes in investor preferences; for example, excess demand can drive up asset prices because investors expect preferences for green assets to have durably shifted from their previous level. As market prices increase and capital gains accrue to investors, these investments outperform but also exhibit increasingly lower expected returns.

As Pastor, Stambaugh and Taylor (2021) and others point out, the inverse relationship between price and expected return or yield is at its simplest in the case of bonds. For a buy-and-hold investor, the yield of a bond is the best estimate of its expected return, as bond prices change, its yields and expected returns change inversely. This is because bonds have no exposure to the upside – ie, the growth of the borrowers' business. The same mechanism applies to the price and yield one the most clear-cut types of sustain-

able investments: green power infrastructure.

Green power infrastructure can take several forms but, at its greenest, it can be narrowly defined as wind and solar power projects: new investments producing electricity (largely) without emitting greenhouse gases and potentially displacing existing power sources that do. In other words, with constant energy needs, wind and solar power projects are carbon-negative investments. This category of investment thus provides a convincing case of what the *greenest* types of green infrastructure investments might look like.

The way such projects are created and financed is what makes them resemble a bond. Solar and wind farms are typically incorporated as a standalone special-purpose company with a finite life based on the economic life of the physical asset and on its business model, typically a long-term power purchase agreement (PPA) or a regulated electricity market. Such projects raise asset-backed finance once, sink capital into a finite physical asset, and its investors are repaid over a period of 25 to 30 years. Like bonds, such a company has very limited upside or growth options. Wind farms can be repowered and PPAs extended, but infrastructure assets are capacity-constrained by design. Infrastructure companies thus have a maximum potential revenue defined mostly by *ex-ante* choices of size and technology. Hence, like many other project-based infrastructure investments, wind and solar project equity investments are akin to a bond with risky coupons.

It follows that if increasing demand for green infrastructure leads to better performance through capital gains, it must be because their yield or costs of capital is falling. Once excess demand has been absorbed by the market, the long-term performance of greener infrastructure should be lower than that of less green infrastructure investments.

In our research, we consider the question of what drives the past and future financial performance of green infrastructure in several steps. We first review the historical performance of investments in unlisted wind and solar project equity using the infraGreen[1] index. We show that green infrastructure investments have indeed outperformed the market, including Core infrastructure, which is a natural benchmark for such projects. Until 2019, they also outperformed Core+ infrastructure, a riskier subset of unlisted infrastructure investments. In effect, over the past 10 years, green infrastructure has exhibited a very attractive risk-adjusted return profile, with higher annualised returns than core infrastructure and lower volatility than Core+ infrastructure.

We then follow the literature and examine the difference of performance between two portfolios created using asset-level data available in the EDHEC-*infra* database: a *green* power portfolio of unlisted equity investments in wind and solar projects *only*, and a *brown* power portfolio of unlisted equity investments in coal and gas power projects *only*. As argued above, we consider all the investments in the first portfolio to be equally (and highly) green. Likewise, coal and gas power projects are unequivocally brown[2]: coal and gas power projects are net contributors to greenhouse gas emissions. Conventional power generation emitted 13.5Gt CO_2e in 2020, ie, it is the leading contributor to total energy-related emissions (31Gt CO_2e – IEA [2021]), ahead of the transportation and industry sectors. Even though the greenhouse gas emissions of coal and gas power projects vary and can, to some extent, be reduced or captured, even with constant energy demand, these investments are always carbon positive. In other words, our green power portfolio is always greener than our brown power portfolio.

Over a period extending from 2011 to 2021, the brown power portfolio outperformed green power by a cumulative 138bp. However, during that period, green power outperformed or matched the performance of brown power between 2012 and 2015 and also between 2018 and 2020. We show that these are also the two periods during which the cost of capital spread between green and brown power widened significantly as the market value of green power assets increased.

Next, we examine the differential performance of green and brown power investments through a 'green-minus-brown' (GMB) portfolio of their returns over the past decade. Controlling for the effect of well-documented risk factors like size, leverage and profits, this portfolio produces a statistically significant negative 'alpha'. The realised green or brown power excess returns are also better explained by adding a GMB 'effect' to the usual set of risk factors. *Prima facie*, this result could be interpreted as the presence of a 'green' risk factor in the returns of green and brown power infrastructure investments.

To determine the potential persistence of this effect, we examine the expected returns of green and brown power using data from infraMetrics and show that there is a significant and increasing spread between the weighted average cost of capital of the two portfolios. The weighted average cost of capital (WACC) spread or *green price premium* between the green and brown power portfolios is consistently negative and growing: in 2021, it had widened to almost –350bp from about –100bp a decade earlier.

High realised performance has been accompanied by a significant decrease in the cost of capital of green power infrastructure. In effect, all infrastructure investments have become more popular among investors in the past decade and have seen a reduction in their cost of capital, including brown power. However, the green power has seen a much larger decrease. Between December 2011 and December 2021, the infrastructure market saw a global reduction in WACC of 177bp (from 7.23% to 5.45%), while green power saw a greater reduction of 263bp, but the WACC of brown power is only 11bp lower in 2021 than it was in 2011.

We show that the evolution of the cost of capital spread of the two legs of the GMB portfolio explains away its negative alpha. In other words, taking yield compression into account, standard pricing factors suffice to explain the realised performance of the GMB portfolio.

We argue that the yield compression observed since 2011 is at least in part due to excess demand in the market for green power infrastructure – ie, demand that cannot be met immediately by a supply of green power investments. To show this effect, we construct a measure of excess demand for green power investments using the share of secondary transactions in all investments made by infrastructure investors in green energy. We argue that periods during which secondary transactions represent a smaller fraction of the overall market transaction volume are periods of lower liquidity – during which excess demand for green power assets is likely to have been higher. We show that this measure of the green power market liquidity is strongly related to the performance and WACC spread of the GMB portfolio, as well as the realised performance of the green power portfolio. In other words, when the market for renewable power projects is less liquid and excess demand is more likely to build up, we tend to see an increase in the performance of the GMB portfolio and in the WACC spread between green and brown assets.

We conclude that, while green power

1 The infraGreen index is available on EDHEC*infra*'s infraMetrics platform.

2 Irrespective of the debate on the inclusion of natural gas generation in the EU taxonomy (see Blanc-Brude et al [2021]).

assets have experienced a period of strong performance (realised returns), they are likely to deliver lower returns going forward, since this performance was largely driven by the compression of their cost of capital, itself largely related to the build-up of excess demand in the market for green assets. Moreover, while the green price premium has increased in line with excess demand, the supply of green power investments has also increased considerably and the GMB WACC spread has been flat since 2019. As green infrastructure plays an increasingly important and ubiquitous role in investors' portfolios, a consensus on the price and expected returns of green power is increasingly likely and new shifts in demand for such assets less so. In effect, green power may be one the few asset classes in which green pricing has already peaked (around mid-2019).

These results are important in understanding the role that renewables and conventional energy are likely to play in investors' portfolios going forward, since increasing allocations to green energy should not be based on returns assumptions derived from historical returns. Indeed, as the supply of renewable investments has increased and, in some markets, become one of the dominant sources of energy, investor preferences for such assets should stabilise and excess demand disappear. A recent peer-group survey of asset allocations within the infrastructure asset class found that renewable energy already represents one quarter to one third of most investors' infrastructure portfolios (Blanc-Brude et al [2022]). While investment in green infrastructure is likely to keep increasing on aggregate, its weight in infrastructure portfolios is unlikely to keep increasing monotonically.

Durably lower expected returns and cost of capital for green power is of course a good thing, since this reduces the overall cost of the energy transition. However, investors should not expect to receive high returns while contributing to the energy transition (have a positive impact) as long as they are only exposed to a pure, unleveraged basket of green power investments.

Conclusions

The premise that green investments may have different returns than brown ones partly springs from the notion of climate 'transition risk': the expectation of higher future costs or lower future revenues for firms that emit greenhouse gases due to new regulations and shifts in consumer behaviour. However, the manner, timing and magnitude with which transition risks may materialise have been and remain largely unknown to investors. Today, it can seem unlikely that asset prices already fully reflect these risks when they remain very hard to assess and quantify.

When it comes to renewable energy projects and their fossil fuel (coal and gas) equivalents, however, the writing is already on the wall: wind and solar projects will be impervious to carbon taxes and coal and gas will not. In effect, coal projects are already being divested and phased out by large utilities, implying that their future value is considered to trend towards zero. This knowledge has already impacted asset prices in the case of green and brown power investments. The gradual realisation by investors that they have an increasing preference for green power investment and want to hold less conventional power investment has taken place over the past decade. In our 2022 survey of about 350 large investor portfolios of infrastructure assets, EDHEC*infra* found not only that renewable energy corresponds to between one quarter and one third of investors' infrastructure holdings by value at the end of 2021, but also that conventional gas and coal power projects represent as little as 1% to 3% of their portfolio, with the notable exception of North American investors, who hold 10% of their infrastructure investments in brown power assets. In other words, brown power investments have largely been divested by mainstream investors and green ones have already been integrated into portfolios on a significant scale. The shift in demand for green and brown power assets has already occurred.

One might add that higher demand for green power is not the only possible reason for the yield compression observed. For instance, infrastructure investment has been characterised by a significant evolution in the nature of investors valuing such assets, with the principal market increasing in size and scope and new cohorts of buyers and sellers showing increasing comfort with long-term, illiquid investments – ie, different risk preferences to previous generations of investors in infrastructure equity, who faced higher hurdle rates e.g., construction firms.

In 2011, green power projects had expected returns of ~8% and brown power projects ~9%. Their 10-year annualised total returns in 2021 were 16% and 17% respectively. These two figures may seem related but correspond in fact to very different economic fundamentals. The high historical performance of green power is explained by a significant compression in yields (expected returns) especially between 2012 and 2015 and the corresponding capital gains. Conversely, the performance of brown power was more driven by cash returns and less by yield compression. In effect, unlike other infrastructure investments, brown power investments have seen a slight increase in their expected returns since 2018.

Hence we find that the impact on performance of such shifts in the demand for green and brown investments cannot be equated with the appearance of a new 'green' asset pricing risk factor. Instead, as predicted by theory (see Pastor, Stambaugh and Taylor [2021]), demand shocks have led to relatively high realised performance in the green power market but also lower expected returns.

For this situation to persist, there needs to be continued disagreement in the market about the future value of greener investments. Once all investors agree about the future value of greener or less green investments, investors are left holding the market portfolio, which includes current and future preferences for greener assets.

Going forward, as excess demand for green power investments is gradually met with additional supply of green power assets and effective allocations to green power become significant, our findings suggest that both the realised and expected returns of green power investments can be expected to converge.

Such a convergence, which reflects a long-term pricing equilibrium, leads us to conclude that there is no reason for superior performance by green infrastructure investments to continue. The so-called 'green premium' observed in the past does not correspond to the reward for a superior risk factor but instead to a temporary phenomenon of excess demand, which the supply side of the market eventually satisfied.

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Chasing the environmental factor

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This paper analyses whether US stock excess returns are pricing in exposure to a climate/environmental risk factor. We try to answer this question through a latent factor model: the climate factor is estimated by starting from a large panel of US stock excess returns and a large set of firm-specific environmental related characteristics (eg, emissions and environmental scores).

This environmental factor that we estimate can be interpreted (ex-post) as an emissions factor and it is only relevant to explaining the returns of stocks within the oil and utilities sectors.

Surprisingly, stocks of companies within other high-emitting sectors, such as chemicals and steel, are not affected by this factor.

Introduction

Climate-aware investment management is still in its infancy but is growing fast. As documented by Krueger, Sautner and Starks (2020) and Strobel and Wurgler (2021), investors are paying more and more attention to climate and environmental matters. Consequently, their demand for means to assess their portfolio's exposure against these new types of risks is also increasing. Following this trend, data and analytics providers specialising in climate and environmental scores have proliferated. However, ESG metrics diverge across providers (see among others Berg, Kolbel and Rigobon [2022]), and environmental metrics, at least beyond Scope 1 and 2 greenhouse gas emissions estimates (Busch, Johnson and Pioch [2020]), are also divergent.

Furthermore, it is not yet clear if companies with low environmental footprints should earn lower or higher returns. Indeed, despite the rapidly increasing number of academic studies trying to assess the impact of climate risks on equities, the 'sign' of the effect is still not clear, and the reported results are sometimes in conflict with one another. Different definitions of 'green' give rise to different results. Bolton and Kacperczyk (2021, 2022), Hsu, Li and Tsou (2022), and Alessi, Ossola and Panzica (2021), among others, find that high polluting companies earn higher returns because they are exposed to regulatory risk (eg, a carbon tax). On the other hand, Pastor, Stambaugh and Taylor (2022), In, Park and Monk (2019), and Cheema-Fox et al (2021) find that companies with a good environmental score outperform 'brown' companies because of the recent shift in investor preferences for green assets. This preference shift is the cause of abnormal returns, and in the future, green companies are not expected to persistently outperform their brown peers.

In this work we contribute to the climate finance literature by assessing whether ESG and environmental (which we hereafter refer to as environmental) characteristics of companies line up with excess stock returns. Instead of defining a greenness measure and then assessing whether it is related to a risk premium, we use a conditional latent factor model: the instrumented principal component analysis model (IPCA) developed by Kelly, Pruitt and Su (2019), which we extend to deal with financial and non-financial characteristics separately.

The model

In their seminal work, Kelly, Pruitt and Su (2019) develop the IPCA model to extract a *small* number of latent factors (and their betas), starting from a panel of equity excess returns and a *large* set of observable company-level characteristics, which are the instruments used to infer the betas.

The general IPCA specification for the excess return $r_{t+1,i}$ on the i-th asset of the N_{t+1} assets observed at time t+1 and described by K latent factors f_{t+1} is:

$$r_{t+1,i} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1} \qquad (1)$$

where the dynamic factor betas $\beta_{i,t}$ and alpha $\alpha_{i,t}$ are inferred from the L-dimensional vector $z_{i,t}$ that contains the i-th asset's observable characteristics valued at time t (and a constant):

$$\alpha_{i,t} = z'_{i,t}\Gamma_\alpha + \varepsilon_{\alpha,i,t} \text{ and } \beta_{i,t} = z'_{i,t}\Gamma_\beta + \varepsilon_{\beta,i,t} \qquad (2)$$

The $L \times K$ matrix Γ_β and the L-dimensional vector Γ_α are the (constant-in-time and constant-across-assets) parameters that map characteristics into betas and alphas, respectively, and by their inspection one can understand the 'identity' of the estimated latent factors. It is worth saying that to properly compare the different values in Γ_β and Γ_α, we need to standardise the characteristics by computing, for each date, the respective cross-sectional ranks and normalising them (to the [–0.5, 0.5] interval). From equation (2) it is clear that the values of an asset's betas and alpha change when the asset characteristics change. Nevertheless, the inclusion of $\varepsilon_{\beta,i,t}$ and $\varepsilon_{\alpha,i,t}$ indicates that alphas and factor loadings may not be perfectly determined by the observable instruments. It is also important to note that by indexing characteristics with time t and returns with $t+1$, IPCA aims to extract predictive power for future returns from prevailing observable information available at the forecast time.

To fully understand the innovative contribution of this methodology to the asset pricing literature, it is worth mentioning that characteristics are often used to proxy companies' exposure to risk factors, such as size and book-to-market in the three-factor model of Fama and French (1993). Typically, we can build the mimicking portfolio of the risk factor associated to a specific characteristic, say, size, by sorting companies by size into quantiles and

then using the extreme quantiles for the long and short legs of the portfolio. For instance, stocks with size ratings above the 70th percentile (below the 30th percentile) could be chosen as constituents of the short (long) leg of the mimicking portfolio. In this way, any observable characteristics can be used to build a factor. The consequence is the 'factor zoo' documented by Harvey and Liu (2020): over 400 factors have been published in top academic financial journals, and this number is definitely unrealistic. The main idea under the IPCA model is that if there are many characteristics which are potentially informative of returns, we can reduce the dimensionality of the factors (built as long-short portfolio on characteristics) by computing the first k principal components of these factors, where k is arbitrarily chosen, but has to be far smaller than the number of characteristics.[1] This dimension reduction allows us to concentrate the useful information contained in a large number of characteristics in few factors.

In their work, Kelly, Pruitt and Su (2019) use 36 financial characteristics (such as market capitalisation, total assets, book-to-market) to extract five factors and show how their model explains the cross section of equity returns more accurately than existing factor models.

In this work, we extend the original IPCA model to allow for two separate groups of characteristics and constrain each of the IPCA factors to depend on only one of the two groups. We integrate the characteristics used by Kelly, Pruitt and Su (2019) with an additional set of environmental characteristics and ESG scores (described in the next section) to extract five *financial* factors and one *environmental* factor. Therefore, starting from a panel of equity excess returns and two sets of observable company-level characteristics that we observe for each company (namely, financial characteristics and environmental characteristics), we can extract two groups of factors. The first group depends only on financial characteristics, and the second group only on environmental characteristics. This innovation enables us to clearly interpret the estimated factors as either purely financial or purely environmental.

Data

To perform our analysis, we need to collect financial and environmental characteristics, and the returns. We focus on US stocks in the period July 2008–December 2021.

Among the financial characteristics used in Kelly, Palhares and Pruitt (2021), we select those whose contribution to the model was found to be statistically significant. We retrieve values for them from the Global Factor Data open-source dataset by Jensen, Kelly and Pedersen (2022). The financial characteristics that we observe for all the companies in our sample for at least one period are: total assets, book to market, market beta, earning to price, free cashflow, idiosyncratic volatility, investment, size, share turnover, leverage, profit margin, ROE, bid-ask spread, closeness to 52-week high, momentum, long-term reversal, short-term reversal and a characteristic which is constant over time and among stocks. It captures the systemic risk common among all the stocks.

The environmental characteristics that we use are from either the MSCI ESG IVA dataset or Eikon. We use ESG scores, 'E' scores, emissions scores both from MSCI and Eikon; carbon intensity and carbon emissions from Eikon; and the environmental score weight from MSCI, which is intended to measure the salience of environmental risks for firms. Since emissions, carbon intensity and the weight of the environmental score highly depend on sectors, we decompose each of these three characteristics in a sectoral component and an idiosyncratic component. As we observe that the three sectoral components are highly correlated, we keep only the sectoral carbon intensity in order to avoid multicollinearity. (For robustness check, we perform the analysis substituting sectoral carbon emissions for sectoral carbon intensity as well, and the results do not change.)

To make sure that environmental and ESG characteristics are not informative of returns only because they are correlated with company fundamentals, we orthogonalise environmental characteristics with respect to financial characteristics at each date, by running for each environmental characteristic a cross-sectional regression on the financial characteristics. It is worth noting that one could orthogonalise financial characteristics, with respect to environmental characteristics, without loss of generality. However, since we are interested in understanding whether an environmental risk factor exists on top of standard factors, we decided to orthogonalise environmental characteristics with respect to financial characteristics by regressing each environmental characteristic on the financial characteristics.

Empirical analysis

Turning to our empirical results, figure 1 displays the cumulative returns of our environmental factor.

To understand better the 'identity' of this environmental factor, it is worth recalling that it is (almost) the first principal component extracted by long/short portfolios built on the environmental characteristics. The 'weights' of these portfolios in forming the first principal component (that is, our environmental factor), are informative of which environmental characteristics determine the companies' exposure to the factor. Figure 2 shows that characteristics related to emissions are the main driver of the firms' exposure to this factor. In fact, sectoral carbon intensity, adjusted carbon emissions and both Eikon's and MSCI's emission scores are the first four characteristics in absolute value. Eikon's emission score is a rating given by Eikon that assesses the commitment of the company to reducing its emissions, and it is normalised across industries. Similarly, MSCI's emission score is also informative of a company's commitment in reducing its emissions but it is not normalised across industries.

We now assess the explanatory power of our IPCA model for stock returns. Figure 3 displays in-sample R^2s. The in-sample analysis is performed by estimating the model parameters only once using the full dataset. Then, in order to track the marginal contribution of the different model components in explaining returns, in figure 3 we show values of the R^2s computed by using different subsets of our estimated factors and/or alphas, namely:

- only first k financial systematic risk factors (k-th column with k = 1,... 5),

1. Cumulative returns of the latent environmental factor

The annualised average return is 4.4%, annualised standard deviation 11.0%, and annualised Sharpe ratio 0.40.

1 This is a simplified version of the model; however, the intuition of IPCA is the same.

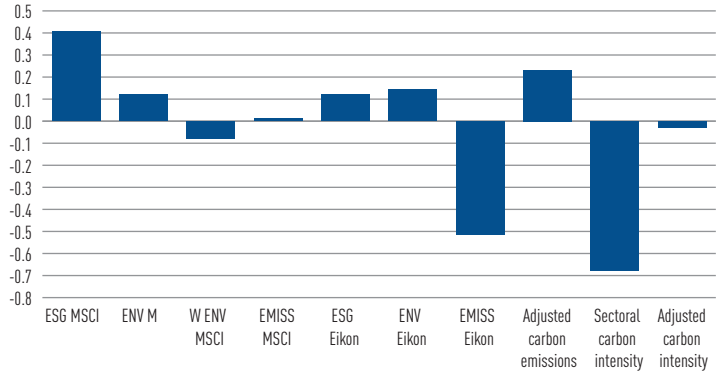
- the financial systematic risk factors and financial component of alpha (column 6), the financial systematic risk factors and the entire alpha (column 7), and
- all components of the model specified (column 8).

It is worth specifying that we estimate the full model only once, therefore the different columns of figure 3 enable us to compare directly the incremental informational content of the different building blocks of our model. Comparing the last two columns in the figure, row all sectors, we observe that stock returns are remarkably well described by systematic financial factors, leaving little room for a common undiversifiable risk factor with an environmental connotation. In fact, the R^2 increment due to the environmental factor is extremely limited (+0.43%). It is worth saying that an easy way to increase this figure would be to orthogonalise financial characteristics with respect to environmental characteristics and therefore to cluster information that is common among the two sets of characteristics in the environmental factor. However, this does not increase the overall performance of the model.

However, since environmental characteristics may be particularly relevant only for some industries, we group stocks according to their sectors (we use Fama-French 30 sectors definitions). Then, for each group, we assess how the IPCA environmental factor explains returns of stocks in that sector by measuring the R^2s. In the last two rows of figure 3, we show the performance measures for only the sectors that are affected by the environmental factor: oil and utilities. The utilities sector's R^2 increases from 27.84% to 30.12%, stocks in the oil sector are similarly affected by the environmental factor: their R^2 increases from 45.29% to 47.73%.

Importantly, other sectors that are highly affected by emissions (either directly or indirectly), namely chemicals, transportation, steel and automotive, are on average not affected by the environmental factor, and do not seem to price an environmental risk at all (figure 4). Exploring the causes (and consequences) of different (and little) climate risk exposure for different sectors constitutes an interesting avenue for future research.

2. Characteristics related to emissions are the main driver of the firms' exposure to this factor



3. Assessing the explanatory power of our IPCA model for stock returns

Sector	F1	F1:F2	F1:F3	F1:F4	F1:F5	F1:F5 +α^f	F1:F5 +α	F1:F5 + G1 +α
All sectors	28.19	29.78	30.84	33.12	35.41	35.50	35.50	35.93
Oil	41.58	41.19	43.91	44.90	45.18	45.28	45.29	47.73
Utilities	8.65	8.74	10.74	14.17	27.74	27.73	27.84	30.12

This table shows in-sample R^2s. The model is estimated once on the entire asset universe, with five financial factors, one environmental factor. The R^2s are computed by using either all the stocks, stocks only in the oil sector, or stocks only in the utilities sector. In the first column (F1), we compute the different R^2s by using only the first financial factor, then we use the first two financial factors (F1:F2), and so on until we use the five financial factors (column F1:F5). The sixth column shows the R^2ss computed by using all the financial factors and the financial component of the alpha namely α^F. In column F1:F5 + α we include the environmental component of the alpha and in the last column we finally add the environmental factor. The difference between the last two columns is the marginal contribution of the environmental factor to the model.

4. Stocks in other sectors highly affected by emissions are not affected by the environmental factor

Sector	F1	F1:F2	F1:F3	F1:F4	F1:F5	F1:F5 +α^f	F1:F5 +α	F1:F5 + G1 +α
Chemicals	39.57	41.13	41.96	42.61	44.54	44.43	44.42	44.24
Transportation	31.81	32.36	32.70	32.85	36.51	36.57	36.57	35.87
Steel	40.34	40.41	40.57	39.55	40.60	40.57	40.58	40.63
Automotive	41.54	43.73	44.38	45.02	46.13	46.18	46.16	46.26

This table shows in-sample R^2s. The model is estimated once on the entire asset universe, with five financial factors, one environmental factor. The R^2s are computed by using either stocks in only the chemicals sector, only the transportation sector, only the steel sector, or only the automotive sector. In the first column (F1), we compute the R^2s by using only the first financial factor, then we use the first two financial factors (F1:F2), and so on until we use the five financial factors (column F1:F5). The sixth column shows the R^2s computed by using all the financial factors and the financial component of the alpha, namely α^F. In column F1:F5 + α we include the environmental component of the alpha and in the last column we finally add the environmental factor. The difference between the last two columns is the marginal contribution of the environmental factor to the model.

Conclusions

We study to what extent environmental firm characteristics affect equity returns. This is particularly relevant for investors, since ESG and climate-aware investing has gained traction quickly, but it is not yet clear whether or how environmental measures affect returns. To answer this question, we use an innovative methodology that allows us to control for a rich set of information potentially useful to explain returns. With our methodology, we extract an environmental factor and find that companies' betas to this factor are mainly driven by sectoral carbon intensity and Eikon's emissions scores. Sectoral carbon intensity is the average carbon intensity (Scope 1 and Scope 2 emissions normalised by revenues) of companies operating in the same sector. On the other hand, Eikon's emissions score is a metric that is sector neutral and that measures the effort of a company in reducing its emissions compared to its peers. We find that this factor is important for the in-sample pricing of stocks only in the oil and utilities sectors, above and beyond financial factors (which suffice

to explain the cross section of stock returns of the companies in the other sectors). However, the environmental factor's contribution to explaining returns is quite modest.

Emissions-related characteristics are the main drivers of the environmental factor, and this factor matters only for companies operating in either the oil or utilities sectors, which is not a surprise as these two sectors are among the most polluting. What is more surprising is that stocks within other high-emitting sectors are not affected by our environmental factor.

It is difficult to understand why this is the case. Unless damages are expected to materialise so far into the future that they become negligible after discounting, we would expect asset prices to be strongly affected by climate risk: either because we do little and are hit by the full consequences of 3°C or more of warming, namely physical risk; or because we do a lot, and we have to rewire the whole economy, namely transition risk. This suggests that prices sooner or later will have to adjust: expected cashflows and earnings ultimately turn into realised cashflows and earnings. Having said that, we do not have a clear view about why high-emitting sectors are affected differently by our environmental factor. Analysing the reasons (and the consequences) of these differences would be an interesting avenue for further research.

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The impact of climate change news on green-minus-brown portfolios

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Recent literature has sought to investigate the correlation between climate news and equity market performance, with the aim of quantifying a measure of a so-called 'climate beta'.

Using a variety of language models and high-quality English-language newspaper sources, including the Financial Times and New York Times, we construct an unexpected climate news index (UCNI) for each model and source.

We measure the impact of these UCNIs, plus an aggregate UCNI over all the news sources, on a range of green, brown, and green-minus-brown (GMB) equity portfolios, constructed by sorting S&P 500 firms based on their carbon intensity.

For most of the language models considered, the sensitivity of returns to an increase in the corresponding aggregated UCNI index, is negative and statistically significant at 1% for brown portfolio returns, but it is not significant for green portfolio returns.

In recent years, several papers have examined the link between climate news and equity market returns, hoping to identify a measure of a so-called 'climate beta', beginning with Engle (2020). Using a variety of language models and high-quality English-language newspaper sources, including the Financial Times and New York Times, we construct an 'unexpected climate news index' (UCNI) for each model and source. We measure the impact of these UCNI, plus an aggregate UCNI over all the news sources, on a range of green, brown, and green-minus-brown (GMB) equity portfolios, constructed by sorting S&P 500 firms based on their carbon intensity. We find that the relationship between the UCNI and the green, brown and GMB portfolio returns is overall not statistically significant for individual news sources across all the language models. However, it does become significant for all the aggregate UCNI indices, suggesting that combining different news sources increases the signal-to-noise ratio of the climate beta. For most of the language models considered, the sensitivity of returns to an increase in the corresponding aggregated UCNI index is negative and statistically significant at 1% for brown portfolio returns, but is not significant for green portfolio returns. This is for the period from July 2012 to November 2021. These results suggest that the UCNI factor extracted from an aggregate news index is a climate risk proxy whose beta coefficient can explain the returns of brown and hence GMB portfolio performance.

News data

To perform this analysis, we require digitised, daily, English-language, high-circulation and high-quality news sources with a European and US perspective, including at least one with a dedicated financial market focus. For these reasons we have chosen the following news data sources:

- The Financial Times (FT) digital archive. The Financial Times is widely recognised as the leading European English-language financial newspaper. It is published daily, except Sundays, and covers not just business news, but also world politics and current affairs.
- The Lexis Nexis (LN) database of newspapers. This provides access to many thousands of newspapers internationally. From these we selected the New York Times (NYT), the Los Angeles Times (LAT), The Guardian (UKG) and The Daily Telegraph (DT).

We use articles from these news sources, grouped at a daily frequency, over the period from 2 January 2005 to 3 November 2021. We assume that an article appears in the morning of the first publication date. This can be a different time depending on whether the news source is in the US or Europe. As Europe is several hours ahead of the US, the arrival of news from US and European news sources will impact the US equity market on the same day. To align the arrival of weekend news with the financial markets, we adjust the publication date of news stories that appear on a Saturday or Sunday to the following Monday, the earliest date on which this news can impact the US equity market. We do not rely on any tagging provided by the news sources.

We wish to extract only climate change-related articles and do so by selecting only those articles that contain one or both bigrams 'climate change' and 'global warming'. Figure 1 shows the counts of the total number of selected articles per newspaper, per year. We see that The Guardian is the leading publisher of climate change-related articles over time among our corpus of news sources, followed by the Financial Times and The Daily Telegraph.

We consider news in the form of newspaper articles and so each article has a headline and content. The headline is typically added by a sub-editor who has read the article and wishes to summarise the key message of the article for the reader. To assist the reader, the headline usually reflects the most important part of the article and any associated positive or negative sentiment. For this reason, we examine both the article headline and the article content to see if the headline can provide a clearer measure of article focus and sentiment than an analysis of its longer and more complex content.

To quantify the newspaper media's attention to climate change, we first need to identify a climate change article. Care needs to be taken to avoid false positives. Hence, we search for bigrams – combinations of two words – that ensure the subject matter is related to climate change. Work by Engle et al (2020) and others has done this using the search term 'climate change'. However, the bigram 'global warming' has also been widely used as a synonym. To determine whether we should include it, we perform searches for articles that contain (i) 'climate change', (ii) 'global warming', and (iii) one or both of 'climate change' or 'global warming'. We focused on the Financial Times news source and calculated the fraction of daily articles that are returned by these search terms. Using the fraction of articles, rather than the number, corrects for the fact that the total number of daily Financial Times articles has varied significantly over this period.[1] All three of these time series are shown in figure 2. We observe that use of the bigram 'global warming' has declined in relative terms over time, but it is still used. The bigram 'climate change' has clearly become the dominant bigram. To ensure that we capture as many climate change articles as possible, and especially those in the earlier period of analysis, we include both in our definition of a climate change article. Using this definition, figure 1 shows the count of the total number of such articles per newspaper, per year.

Climate change news indices overview

We explore several approaches for constructing a climate change news index (CNI) from newspaper articles. If there is a link between climate change news and market price movements, then we would expect the link to be strongest for the

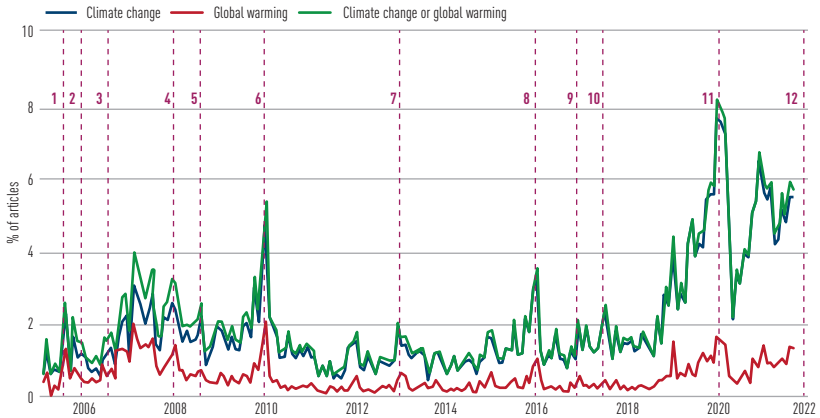
1 Over the 2005–21 period the monthly number of Financial Times articles ranged from around 2,000 in 2006 to over 6,000 in 2014, then back down to around 3,000 in 2020.

1. Counts of climate change articles by year for each news source

Year	FT	DT	UKG	LAT	NYT
2005	339	413	1,127	313	294
2006	523	645	1,673	611	385
2007	1,304	1,241	2,676	1,053	1,198
2008	1,113	723	2,499	762	997
2009	1,495	885	3,914	673	1,169
2010	1,093	1,023	2,480	548	666
2011	706	783	1,932	329	334
2012	739	899	1,853	306	287
2013	800	822	1,914	339	332
2014	800	639	2,284	468	399
2015	1,212	715	5,278	771	600
2016	892	429	4,881	660	532
2017	1,003	465	2,002	776	491
2018	1,062	566	2,570	697	389
2019	2,040	1,393	4,051	984	618
2020	1,909	1,180	3,091	697	485
2021	2,218	1,866	3,718	1,076	701

This figure reports the count of climate change articles by year in the Financial Times, The Daily Telegraph, The Guardian, Los Angeles Times and The New York Times. Note that 2021 only includes articles up to 3 November.

2. Financial Times attention to the climate change topic



This figure measures the newspaper media attention to the subject of climate change from 2005–21 by calculating the percentage of daily FT articles that contain the term 'climate change', the percentage that contain the term 'global warming' and the percentage containing either term. We apply a 30-day moving average. The vertical lines are climate change-related events – see figure 3 for the corresponding numbered list of events.

3. Most active climate news events

Event no	Date	Description
1	8 July 2005	G8 Summit Scotland
2	9 Dec 2005	Montreal CC conference
3	21 Jun 2006	UK CC and Sustainable Energy Act 2006
4	14 Dec 2007	Bali UN CC Conference
5	9 Jul 2008	G8 Summit
6	19 Dec 2009	Copenhagen UN CC Conference
7	7 Dec 2012	Doha UN CC Conference
8	12 Dec 2015	Paris Agreement signed
9	7 Nov 2016	Marrakech UN CC Conference
10	1 Jun 2017	US President Trump withdraws from Paris Agreement
11	Dec 2019–Jan 2020	Australian wildfires, high temperatures
12	13 Nov 2021	G8 Summit Scotland

This figure identifies the most active climate news events seen in figure 2. For conferences we have used the conference end date, when the final agreement is usually announced.

index that best captures the quantity, content and sentiment of the climate change news. The index construction approaches we use, in order of increasing level of sophistication, are as follows:

- Attention – The number of climate change articles published each day.
- Similarity – The TF-IDF[2] cosine similarity between each day's climate change articles of the newspaper and a representative climate change document.
- Concern – Climate change concern using word frequencies based on the LIWC lexicons.[3] Concern is high if the number of 'negative words' in a climate change article is higher than the number of 'positive words' and the fraction of 'risk words' is high.
- VADER – We use a rules-based lexical approach called VADER that assigns a sentiment polarity score to specific words to determine if the climate change article sentiment is positive or negative.
- BERT with Fine-Tuned Sentiment – We take a BERT language model as described in Devlin et al (2018) and fine-tune it to identify sentiment using human-labelled, finance-related training examples.
- ClimateBERT with Fine-Tuned Sentiment – We take the domain-specific Climate-BERT model by Webersinke et al (2021) and fine-tune it to identify sentiment using human-labelled, finance-related training examples.

Our simplest attention-based measure counts the daily number of climate change articles published. Such an approach was analysed in the media bias model of Gentzkow and Shapiro (2010), who noted that the number and length of the articles reflect reader interest. For the next level of sophistication, we use an approach that detects actual semantic meaning within the news articles by quantifying the degree of emotional concern. This is a challenging task as the emotional sentiment of long and highly articulate articles is not always simple to extract. For this reason, we then turn to state-of-the-art language models such as the BERT Transformer-based model from Devlin et al (2018), and finally to the CBERT model by Webersinke et al (2021), which has been specifically designed to better understand climate-related texts. We developed two language models for the VADER, BERT and CBERT approaches presented earlier: one using headlines (VAD-H, BERT-H and CBERT-H) and another using article content (VAD-S, BERT-S and CBERT-S) for sentiment analysis.

We use these different approaches to construct a family of climate news indices (CNIs), each a daily time series from 2005 to 2021. We do this for both the article content and the article headline. The headline is short and should indicate the sentiment of the article. As such it may be easier to extract the article's sentiment from the headline than the entire article.

To perform a market analysis using our CNIs, we must first isolate the unexpected component of the daily climate change news index changes. To do this, we assume that the CNI obeys an AR(1) process where the changes in unexpected climate change news are the innovations. Calibrating the CNI to this process allows us to extract a family of unexpected climate change news innovation (UCNI) indices. We refer the reader to Maeso et al (2023) for further details on the construction of these indices.

A source-aggregated climate change news index

In addition to the set of CNIs for each news source, we also wish to construct a single aggregated index across all five news sources. Doing this increases the total number of articles being used in the construction of this index and might be expected to reduce any statistical noise in the article counts and so enhance any signal that may exist across the individual indices.

Rather than simply average the individual newspaper indices, we first standardise them so that each index has a unit standard deviation over a three-year period of T dates. This ensures that a newspaper index that experiences a high level of variability in both article number and sentiment score is adjusted to be more comparable with a newspaper index that has a lower variability. Hence, for each news source b, and index $CNI^b(t)$, the standard deviation of the index is calculated as:

$$\sigma_b = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(CNI^b(t) - \overline{CNI^b}\right)^2}$$

where:

$$\overline{CNI^b} = \frac{1}{T}\sum_{t=1}^{T} CNI^b(t)$$

The aggregated index is given as follows:

$$CNI^{Agg}(t) = \frac{\overline{\sigma}}{n_B}\sum_{b=1}^{n_B}\frac{CNI^b(t)}{\sigma_b}$$

where $\overline{\sigma} = 1/n_B \sum_b \sigma_b$. The aggregate index at date t has been standardised by a volatility estimated over a three-year rolling window prior to t, so there is no look-ahead bias.

Climate change news and equity portfolios

We first assign each stock of the 500 US stocks with the largest capitalisation (according to CRSP) to one of the three categories of 'green', 'neutral' and 'brown' on a given date. To identify which stocks are green and which are brown, we use a selection method that is based on the carbon intensities of individual companies. These have been determined using combined Scope 1 and Scope 2 emissions from FactSet's ISS ESG carbon emissions data. A stock is labelled as green if the corresponding company has low CO_2 emissions per unit of revenue and similarly a stock is labelled as brown if the corresponding company with high CO_2 emissions per unit of revenue. The remaining stocks are labelled as neutral. Vaucher et al (2023) underline that several papers such as Ardia et al (2022) rely on this metric to sort stocks, but other papers use up to 10 different metrics such as environmental scores or to sort stocks (see Görgen et al [2020] for more details).[4]

Given a set of climate CNIs described above, the next step is to determine whether these indices have an impact on equity returns. We examined three liquid US stock portfolios engaged respectively in a green strategy, a brown strategy and a GMB portfolio strategy that we expect to be sensitive to climate change risk. The green portfolio and brown portfolio are equally weighted and consist of the 30% of stocks with respectively the lowest and highest carbon intensity.[5]

The CNI indices that we have calculated may embed some auto-correlation effects and these must be removed if we are to correctly capture the unexpected changes in the climate news index. The unexpected climate news innovations

2 TF-IDF is the Term Frequency Inverse Document Frequency metric. It measures how important a word is to a document located in a collection of documents.

3 See https://www.liwc.app/

4 Vaucher et al (2023) emphasise that sorting stocks according to carbon intensity may lead to large weights toward sectors that are not relevant from a climate policy standpoint according to the classification of economic activities developed after Battiston et al (2017) to assess climate transition risk. This classification is called Climate Policy Relevant Sectors (CPRS).

5 We also tested an alternative approach for the GMB portfolio construction developed by Vaucher et al (2023). The long (green) leg of the GMB portfolio is built as an equally-weighted (EW) portfolio of the 50% of the stocks with the lowest carbon intensity selected within each of the six CPRS sectors. Conversely, the short (brown) leg is built as an EW portfolio of the 50% of the stocks with the highest carbon intensity selected within each of the six CPRS sectors. The findings generated via this alternate methodology concur with those obtained through the initial methodology.

index, $UCNI_t$, is defined by:

$$UCNI_t = \Delta CNI_t - \mathrm{E}\left[\Delta CNI_t \middle| I_{t-1}\right]$$

where I_{t-1} is the information to time $t-1$. Each value of the $UCNI_t$ is calculated as the residual of an AR(1) process calibrated to the $CCNI_t$ over the previous three years. The aggregate $UCNI_t$ for the different language models are shown in figure 4.

Then we examine whether differences in exposure to the climate news index help us to explain expected returns of green, brown, and GMB portfolios. The linear regression we wish to fit is the following:

$$\begin{aligned} r_t - r_{ft} = \alpha &+ \beta_{UCNI} \cdot UCNI_t + \beta_{MKT} \cdot MKT_t \\ &+ \beta_{HML} \cdot HML_t + \beta_{SMB} \cdot SMB_t \\ &+ \beta_{CMA} \cdot CMA_t + \beta_{RMW} \cdot RMW_t \\ &+ \beta_{WML} \cdot WML_t + \varepsilon_t \end{aligned} \quad (1)$$

where *MKT* is the excess market return, *SMB* the small minus big (size) factor, *HML* the high minus low (value) factor, *RMW* the robust minus weak (high profitability) factor, *CMA* the conservative minus aggressive (low investment) factor, and *WML* the winners minus losers (momentum) factor.

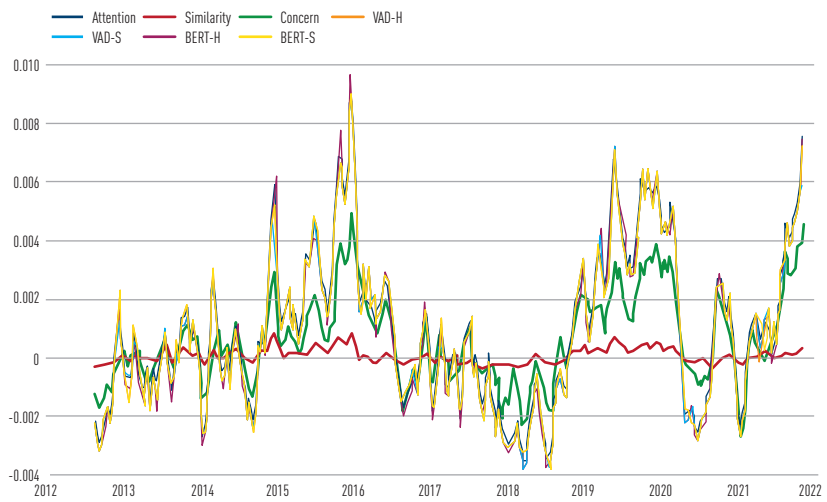
The left-hand side is the daily excess return of the portfolio under study where r_{ft} is the risk-free rate. We want to determine if, for the linear regression, the factor loading on the aggregated $UCNI_t$ is statistically significant. This will test the model of Pastor et al (2021) which predicts a strictly positive β_{UCNI} coefficient for the green and GMB portfolios and a strictly negative β_{UCNI} coefficient for the brown portfolio. We will also study the statistical significance of β_{UCNI} coefficients.

We apply the linear regression written in equation (1) to the green, brown and GMB portfolios. Figure 5 reports the β_{UCNI} coefficient for the green portfolio. These results have low significance and hence the impact of climate news on green stock returns is low.

Figure 6 shows the equivalent UCNI beta for the brown portfolio for the different news sources, including the aggregate news source. We note that the betas are all negative, implying that a day with high unexpected negative concerns is, on average, always associated with a negative impact on the returns of brown stocks. Significance for the individual news source betas is reasonably high with some at 10%, 5% and one at 1% significance (CBERT-H). However, for the aggregate index, the significance improves substantially, and five of the nine indices have significance at 1%, three having significance at 5% amongst the other four.

Figure 7 shows the UCNI beta coefficient for the GMB portfolio for the linear regression performed over the period from July 2012 to November 2021. The first observation is that the betas are mostly positive: unexpected negative climate sentiment is associated with a positive return due to a fall in value of the short position in the brown stocks. Once again, the climate beta statistical significance is greatest for the aggregate indices, with six out of nine climate betas showing statistical significance at 5%.

4. UCNI aggregated indices – 30-day moving average



This figure displays the UCNI for the aggregated news source over the period July 2012 to November 2021

5. UCNI beta for the green portfolio

Year	FT	DT	UKG	NYT	LAT	Aggregate
Attention	0.0042	-0.001	-0.004	-0.0037	-0.0002	-0.0006
Similarity	-0.0048	0.0379	0.0096	-0.0098	0.0381	0.0514
Concern	0.0027	0.047	-0.0021	-0.0068	0.0039	0.0058
VAD-H	0.005	-0.0012	-0.0037	-0.0034	-0.0003	-0.0003
VAD-S	0.0063	-0.0017	-0.0042	-0.0046	0.0004	-0.0005
BERT-H	0.0017	-0.0006	-0.0054	-0.0039	-0.0015	-0.0023
BERT-S	0.0054	-0.0017	-0.003	-0.0027	0.0016	0.0009
CBERT-H	0.0016	-0.0044	-0.0043	-0.0095*	0.0012	-0.0051
CBERT-S	0.0089*	-0.0012	-0.0038	-0.0036	-0.0007	0.0007

This figure shows the value of the corresponding UCNI beta and significance for the green portfolio by news source and index construction methodology. We use * to denote statistical confidence at 10%.

6. UCNI beta for the brown portfolio

Year	FT	DT	UKG	NYT	LAT	Aggregate
Attention	-0.0135	-0.0165**	-0.0157**	-0.0102	-0.0139*	-0.0295***
Similarity	-0.0296	-0.0807	0.059	-0.0522	-0.1022**	-0.1735*
Concern	-0.0202*	-0.0087	-0.0111	-0.0231*	-0.0186	-0.0435**
VAD-H	-0.0127	-0.0142*	-0.0158**	-0.0099	-0.0144*	-0.0296***
VAD-S	-0.0142	-0.0142*	-0.0156**	-0.0084	-0.014*	-0.0296***
BERT-H	-0.0151*	-0.0112*	-0.0117*	-0.0099	-0.0097	-0.0257**
BERT-S	-0.0154*	-0.0102	-0.014**	-0.0099	-0.0087	-0.0272**
CBERT-H	-0.0116	-0.0179***	-0.014**	-0.0026	-0.016**	-0.0311***
CBERT-S	-0.011	-0.0185**	-0.016**	-0.0145	-0.0149*	-0.0334***

This figure reports the value of the corresponding UCNI beta and significance for the brown portfolio by news source and index construction methodology. We use *, **, *** to denote statistical confidence at 10%, 5% and 1% respectively.

7. UCNI beta for the green minus brown portfolio

Year	FT	DT	UKG	NYT	LAT	Aggregate
Attention	0.0177*	0.0156*	0.0117	0.0065	0.0136	0.0289**
Similarity	0.0248	0.1187*	-0.0494	0.0424	0.1403**	0.2249*
Concern	0.0229	0.0134	0.009	0.0162	0.0225	0.0493**
VAD-H	0.0177	0.013	0.0121	0.0065	0.0141	0.0293**
VAD-S	0.0205*	0.0125	0.0114	0.0038	0.0144	0.0291**
BERT-H	0.0168	0.0106	0.0064	0.0059	0.0082	0.0235*
BERT-S	0.0208*	0.0085	0.011	0.0072	0.0102	0.0282**
CBERT-H	0.0132	0.0136	0.0098	-0.0069	0.0172*	0.026*
CBERT-S	0.0199*	0.0174**	0.0122	0.0108	0.0141	0.0341**

This figure displays the value of the corresponding UCNI beta and significance for the green minus brown portfolio by news source and index construction methodology. We use *, **, *** to denote statistical confidence at 10%, 5% and 1% respectively.

8. UCNI-conditional annualised performance of green, brown and GMB portfolios for the aggregated news source

	Green	Brown	GMB
Attention			
Low	21.8%	19.4%	2.4%
Medium	33.3%	25.0%	8.2%
High	-0.5%	-10.4%	9.9%
Similarity			
Low	31.2%	24.6%	6.6%
Medium	3.4%	3.5%	-0.2%
High	20.8%	5.4%	15.4%
Concern			
Low	24.7%	21.0%	3.7%
Medium	25.2%	21.8%	3.4%
High	5.5%	-9.3%	14.8%
VAD-H			
Low	22.7%	20.3%	2.4%
Medium	30.2%	23.3%	6.9%
High	2.5%	-10.1%	12.6%
VAD-S			
Low	23.1%	19.6%	3.5%
Medium	30.0%	23.2%	6.8%
High	2.3%	-9.3%	11.6%
BERT-H			
Low	28.6%	24.6%	4.0%
Medium	23.0%	15.0%	8.1%
High	3.8%	-6.1%	9.9%
BERT-S			
Low	20.4%	19.5%	0.9%
Medium	34.0%	22.2%	11.8%
High	1.0%	-8.2%	9.2%
CBERT-H			
Low	21.1%	18.1%	3.0%
Medium	28.0%	19.6%	8.4%
High	6.3%	-4.2%	10.5%
CBERT-S			
Low	27.6%	23.2%	4.4%
Medium	27.1%	22.5%	4.5%
High	0.7%	-12.3%	13.0%

This figure shows the conditional annualised performance of green, brown and GMB portfolios and S&P500 portfolios for the different aggregated news index methodology. (H) stands for headlines and (S) for sentences.

Portfolio performance conditional on the UCNI

We examine whether unexpected climate news innovations can help predict the conditional performance of brown versus green stocks. To do this, we study the average daily performance of the GMB portfolio and the S&P 500 index over the period from July 2012 to November 2021, conditional on the level of the daily UCNI index. We define three different regimes, which we call low, medium and high. The low regime corresponds to days when the UCNI time series is below the first tercile, the medium regime to days when the UCNI time series is between the first and the second terciles, and the high regime to daily periods when the UCNI time series is above the second tercile.

Figure 8 reports the conditional performance of the green, brown and GMB portfolios with respect to UCNI calculated from the Aalised return of the GMB portfolio over the high regime is greater than that over the medium and low regime for all the methodologies under study. We also find that the average annualised return of the GMB portfolio in the high regime is greater than that over the low regime for all the methodologies under study. For example, choosing the ClimateBERT sentences index it is 13.0% in the high regime versus 4.4% in the low regime. We see that when the UCNI is in the high tercile, the return of the brown portfolio is negative for all the indices except the similarity index.

Conclusion and extensions

Our evidence suggests that the UCNI factor built on an aggregate index of high-quality newspapers has an explanatory power over the brown portfolio returns, and hence over GMB portfolio returns. The improved significance of an aggregate index over individual indices points to the fact that individual newspapers may publish climate change articles even when there is no climate change event to report. By aggregating these newspapers, we reduce the importance of these idiosyncratic articles while retaining the importance of the climate articles which they all publish – those which report on actual unexpected climate news events.

Our findings agree with the general observation by Ardia et al (2022), who find that green firms outperform brown firms when there are unexpected increases in climate change concern. Unlike Ardia et al (2022), we find that this is not because green stocks rise in value, but because brown stocks fall in value. This result is consistent with the results of Bua et al (2020) and is true for simple attention measures which do not study the article sentiment. This implies that unexpected climate news is generally bad for brown assets, perhaps because brown firms may have more to lose from climate change news than green assets have to gain.

Furthermore, we find that, conditional on the level (low, medium, high) of the UCNI, the average return of GMB portfolios over the period from July 2012 to November 2021 is always increasing with the level of the UCNI across all the different index types. This adds supports to the hypothesis that there is a role played by climate change concern on the longer-term performance of GMB portfolios.

Out of all the language models used, the most advanced domain-specific ClimateBERT model did not materially outperform the simpler attention-based model. This indicates that it is the number of articles, rather than their content, that drives climate risk awareness. It may also imply that the ability of these state-of-the-art language models to extract sentiment from high quality newspaper articles is limited. This may be due to the complexity of the language found in these newspapers' articles or to the desire of serious newspapers to be even-handed and moderate in tone.

There are several possible extensions of our paper. First, we may wish to add more individual news sources to the aggregated index to see the impact on the

significance of the aggregate index. Second, it would be of interest to explore aspect-based sentiment approaches such as Peng et al. (2020). Using such an approach we can ensure that the target of the expressed sentiment is indeed a climate change-related matter. It may then be possible to distinguish between green and brown targets. Third, it would be of considerable interest to determine whether the out-of-sample performance of the aggregate UCNI is sufficient to enable us to use it for portfolio hedging as initially proposed by Engle et al (2020).

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Climate scenarios for financial risk analysis

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Climate scenarios have become an important tool for investors, including those in the insurance and reinsurance industry who traditionally dealt with disaster risks.

To meet supervisory requests, many investors must now disclose and assess their climate-related financial risks using climate scenarios (eg, those developed by central banks and financial regulators for Greening the Financial System).

Our understanding of the characteristics of these scenarios in comparison to short-term scenarios traditionally used for stress-testing is still limited.

Here we provide an overview of the existing scenarios, discussing current challenges and opportunities for further development.

Climate-related financial risks

The assessment of climate-related financial risks plays an important role in the agenda of central banks and financial supervisors. In 2015, the then governor of the Bank of England and Financial Stability Board chair Mark Carney, in his speech to Lloyd's of London about the 'tragedy of the horizons', warned the financial industry about the losses that it could face due to the unfolding of climate risks (Carney [2015]). In particular, Carney identified three main channels through which climate risks could affect the financial industry, namely physical, transition and liability risks. These are characterised by different drivers, and thus by different entry points in the economy, and transmission channels to the agents in the economy, to investors and sovereigns:

- *Physical risks* refer to the impacts on business performance and, through that, on the value of firms' financial assets and investors' portfolios, induced by *acute risks* – ie, weather-related events such as floods and hurricanes – and *chronic risks*, eg, temperature increase, sea-level rise and biodiversity loss. For instance, a flood that critically damages a firm's productive plants could impair the firm's profitability and even lead to bankruptcy, if the affected plants are a core part of the firm's business. The economic loss can then translate to a financial loss, whereby the loss in performance translates to a negative adjustment in the financial assets (eg, stocks, bonds) or an inability to repay outstanding loans that eventually affects investors directly. If these activities have liability cover, eg, insurance, then insurance (and reinsurance) firms could also suffer from larger claims.
- *Transition risks* refer to the impacts on business performance and, through that, on the value of firms' financial assets and investors' portfolios, induced by a change in the climate policy and regulatory environment (eg, a late and sudden introduction of a carbon tax), technological shocks and changes in consumers' preferences. For instance, a late introduction of a carbon tax would lead to larger costs and lower profits for firms that extract, produce or use fossil fuels for their business, as fossil fuel combustion is a main driver of CO_2 emissions.[1]

This economic loss can then translate into a financial loss, whereby the loss in a firm's performance translates into a negative adjustment to financial assets or an inability to repay outstanding loans, eventually affecting investors through stranded carbon assets (ie, assets whose value could decrease abruptly as a result of a phase-out of fossil fuels and high-carbon activities). See Leaton (2011) and McGlade and Ekins (2015).

- *Liability risks* refer to economic and financial actors who have experienced losses from the effects of climate change or climate policies and regulations and seek compensation from those they hold responsible. We already see examples of liability risks involving fossil fuel extractive companies and sovereigns that passed legislation aimed at preventing new fossil fuels explorations (see, eg, the case of Rockhopper Exploration against Italy[2]).

The analysis of climate risks is particularly relevant to the insurance and reinsurance industry. On the one hand, insurers and reinsurers are expected to provide tailored financial instruments, including disaster risk financing, agricultural insurance, property catastrophe risk insurance and expertise to help governments and businesses copying with disasters. Yet, at the current time, the most catastrophic losses, including those caused by climate change, are not covered by insurance, leaving millions of households and businesses facing a large and widening protection gap.[3] Furthermore, the same insurance industry has already highlighted that unmitigated climate change could lead to risks that would be uninsurable, in particular in the absence of timely policy action for mitigation (eg, carbon pricing) and adaptation finance.

On the other hand, insurance and reinsurance firms are increasingly required by regulators to disclose and assess climate risks on both sides of the balance sheet, considering uncertainties of scenarios and different time horizons, and to develop climate risk management strategies.[4]

1. Climate physical and transition risks transmission to the economy and investors: direct, indirect, spillover and cascading impacts

Climate risks	Direct impact (entry point)	Indirect impact (finance)	Spillover and cascading impacts
Acute risks (eg, floods, hurricanes, droughts), chronic risks (eg, sea-level rise, biodiversity loss)	Negative: economic activities (eg, plants, buildings) in areas exposed to physical risks with poor/ no adaptation	Negative: investors, through adjustments in value of financial contracts, insurance liability, collaterals	Negative: supply chain, value chain, trade and balance of payments, sovereign debt
Climate policies (eg, carbon tax) environmental regulation, technological shocks, preferences	Negative: high-carbon and fossil fuel firms, due to higher production costs affecting activity's economic viability. Positive: low-carbon firms (price competitiveness and productivity)	Negative for investors who are exposed to high-carbon and fossil fuel firms. Positive for investors who are exposed to low-carbon firms. Mechanism: adjustments in value of financial assets, insurance	Negative: fossil fuels supply chain, trad of high-carbon goods and fossil fuels, and thus balance of payments and sovereign debt. Positive: low-carbon supply chain, trade of low-carbon goods, and thus balance of payments, sovereign debt

Climate risk scenarios

The use of scenarios is not a novelty in stress-test exercises. However, the novelty of climate scenarios compared with traditional stress-test scenarios is the longer time horizon (starting from 10 years for transition risk up to 2100 for physical risks). The need to consider longer time horizons corresponds with the nature of climate risks, whose greatest negative impacts on the economy are expected to play out in the mid-term as a consequence of poor mitigation leading to increases in emissions concentration in the atmosphere and a lack of investment in adaptation. Furthermore, the data and models to develop climate scenarios differ from standard scenarios.

Physical risks

Between 2011 and 2021, economic losses from natural disasters globally reached $363bn;[5] some 80% of the economic losses due to natural disasters are triggered by extreme weather and climate-related events.[6] Disaster risk derives from the interaction of social and environmental processes, and is defined as the combination of physical hazards and the vulnerabilities of exposed elements (Cardona et al [2012]). Vulnerability of households and business to climate risks is heterogeneous across countries and geographies.

Physical risks are particularly relevant to the insurance and reinsurance industry, which has long used catastrophe risk models to assess them. Acute physical climate risks (ie, weather events or hazards) have traditionally been analysed with probabilistic risk assessment models and catastrophe risk models used, for instance, by the insurance industry. These models translate the strength of a meteorological event (eg, wind) into the power of a hazard related to that (eg, hurricanes) and from that, through a damage function, into the economic losses for the activities located in areas hit by the hazard.

These models build on loss and damage data provided by loss databases that contain a record of events and related economic losses. However, only a few large-scale, consistent, open-access disaster risks and losses databases exist. Many are hazard-specific (eg, the European Commission Joint Research Centre Global Database of Drought Events for droughts, the Global Risk Data Platform (UNEP-GRDP) for storms, floods and cyclone wind, and Fathom-Global for flood hazard data. In addition, the accuracy and consistency of reporting

1 The later the introduction of the tax, the higher the value and thus the larger the costs for high-carbon firms. This is due to the fact that the more we wait to introduce the tax, the lower the carbon budget (ie., the amount of anthropogenic CO_2 emissions that can still be introduced in the atmosphere given a certain temperature target (Allen et al [2009]) available coherent with the Paris Agreement target of 2°C temperature increase by 2100.

2 In 2022, after a five-year arbitration under the Energy Charter Treaty, Italy was ordered to pay €190m to Rockhopper Exploration, a UK oil and gas company, over a ban on near-shore drilling that prevented the opening of a new oilfield in the Adriatic Sea.

3 See, eg, Swiss Re: https://www.swissre.com/risk-knowledge/mitigating-climate-risk/natcat-country-profiles-infographic.html#/

4 Recent examples are Art. 262 of the delegated Solvency II regulation; the European Supervisory Authorities' Joint Regulatory Technical Standards on Environmental Social Governance (ESG) disclosure; the Securities and Exchange Commission (SEC) and the National Association of Insurance Commissioners (NAIC) proposals for climate risks disclosure. In the EU, the European Insurance and Occupational Pension Authority (EIOPA) provided an application guidance for climate scenarios analyses in the Own Risk and Solvency Assessment (ORSA) that considers the scenarios reviewed by the Intergovernmental Panel on Climate Change (IPCC) and the scenarios developed by the Central Banks and Financial Regulators' Network for Greening the Financial System (NGFS) (EIOPA 2022a).

5 https://www.statista.com/statistics/510894/natural-disasters-globally-and-economic-losses/

6 UNISDR (2017).

across databases for the same hazard hitting the same country is often low, due to different data collection and cleaning procedures. Examples of open-access disaster risks databases include EM-DAT[7] (which provides aggregate losses at national level at the global scale) and DesInventar Sendai[8] (which records losses at the subnational level disaggregated by type of activity but mostly covering low-income and emerging countries).

An analysis of the evolution of disaster risk and overall the 'health' of the climate is provided every seven years by the IPCC, which releases a report divided into chapters and working groups, the first one covering the physical science basis (IPCC [2021]). Scenarios used by the IPCC are characterised by four representative concentration pathways (RCPs), which consist of pathways of GHG emissions levels and other radiating forces (ie, the difference between incoming and outgoing energy in the Earth's climate) that might occur up to 2100:

- RCP2.6 – a stringent mitigation scenario, which corresponds to less than 2°C of (global average) temperature increase above pre-industrial levels;
- RCP4.5 and RCP6.0 – intermediate GHG emissions scenarios leading to a 2.7–5°C increase;
- RCP8.5 – the high-end scenario characterised by high GHG emissions.

The shared socioeconomic pathways (SSPs), by contrast, represent different narratives of socio-economic and geopolitical developments to explore how societal choices (eg, reliance on fossil fuels, trade agreements and barriers, demographic growth) would affect GHG emissions and, therefore, the achievement of the temperature targets of the Paris Agreement. The RCPs can be combined with the SSPs to analyse the role of climate policies that would enable us to mitigate and adapt to climate change, as in the sixth assessment report CMIP6 global climate modelling exercise.

Transition risk

The IPCC reviews the trajectories of energy technologies (eg, primary energy/coal, secondary energy/electricity/wind) and their uses in economic activities, provided by process-based integrated assessment models (IAMs – Weyant [2017]). These are scientific models that link components of demographics and the economy into one 'integrated' modelling framework along with the biosphere, the atmosphere and the climate. Process-based IAMs provide scenarios of climate change mitigation coherent with a given temperature target (eg, below 2°C). They include a detailed representation of the physical system, energy systems, land-use change, agriculture, infrastructure, technology, etc. Process-based IAMs also provide a detailed description of the impacts of mitigation scenarios on the energy demand and emissions trajectories and on energy technology (fossil fuels, including coal, oil, gas, and renewable energy, including wind, solar, hydropower, etc). However, they have a relatively simple low granularity in the representation of the economy, composed of a few representative sectors whose investment decisions are based on either welfare maximisation or cost minimisation.

Given a certain *carbon budget* consistent with a specific temperature target, eg, 1.5°C or 2°C, these models provide the minimum-cost trajectory consistent with a given target and the cost of a global carbon tax on fossil fuel energy. They also show how the energy demand by technology, by country or region, should adjust (ie, increase or decrease) through time.

How climate scenarios help us understand climate risks for the insurance sector

The European Insurance and Occupational Pension Authority (EIOPA) and the Bank of England[9] are recent examples of supervisory calls for the insurance and reinsurance industry to run climate stress-test using climate scenarios (EIOPA [2022b], Bank of England [2022]).

EIOPA recommended the scenarios developed by the NGFS in collaboration with the process-based IAM community for transition risk,[10] and with the catastrophe risk modelling community to approach physical risks (using CLIMADA – see Bresch and Aznar-Siguan [2021]). These scenarios, which were launched in 2020, are now at their third release (NGFS [2022]) and are continuously updated to keep pace with advances in the science of climate change, data availability and modelling.

The NGFS scenarios build on the IPCC scenarios, characterised by SSPs and RCPs discussed above, and attach to that explicit dimension of physical and transition risk, depending on how climate policy (ie, a carbon tax) is introduced.

In this regard, the NGFS scenarios are characterised by different levels of physical and transition risks, driven by scenario-specific characteristics including:

- *The level of policy ambition*, ie, whether the temperature objectives are consistent with the Paris agreement (1.5°C, 2.0°C) or higher, which would yield higher physical risk.
- *The timing of the policy response*, either immediate or delayed after 2030. The more delayed the policy action, the smaller the remaining carbon budget for any level of policy ambition, leading to greater transition risk, especially for high ambition scenarios (1.5°C).
- *The level of policy coordination* across countries and the effects of different carbon prices across economic sectors. The more variation in regional or sectoral policies, the greater the transition risk.
- *The pace of technological change*. On the one hand, the faster the technological development, the larger the economic disruption experienced by incumbent firms. On the other hand, the faster green technology develop, the easier it will be to decarbonise the economy and reach global climate goals.
- *The availability and deployability of carbon sequestration and CO_2 removal technologies (CDR)*, which would translate into less deep emissions cuts, reducing transition risk.

Today's NGFS scenarios provide a common reference point for understanding how climate change (physical risk) and climate policy and technology trends (transition risk) could evolve given the potential introduction of climate policies (carbon tax), GHG emissions trajectories and other variables. These futures are translated into narratives of how the transition could occur and their implications in terms of physical and transition risks (NGFS [2022]). It is important to highlight that the NGFS scenarios are not forecasts of what will happen in the future but provide trajectories of how the energy demand of individual sectors, by country or region, should adjust (ie, increase or decrease) through time, to decarbonise the economy and achieve a pre-specified carbon budget objective.

In their third revision, the NGFS scenarios explore a set of six scenarios

7 EM-DAT – The International Disaster Database: www.emdat.be/

8 DesInventar Sendai, a disaster information management system: www.desinventar.net/

9 Note that the Bank of England's Climate Biennial Exploratory Scenario (CBES) includes different scenarios from the EIOPA's exercise. The CBES includes three scenarios exploring both transition and physical risks, to different degrees. The exercise considered two possible routes to net-zero UK greenhouse gas emissions by 2050: an 'Early Action' (EA) scenario and a 'Late Action' (LA) scenario. A third 'No Additional Action' (NAA) scenario explores the physical risks that would begin to materialise if governments around the world fail to enact policy responses to global warming.

10 The NGFS adopted three of the existing process-based IAMs – GCAM, MESSAGE-Globiom and REMIND-MagPie.

and sub-scenarios, summarised in figure 2:

- *Orderly scenarios (OS)*, which assume that climate policies (ie, a carbon tax) are introduced early and become gradually more stringent. OS include: 1) *net-zero 2050*, which aims to limit global warming to 1.5°C through stringent climate policies and innovation, reaching global net-zero CO_2 emissions around 2050, and 2) *below 2°C*, in which the stringency of climate policies gradually increases, giving a 67% chance of limiting global warming to below 2°C. OS are characterised by low transition risk and low physical risk because mitigation is done early.
- *Disorderly scenarios (DS)*, which explore higher transition risk due to policies (ie, a carbon tax) being delayed or divergent across countries and sectors. The later the policy introduction, the costlier, eg, carbon prices are typically higher for a given temperature outcome if introduced after 2030. DS include: 1) *divergent net zero*, which reaches net zero around 2050 but with higher costs due to divergent policies introduced across sectors, leading to a quicker phase out of oil use, and 2) *delayed transition*, which assumes that annual emissions do not decrease until 2030, thus requiring a strong carbon tax to limit warming to below 2°C, and that the use of negative emissions is limited. DS are characterised by high transition risk because policies are introduced later and are thus costlier. However, physical risk is low because mitigation is eventually done.
- *Hot house world scenarios (HHW)*, which assume that some climate policies are implemented in some jurisdictions, but globally efforts are insufficient to halt significant global warming. HHW scenarios include *nationally determined contributions (NDCs)*, ie, all pledged targets even if not yet backed up by implemented effective policies, and *current policies*, which assume that only currently implemented policies are preserved, leading to high physical risks. HHW scenarios result in severe physical risk including irreversible impacts like sea-level rise.

Operationalisation of climate scenarios for financial risk analysis

Several central banks and financial supervisors across the world have conducted climate stress-tests on the banks and other financial institutions under their supervision, using the NGFS scenarios. These include the European Central Bank (eg, Alogoskoufis et al [2021]), Banque de France (Allen et al [2020]), the Austrian National Bank (Guth et al [2021]) and the French Regulatory Authority (Clerc et al [2021]). In the EU, banks and financial institutions such as insurance firms are required to use the NGFS scenarios in their climate stress tests and scenario analyses (see, eg, ECB [2022]).

But what does it mean in practical terms to use the NGFS scenarios for climate stress-tests? The methodological framework now used by several of these actors to translate climate scenario trajectories developed by process-based IAMs into financial risk analysis was introduced by Battiston et al (2017) in the context of climate stress-testing of the financial system.

Using NGFS scenarios for climate financial risk assessments consists of the translation of output of trajectories provided by the process-based IAM for different types of economic activities depending on their energy technology input (eg, primary energy/fossil, secondary energy/electricity/wind) into adjustments of sectoral performance (eg, profits). The adjustment in sectoral performance occurs across policy scenarios as a difference in the output of the activity when moving from a baseline scenario of current policy to a 2°C or to a 1.5°C scenario (see, eg, Monasterolo, Zheng and Battiston [2018]).

The adjustment in performance is translated into adjustments in the firm's risk metrics, eg, the probability of default (PD) or loss given default (LGD), which is then translated into the adjustment of the valuation of financial contracts and securities (eg, stocks, bonds) owned by the investor (Battiston et al [2017]; Monasterolo and Battiston [2020]).

The adjustments in financial valuation of contracts and securities are then used as an input for the adjustment in financial risk metrics (eg, climate VAR, climate ES) of the investor who holds firms' contracts and securities, conditional on the climate scenarios (Battiston et al [2017]).

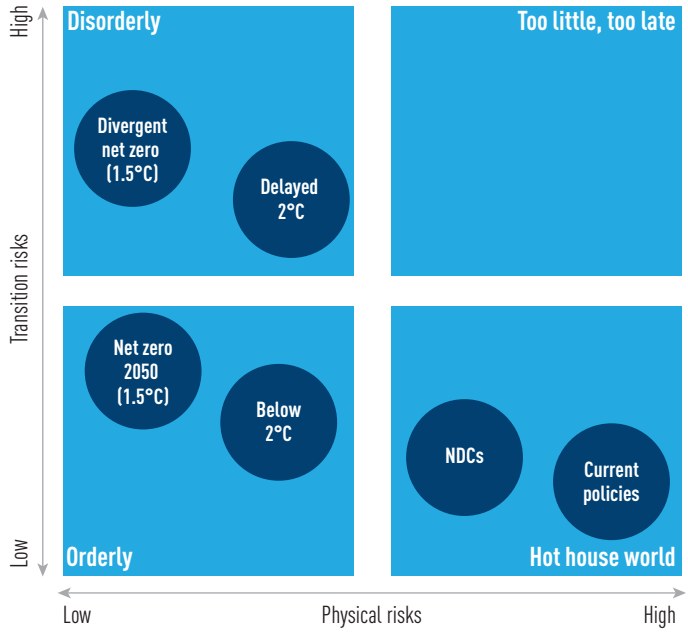
Finally, an analysis of the reverberation of losses can be conducted, usually using a financial network model, considering second, third and fourth round losses (eg, in networks of banks and investment fund – Roncoroni et al [2021]).

Scenario limitations and opportunities for development

Climate scenarios play an increasingly important role in financial risk assessment as a result of evolving regulatory requirements and voluntary adoption for internal risk management. However, while scenarios have gone through several rounds of updates already, some limitations persist.

First, current climate scenarios do not properly account for acute risks from extreme weather events (Ranger Mahul and Monasterolo [2022]). In the NGFS scenarios, acute risks from natural disasters are underrepresented. So far, physical risk scenarios have a good representation of hurricanes and yet partially of floods (at a less granular

2. Narratives of the NGFS scenarios



Source: adapted from NGFS, 2022

resolution). However, other main sources of stress such as droughts, which have been particularly relevant for the EU in the past summer, and water scarcity, are not considered yet. Furthermore, the translation of hazards into economic losses is still done at an aggregate level. A more granular representation of the productive assets exposed to losses from natural disaster would contribute to a better assessment of economic and financial risks for firms owning the assets, and their investors (Bressan, Monasterolo and Battiston [2022]).

Second, the scenarios currently neglect the fact that climate-related risks do not happen in isolation, but they may compound with shocks of other nature, such as pandemics and debt crises. This is for instance the case of several countries in the African continent that were already affected by drought when COVID-19 emerged. Other examples include several Caribbean countries that have been affected by tropical cyclones during the COVID-19 crisis; some were already under fiscal surveillance of the IMF, such as Barbados. Accounting for compound risk matters in designing an effective fiscal and financial response. Indeed, research shows that when climate risks compound, either among themselves (such as the case of multiform floods – Kruczkiewicz et al [2022]) or with other forms of risks such as pandemics, they can amplify the magnitude and duration of economic losses (Dunz et al [2021]).

Third, the climate scenarios recommended by the regulators focus on the stand-alone damages caused by climate change in isolation. There are, however, relatively rare but plausible cases of more than one stress event, of different natures, happening at the same time (eg, high climate damage combined with a pandemic or a war – as was again the case for African nations already hit by droughts and COVID-19. If this joint occurrence materialises, the compound damages can be much higher than the sum of the stand-alone damages (see, eg, Dunz et al [2011]). To the extent that these 'joint catastrophes' are considered sufficiently likely to warrant attention, this should influence the design of an effective fiscal and financial response. Unfortunately, the stand-alone nature of the climate scenarios recommended by the regulators does not enable this rare but potentially very severe compounding of effects to be taken into account. Thought should be given to how this shortcoming could be fixed – or, at the very least, scenario users should keep in mind these limitations when assessing the model outputs.

Fourth, spillover and cascading climate risks are still neglected by climate scenarios. On the one hand, research shows that climate transition risks are not constrained within a country's borders (imagine the introduction of climate policies and regulations in a country that ratified the Paris Agreement). Transition risk can spill over from a country that introduced climate policies – such as carbon pricing – to its fossil fuel trading partner. The fossil fuel exporting country would be indirectly and negatively affected by the introduction of climate policies in its trading partner through lower quantity exported and prices, which in turn would negatively affect the balance of payment, fiscal revenues and sovereign debt (Gourdel et al [2021]). Consider for instance the case of China, which is a main importer of fossil fuels from Indonesia. Since China recently introduced ambitious regional carbon pricing, its future import of coal from Indonesia would decline. This, in turn, would negatively affect exports of Indonesia's mining firms, their profitability and contribution to Indonesia's fiscal revenues, with negative implications for Indonesia's balance of payment and sovereign debt/GDP.

Fifth, climate scenarios are currently constructed without accounting for the role of the financial system. In particular, they do not account for the impact of investors' expectations on the realisation of the scenarios themselves. This is a limitation to the relevance of climate scenarios for the analysis of climate risks and opportunities from climate-aligned portfolio rebalancing (Battiston et al [2021]). Indeed, if investors trust that countries will embrace a decarbonisation trajectory, eg, by introducing a carbon tax, they will adjust risk perception and reallocate capital towards low-carbon activities. This is because estimates of the value of investments in low resilience activities under transition scenarios are typically lower than in business-as-usual scenarios. Therefore, investors' expectations and interplay with policy credibility play a main role for aligning investors' incentives to the transition objectives, and thus for failing or making the mitigation.

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EDHEC-Risk Climate Impact Institute Professor Monasterolo receives Banque de France Young Researchers in Green Finance Prize

I warmly congratulate Irene Monasterolo for her research work aimed at better understanding the role of finance in achieving climate objectives and better assessing the associated financial risks and opportunities, particularly through her pioneering work on climate change stress tests, which are crucial for financial stability. This prize highlights the contribution of many women scientists to green finance

Emmanuelle Assouan,
Deputy Director General for Financial Stability and Operations, Banque de France and Deputy Secretary General, French Prudential Supervision and Resolution Authority

About the Award

The Banque de France created the "Young Researchers in Green Finance" prize in 2019 to support academic research advancing the frontiers of knowledge on the greening of the financial system and providing decision-making and analysis-capacity tools to central banks and supervisory authorities.

Past Winners of the Award:
2021 - Mathias Reynaert,
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2020 - Olivier David Zerbib,
Associate Professor of Finance, EDHEC Business School, Affiliate Member, EDHEC-Risk Climate Impact Institute
2019 - Fanny Henriet,
Associate Professor, Paris School of Economics

About the Laureate

Irene Monasterolo is Professor of Climate Finance at EDHEC Business School and the Director of the research programme on The Impact of Finance On Climate Change Mitigation And Adaptation at EDHEC-Risk Climate Impact Institute.

She writes on topics related to climate change and the financial system, including tail-risk scenarios, climate stress tests, and green finance policies and regulations.

Professor Monasterolo has collaborated with leading financial institutions including the World Bank, the International Monetary Fund, the European Central Bank, and the European Insurance and Occupational Pension Authority.

She holds a PhD in Agri-food economics and statistics.

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