TECHNICAL DOCUMENTATION

Climate Scenario Probabilities

Scientific Climate Ratings
An EDHEC Venture

V1.00.01 – July 2025

About Scientific Climate Ratings

Scientific Climate Ratings is a new venture born from EDHEC's Climate Finance applied research ecosystem. It delivers forward-looking ratings that quantify the financial materiality of climate risks for infrastructure companies and investors worldwide. Leveraging high-resolution geospatial data, proprietary climate risk models, and the world's largest financial dataset for infrastructure assets, Scientific Climate Ratings evaluates both transition risks (linked to the shift toward a low-carbon economy) and physical risks (arising from climate hazards such as floods, storms, heatwaves, and wildfires).

The ratings offer a dual perspective:

- Potential Climate Exposure Ratings assess current exposure to future climate risks under a "continuity" scenario, reflecting the most likely pathway based on today's global policies and trends.
- Effective Climate Risk Ratings go further by integrating climate risk data into financial valuation models across multiple scenarios — each weighted by its probability of occurrence — to estimate the financial effects of climate-related risks until 2035 and 2050.

While initially focused on infrastructure, Scientific Climate Ratings will soon extend its methodology to the listed equities segment, applying the same scientific rigor and forward-looking approach to a broader set of financial assets.

Scientific Climate Ratings aims to set a new standard in climate risk management — driving informed and responsible decision-making for a more resilient future.

Table of Contents

This document summarises the development of **climate scenario probabilities**, which is part of the ***Effective Climate Risk Rating (ECRR)***. It explains the general approach, provides the data sources used, justifies the methodology, and presents the results. For general information on the ECRR, please see its technical documentation.

All procedures were developed by the *EDHEC Climate Institute*, hereafter referred to as ECI or "we."

1. General Approach

The present document explains how probabilities can be assigned to climate scenarios, where each scenario represents a possible trajectory for key reference quantities such as economic output, CO2 emissions, and temperature. The procedure is general but specifically applied to the scenarios provided by Oxford Economics. The core motivation for assigning probabilities to these scenarios is to ensure a more comprehensive and realistic assessment of future climate-related risks and opportunities. Rather than treating all scenarios as equally likely, arbitrarily selecting one as the "most probable," considering the "worst case," or choosing a given risk type, assigning probabilities allows for a more rigorous integration of uncertainty into decision-making.

By weighting scenarios according to their likelihood, we can better capture the range of plausible futures and incorporate these insights into risk assessment. This probabilistic approach prevents reliance on extreme or overly simplistic assumptions and enables a more balanced evaluation of both expected outcomes and tail risks. It allows for a systematic way to account for uncertainty in the speed and effectiveness of emissions abatement efforts, which is a major determinant of future climate and economic conditions.

The assignment of probabilities to climate scenarios is based on estimating a probability distribution for the aggressiveness of abatement speed. This is achieved using the scenario engine developed by ECI (Rebonato et al., 2025). While full details of this methodology can be found in that work, this note briefly outlines the key conceptual steps leading to the probability distribution to ensure self-containment.

2. Methodology

The starting point is the distribution of estimates for the social cost of carbon (SCC; i.e., carbon tax) elicited from professional economists. This raw data has been collected in a thorough meta-study (Tol, 2023). The reported estimates in the study cover an extremely wide range, and the raw data must first be 'curated' by removing outliers, creating feasibility bands, weighing studies of different quality appropriately, and expressing the estimates in equivalent monetary units. This curated data follows the distribution shown in Figure 1.

The next step is to recognise that the economists' views on carbon tax do not coincide with politicians' actions. Therefore, the distribution in Figure 1 is adjusted so that the expectation of the carbon tax matches the traded prices of carbon permits.[1] When calculating these adjustments, we retrieve the politicians' probability distributions for the SCC. These are shown in Figure 2 for three possible values of the carbon permits.

[1] The adjustments to the observed prices to account for partial coverage of emissions by traded permits and the existence of carbon subsidies are discussed in detail in Rebonato et al. (2025).

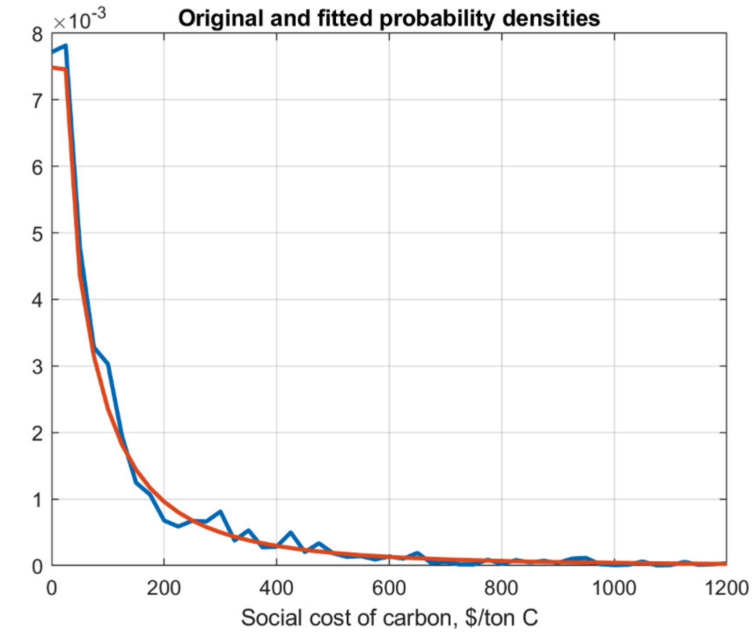

Figure 1: The fit to the empirical distribution of SCC obtained, using a mixture of a truncated Gaussian and a lognormal distribution. The x-axis presents the SCC in 2010 in USD per ton of carbon.

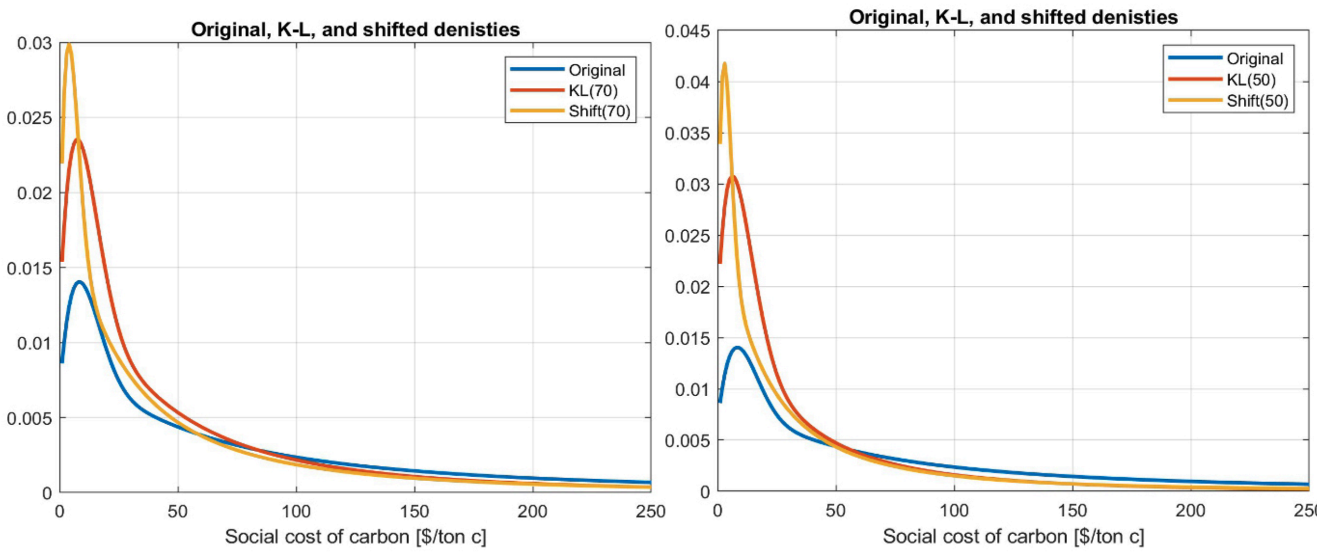

Figure 2: The original (blue line), shifted (yellow line), and Kullback-Leibler (red line) probability densities for two cases: <SCC>= $70 (left panel) and <SCC>= $50 (right panel). The x-axis presents the SCC in 2010 in USD per ton of carbon.

Next, we obtain the link from the shifted distribution of carbon taxes to the distribution of the degree of aggressiveness of the abatement policy. The abatement function μ is linked to emissions e, to the emission intensity σ, and to gross economic output γ_g by the relationship:

$$e(t) = \sigma(t) \cdot (1 - \mu(t)) \cdot \gamma_g(t) \quad (1)$$

We model the abatement function μ as a function characterised by a single free parameter κ that describes the speed of the abatement policy:

$$\mu(t) = \mu(0) \cdot exp(-\kappa \cdot t) + [1 - exp(-\kappa \cdot t)] \quad (2)$$

The additional, non-free parameter of the distribution μ_0 is calibrated to recover today's abatement. Figure 3 displays the single-parameter function $\mu(t;\kappa)$ for different values of the abatement speed κ. Despite its simplicity, Rebonato et al. (2025) show that this functional form can be used as a 'stand-in' for the wide variety of abatement functions that share the same emission-weighted average emission.

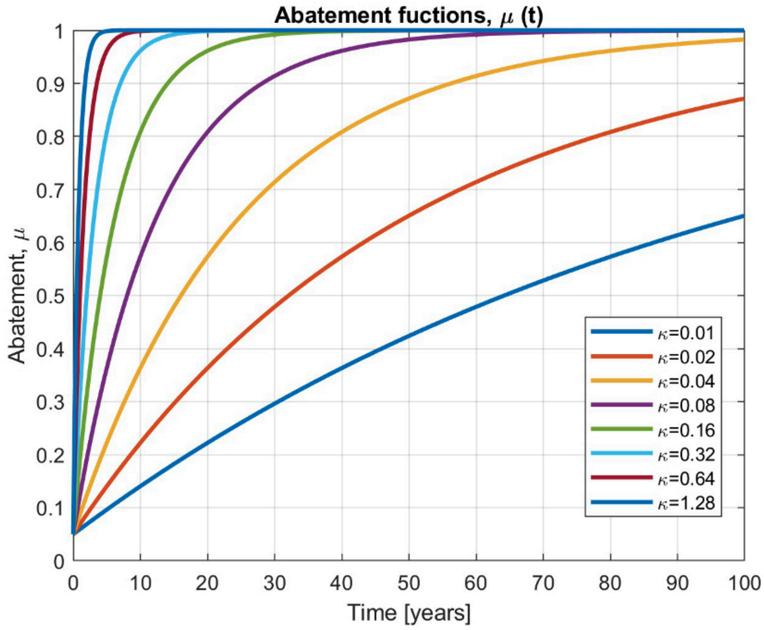

Figure 3: The abatement function $\mu(t)$ for different abatement speeds κ. Time in years on the x-axis.

The reason for choosing this simple, functional form for the abatement function is that the well-known integrated assessment model – the DICE model (Nordhaus & Sztorc, 2013) – can establish a close correspondence between the optimal abatement speed κ and the SCC. This relationship is shown in Figure 4.

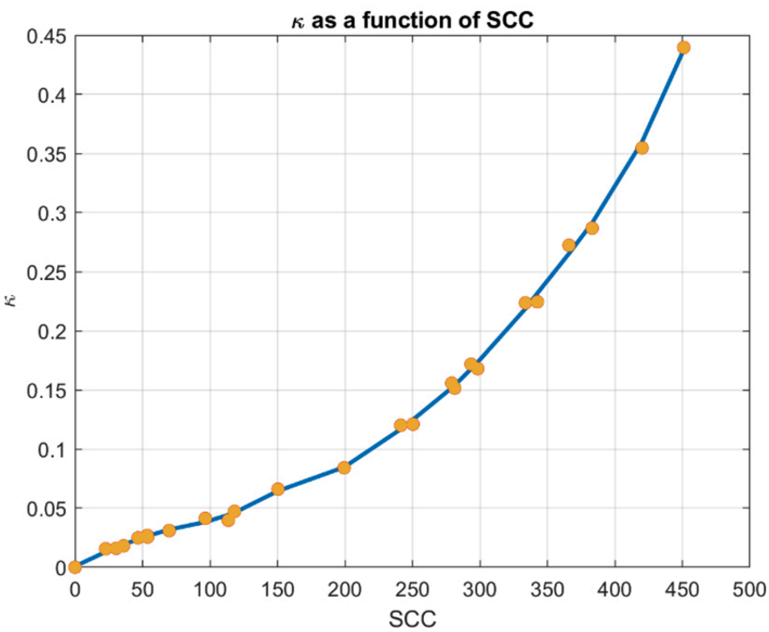

Figure 4: The abatement speed κ1 (years−1, y-axis) as a function of the optimal SCC (in USD/ton CO2, x-axis). The continuous curve is a LOWESS (Cleveland, 1979) quadratic smooth fit to the calculated points, shown as filled dots.

Given this tight and precise relationship between the equivalent abatement speed and the optimal carbon tax, one can finally obtain a probability distribution for the aggressiveness of the abatement speed κ. This is shown in Figure 5.

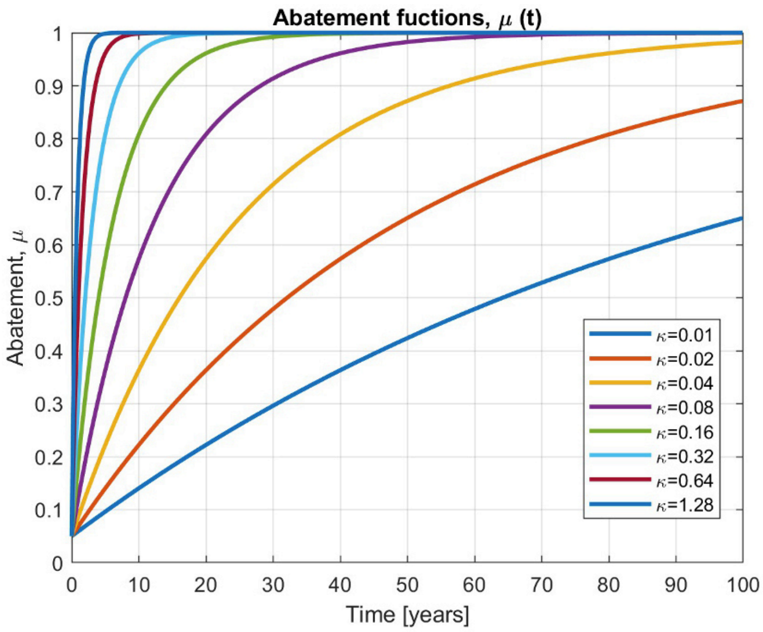

Figure 5: The probability density of the effective abatement speed κ for the unshifted distribution (blue line, labelled 'Unshifted'), the shape-preserving shifted distribution (red line, labelled 'Shifted'), the minimum-divergence K-L shifted distribution (yellow line, labelled 'K-L'), and the Maximum-Entropy distribution (purple line, labelled 'ME').

The last step is to feed this distribution of abatement speeds into the ECI scenario simulation engine to obtain an unconditional distribution for several macro-financial quantities. For some of the key quantities modelled in the Oxford Economics scenarios (e.g., economic output, emissions, and temperature), we can obtain a full distribution at every time step of the simulation.

3. Results

The goal is to use our approach to assign probabilities to climate outcomes in a way consistent with the Oxford Economics assumptions.[2] Generally, the Oxford Economics assumptions and modelling choices are quite different from the default assumptions and choices we adopt in our scenario model. The purpose of the exercise is to see whether our probability-based modelling approach is flexible enough to recover the Oxford Economics dynamics and to obtain probabilities consistent with Oxford Economics' "view of the world."[3]

[2] We use Oxford Economics as a representative example of narrative-based climate scenarios to show how this probability-based scenario approach can be applied. Most of our considerations can be applied to similar scenario models.

[3] We do not imply that Oxford Economics' approach is in any way wrong or deficient when highlighting differences between the macroeconomic and financial assumptions of the Oxford Economics scenarios and the assumptions made in the default configuration of our model. We simply welcome and make a virtue of the significant difference in modelling choices to stress-test the flexibility of our modelling approach.

3.1. Features of the Oxford Economics Scenarios

Oxford Economics provides seven scenarios that describe possible pathways for a large number of macro-financial quantities from 2023 to 2050 (we focus on 17 variables). In each scenario, one single pathway is assigned to each of these financial quantities. The Oxford Economics scenarios (and the labels we use to identify them in tables and figures) are:

1. Climate Catastrophe (Cl Cat)
   This scenario explores the severe economic and environmental consequences of unmitigated climate change, where rising temperatures and extreme weather events significantly disrupt economies and societies.
2. Baseline (Baseline)
   Serving as a reference point, the baseline scenario assumes a continuation of current policies and trends without significant changes, providing a benchmark against which other scenarios are compared.
3. Climate Distress (Cl Distr)
   This scenario examines the economic impacts of delayed or insufficient climate action, leading to heightened physical risks and associated economic stresses.
4. Delayed Transition (Del Trans)
   This scenario considers the effects of postponing the implementation of climate policies, resulting in a more abrupt and potentially disruptive transition in the future.
5. Slow and Constrained (Slow Con)
   This scenario analyses the economic implications of a slow and constrained transition to a decarbonised economy.
6. Net Zero (NZ)
   This scenario explores the pathway and economic outcomes of achieving net-zero greenhouse gas emissions by a specified target date, involving significant transformations in energy production, consumption, and technology.
7. Net Zero Transformation (NZ Tr)
   Building upon the Net Zero scenario, this narrative delves into the comprehensive societal and economic changes required to attain net-zero emissions, emphasising innovation, policy shifts, and behavioural changes.

Despite the very high number of variables that the Oxford Economics scenarios project, the effective dimensionality of their model is low. Table 1 shows the percentage of the variability explained by the first four principal components of all seven Oxford Economics scenarios. For the 17 macro-financial variables, three principal components always explain more than 99 percent of the overall variability, and as few as two always account for more than 95 percent.

Table 1: The percentage of the total variability explained by the first four principal components for the seven Oxford Economics scenarios.

	Cl Cat	Baseline	Cl Dist	Del Trans	Slow Con	NZ	NZ Tr
1st eig	85.47%	86.38%	82.46%	93.92%	91.04%	92.09%	93.27%
2nd eig	96.63%	96.81%	95.22%	98.48%	96.50%	97.25%	97.98%
3rd eig	99.68%	99.65%	99.22%	99.41%	99.03%	99.30%	99.11%
4th eig	**99.88%**	**99.89%**	**99.80%**	**99.79%**	**99.80%**	**99.86%**	**99.83%**

A small number of principal components may explain a lot, but, in general, they are complex combinations of the original variables. Fortunately, regressions show that three key variables (economic output, emissions, and temperatures) – variables that are also simulated by the ECI engine – afford almost the same explanatory power as the first three principal components. Tables 2, 3 and 4 display the paths sampled at five-year intervals for these quantities.

First, we observe that three scenarios (Net Zero, Net Zero Transformation, and Delayed Transition) display extremely aggressive decarbonisation paths. Second, there is relatively little variability in the economy's growth rate, with the highest and lowest growth rates being 2.56 and 1.17 percent, respectively. This variability mainly arises from superimposing scenario-dependent climate damages onto a relatively constant GDP path.[4] The bulk of the variation across scenarios comes from the emission patterns. Last, and perhaps most important, we note that, in the Oxford Economics world, if the 2050 temperature is low, the GDP must grow significantly. There is no possibility for low temperatures and low GDP (i.e., no chance for a world in which temperatures are low because of reduced economic activity). Conversely, the paths of lowest GDP growth are always associated with the highest temperatures.

Table 2: Emissions paths for the seven Oxford Economics scenarios. The figures reflect emissions of CO2 in gigatons.

	Cl Cat	Slow Con	NZ	NZ Tr	Del Trans	Cl Distr	Baseline
2025	39.4	35.6	36.4	36.0	38.8	39.1	**38.8**
2030	43.6	22.6	26.3	26.4	37.9	40.9	**38.4**
2035	47.4	17.8	18.2	19.5	27.5	42.1	**36.9**
2040	50.3	14.5	10.9	11.7	18.3	43.1	**35.4**
2045	52.2	12.3	5.3	4.3	7.6	43.7	**34.1**
2050	**53.5**	**10.9**	**1.1**	**0.3**	**-0.3**	**44.1**	**32.8**

[4] This observation will become important in Section 3.2.

Table 3: Temperature anomalies for the seven Oxford Economics scenarios (in °C).

	Cl Cat	Slow Con	NZ	NZ Tr	Del Trans	Cl Distr	Baseline
2025	1.39	1.39	1.39	1.39	1.39	1.39	**1.39**
2030	1.51	1.48	1.46	1.46	1.49	1.5	**1.49**
2035	1.67	1.57	1.53	1.53	1.59	1.64	**1.6**
2040	1.86	1.65	1.58	1.58	1.66	1.79	**1.72**
2045	2.06	1.71	1.62	1.61	1.7	1.95	**1.83**
2050	**2.28**	**1.78**	**1.65**	**1.64**	**1.72**	**2.12**	**1.94**

Table 4: Percentage increase in GDP from 2025 for the seven Oxford Economics scenarios.

	Cl Cat	Slow Con	NZ	NZ Tr	Del Trans	Cl Distr	Baseline
2025	100.0	100.0	100.0	100.0	100.0	100.0	**100.0**
2030	112.8	115.8	111.5	110.0	113.5	113.3	**113.8**
2035	124.0	130.8	126.1	124.3	121.8	125.7	**127.6**
2040	131.7	144.8	143.9	140.3	136.1	136.6	**141.7**
2045	135.1	156.5	164.5	158.4	153.2	145.3	**156.1**
2050	**134.1**	**164.1**	**189.9**	**180.0**	**172.5**	**151.2**	**170.7**

In the terminology of Giglio et al. (2021), the Oxford Economics scenarios inhabit a 'Barro universe' – a universe in which climate damages are so large that they cause GDP to be low. While this 'Barro view of the world' is possible, there can also be a different causal link: high economic activity causing high emissions, high concentrations, high temperatures, and hence, high damages.

There is not enough empirical evidence at the moment to determine whether the causal link goes from high damages to low GDP growth or from high GDP growth to high emissions, but arguably, a scenario engine should leave the door open to both possibilities. The ECI simulation engine allows for the modelling of both worlds, and, in the context of this analysis, we modify its degrees of freedom to behave similarly to the Oxford Economics scenarios. The reason for doing so is clear: If the same relationships among variables enforced by the Oxford Economics model can be mimicked by the ECI scenario engine, then the scenario probabilities obtained by the ECI model can be associated with the Oxford Economics scenarios.

3.2. Assigning Probabilities to the Oxford Economics Scenarios

In order to assign probabilities to the Oxford Economics scenarios, we recall that emissions e_t are linked to the no-control emission intensity σ_t, the abatement function μ_t, and the GDP γ_t (see Equation 1). We further assume that the Climate Catastrophe scenario corresponds to little-to-no abatement. In the case of no abatement, emissions are given by $e_t = \sigma \cdot \gamma_t$. Since both emissions and GDP are given in the Oxford Economics scenarios, we can impute the no-control emission intensity function σ_t from the Oxford Economics Climate Catastrophe scenario. This function is 'universal' and not scenario-dependent. Therefore, we can use it for all the Oxford Economics scenarios to obtain scenario-dependent abatement schedules μ_j, where the superscript j denotes the scenario.

Figure 9 shows how similar these Oxford Economic abatement functions are to the stylised abatement functions in Equation 2. These stylised functions are characterised by their abatement speed κ, for which we can obtain a probability distribution. Additionally, if the three explanatory variables – that account for 99 percent of the variability among Oxford Economics variables – behave similarly in our model, we have an equivalent probability-based description for all the Oxford Economics variables. The remaining step in the procedure is, therefore, to show how the ECI model can be calibrated to reproduce the Oxford Economics joint dynamics for the key explanatory variables.

Following several recalibration steps, our model behaves very similarly to the Oxford Economics model, and we are ready to assign probabilities to the Oxford Economics scenarios. From our recalibrated simulations, we can estimate the expectations of, and the covariance between, the three key variables (economic output, emissions and temperature) at each point in time. These are functions of the abatement distribution we have previously determined. The Oxford Economics scenarios provide paths for the same variables. If the scenarios were independent random samples from their underlying population, equally weighted sample expectations and covariances would provide the best estimate of the corresponding statistics for the population. However, as the Oxford Economics scenarios have not been randomly and independently selected, we can ask the following questions:

- **What weights do we have to assign to the Oxford Economics scenarios** to match the expectations and covariances produced by the Oxford Economics engine and by our model?

- **How close are the estimates of quantities produced by our model and by the Oxford Economics approach?**
  Figure 6 and Figure 7 show that set probabilities can indeed be found, enabling a close match between Oxford Economics and the ECI expectations and covariances.

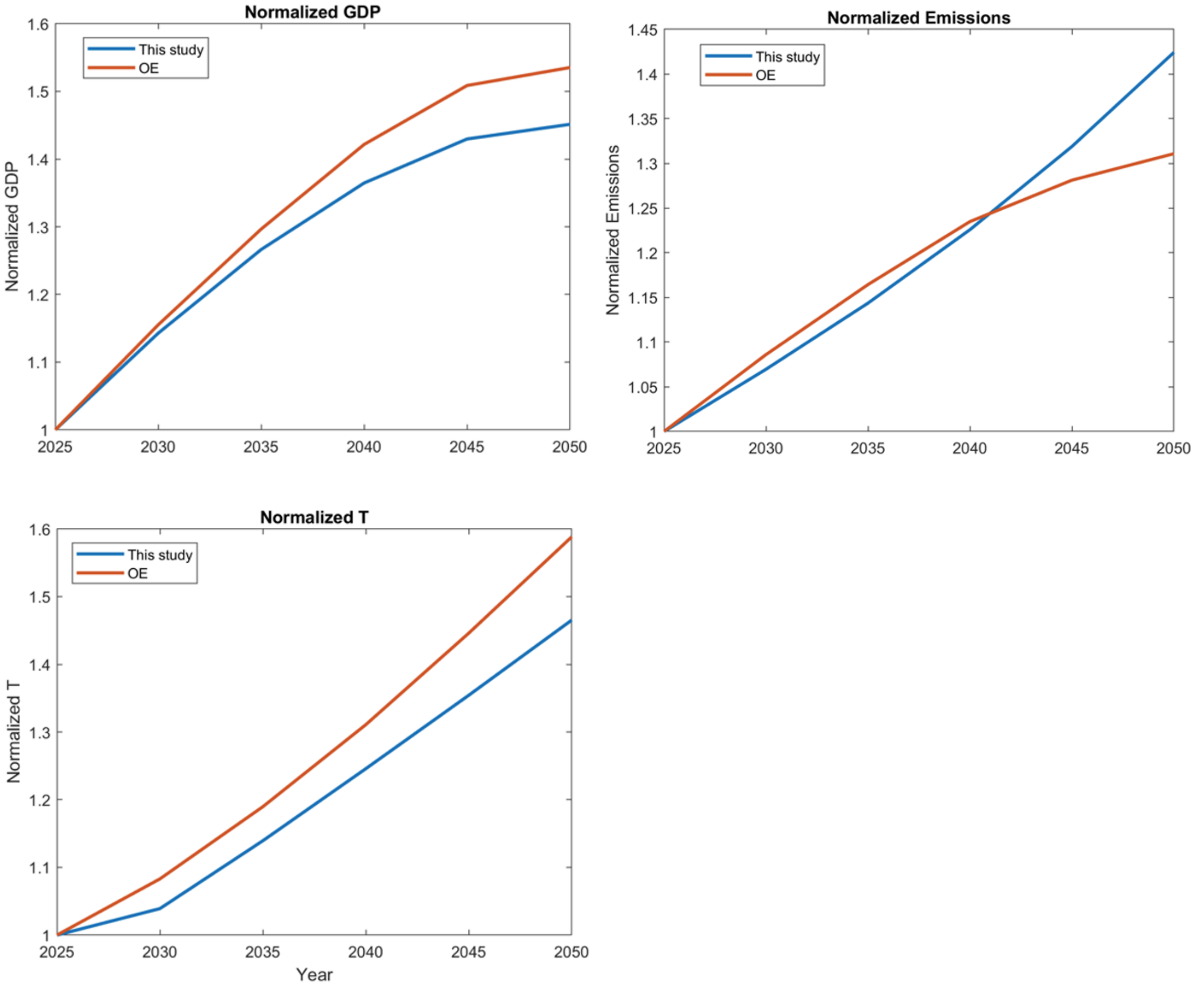

Figure 6: The time-dependent expectations of the normalised GDP (top left), carbon emissions (top right), and temperature anomaly (bottom).

- What do these probabilities look like?

  The best-fit probabilities are shown in Table 5. What is apparent is a strong polarisation of the distribution: Taken together, the only two scenarios associated with growing emissions paths account for more than 95 percent of the total probability, with the more severe Climate Catastrophe scenario taking the lion's share of the probability mass (78%). At the opposite end of the probability spectrum, we have very 'optimistic' scenarios – scenarios that have such high abatement speeds that our models assign them very low probabilities.

Table 5: Probabilities assigned to the various Oxford Economic scenarios that best recover the expectations of, and covariances among, the rescaled variables (GDP, emissions, and temperature).

Cl Cat	Slow Con	NZ Tr	NZ	Del Trans	Cl Distr	Baseline
78.0%	0.7%	0.2%	0.2%	0.4%	17.1%	3.4%

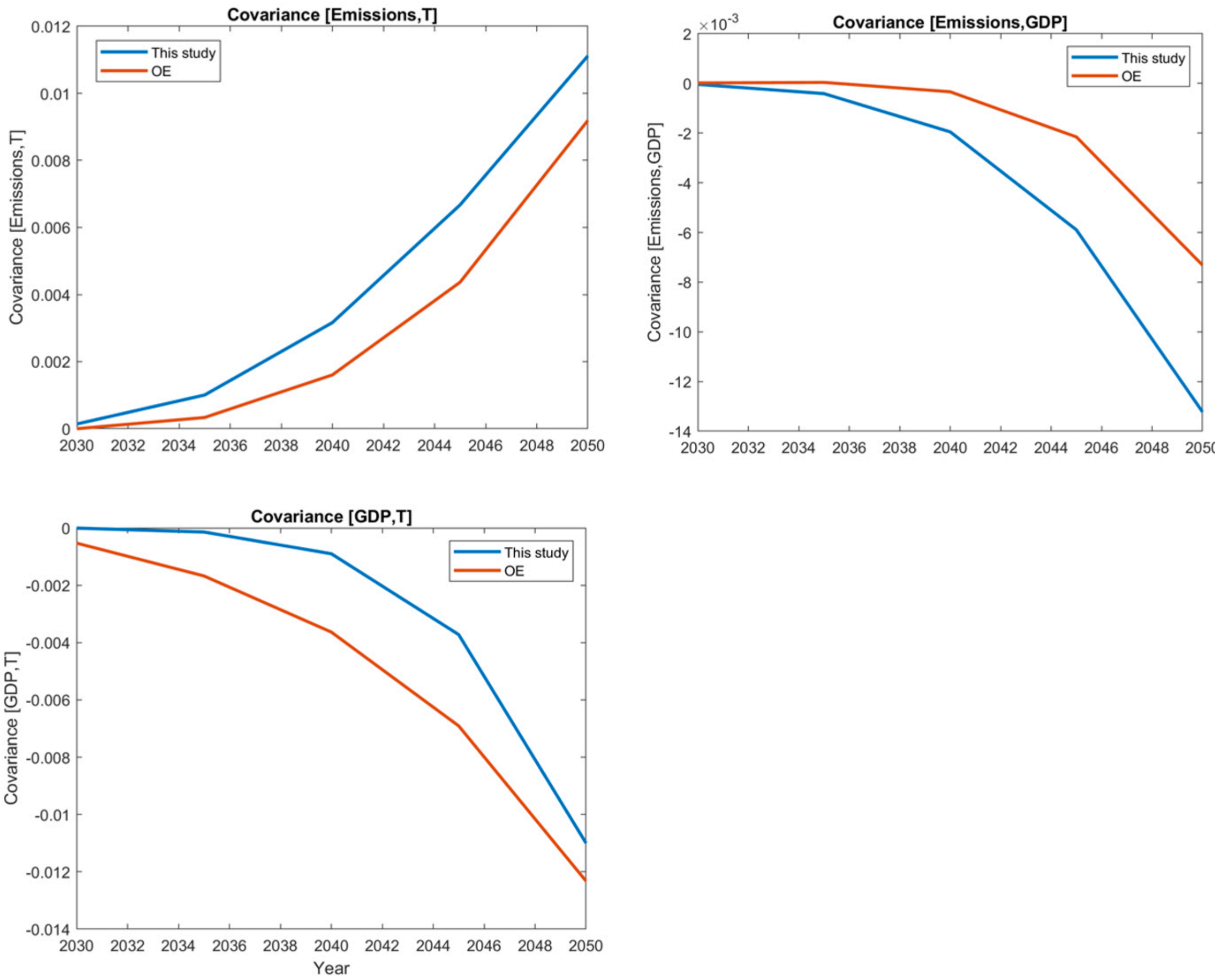

Figure 7: The time-dependent covariances between the normalised GDP, emissions, and temperature anomaly.

- **Is this very pronounced concentration of probability masses on the slowest abatement scenarios justifiable?**
  We can answer this question (and explain why the probability density is so concentrated) along two different lines. First, from the Oxford Economics data, we can reconstruct the carbon tax as a percentage of GDP for the various scenarios. The obtained results are displayed in Figure 8. We note that the Net Zero scenario implies a rapid and implausibly high increase in carbon tax that would climb within five years to a level equal to the sum of what the world currently spends on education and defence. Conversely, the scenarios to which our model assigns the highest probabilities (Climate Catastrophe and Climate Distress) are the ones associated with the lowest carbon taxes as a function of GDP.

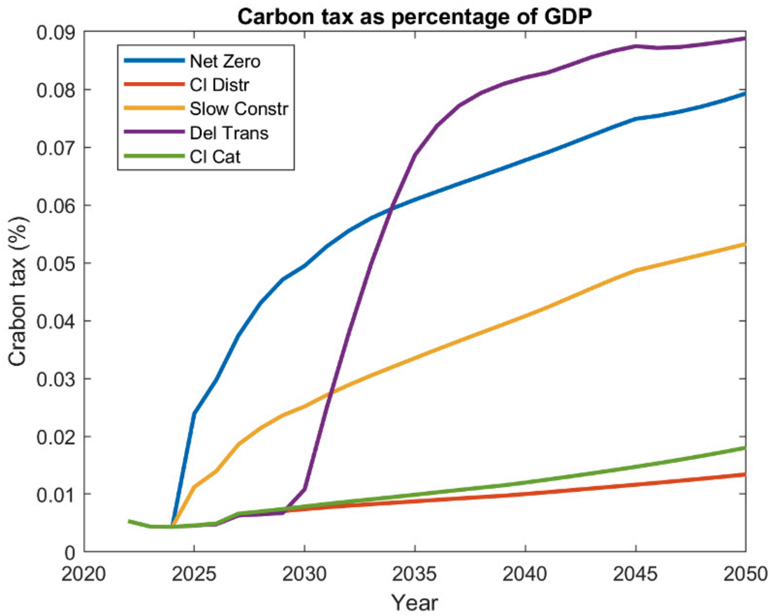

Figure 8: The evolution of the carbon tax for the various scenarios in the Oxford Economics model, expressed as a fraction of the same-time GDP.

We can look at these probabilities from a different perspective: Figure 9 shows that all 'optimistic' scenarios imply that in 25 years the economy will be 80 percent decarbonised. Based on the current and persistent disconnect between recommendations and abatement actions, these decarbonisation paths are given very low probabilities. As one can read from the graphs in Figure 5, the scenarios with high abatement speeds (high carbon taxes) have very low probabilities, and the maximum probabilities are found for the lowest values of the abatement speeds κ.

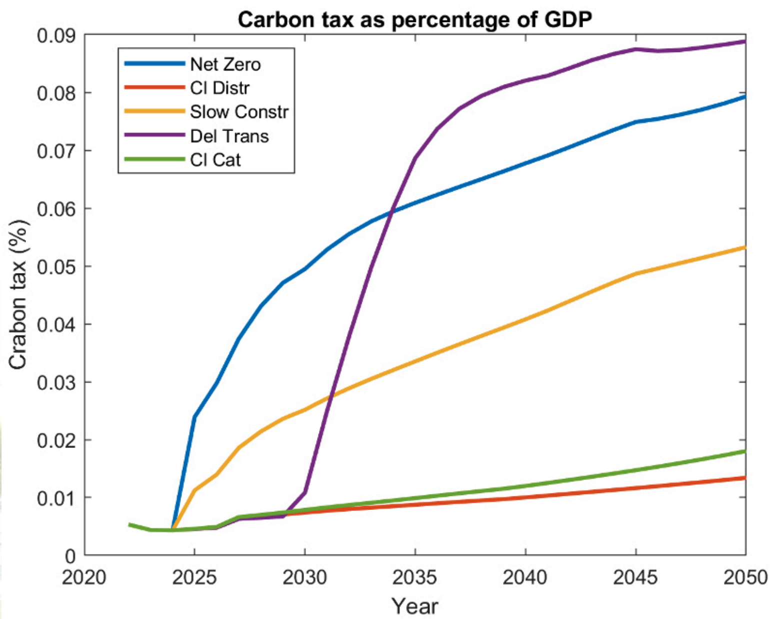

Figure 9: The abatement functions μt associated with the various scenarios.

In sum, the high concentration of probability mass that we associate with two of the Oxford Economic scenarios stems from the polarised choices of abatement policies associated with the various scenarios, with the most severe scenarios (Climate Catastrophe, Climate Distress, and Baseline) in one group (with an average κ of 0.013) and all other, more optimistic scenarios in the other group (with an average κ of 0.057). Since we have imposed that the probabilities should add up to one, a less polarised assignment of probabilities to scenarios would have arisen if some intermediate abatement policies had been included in the Oxford Economic set. This would have shifted some of the probability mass away from Climate Catastrophic and Climate Distress. The very optimistic scenarios (of the Net Zero family) would, however, have remained of low likelihood.

4. Conclusions

We have shown how to assign unconditional probabilities to climate scenarios in general and to the Oxford Economics scenarios in particular. We have anchored our probabilistic estimates to real-world data by requiring that the expectation of the SCC from our models should match an empirically observable proxy for this quantity (i.e., the cost of traded carbon permits). The quantification of the policy uncertainty was achieved by finding the probability distribution for an effective abatement speed – a quantity that we have shown to characterise parsimoniously a variety of abatement schedules. The probabilistic characterisation of the Oxford Economics scenarios was achieved first by showing that the ECI simulation engine can be calibrated so as to reproduce the dynamics of the Oxford Economics variables and then by importing the probabilities of the recalibrated ECI scenario engine onto the Oxford Economics scenarios. As a result, we find a close match between the macro-financial quantities projected by our engine and by the Oxford Economics model. We have provided explanations for the highly polarised probabilities that we have estimated.

References

Cleveland, W.S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association, 74(368)*, 829–836. https://doi.org/10.1080/01621459.1979.10481038

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics, 13*, 15–36. https://doi.org/10.1146/annurev-financial-102620-103311

Howard, P.H. & Sterner. T. (2017). Few and not so far between: A meta-analysis of climate damage estimates. *Environmental and Resource Economics, 68*, 197–225. https://doi.org/10.1007/s10640-017-0166-z

Nordhaus, W.D. & Sztorc, P. (2013): DICE 2013R: Introduction and user's manual. Available at: http://acdc2007.free.fr/dicemanual2013.pdf. More information: https://williamnordhaus.com/dicerice-models

Rebonato, R., Melin, L., & Zhang, F. (2025). Climate scenarios with probabilities via maximum entropy and indirect elicitation. *SSRN*. http://dx.doi.org/10.2139/ssrn.5128228

Tol, R.S.J. (2023). Social cost of carbon estimates have increased over time. *Nature Climate Change, 13*, 532–536. https://doi.org/10.1038/s41558-023-01680-x

Disclaimer

This Technical Documentation ("Documentation") was created and distributed by EDHEC Business School - Scientific Climate Ratings. Scientific Climate Ratings owns and retains all intellectual property rights over the Documentation and its content. Only Scientific Climate Ratings and its authorised collaborators can distribute, reproduce, modify, commercialise, or create derivative works based on this Documentation.

The Documentation contains data, analyses, scores, and ratings solely related to the climate risks (physical and transitional) of the entities studied. It does not constitute an "investment recommendation" under European Regulation No. 596/2014 ("Market Abuse Regulation") or any recommendation to buy, sell, or hold a security

The Documentation is for informational purposes only and may not be used for structuring, financing, or evaluating credit or ESG risks. It is intended exclusively for the company under study and cannot be distributed to third parties without prior written authorisation from Scientific Climate Ratings. Data related to third parties in the benchmark cannot be disclosed.

Scientific Climate Ratings strives for the careful selection and review of the data used, obtained from sources it believes reliable. However, Scientific Climate Ratings and its suppliers provide the information "as is" and do not warrant or guarantee the accuracy, completeness, or timeliness of the information and expressly disclaim liability for any damages resulting from the use of this Documentation. The information is subject to modifications and updates, and the Documentation cannot replace the expertise of decision-makers in their business or investment choices.

The ratings produced by Scientific Climate Ratings correspond to an opinion constructed with best efforts and precautions. Nonetheless, these ratings remain subjective opinions for which it does not certify the accuracy. In no way can Scientific Climate Ratings or EDHEC be held responsible for any errors or inaccuracies that may result from its ratings production process. As such, it does not claim any responsibility for the moral or material consequences relating to the use of these ratings.

Scientific Climate Ratings, its directors, employees, representatives, advisers, and suppliers disclaim all warranties regarding the information's merchantability, completeness, accuracy, or suitability for any particular use. No company in the group is bound by this Documentation.

The laws of England and Wales shall govern this disclaimer and any disputes arising from or related to this Documentation, without regard to conflict of law principles. Any legal action, suit, or proceeding arising out of or relating to this Documentation or the disclaimer shall be instituted exclusively in the English courts , and each party irrevocably submits to the exclusive jurisdiction of such courts in any such action, suit, or proceeding.

By accessing, viewing, or using this Documentation, you acknowledge that you have read, understood, and agree to be bound by this disclaimer. If you do not agree to these terms, you must not use this Documentation.

Contact: support@scientificratings.com

Scientific Climate Ratings
An EDHEC Venture

contact@scientificratings.com

PARIS
18 Rue du 4 Septembre
75002 Paris - France

SINGAPORE
One George Street, #15-02
Singapore 049145 - Singapore

LONDON
10 Fleet Place
London EC4M 7RB - United Kingdom