



## Incorporating Forward-Looking Data in Probabilistic Analysis of Net-Zero Commitments

### Ideas and First Results

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# Agenda

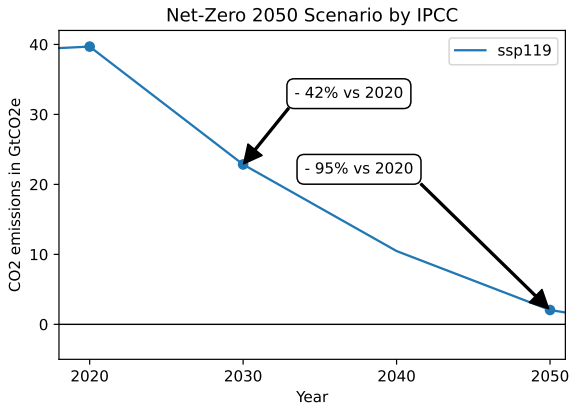
Probabilistic Model

Forward-Looking Transition Plans

NLP Methods to Measure Corporate Disclosure

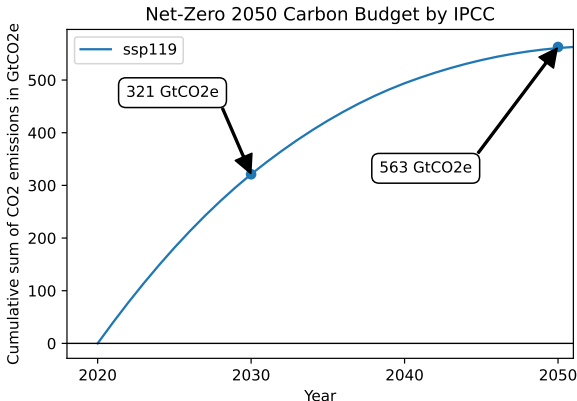
Forward-Looking Probabilities in Bayesian Nets

## IPCC's Net-Zero Scenario: The Scale of Reduction



**Figure:** SSP1-1.9 Scenario by the IPCC. Source: IPCC, 2021 and Authors' Calculations.

## IPCC's Net-Zero Carbon Budget



**Figure:** Carbon Budget of the SSP1-1.9 Scenario by the IPCC.  
Source: IPCC, 2021 and Authors' Calculations.

## Proliferation of Corporate Net-Zero Targets

- ▶ The number of companies who apply to the Science-Based Targets initiative (SBTi) increases rapidly and to date amounts to 11,000 companies, covering more than 40% of the global market cap and 25% of global revenue by August 2025, see SBTi (2025).
- ▶ Net-zero targets constitute 38% of all SBTi's approved targets as of mid 2025, see SBTi (2025).
- ▶ Case studies in Corporate Climate Responsibility Monitor (CCRM) show that such commitments are of low integrity and that real emissions reductions are assessed to be much lower than promised, see CCRM reports 2022-2025.

## Probability of Net-Zero

- ▶ We develop a probabilistic model to analyze firms' efforts towards a net-zero scenario.
- ▶ Specifically, we assess the probability of a company respecting its calibrated net-zero budget.
- ▶ The probabilities are dynamically updated with the arrival of new data.
- ▶ In addition to the historical data and sectoral decarbonization capacities, we consider forward-looking climate-related disclosure relevant for the net-zero transition to obtain adjusted forward-looking probabilities.

## Probability of Net-Zero: Our Approach

- ▶ We calibrate sectoral climate scenarios to the firm level by assuming proportional yearly emissions change rates, obtaining a reference calibrated net-zero emissions pathway and the corresponding calibrated net-zero budget.
- ▶ Using historical emissions data, we estimate the average yearly change rate and the yearly volatility of emissions.
- ▶ We assume that firm's projected emissions are a geometric Brownian motion with a historical or a scenario-dependent drift and a historical volatility.
- ▶ We approximate cumulative projected emissions and compute the probability that they lie below the calibrated net-zero budget.

## References I

- ▶ Chekriy, K., Kiesel, R., Stahl, G., 2024. A Probabilistic Approach of Assessing and Ranking Firm's Transition Efforts. Available on SSRN.
- ▶ Chekriy, K., Kiesel, R., Stahl, G., 2025. Probabilistic Assessment of Corporate Net-Zero Transition. Available on SSRN.
- ▶ IPCC, 2021. Climate Change. The Physical Science Basis.
- ▶ Kiesel R., Stahl G., 2023. An Uncertainty-based Risk Management Framework for Climate-Change Risk. Annals of Actuarial Science , Volume 17 , Issue 3.
- ▶ Le Guenedal T., Lombard F., Roncalli T., Sekine T., 2022. Net Zero Carbon Metrics.
- ▶ SBTi, 2025. SBTi Trend Tracker 2025.



## Forward-Looking Transition Plans

- ▶ Prospective transition plans need to be included in transition assessment methodologies to improve the output as the underlying models are highly reliant on future transition assumptions.
- ▶ Assessing firms' transition-relevant disclosure might be also helpful to identify transition drivers and distinguish proactive transition from short-term trends.
- ▶ Annual and sustainability reports constitute an important communication channel to stakeholders and often contain material data on future transition plans and actions.

## Transition-Relevant Questions

- ▶ We use 32 questions characterizing a credible transition plan selected from the CDP's questionnaire, TCFD disclosure recommendations and proposed questions and criteria by Colesanti Senni et al. (2024).
- ▶ We ask transition-relevant questions like
  - ▶ "Does a company has a net-zero target?",
  - ▶ "Does the company use climate scenarios during its climate risk assessment?",
- ▶ We additionally provide extensive sector-specific explanations for each question describing important criteria that need to be fulfilled, e.g. does the net-zero target refer to GHG emissions, were the base and target year disclosed and do they match the requirements of sectoral scenarios.

## Retrieval Augmented Generation

- ▶ We perform Retrieval Augmented Generation (RAG), which combines two main phases:
  - ▶ Retrieval: finding relevant text pieces from provided reports.
  - ▶ Generation: using a large language model (LLM) to generate response based on the passed retrieved information along with some instructions on the output and analysis.
- ▶ We use a hybrid RAG approach, combining sparse (keywords-based) and dense (semantic search) retrieval, to improve the retrieval for niche language such as climate-related language, see Mankour et al. (2025).

## Compliance Score & Regression Model

- ▶ For each question  $k$ , the compliance score of the firm  $i$ ,  $CS^{i,k} \in [0, 1]$ , denotes the percentage of criteria (provided in the question's explanation) met on that specific question.
- ▶ For a multi-sectoral dataset of 240 firms, we solve

$$\Delta\%_{2018-21} GHG^i = \alpha + \beta_{CS} CS_{2016-18}^{i,k} + \beta_M M^i + \beta_X \Delta\%_{2018-21} X^i + \epsilon^i,$$

where for firm  $i$ ,  $CS_{2016-18}^{i,k}$  denotes the compliance score for the question  $k$  during 2016 and 2018;  $\Delta\%_{2018-21} GHG^i$  and  $\Delta\%_{2018-21} X^i$  denote the change rate in emissions and financial control variables during 2018-2021, respectively;  $M^i$  is the sectoral materiality variable denoting the transition materiality (SASB) and  $\epsilon^i$  the error term.

## Regression Results

- ▶ We find that the following questions have a significantly negative ( $***p < 0.1$  or less) impact on emission change in the last three reporting years:
  - ▶ metrics & targets disclosure area: the net-zero target's emission reductions (Q2:  $-0.79^{***}$ ), the net-zero target's alignment with orderly climate scenarios (Q5:  $-0.42^*$ ), the intermediate target's emission reductions (Q7:  $-0.4^{***}$ ) and Scope 1 disclosure (Q11:  $-0.14^*$ ),
  - ▶ governance disclosure area: the presence of the shareholder feedback mechanism for emission reduction targets (Q18:  $-0.69^*$ ),
  - ▶ strategy disclosure area: the disclosure on the strategy to move away from fossil-fuel-related assets (Q27:  $-0.43^{**}$ ),
  - ▶ risks & opportunities disclosure area: the usage of climate scenarios during the internal risk assessment (Q31:  $-0.52^{***}$ ).

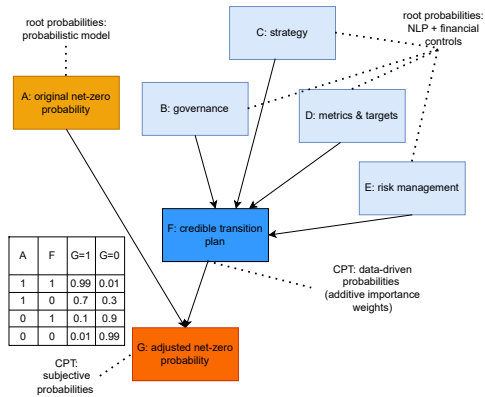
## Importance Scores

- ▶ We perform the ridge regression with selected penalization, where the highly collinear predictors are penalized to reduce the variance and increase the predictive power of the model. We minimize for  $\beta_{CS}, \beta_M, \beta_C$

$$\|\Delta\%_{[t_0, t_0+s]} GHG - \beta_{CS} CS_{2016-18} - \beta_M M - \beta_C \Delta\%_{2016-18} X_c\|_2^2 + \lambda \|\beta_{CS}\|_2^2, \quad t_0 \in \{2018, 2019\}, s = 1, 2, 3$$

- ▶ As a result, we obtain ridge weights (coefficients) which we normalize to obtain the "importance" weights for TCFD's four key climate-related disclosure areas: metrics & targets (Q2: 0.06, Q7: 0.07, Q11: 0.23), governance (Q18: 0.09), strategy (Q20 (alignment of financial flows): 0.11, Q27: 0.18), risk management (Q31: 0.26).

# The Bayesian Net



**Figure:** The Bayesian Net Modelling Conditional Dependencies Between "Transition Efforts Aligned", "Past Transition Efforts Aligned" and "Credible Transition Plan" with its Key Pillars.

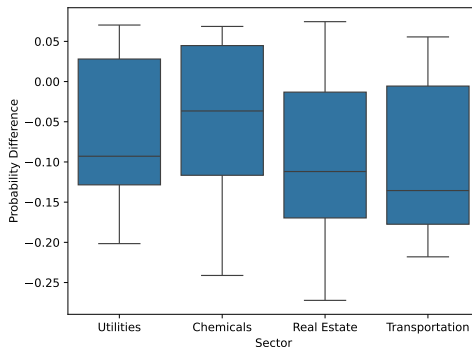
## Individual Analysis

firm	govern- ance	strategy	metrics & tar- gets	risk man- agement	$\Delta p$
Verbund	0.2	0.6	0.57	0.8	0.88 → 0.78
Meridian Energy	0.3	0.3	0.82	0.6	0.1 → 0.14

**Table:** Combined compliance scores for the climate-related disclosure areas of governance, strategy, metrics & targets and risk management as well as original and adjusted probabilities of two utility firms Verbund AG and Meridian Energy Ltd.



## Probability Difference

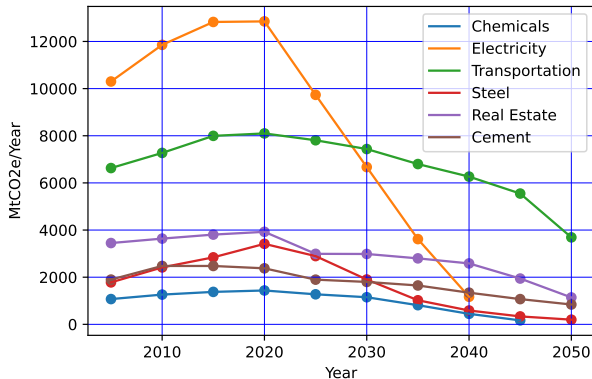


**Figure:** The difference between the original probability of staying below the net-zero budget and adjusted probability resulting from the Bayesian net.

## References II

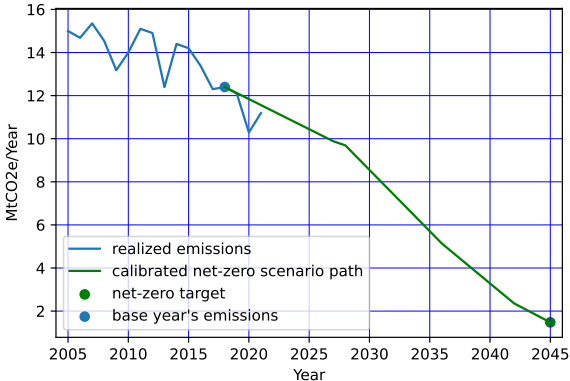
- ▶ Chekriy, K., Kiesel, R., 2025. Incorporating Forward-Looking Data in Probabilistic Analysis of Net-Zero Commitments. HECF Working Paper.
- ▶ Colesanti Senni, C., Schimanski, T., Bingler, J., Ni, J., Leippold, M., 2024. Combining AI and Domain Expertise to Assess Corporate Climate Transition Disclosures. Swiss Finance Institute Research Paper No. 24-92.
- ▶ Mankour, R., Chafai, Y., Saleh, H., Hassine, G. B., Barreau, T., Tankov, P., 2025. Climate Finance Bench.
- ▶ TCFD, 2017. Recommendations of the Task Force on Climate-Related Financial Disclosures.
- ▶ CDP, 2023. Are Companies Developing Credible Climate Transition Plans? Disclosure to key climate transition-focused indicators in CDP's 2022 Climate Change Questionnaire.

## Scenario Calibration



**Figure:** NGFS Scenarios for Different Sectors (GCAM 5.3+ Model).  
Source: NGFS IIASA Scenario Explorer.

# Scenario Calibration



**Figure:** Historical Scope 1 and Scope 2 Emissions of a Chemical Company and a Calibrated Net-Zero Scenario.

## Firm's Emissions

- ▶ Le Guendal et al., 2022, propose the following discrete and deterministic representation of carbon emissions

$$\mathcal{CE}_t = \mathcal{CE}_0(1 - \Delta R)^t = \mathcal{CE}_0 \exp(\log(1 - \Delta R) t),$$

where  $0 < \Delta R < 1$  is a constant emission reduction rate.

- ▶ We extend this representation by adding a stochastic component to it, making it time-continuous and assuming a non-constant annual emission reduction rate.

## Firm's Emissions

- ▶ We assume that the carbon emission dynamics satisfy the following SDE over the transition period  $[0, T]$

$$\frac{de_t}{e_t} = \mu_t dt + \sigma dW_t, \quad (1)$$

where  $\mu_t := \log(1 - \Delta R_t)$  denotes the drift,  $0 < \Delta R_t < 1$  are emission reduction rates corresponding to the calibrated net-zero emissions pathway,  $\sigma > 0$  is the volatility of historical emission reduction rates and  $W_t$  is a Brownian motion.

- ▶ The solution to (1) gives the carbon emission process

$$e_t = e_0 \exp \left[ \int_0^t \mu_s ds - \frac{\sigma^2}{2} t + \sigma W_t \right]. \quad (2)$$

## Firm's Cumulative Emissions

- ▶ We compute firm's cumulative emissions by

$$ce(0, t) = \int_0^t e(s) ds. \quad (3)$$

- ▶ Cumulative emissions in (3) can be approximated using Monte Carlo integration, analytical approximations or numerical methods.
- ▶ Given the cumulative emissions value  $\tilde{ce}_s$  over  $[0, s]$ , we compute the probability of staying below the amount of carbon budget

$$\mathbb{P} \left( ce(s, T) \leq b_T^{\text{NZ}} - \tilde{ce}_s \right), \quad (4)$$

where  $b_T^{\text{NZ}}$  is the calibrated net-zero carbon budget.

# Simulated Carbon Emissions and Probabilities of Reaching Net-Zero Emissions



# Simulated Carbon Budget and Probabilities of Staying below the Net-Zero Budget

# Retrieval Procedure

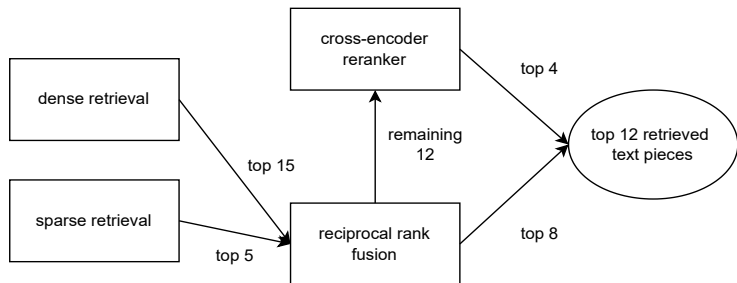


Figure: Hybrid retrieval pipeline.

## Hybrid RAG

- ▶ Dense retrieval retrieves semantically similar passages.
- ▶ Sparse retrieval retrieves based on exact matches (tf-idf; keywords-based).
- ▶ Using dense and sparse retrieval to find  $M > k$  top matches maximizes recall (completeness of the retrieval).
- ▶ Finally, we perform reranking using a cross-encoder reranker who rescores candidates with fine detail, from which  $k$  candidates might be selected.
- ▶ The retrieved data and the query are jointly encoded. The cross-encoder provides a score indicating how related the retrieved data and the question are, which maximizes precision (accuracy of the retrieval).

## Minimal vs. Hybrid RAG for GPT-4o

- ▶ Correct answers: 48% -> 56%.
- ▶ Incorrect answers: 42% -> 32%.
- ▶ Incomplete answers: 10% -> 12%.
- ▶ See the analysis by Mankour et al. (2025).

## Prompt

The prompt provides

- ▶ the role the AI takes on;
- ▶ basic data on the company;
- ▶ **k** retrieved text pieces for the question at hand;
- ▶ the question at hand with an explanation;
- ▶ instructions that involve output format, scoring idea and maximum answer length;
- ▶ examples of the output.

## Question and Explanation

- ▶ Question: Does a company have a net-zero emission reduction target?
- ▶ Explanation: A net-zero emission reduction target aims to reduce GHG emissions of Scope 1, Scope 2 and Scope 3 emissions categories to almost zero. The target refers to absolute GHG emissions. Scope 1 and Scope 2 emissions should be completely included in the target. Material Scope 3 emissions are included in the target...

## Output

- ▶ "Answer": "YES",
- ▶ "Score": 0.7,
- ▶ "Explanation": "The company has a net-zero target for Scope 1 and Scope 2 relating to GHG emissions (DOCUMENT x, PAGE 64). The company also considers Scope 3 emissions, but it is not clear which categories of Scope 3 emissions are included (DOCUMENT x, PAGE 64, PAGE 65). The target year is 2050, the targeted emission reduction is 90% (DOCUMENT y, PAGE 65, DOCUMENT z, PAGE 47). The firm does not provide the base year."

## Demonstration & Prediction Models

► Demo model:

$$\Delta\%_{2018-21} GHG^i = \alpha + \beta_{CS} CS_{2016-18}^{i,k} + \beta_M M^i + \beta_X \Delta\%_{2018-21} X^i + \epsilon^i,$$

► Prediction model ( $t_0 \in \{2018, 2019\}$ ,  $s = 1, 2, 3$ ):

$$\Delta\%_{t_0, t_0+s} GHG^i = \alpha + \beta_{CS} CS_{2016-18}^{i,j,k} + \beta_M M^i + \beta_X \Delta\%_{2016-18} X^i + \epsilon^i,$$

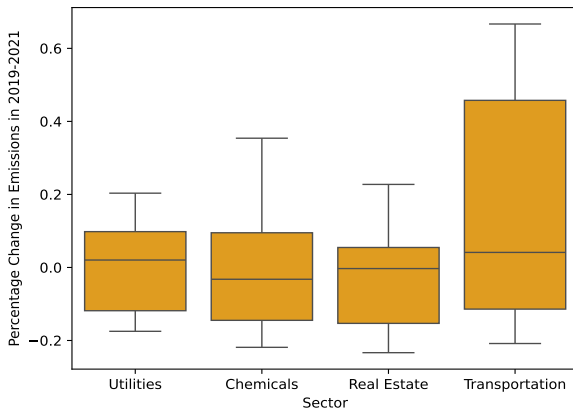


## Predictive Performance

$[t_0, t_0 + s]$	singe CSs' OLS	multicollinear OLS	ridge OLS
2018-2019	0.22	0.23	0.2
2018-2020	0.31	0.32	0.27
2018-2021	0.49	0.5	0.32
2019-2020	0.12	0.13	0.11
<b>2019-2021</b>	0.2	0.2	0.18
2019-2022	0.43	0.44	0.38

**Table:** Cross-validated RSME values considered for percentage change in independent variable (ranging from zero to one) for different statistical models and time periods. The compliance scores were computed during 2016-2018 for selected significant questions. The percentage change in control variables was computed during 2016 and 2018.

## Sectoral Emissions



**Figure:** Emissions percentage change for different sectors during 2019-2021.