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Climate Transition Risk Metrics: Understanding Convergence and Divergence across Firms and Providers

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Abstract

Climate risks are now fully recognized as financial risks by asset managers, investors, central banks, and financial supervisors. Against this background, a rapidly growing number of market participants and financial authorities are exploring which metrics to use to capture climate risks, as well as to what extent the use of different metrics delivers heterogeneous results. To shed a light on these questions, we analyse a sample of 69 transition risk metrics delivered by 9 different climate transition risk providers and covering the 1,500 firms of the MSCI World index. Our findings show that convergence between metrics is significantly higher for the firms most exposed to transition risk. We also show that metrics with similar scenarios (i.e. horizon, temperature target and transition paths) tend to deliver more coherent risk assessments. Turning to the variables that might drive the outcome of the risk assessment, we find evidence that variables on metric's assumptions and scenario's characteristics are associated with changes in the estimated firms' transition risk. Our findings bear important implications for policy making and research. First, climate transition risk metrics, if applied by the majority of financial market participants in their risk assessment, might translate into relatively coherent market pricing signals for least and most exposed firms. Second, it would help the correct interpretation of metrics in financial markets if supervisory authorities defined a joint baseline approach to ensure basic comparability of disclosed metrics, and asked for detailed assumption documentations alongside the metrics. Third, researchers should start to justify the use of the specific climate risk metrics and interpret their findings in the light of the metric assumptions.

Keywords: financial climate risks, corporate finance, climate risk metrics, climate transition risk, spearman's rank correlation, hierarchical cluster analysis, Ward's minimum variance criterion, Lasso regression analysis

JEL Classification: C83, D53, D81, G12, G32, Q54

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1 Introduction

Risk assessments are at the cornerstone of financial decisions. It is now widely agreed in the scientific literature that climate risks could materialise into financial gains and losses and, as such, are also financial risks (Caldecott et al., 2016; Gros et al., 2016; Battiston et al., 2017; Stolbova et al., 2018; Roncoroni et al., 2019; Bretschger and Karydas, 2019). This fact is also recognised by financial market actors and supervisors (NGFS, 2018; BCBS, 2020; Bolton et al., 2020). There is however less agreement on how to measure and value climate financial risks. Traditional approaches, based on historical data and the associated fitted distributions to identify expected values and extreme losses or gains, are not well-suited for the type of risk associated with climate change and the transition to a low-carbon economy. Non-linearity, non-stationarity, path-dependencies and endogeneity render the assessment of these risks difficult (Weitzman, 2011; Chenet et al., 2019; Battiston et al., 2019; Karydas and Xepapadeas, 2019). Various actors have therefore started to set up forward-looking approaches to assess climate-related physical and transition risks - in most cases by aid of scenario analysis.

Yet, as shown in Bingler and Colesanti Senni (2020), the specific setup of such approaches could differ substantially. Whilst this does not come at a surprise, given that a variety of approaches is required to accommodate the various beliefs and expectations about possible future developments, a high degree of divergence of climate risk metrics might hamper markets to reflect climate risks in pricing signals. In addition, financial supervisors are increasingly asking their supervised financial institutions to report on their climate risk assessment and management approach. At the same time, there exists some uncertainty on which climate risk metrics to ask for. Supervisors and financial institutions need to properly understand what a specific metric actually means, in order select the metrics required, and to understand the risk exposure and adequateness of potential risk mitigation approaches. Yet, research finds that firms tend to disclose rather favorable information Kim and Lyon (2015); Marquis et al. (2016). This suggests that there might be an incentive for firms to pick those climate-related metrics, which make them look less climate risky, which might yield to asymmetric information issues in financial markets (Fabrizio and Kim, 2019; Bingler et al., 2021a).

It has been shown that environmental, social and governance (ESG) criteria could vary considerably across metric providers, for the same firm (Berg et al., 2019). This does not come at a surprise, given that for ESG metrics, various indicators are aggregated into one final score. Climate risk analyses cover a very specific element of environment-related risks. Still, various approaches with differing output metric, depth of risk analysis, underlying scenarios and modelling assumptions might yield very different values. We have shown in previous research that a considerable degree of divergence exists across various providers of transition risk metrics - but at the same time, analyses tend to agree on the most and least exposed firms (Bingler et al., 2021b). Focusing on physical risk metrics, Hain et al. (2021) find considerable divergence across six different measurement approaches, too. Given the deep uncertainty around climate risks, this divergence is not avoidable, and per se not an issue, as long as the key drivers of risk are properly understood.

Such understanding is not only key for investors and supervisors, who use the metrics in practice. It is also a very important component currently overlooked in research. To date, academic research on climate risks and asset pricing find a considerable degree of divergence on whether risks are actually priced in or not, and whether this is done sufficiently or not (Gros et al., 2016; Campiglio et al., 2019; Hong et al., 2019). Whilst the various asset classes and maturities are one reason for the diverging academic results, the studies barely relate their result to the climate risk indicator they use. With the present analysis, we aim to foster the notion that the selection process for climate risk metrics both in research and practice should be an explicitly documented choice, reflecting the users' beliefs and appropriateness of a specific metric for a specific analysis.

In order to enable a more explicit selection process, this study has two aims. Overall, we focus on climate transition risk metrics. First, we replicate the Bingler et al. (2021b) study, this time with a considerably larger sample of 1,500 firms of the MSCI World index, and with 69 climate risk metrics from 9 different providers. In this first part of the analysis, we analyse whether our findings from the previous report also hold for the larger global sample, namely: (1) Do climate risk metrics currently available give similar pictures of a firm's exposure to transition risks (i.e. do all available metrics identify the same firms as being the most exposed to climate risks?), and (2) Do we see a higher convergence in assessment when providers rely on similar methodologies? In a second step, we assess which scenario and modelling choices affect the outcome of the climate risk assessment. We assess the association of the temperature target, the time horizon, the output type, consideration of firm-specific climate targets and capex plans, and the overall model approach with the magnitude of the associated risk across firms and providers. In addition, we conduct within-tool analyses for those providers where we have various scenario and model specifications available.

Our results confirm the early findings of Bingler et al. (2021b), that is: 1) climate risk metrics display a significant degree of diversity, which reflects the complexity of assessing climate risks, as well as the different methodologies and data underpinning these metrics, and 2) risk assessments across metrics tend to converge on which firms are most exposed to transition risks. In addition, our results show that the hypothesis underlying metrics affect the coherence between two metrics from different providers: metrics sharing similar horizons, temperature targets and hypotheses about the shape of the transition (i.e. orderly vs disorderly) tend to have a higher degree of convergence than when they diverge in these dimensions.

With regards to drivers of the risk output, we find evidence that both metric's assumptions and scenario's characteristics are associated with changes in the estimated firms' transition risk. Our across-tools analysis shows that the individual model choice variables are in most cases strongly statistically significant. The model output, the model approach and the consideration of climate targets vary in their significance and relative strength, but firms' capex plans are across all model specifications strongly statistically significant and associated with the highest coefficient estimated, showing a positive correlation. This does not only hold for the average effect, i.e. on the estimated mean of the risk magnitude (considering capex is associated with higher risk estimates on average), but also with a statistically significant reduction of the standard deviation and the skewness, and a statistically significant increase in the kurtosis of the distribution of the risk assessments. When it comes to the within-tool analysis, we see, that the temperature target and the time horizon specifications are statistically highly significant. The estimated magnitude of their effect on the final output is, however, relatively small, compared to the other model choice variables.

Our findings bear important implications for policy makers and researchers. Whilst climate transition risk rankings tend to converge for most and least exposed firms, users of those metrics should still put efforts into properly understanding the climate risk metrics in use for disclosures and analysis. Given that climate transition risk rankings tend to converge for most and least exposed firms, the metrics are expected to translate into financial market price signals if applied by many actors. When asking for climate risk disclosures, financial supervisory authorities should define a joint baseline approach to ensure basic comparability of disclosed metrics, and should ask for detailed assumption documentations alongside the metrics to enable third party users to better understand the results. Finally, researchers should start to justify the use of the specific climate risk metrics and interpret their findings in the light of the metric assumptions. This might help to better understand the various results on existing and future research, for example on the issue whether markets price-in climate risks in asset prices.

The remainder of this paper is structured as follows: In section 2, we first describe the data used and the methodological approach adopted in this study. In section 3, we report the main findings concerning the convergence and divergence of climate risk metrics, whereas in section 4 we look at the association between risk exposure and tool's characteristics, both across- and the within-metrics. Our conclusions are summarized in section 5, where we also highlight key areas for future research, and implications for asset managers, investors, central banks and financial supervisors.

2 Data

In the present study, we focus on the sample of companies included in the MSCI World Index as of 31 January 2020. Moreover, we consider forward-looking climate risk metrics, assessing the transition risk at the individual firm level. One of the metric included is an alignment metric, whose can be used understand as a proxy for risk by means of gap analysis.

It is important to broadly understand the structure of these metrics. Most forward-looking climate transition risk tools employ various building blocks, such as climate transition scenarios, firm-level economic impact analysis, and financial impact analysis. Figure 1 provides a generic example to illustrate the structure of most financial climate transition risk tools, which are often used to transform status quo data into scenario analysis-based forward-looking exposure and/or risk data. A variety of assumptions and modeling choices are usually being made, before a final climate risk output metric is produced. A detailed overview over most important modelling choices can be found in Bingler and Colesanti Senni (2020).

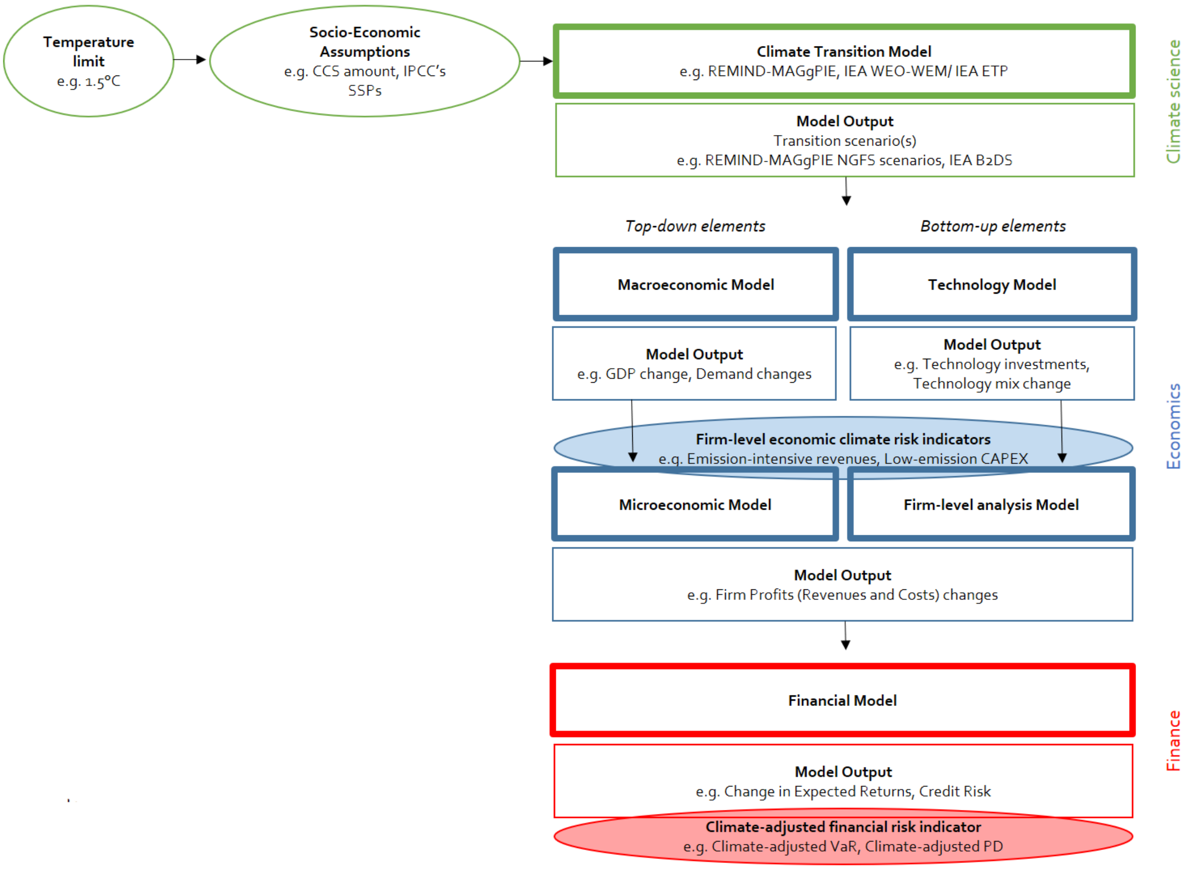

Figure 1: Example structure for a generic climate transition risk tool: deterministic approach, no feedback- and second-round effects.

Table 1: Data provider

Provider	Type	Tool name	Metric name	Output type
2 Degrees Investing Initiative & Asset Resolution	Think tank	PACTA		alignment gap
ClimateWise from CISL	Academia	Transition risk framework	Transition risk exposure matrix	risk score
Entelligent	Financial services	Smart Climate Technology	E-Score	risk score
ESG+	Financial services			risk score
ISS ESG	Financial services	Portfolio Climate Impact	Carbon risk rating Climate VaR Climate margin	risk score financial metric financial metric
Moody's Corporation	Financial services			financial metric
MSCI ESG Research	Financial services		Climate VaR Warming potential	financial metric alignment gap
PWC / The CO-Firm	Financial Services	Climate Excellence	EBITDA change	balance sheet effect
right. based on science	Think tank	XDC model		alignment gap
S&P Global Market Intelligence	Financial Services	S&P Global Corporate Sustainability Assessment (CSA)	Climate strategy metric	risk score
Sustainaccount	Financial Services	ESG Enterprise Suite		balance sheet effect
University of Augsburg	Academia	Carima	Carbon beta	risk score
Planetrics	Think tank	Climate Risk Metric Toolkit	Profit impairment	financial metric alignment gap
Zero-carbon 2030				risk score

2.1 Sampling procedure

We contacted 25 providers of climate risk data, and asked them to provide us with their climate transition risk assessments for our company sample. Several providers delivered forward-looking climate transition risk data for various temperature targets, time horizons and assumptions about the transition path. Eventually, 22 providers replied, and eventually, 14 agreed to participate in this study. The overview of the tool providers is displayed in table 1. In addition, we asked each provider to fill-in a detailed questionnaire on the key assumptions and drivers of their metrics. This served to ensure that we get a comparable sample of risk data, and to collect the values for the variables we were interested in for the regression analyses. The values of each variable by provider have been cross-checked manually, and in case there was any inconsistency or some irregularities, we contacted the data provider and asked for clarification. In addition, providers could voluntarily fill-in a second questionnaire on the general approach of their tool, describing their methodology more in-depth. For those providers who filled-in this form, the information is displayed in the Appendix.

After removing duplicates, we restricted our analysis sample to 69 metrics from 9 providers, who fulfilled the following criteria: (1) the metrics provided aggregate information on climate risks at firm level (i.e. no stand-alone status quo indicators like CO_2-emissions), and (2) data were provided for more than half of the firms in the sample.[1]

These final providers share the following common basic characteristics: If applying scenario analysis, the scenarios all assume a certain amount of CO_2 removal, usually via negative emission technologies and/or natural sinks. In addition, the tools share the following characteristics: (1) the underlying unit of analysis (i.e. firm-level, instead of sector-based approaches), (2) the regional disaggregation (i.e. country- or region-specific, instead of a generalised global approach), (3) the emission scope considered (i.e. scope 1, 2 and 3, instead of just scope 1

[1] We aim to conduct another follow-up study with a slightly adapted focus to make use of the data which we unfortunately could not use for the present study.

and 2), and (4) the emission data source (i.e. a combination of self-reported and in-house data estimates).

Based on these joint specifications, we selected a set of variables that are likely to exert an influence on the final risk value. These variables have been identified by aid of a two-phased approach: First, we identified most important drivers of climate risks as identified in a previous conceptual paper, where we analysed a sample of 16 climate risk tools based on various criteria and characteristics (Bingler and Colesanti Senni, 2020). We assembled these drivers and cross-checked individually with each of our sample tool providers whether they would agree that these variables were the main drivers of their model results, or whether we were missing out on some aspects. This enabled us to set up a final set of variables with the following core variables: the temperature target, the time horizon of the analysis, the type of tool output, the inclusion of firms targets and CAPEX plans in the analysis, and the overall approach of the tool. We gathered the variable data for each of the individual risk assessments by aid of a questionnaire sent out to the tool providers, where they then provided us with the value for each variable for the data they provided for the present analysis. The explanatory variables enable us to identify most important drivers of the results, based on various scenario- and tool specifications.

2.2 Sample

Our final analysis sample consists of 105466 observations. The dataset is composed of the assessments from 69 different climate transition risk metrics, from 9 different climate risk data providers, for the 1565 MSCI World index constituents as of 31 January 2021. In the following analysis, we will, when this helps the exposition, focus on a subsample of metrics, which were selected based on having a 2°C temperature target and a time horizon of 2050.[2] In addition, the dataset contains the selected additional variables on the various tool and scenario specifications, by climate transition risk metric. These are the following:

Scenario-specific variables: (1) Temperature target in degrees Celsius, a categorical variable, with the 5 categories '1.5°C', 'below 2°C', '2°C', '3°C', 'not applicable' (i.e. not an input in the tool's assessment approach). (2) Horizon of the analysis,[3] a categorical variable, with the 6 categories '2025', '2030', '2040', '2050', '2100', 'not applicable' (i.e. not an input in the tool's assessment approach).

Provider-specific variables: (1) Output type, a categorical variable, with the 4 categories 'Balance sheet metric'[4], 'Financial asset metric'[5], 'Alignment gap', 'Risk score'. (2) Individual dummies for the inclusion of (a) Firm climate target, and (b) CAPEX in the tool methodology. (3) Model approach, a categorical variable with the 3 categories 'Top-down', 'Bottom-up', and 'Combined' (of top-down and bottom-up).

[2]The choice of this subsample is based on the fact that we could identify several tools providing this specification, so that the subsample is still representative while facilitating the exposition.

[3]Note that this is not the horizon of the scenario. For example, a tool might employ a scenario that runs until 2100, but the horizon of the analysis is for example the risk in 2030 or in 2050.

[4]Assessing the effect of a scenario outcome on the cost and return structure of a specific firm.

[5]Assessing the effect of a scenario outcome on the value of a financial asset (bond, equity etc) and/or a portfolio of financial assets.

Table 2: Convergence within providers - Regression analysis

	Without fixed-effect		*With fixed-effect*	
	Absolute Distance	Agreement Rate	Absolute Distance	Agreement rate
Intercept	1.45***	0.245***	1.45***	0.245***
Same Provider	−1.07***	0.478***		
Provider A			−1.35***	0.655***
Provider B			−0.88***	0.352***
Provider C			−0.77***	0.305***
Provider D			−1.34***	0.689***
Provider E			−1.12***	0.445***
Provider F			−0.94***	0.354***

*p<0.1; **p<0.05; ***p<0.01

3 Assessing convergence across risk metrics

To assess the convergence between metrics, for each metrics, we first rank the firms according to their estimated risk exposure. We then class them in five risk categories – from 1 for the least exposed firms to 5 for the most exposed firms. To assess the degree of convergence between to metrics, we use to indicators:

1. The average difference for a firm risk category between the two metrics, ("Absolute distance"). The lower the Absolute distance, the higher the coherence between two metrics.

2. The percentage of firms with identical risk categories in the two metrics ("Agreement rate"). The higher the Agreement rate, the higher the convergence between two metrics.

3.1 Convergence within providers

Our findings indicate a high degree of coherence between the risk assessments delivered by the same provider. We observe however a significant degree of heterogeneity when the risk assessments are delivered by different providers. As shown in Table 2 (Specification without fixed-effect), the degree of coherence increases massively when two metrics are supplied by the same provider. This degree of coherence within metrics from a same providers however differs between providers: it is almost perfect for some and lower for others (see 2, Specification with fixed-effect). This suggests that, for some providers, the ranking of firms is not significantly influenced by the scenario, the horizon, and the transition path underlying the different metrics of the provider. For other providers, these dimensions have an impact on firms' ranking.

Our results also indicate that, when two metrics are delivered by two different providers, then a lower degree of coherence is observed between them. For example, our regression results in Table 3 show that the Agreement rate between two metrics stemming from two different providers is estimated to 25%, that is 20% more frequently than if the two metrics were perfectly heterogeneous. This results confirm the significant degree of heterogeneity in the risk assessments delivered by different providers that we observed in our previous similar study Bingler et al. (2021b). Here again, the heterogeneity in risk assessments that we find reflects the significant complexity and uncertainty in the analysis of climate risks.

Table 3: Drivers of coherence across provider - Regression analysis

	Absolute Distance	Agreement Rate
Intercept	1.56***	0.208***
Same Horizon	−0.02*	0.007**
Same Temperature	−0.07***	0.012***
Same Shape	−0.07***	0.018***
Same Output	−0.01	0.015***

*p<0.1; **p<0.05; ***p<0.01

Our results show that metrics sharing similar scenario characteristics, have similar horizon, temperature target and hypotheses on the shape of the transition improves the coherence between metrics both when measured with the Absolute Distance and the Agreement rate. The evidence on the type of output is less univocal: sharing the same type of output increase coherence when measured with the Agreement Rate but not with the Absolute distance. Note, however, that, although statistically significant, the impact of similar hypothesis only moderately improves the coherence between two metrics: the level of heterogeneity between them remains relatively important even when two metrics are based on similar hypotheses.

3.2 Convergence across providers

We now turn to the drivers of the coherence between two metrics from different providers. More specifically, we explore whether the characteristics of the scenarios underlying each provider's methodology impact the coherence between two metrics. For that we assess whether the coherence between two metrics increases when they are based on similar hypotheses for the horizon of their assessments, for the temperature target that they consider and for the shape of the transition that they model.[6] Following the results of Bingler et al. (2021b) showing that the output that a metrics deliver might also matter for its coherence with other metrics, we also check whether metrics based on similar output display a higher convergence. We distinguish between two groups of output: financial indicators (e.g. future earnings, value-at-risk, stock price change) and other indicators (e.g. risk score, alignment measure). The results are presented in Table 3.

3.3 Convergence on high-exposed firms

Finally, we confirm another important result of Bingler et al. (2021b), that is that metrics from different provider tend to converge more for firms that are the most exposed to transition risk. For that, we estimate the excess frequency of observing a combination of assessments for the same firm in our sample compared to the frequency that would occur if assessment were fully heterogeneous. To reflect the fact that characteristics of metrics might impact the coherence between (see previous section), we only compare only the pairs of assessment for metrics that have similar horizon, temperature targets, hypotheses on the shape of the transition and output indicators. The results are presented in Figure 2.

[6] Concretely, we divide metrics between those with an assessment horizon between 2025 and 2040, and those with a longer horizon, between the metrics with a temperature target of 2°C or below and those above 2°C, and those that models an orderly or a disorderly transition.

(a) Difference in pairs

0	30
1	6
2	-8
3	-27
4	-20

(b) Per quintile pairs

Highest quintile	1	2	3	4	5
1	6				
2	-6	13			
3	-2	40	34		
4	-11	22	3	-8	
5	-20	-42	-45	-15	105

Lowest quintile

Figure 2: Excess frequency of observed risk assessments pairs vs. independent metrics (in %)

4 Understanding the drivers of risk assessments

4.1 Data preprocessing for the regression analysis

The assessments produced by the different metric providers are expressed in different units and scales, which makes comparison difficult. To overcome this issue, we rescale the risk assessments according to

$$y^*_{i,j} = \frac{y_{i,j} - min_i(y_{i,j})}{max_i(y_{i,j}) - min_i(y_{i,j})}$$

where i denotes the firm and j the provider. The rescaling produces a new vector of assessments for each specification from the different providers, with values ranging between 0 and 1. Clearly, this rescaling technique implies that, within and across providers, we loose information about trends in risk assessments. For instance, if a provider assesses all the companies as very risk expose within an interval of low riskiness and another assesses most of the companies as low risk exposed but within a larger interval of riskiness, companies assessed by the first provider will automatically appear as more risk exposed.

4.2 Descriptive statistics and sample visualisations

The companies in our sample can be grouped 11 different sectors (Consumer Discretionary, Industrials, Information Technology, Financials, Materials, Consumer Staples, Health Care, Energy, Real Estate, Utilities and Communication Services) according to the GICS classification plus a residual category (Other). Accordingly, Figure 3 summarizes the distribution of the normalized risk assessments in our sample by sector. The figure shows that the risk distribution in the Energy sector is significantly higher compared to the other sectors. A similar conclusion, although the difference is not significant for all the sectors, can be drawn for the Materials and Utilities sectors.[7] This implies that, across the metrics included, companies in these three sectors are assessed as more risk exposed.

[7]We use the Wilcoxon test to check whether the median value of one sector is significantly larger than the one in the other sectors.

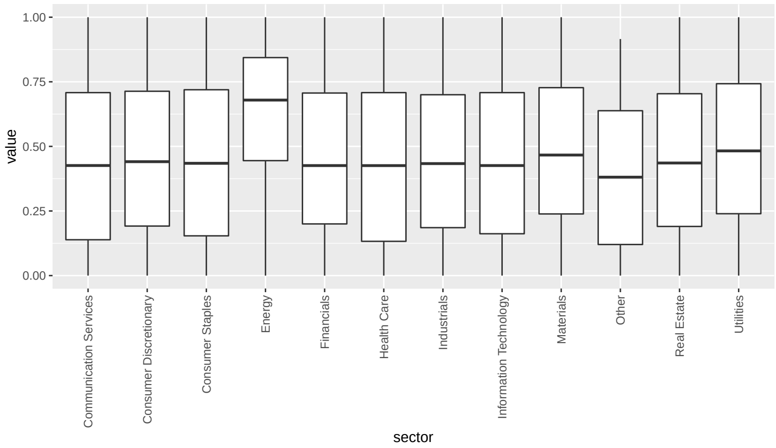

Figure 3: Boxplot of the risk metrics distribution by sectors

Table 4: Descriptive statistics of mean normalized risk values by sector

Sector	**Min**	**Mean**	**Max**	**Standard deviation**	**N firms**
Communication Services	0.31	0.39	0.50	0.04	92
Consumer Discretionary	0.30	0.41	0.64	0.06	169
Consumer Staples	0.26	0.41	0.62	0.06	116
Energy	0.43	0.58	0.77	0.08	51
Financials	0.30	0.39	0.72	0.05	228
Health Care	0.24	0.39	0.51	0.05	156
Industrials	0.20	0.38	0.61	0.06	244
Information Technology	0.26	0.38	0.49	0.05	182
Materials	0.33	0.46	0.75	0.08	120
Other	0.27	0.35	0.40	0.07	3
Real Estate	0.24	0.45	0.65	0.09	98
Utilities	0.21	0.45	0.62	0.10	84

In order to better understand the risk values by sector, we first computed the average assessment of a company across all providers and then computes its minimum, mean and maximum values by sector. Table 4 summarizes the results, together with the standard deviation and the number of observations in each sector. The table shows that the range of average risk values is relatively large across all sectors. The energy sector has the highest mean risk values (0.58), with a relatively high standard deviation (0.08), overcame only by the Real Estate (0.9) and Utilities sectors (0.1). The highest overall risk value is also observed in the Energy sector (0.77), closely followed by the Materials sector (0.75). The lowest standard deviation is observed in the Communication Services sector (0.04), which is also one of the sectors with the lowest average risk value (0.39). Yet, the range of assessments within each sector indicates that there is considerable variation across tools.

Figures 4 and 5 display pairwise scatterplots, individual distributions and pairwise correlation coefficients for our sub-sample of metrics (2°C temperature target, time horizon 2050). The scatterplots show that most metrics provide considerably different assessments for the same firms (each dot represents a pair of assessments for the same firm). Moreover, the correlation coefficients for most pairs are low, and sometimes even negative. A high pairwise agreement in the analyses exists if a diagonal pattern from the bottom-left to upper-right corner of the scatter plots can be seen or, equivalently, if the correlation coefficient is close to one. Such diagonal pattern can be seen for only three pairs of metrics (14-26, 34-42 and 69-73). For two of those

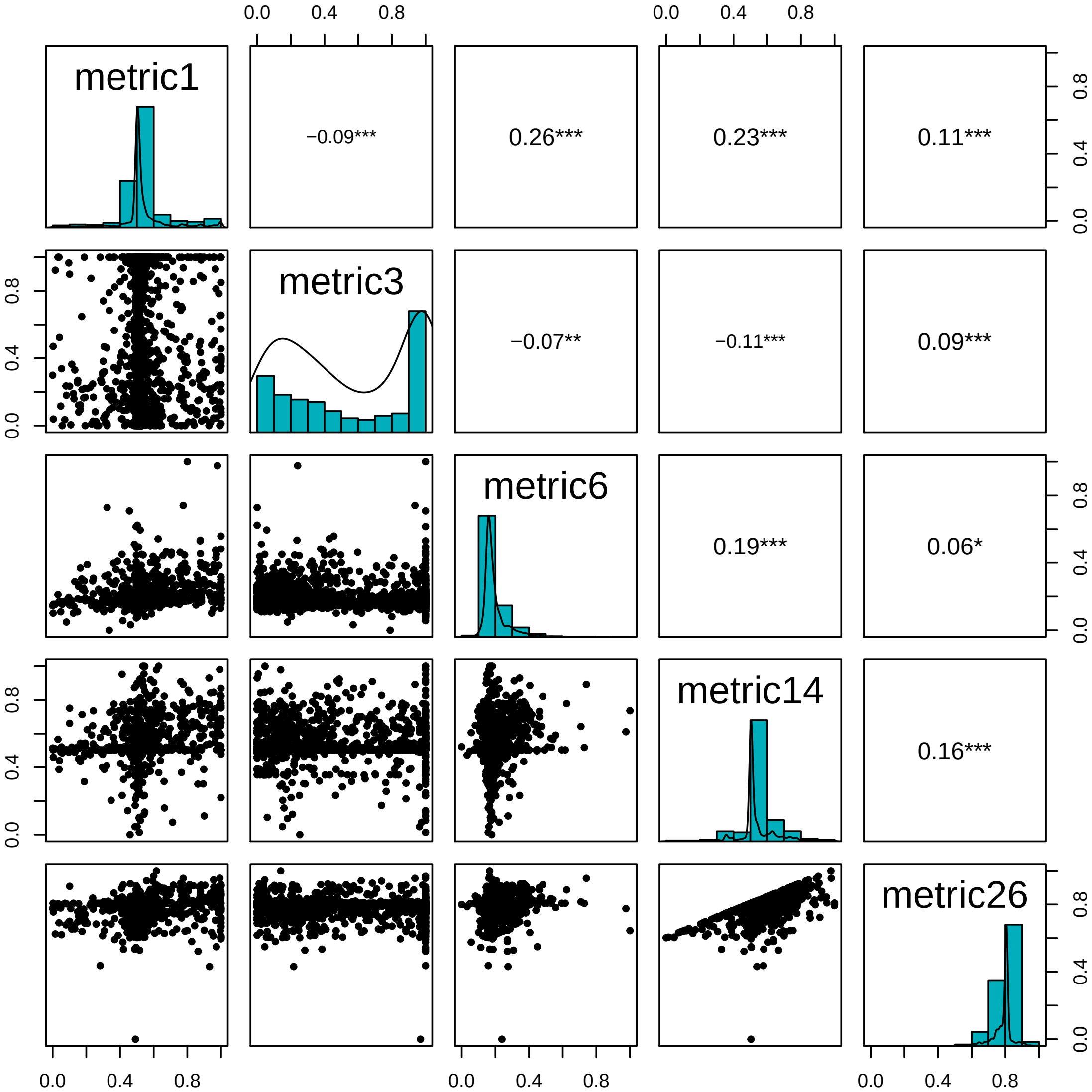

Figure 4: Scatterplots, individual distributions and pairwise correlation coefficients for metrics with 2°C temperature target and time horizon 2050, where *p<0.1, **p<0.05, and ***p<0.01 (1/2)

(34-42 and 69-73), this diagonal pattern is well-behaved from bottom-left to top-right of the plot, which is confirmed by the high correlation coefficients (0.98 and 0.96). For one diagonal pattern (Metrics 14-26), one set of metrics is structurally higher than the other one, which is reflected in the low correlation coefficient (0.16). The three pairs with diagonal patterns are metrics which come from the same providers, and are different only in the assumptions about the specific transition pathway (yet given the same temperature target and horizon). This provides additional hints that the metric providers' risk modelling approach might be an important driver of the results, in addition to the temperature target chosen and the time horizon of the analysis. A good understanding of the modelling approach underlying any metric is hence crucial in addition to understanding the scenario assumptions, in order to be able to correctly interpret the results of climate transition risk analyses.

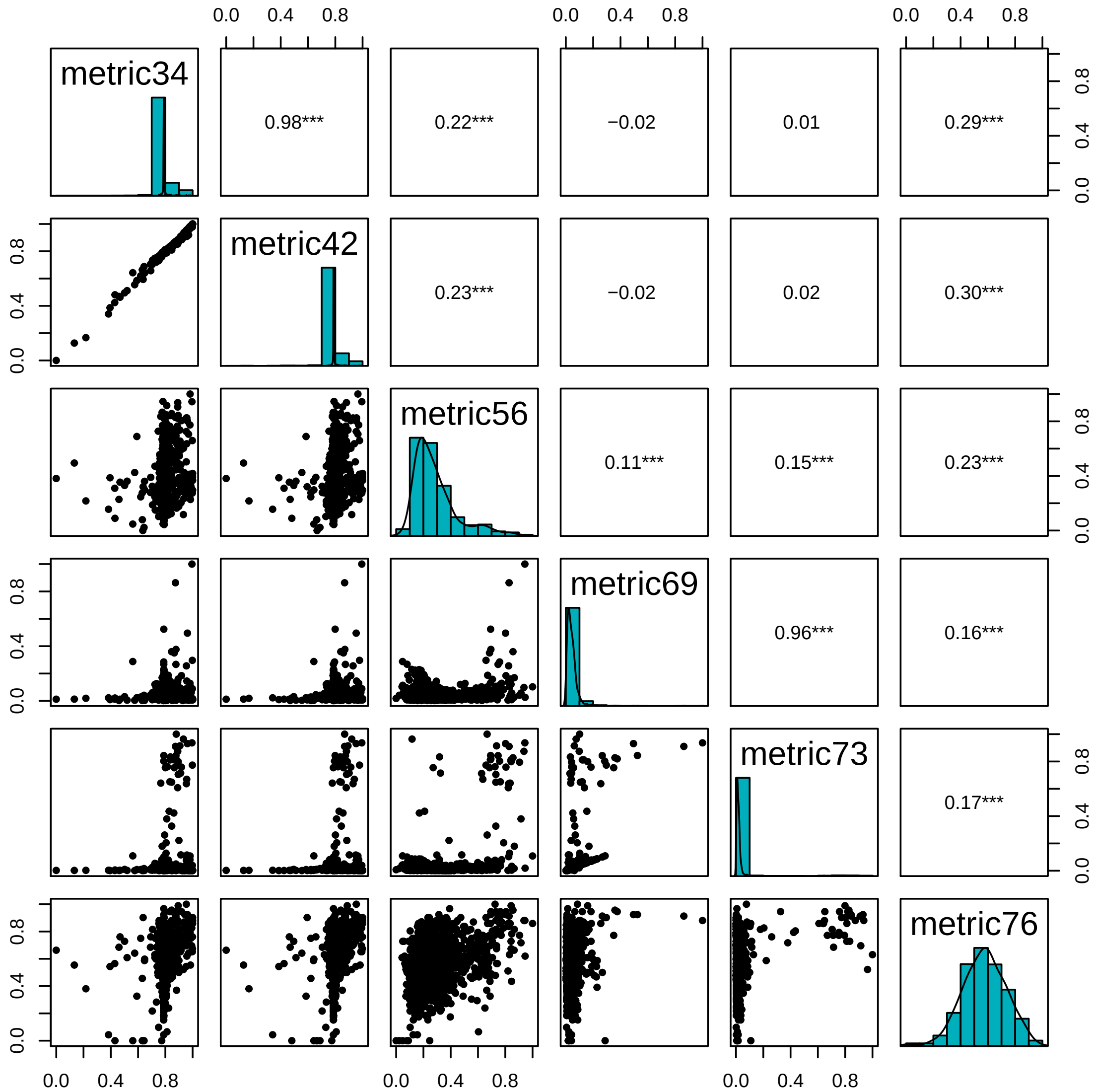

Figure 5: Scatterplots, individual distributions and pairwise correlation coefficients for metrics with 2°C temperature target and time horizon 2050, where *p<0.1, **p<0.05 and ***p<0.01 (2/2)

Table 5: Descriptive overview explanatory variables

Explanatory variable	Categories	Shares
Temperature target	1.5°C	0.12
	below 2°C	0.42
	2°C	0.2
	3°C	0.23
	na	0.29
Time horizon	2025	0.22
	2030	0.22
	2040	0.23
	2050	0.26
	2100	0.01
	na	0.01
Output type	balance sheet effect	0.52
	financial metric	0.35
	gap	0.03
	risk score	0.1
Firm targets	included	0.58
	not included	0.42
CAPEX plans	included	0.58
	not included	0.42
Approach	bottom-up	0.93
	combined	0.04
	top-down	0.03

The scatterplots in Figures 23 - 36 in Appendix A.3 provide additional information on the agreement of risk metrics for our sub-sample (2°C temperature target, time horizon 2050), differentiated by sector. We can see that the Energy sector (dark green dots) is associated with relatively higher risks. Whilst agreement for this sector seems to be higher than for other sectors for some pairs of tools, this pattern cannot be seen for other pairs.

In our analysis, we define six categorical variables which are then used in our regression analysis. For a descriptive variables overview, table 5 provides the shares of the different categories for each of the explanatory variables.

4.3 Robust panel OLS

In order to formally identify the main drivers of the divergence, we first use panel data regression analysis with heteroscedasticity- and cluster-robust standard errors. For reasons of simplicity, we will refer to this as "robust panel OLS´´ in the remainder of the paper. Note that in our case the panel dimension is given by the same firms being assessed across several providers rather than across time. In our specification, we include a constant to ensure that the model is unbiased, and firms fixed effects. Moreover, with the term *robust* we always refer to a robust to outliers regression.

To account for firms' fixed effects we use as dependent variable $\tilde{y}_{i,j} = y_{i,j} - \overline{y}_i$, where $\overline{y}_i = 1/P \sum_{j=1}^{P} y_{i,j}$ is the average exposure of firm $i = 1, \ldots, N_j$ across providers $j = 1, \ldots, P$. Hence, we can investigate which characteristics of the metrics are on average associated with deviation in risk assessments from the mean risk assessment of a specific firm across providers. In our specification, we also include a constant to ensure that the model is unbiased. Our benchmark OLS regression equation is thus

$$\tilde{y}_{i,j} = \beta_0 + \sum_{k=1}^{K} \beta_k z_j^k + \varepsilon_{i,j},$$

where i denotes the company, z_j^k is the k-th characteristic of provider j and K is the total number of characteristics considered.
For our OLS, we use a robust to outliers specification (robust OLS), which is done by iterated re-weighted least squares (IRLS). There are several weighting functions that can be used for IRLS. In our specification we use Huber weights. Moreover, we computed our model for heteroskedasticity- and cluster-robust standard errors, where the clustering is given by the provider. The results of our regression are reported in Table 6.

Our results show that changes in the temperature target are not statistically significant. We observe large uncertainty associated to the coefficients (large standard errors). Hence, we cannot infer that a higher temperature target, compared to the baseline (which is a 1.5°C temperature target), is associated with a lower risk assessment - despite the fact that the estimated coefficients are in line with our expectations (a higher temperature target makes the transition less stringent and hence reduces the risk). Moreover, all estimated temperature target coefficients (-0.129, -0.124, -0.149, 0.228) are lower than any other statistically significant estimated coefficient. Even if the estimators were statistically significant, the temperature target would unlikely be the main driver of the risk metrics.

With regards to the time horizon, the estimated coefficients again meet our expectations: Compared to the baseline, adopting a longer time horizon of analysis is associated with higher risks until 2050 (2030: 0.042, 2040: 0.109, 2050: 0.119). This is in line with the fact that most climate transition scenarios assume transition activities to start relatively slowly in the near future, ratcheting up ambition considerably until 2050, where the climate targets are then fulfilled. Yet, given that most of the coefficients are statistically non-significant, we cannot infer that a longer time horizon is statistically significantly associated with first a higher and later a lower risk, compared to the baseline horizon (2025). The exception is the time horizon 2040, which is statistically significant, but only at the 10% level. For the year 2100, the estimated coefficient (-0.060) suggests that such a long time horizon is associated with a lower risk, compared to 2025. This is likely due to the fact that all transition activities are assumed to be implemented by then at the latest, and that the risks in the very distant future have - albeit being very uncertain - less impact on today's economic and financial values than risks in the near future. However, the coefficient for 2100 is again not statistically significant at any of the standard significance levels. Specifying no time horizon compared to adopting the baseline horizon (2025), is associated with a decrease in risk (-0.4), with a coefficient being strongly statistically significant at the 1% level. Yet, this effect most likely captures the fact that metrics, which do not capture any time horizon, are structurally differently from metrics which do assess climate transition pathways over time. Hence, this effect might also capture modelling differences other than considering the time horizon itself.

In contrast to the temperature target and the time horizon, the types of output produced by the metric are statistically significant, with two estimates significant at the 1% confidence

Table 6: Robust OLS estimation with Huber weights and heteroskedasticity- and cluster-robust standard errors

	Dependent variable: Risk assessment
temp_target_b2	−0.129
	(0.199)
temp_target_2	−0.124
	(0.241)
temp_target_3	−0.149
	(0.176)
temp_target_na	0.228
	(0.215)
time_horizon_2030	0.042
	(0.032)
time_horizon_2040	0.109*
	(0.064)
time_horizon_2050	0.119
	(0.107)
time_horizon_2100	−0.060
	(0.109)
time_horizon_na	−0.400***
	(0.123)
output_finmetric	0.559*
	(0.315)
output_gap	0.578***
	(0.139)
output_riskscore	0.281***
	(0.057)
firm_target_1	0.303***
	(0.085)
capex_1	0.565***
	(0.089)
approach_comb	−0.322***
	(0.054)
approach_topdown	0.096
	(0.155)
Constant	−0.509**
	(0.222)

*p<0.1; **p<0.05; ***p<0.01

level. Holding everything else constant, if the output is a financial indicator, a gap or a risk score, the associated risk is higher than in the case in which the output metric captures balance sheet effects. This effect has a similar magnitude for financial metrics (0.559) and alignment gaps (0.578), and is a bit less pronounced for metrics which are risks scores (0.281). This finding suggests that the metrics' output type is an important driver of the metrics' risk assessments. In other words, the modelling approach adopted to end up with a specific output type is a key driver of the quantified risk exposure.

Considering individual firms' climate targets and CAPEX plans in the climate transition risk metrics quantification is associated with a higher risk, holding everything else constant. The variables are both statistically significant at the 1% level, and exhibit a strong quantitative effect with coefficients of 0.303 (target) and 0.565 (CAPEX). Both variables enable providers to move from standard risk exposure analysis, which is often just a rough approximation of risk, to a fundamentals-informed risk analysis. Intuitively, it is surprising that a firms' climate target is associated with higher risks. Transition-wise, setting a firm target should be associated with lower risks, since the firm would be better prepared for the transition. However, the climate targets are not necessarily enough to align with what would be required for a successful transition to align with climate policies. Hence, one reason for this result could be that analysts looking at the firm climate targets might consider them as, on average, not sufficient, and hence the transition risk would not be reduced by the sheer presence of a target. Additional research on the underlying reasons for this finding would be required. With regards to the CAPEX plans, the finding is in line with expectations: Today's CAPEX plans are rarely aligned with what would be required to achieve the climate targets. They currently tend to lock-in companies into carbon-intensive technologies. Considering this lock-in effect in the risk analysis intensifies the anticipated transition risks.

Finally, holding everything else constant, adopting a combined top-down and bottom-up approach compared to a bottom-up approach is associated with lower risk (-0.322). This coefficient is statistically significant at the 1% level. Adopting a top-down approach yields not necessarily to slightly higher risk levels, compared to a bottom-up approach, given that the coefficient (0.096) is relatively low and not statistically significant.

The above findings have to be interpreted with some caution. For those explanatory variables where we have few observations, their values might capture modelling features of the specific provider other than the variable itself. A solution would have been to include provider fixed effects. However, by construction, when running the regressions with provider dummies, all the variation in the explanatory variables would vanish. This analysis hence aims to encourage further in-depth studies to identify the main drivers of climate risk metrics when it comes to providers' detailed modelling approaches.

4.4 LASSO and reduced linear regression

In order to check how our model would perform in predicting the risk exposure of companies, we also apply a LASSO regression on our model. We then run robust OLS on the reduced model to deal with the issue of biased pure LASSO regression coefficients. For the sake of brevity, we will refer to this procedure as LASSO regression. In our specification, we include as before a constant to ensure that the model is unbiased, and firms fixed effects. Of the 16 dummified variables that we feed into the model, only 1 was dropped, namely `approach_bottomup`, meaning that the variables we choose before all have some important explanatory power, and that our model was not overspecified. As before, we use Huber weights and consider heteroskedasticity- and cluster-robust standard errors. The results are reported in Table 7.

Overall, we see that the LASSO regression estimates confirms the result obtained with the simple robust OLS regression in terms of coefficient signs, and for most cases also in terms of magnitude of the estimated effect. Yet, as would be expected, statistical significance of most coefficients is lower, except for the inclusion of CAPEX and the firm target variables.

The baseline temperature target is 1.5°C as before, so that higher temperature targets are associated with lower risk (-0.143, -0.124, -1.115), which is consistent with the full sample robust OLS estimation. As before, the estimated coefficients are not significant. Again, longer time horizons are associated with higher risk compared to the baseline 2025 until 2050 (0.042, 0.094, 0.087). Differently from before, the coefficients on time horizons 2030 and 2040 and statistically significant, at the 5% level. However, the magnitude of the estimated temperature coefficients and the estimate time horizon coefficients is still relatively low, compared to the further explanatory variables. A financial metric, gap or risk score output is associated with a higher risk compared to metrics capturing balance sheet effects, which is the same result as we obtained with the OLS regression. However, in contrast to the previous estimation, the coefficients are - except the financial metric with a low 10% confidence level - not statistically significant, and considerably lower than before. The sign and magnitudes on the inclusion of firm targets and CAPEX plans are also in line with the standard OLS results (0.203, 0.447), but only CAPEX plans inclusion is statistically significant at the 1% level. Finally, using a top-down instead of a bottom-up or combined approach is associated with lower risk (0.217). This variable is statistically highly significant at the 1% level.

The LASSO regression coefficients suggest that for out of sample understanding of key risk drivers, the time horizon, CAPEX considerations, and the approach seem to be important. The fact that the LASSO did not confirm the statistical significance of the output type, provides a hint that our intuition from the full sample linear regression from before might be reasonable. The output type variables might capture very specific analysis decisions and modelling approaches adopted by the metric provider, which we were not able to capture by the explanatory variables in the present analysis.

Table 7: LASSO-reduced OLS regression, with heteroskedasticity- and cluster-robust standard errors

	Dependent variable: Risk assessment
temp_target_b2	−0.143
	(0.150)
temp_target_2	−0.124
	(0.163)
temp_target_3	−0.115
	(0.150)
temp_target_na	0.198
	(0.181)
time_horizon_2030	0.042**
	(0.018)
time_horizon_2040	0.094**
	(0.039)
time_horizon_2050	0.087
	(0.055)
time_horizon_2100	−0.133
	(0.146)
time_horizon_na	−0.223
	(0.169)
output_finmetric	0.356*
	(0.202)
output_gap	0.193
	(0.148)
output_riskscore	0.082
	(0.088)
firm_target_1	0.203
	(0.137)
capex_1	0.447***
	(0.109)
approach_comb	— — —
approach_topdown	0.217***
	(0.076)
Constant	−0.352*
	(0.202)

*p<0.1; **p<0.05; ***p<0.01
— indicates variable has been dropped by LASSO

Table 8: Robust OLS regressions within tool, with heteroskedasticity-robust standard errors

	Dependent variable: risk assessment				
	Metrics 5-6	Metrics 7-30	Metrics 31-46	Metrics 53-64	Metrics 66-73
temp_baseline	2°C	2°C	1.5°C	1.5°C	NA
temp_target_b2	0.006***	0.004***		−0.021***	
	(0.002)	(0.0003)		(0.001)	
temp_target_2			−0.001***	−0.026***	
			(0.0003)	(0.001)	
temp_target_3		−0.002***	−0.003***		
		(0.0003)	(0.0005)		
time_horizon_2030		−0.001*	0.0003	0.006***	0.003***
		(0.0003)	(0.0003)	(0.001)	(0.001)
time_horizon_2040		−0.0003	0.002***	0.008***	0.007***
		(0.0003)	(0.0003)	(0.001)	(0.001)
time_horizon_2050		−0.0001	0.003***	0.011***	0.009***
		(0.0004)	(0.0003)	(0.001)	(0.001)
ass_adaptation		−0.011***			
		(0.0002)			
ass_immediate			0.00004		−0.002***
			(0.0003)		(0.0004)
Constant	−0.355***	0.269***	0.289***	−0.467***	−0.525***
	(0.001)	(0.0003)	(0.0004)	(0.001)	(0.0004)

*p<0.1; **p<0.05; ***p<0.01

4.5 Within-tool analysis

Some providers deliver multiple specifications for their metrics. Specifically, some providers assessed the companies for different temperature targets, time horizons and transition paths. We thus run robust to outliers linear regressions to investigate the impact of the temperature target and the horizon specification on the output produced by a specific metric. When performing the within-tool analysis we can overcome one of the limitation of the across metrics study in that we can account for trends in risk exposure. We do that by rescaling the risk assessment by the smallest and largest value computed by the provider across all the temperature target / time horizon / transition path specifications instead of within a specific one. In our regression for the within tool analysis, we include as before a constant to ensure that the model is unbiased, and firms fixed effects. We use heteroskedasticity-robust, but not cluster-robust standard errors because we focus on one tool in each regression. Also, note that amount of metrics and, related to this aspect, the explanatory variables vary across the tools, depending on the various metric specifications that were provided. The results are reported in Table 8. Each column represents one provider, with the regression results for the metrics from this specific provider.

Overall, we see that all coefficients are statistically significant, most often at the 1% level. Given our results for the full sample OLS, this shows that within a certain tool, temperature target and horizon settings matter for the risk assessment. Yet, this does not mean that when comparing risk analyses across tools, that these specifications are most important, as we have seen in the full sample results.

The provider delivering Metrics 5-6 produced the results reported in the first column. As expected, for this provider, a below 2°C temperature target is associated with a higher risk (-0.006) compared to a 2°C target. The provider of Metrics 7-30 assessed risks for multiple temperature targets and time horizons under two different assumptions about firms' behavior (without adaptation / inaction; with adaptation / mainstream). In this case considering a 3 instead of a 2°C temperature target decreases the risk as expected (-0.056). Considering a below 2 instead of a 2°C target is associated with a higher risk. Increasing the time horizon is associated with a lower risk compared to the baseline horizon 2025, but the coefficients are not significant. Assuming that additional climate transition activities become mainstream across all firms is associated with a lower risk (-0.011), compared to the situation in which companies are inactive in the transition and just follow those transition activities, because it implies that companies get ready for the transition. For the provider of Metrics 31-46, all the coefficients for the temperature targets have the expected sign, as the risk decrease when considering a higher temperature target compared to a temperature target of 1.5°C. Considering a longer time horizon is associated with higher risks, compared to the baseline year 2025. Yet, the estimate for 2030 is very low, and not statistically significant. This provider assesses a delayed and an immediate transition. The assumption of an immediate transition pathway increases the risk, but not significantly. The results for the fourth providers' Metrics 53-64 show that, again, a higher temperature target is associated with lower risk compared to the baseline of 1.5°C. In addition, for this provider, a longer time horizon is always associated with higher risk. Finally, for the provider of Metrics 66-73, a longer time horizon is always associated with higher risk, compared to the baseline horizon of 2025. Differently from Metrics 31-46, an immediate transition is associated with lower risk (0.024).

Like before, to provide some out of sample performance check of our results, we run a within-metric LASSO regression. The results are reported in Table 9. The results are consistent with the ones obtained with traditional OLS except for the fact that in the case of the provider of Metrics 7-30, 31-46 and 66-73, the variable `time_horizon_2030`was dropped.

Table 9: Results of LASSO regression within tool, with heteroskedasticity-robust standard errors

	Dependent variable: Risk assessment				
	Metrics 5-6	Metrics 7-30	Metrics 31-46	Metrics 53-64	Metrics 66-73
temp_baseline	2°C	2°C	1.5°C	1.5°C	NA
temp_target_b2	0.007*** (0.003)	0.005*** (0.0005)		−0.049*** (0.001)	
temp_target_2			−0.002** (0.001)	−0.056*** (0.001)	
temp_target_3		−0.005*** (0.001)	−0.004*** (0.001)		
time_horizon_2030		— — —	— — —	0.010*** (0.001)	— — —
time_horizon_2040		−0.002*** (0.0005)	0.002*** (0.0005)	0.013*** (0.001)	0.008*** (0.001)
time_horizon_2050		−0.004*** (0.001)	0.005*** (0.001)	0.019*** (0.001)	0.016*** (0.001)
ass_adaptation		−0.019*** (0.0004)			
ass_immediate			−0.0001 (0.001)		−0.007*** (0.001)
Constant	−0.343*** (0.002)	0.271*** (0.0004)	0.288*** (0.001)	−0.440*** (0.001)	−0.522*** (0.001)

*p<0.1; **p<0.05; ***p<0.01
— indicates variable has been dropped by LASSO

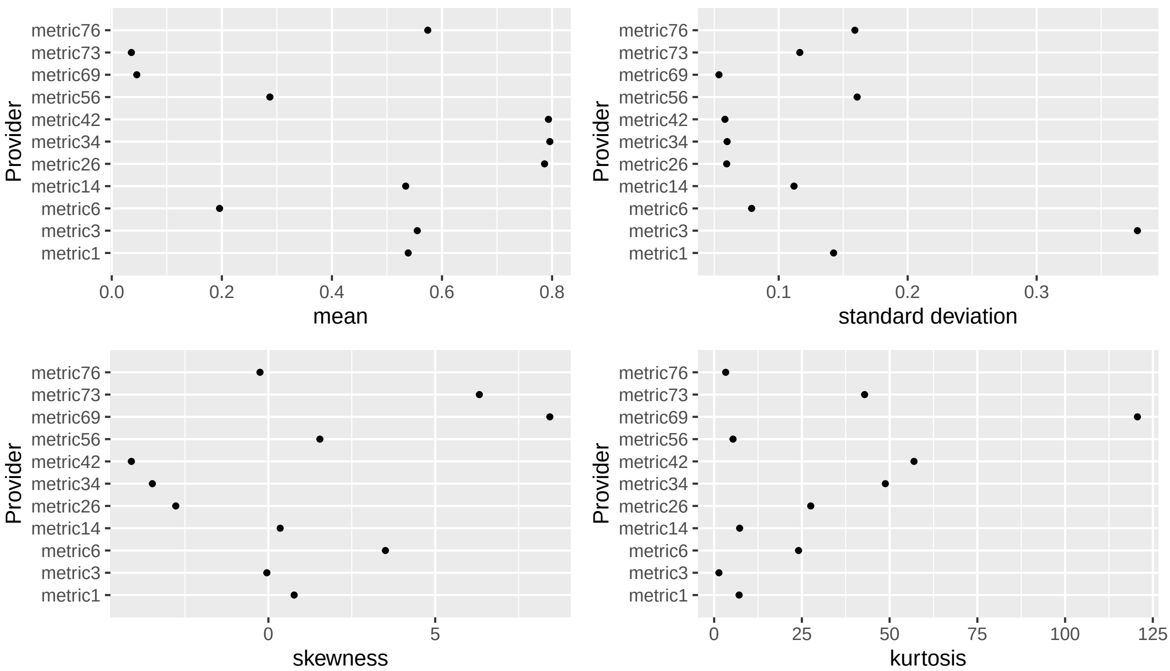

Figure 6: Distribution of the mean, standard deviation, skewness and kurtosis for metrics with 2°C temperature target and time horizon 2050

4.6 Moments of the distributions

Eventually, we would like to assess to which degree the various analysis approaches yield to different risk value distributions. For each metric, we therefore compute the four distribution moments: the mean, the standard deviation[8], the skewness[9] and the kurtosis.[10]

Figure 6 depicts the four moments for the subsample of metrics adopting a 2°C temperature target and 2050 time horizon, whereas Figures 7 and 8 show the results for the entire sample. It can be seen that the mean risk assessment is quite spread across providers. The standard deviation is generally low with few outliers and the same hold for the kurtosis. The skewness tends to be positive but with very large left-skewed distributions (i.e. providers assessing a high risk for most of the companies). Across all the moments clusters in the values can be identified when the metrics are produced by the same provider.

[8] A low standard deviation indicates that the data points tend to be very close to the mean; a high standard deviation indicates that the data points are spread out over a large range of values.

[9] Skewness is a measure of asymmetry of a distribution. It shows the extent to which a given distribution varies from a symmetric, normal distribution. A value larger than 0 implies a right-skewed (tail on the right) distribution, a value lower than 0 a left-skewed (tail on the left) shape.

[10] The kurtosis is a measure of the "tailedness" of the distribution. High value of the kurtosis imply that the distribution tends to have longer tails, or outliers. Low values imply that the distribution tends to have shorter tails, or lack of outliers.

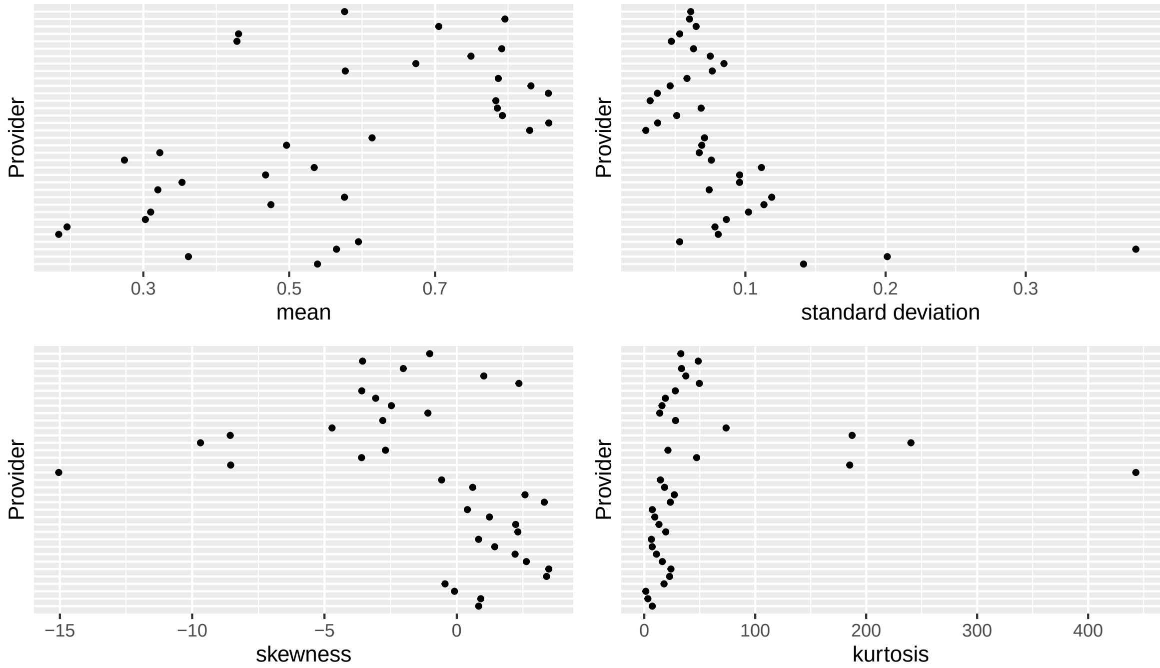

Figure 7: Distribution of the mean, standard deviation, skewness and kurtosis across all providers (1/2)

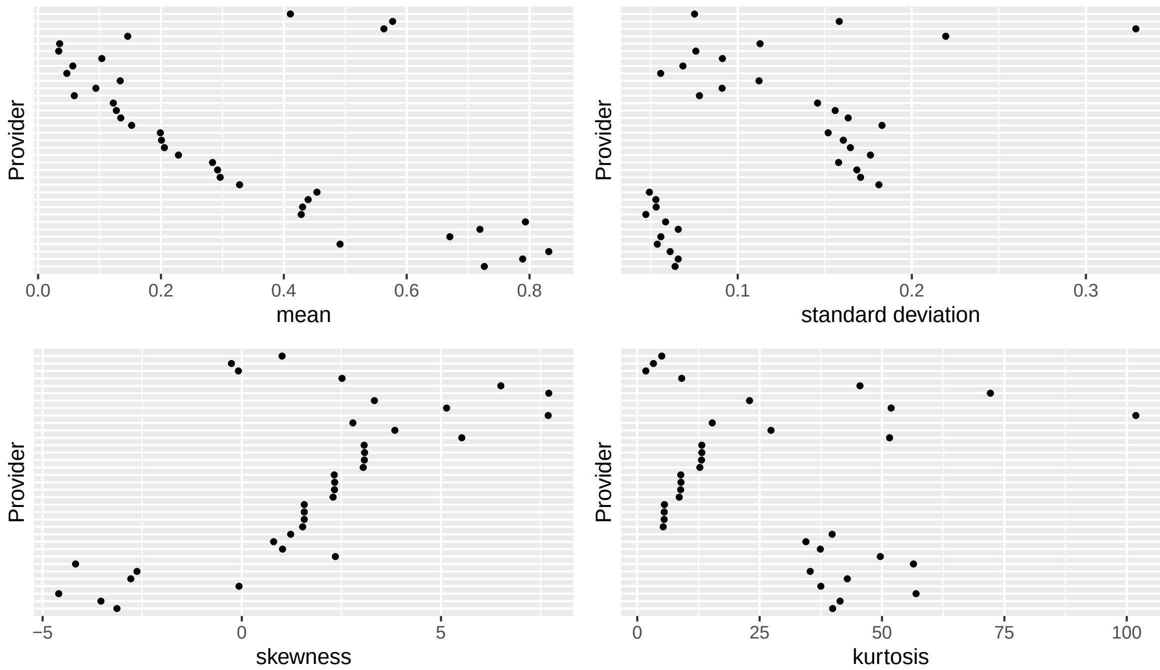

Figure 8: Distribution of the mean, standard deviation, skewness and kurtosis across all providers (2/2)

We then regress the four moments of the distribution on provider characteristics. Note that since we compute a moment for each distribution our sample does not account for individual firm risk assessments, but summarizes the assessments by each provider in four numbers, each of them observed 69 times (the number of provider specifications included in our full sample). We first use a robust OLS regression with heteroskedasticity- and cluster-robust standard errors, but without firms' fixed effects to assess how metrics' characteristics are associated with changes in the mean, variance, skewness and kurtosis of the distribution of risk assessments across providers. The results are shown in Table 10, where each column corresponds to one specific moment of the distribution across providers.

We see that adopting a temperature target below 2°C, compared to a 1.5°C target, is statistically significantly associated with a lower kurtosis of the distribution (-4.777). This implies that when a higher temperature target is assumed, less companies are likely to be assessed as very or very little risk exposed. The same holds for a temperature target of 3°C, compared to the 1.5°C target (-4.659). For all other moments, the temperature targets' coefficients are not statistically significant, except for the lack of a temperature target which is associated with a significantly lower standard deviation (-0.122). The time horizon is also generally insignificant with the exceptions of assuming 2040 as time horizon which is associated with lower kurtosis (-6.761) and time horizon of 2100 which is associated with lower standard deviation. This implies that with a longer time horizon, risk assessments are, on average, more spread than with shorter time horizons. Moreover, no time horizon, which is associated with lower average risk, higher standard deviation and skewness and lower kurtosis. The effect on the skewness is more difficult to interpret because it depends on the initial level, but in general we can say that having no time horizon changes the amount of companies assessed as very much or very low risk exposed.

The type of output is also associated with changes in the moments of the distribution. Financial metrics are associated with a significant (at the 10% confidence level) increase in the average risk, a decrease in the standard deviation and an increase in the kurtosis compared to assessing balance sheet effects. Using gaps or risk scores has the same impact on the mean of the distribution, but they both increase the standard deviation and reduce the skewness.

Including firm targets and CAPEX plans in the analysis increases the average risk, in line with the results that we obtained for the individual firms' risk assessments, and reduce the skewness. The CAPEX has also an additional impact on the standard deviation (which is lower) and on the kurtosis (which is larger).

Finally, using a combined approach compared to a bottom-up approach is associated with lower mean and standard deviation of the distribution, but larger skewness. The top-down approach is associated with a similar effect on the standard deviation whereas the coefficients for the other moments of the distribution are not statistically significant.

We then apply a double LASSO on each of the four distribution moments, in order to identify the most important drivers of the distribution moments.[11] As before, we report the specification for heteroskedasticity- and cluster-robust standard errors, but no firms fixed effects. The results of our estimation are reported in Table 11.

[11]Appendix A.5 provides the results when a random forest approach is used instead.

Table 10: Robust OLS regression with heteroskedasticity- and cluster-robust standard errors

	Dependent variable: Distribution of risk assessment			
	Mean	Standard deviation	Skewness	Kurtosis
temp_target_b2	−0.094	0.007	1.425	−4.777***
	(0.292)	(0.006)	(6.108)	(1.111)
temp_target_2	−0.085	0.003	1.275	−2.647
	(0.307)	(0.006)	(5.990)	(2.426)
temp_target_3	−0.135	−0.006	1.989	−4.659*
	(0.354)	(0.005)	(6.404)	(2.387)
temp_target_na	0.269	−0.122***	−3.246	6.019
	(0.275)	(0.011)	(6.204)	(7.451)
time_horizon_2030	0.036	0.003	−0.695	−6.263
	(0.074)	(0.006)	(1.750)	(3.993)
time_horizon_2040	0.103	0.005	−1.144	−6.761**
	(0.138)	(0.010)	(2.256)	(2.864)
time_horizon_2050	0.116	0.004	−0.880	−4.213
	(0.144)	(0.015)	(2.195)	(6.832)
time_horizon_2100	−0.007	0.037***	−3.253	13.204
	(0.155)	(0.012)	(2.274)	(9.653)
time_horizon_na	−0.403***	0.056*	5.500**	−28.462
	(0.098)	(0.033)	(2.613)	(19.133)
output_finmetric	0.596*	−0.125***	−6.618	46.254***
	(0.339)	(0.020)	(4.364)	(11.599)
output_gap	0.587***	0.082**	−8.110***	23.243
	(0.086)	(0.035)	(1.990)	(20.924)
output_riskscore	0.269***	0.262***	−2.721***	−2.500
	(0.030)	(0.015)	(0.627)	(7.897)
firm_target_1	0.322***	−0.029	−4.885***	14.183
	(0.054)	(0.018)	(1.146)	(10.251)
capex_1	0.562***	−0.102***	−6.166***	20.486**
	(0.097)	(0.014)	(1.308)	(9.688)
approach_comb	−0.333***	−0.196***	4.313***	5.653
	(0.046)	(0.011)	(0.808)	(6.442)
approach_topdown	0.109	−0.258***	−0.261	0.598
	(0.137)	(0.014)	(1.601)	(7.830)
Constant	−0.091	0.185***	6.763	2.446
	(0.203)	(0.015)	(4.942)	(9.722)

*p<0.1; **p<0.05; ***p<0.01

For the mean, of the 16 explanatory variables that we feed into the model, only one was selected in addition to the constant, namely `capex`. In order to explain the differences in the standard deviation, 6 variables were selected by the model: `temp_target_2`, `temp_target_3`, `output_finmetric`, `output_riskscore`, `capex`, and `approach_comb`. With regards to skewness, two variables have been chosen by the model, namely `firm_target`, and `capex`. Finally, for the kurtosis, the two variables `temp_target_3` and `output_riskscore` were selected by the model.

Our results show that adopting a higher temperature target, compared to to 1.5°C, is not considered as important by the model for the mean and the skewness of the risk distributions. Adopting a 2°C temperature target is associated with a lower standard deviation, compared to a 1.5°C target (-0.017), but the effect is not statistically significant. The 3°C temperature target is associated with lower standard deviation (-0.041) and kurtosis (-17.049), but these coefficients are again not significant.

Having as output a financial indicator or gap analysis have been dropped by the model for the mean, the skewness and the kurtosis. However, having as output a financial indicator is associated with a statistically significant reduction in the standard deviation of the distribution compared to assessing balance sheet effects (-0.073). Risk scores are associated with larger standard deviation (0.128) and lower kurtosis of the distribution (-31.986), compared to balance sheet effects. Both estimates are statistically significant at the 1% level. This means that if the output is a risk score, there are less companies assessed as exposed to very high or very low risk. This might be due to the fact that the scores are on a closed interval.

Despite the fact that including firm targets is associated with a lower skewness, the estimated effect is not statistically significant. Including CAPEX plans is associated with an increase of the average risk (0.241), lower standard deviation (-0.063) and lower skewness of the distributions (-2.689).

Finally, using a combined approach is associated with a lower standard deviation compared to a top-down approach (-0.108, statistically significant at the 1% level).

Table 11: LASSO regression on distribution characteristics with heteroskedasticity- and cluster-robust standard errors

	Dependent variable: Distribution of risk assessment			
	Mean	Standard deviation	Skewness	Kurtosis
temp_target_b2	— — —	— — —	— — —	— — —
temp_target_2	— — —	−0.017 (0.013)	— — —	— — —
temp_target_3	— — —	−0.041 (0.025)	— — —	−17.049 (18.737)
temp_target_na	— — —	— — —	— — —	— — —
time_horizon_2030	— — —	— — —	— — —	— — —
time_horizon_2040	— — —	— — —	— — —	— — —
time_horizon_2050	— — —	— — —	— — —	— — —
time_horizon_2100	— — —	— — —	— — —	— — —
time_horizon_na	— — —	— — —	— — —	— — —
output_finmetric	— — —	−0.073*** (0.020)	— — —	— — —
output_gap	— — —	— — —	— — —	— — —
output_riskscore	— — —	0.128*** (0.046)	— — —	−31.986*** (9.578)
firm_target_1	— — —	— — —	−2.001 (2.735)	— — —
capex_1	0.241* (0.130)	−0.063*** (0.020)	−2.689* (1.593)	— — —
approach_comb	— — —	−0.108*** (0.038)	— — —	— — —
approach_topdown	— — —	— — —	— — —	— — —
Constant	0.354*** (0.130)	0.163*** (0.008)	2.084 (2.052)	45.475*** (14.808)

*p<0.1; **p<0.05; ***p<0.01
— indicates variable has been dropped by LASSO

5 Conclusion

With the present analysis, we aimed to support well-informed decision-making when selecting firm-level climate transition risk metrics for research and practice. To this end, we conduced first an assessment of the overall convergence and divergence of the risk metrics for a sample of 1,500 firms of the MSCI World index, with data from 14 different metric providers. Second, we assess which scenario and modelling choices affect the outcome of the climate risk assessment.

Our results confirm the early findings of Bingler et al. (2021b), that is: 1) climate risk metrics display a significant degree of diversity, which reflects the complexity of assessing climate risks, as well as the different methodologies and data underpinning these metrics, and 2) risk assessments across metrics tend to converge on which firms are most exposed to transition risks. In addition, our results show that the hypothesis and the methodology underlying a metrics affect the coherence between two metrics from different providers: metrics sharing similar horizons, temperature targets and hypotheses about the shape of the transition (i.e. orderly vs disorderly) tend to have a higher degree of convergence than when they diverges in these dimensions.

Our results on the drivers of the risk output evidence that both metric's assumptions and scenario's characteristics are associated with changes in the estimated firms' transition risk. In the across-tools analysis, the individual model setup seemed to be an important driver of the results. The consideration of firms' capex plans in the assessment has been identified as key statistically significant variable across various estimation methods. In addition, our results showed that the model output, the model's approach and the consideration of climate targets varied in their significance and relative strength, but matter for the estimates of the mean, and for the other moments of the distribution (standard deviation, skewness and kurtosis). The within-tool analysis show that temperature target and time horizon are statistically highly significant. However, their relative magnitude was again small, compared to the other variables, where such additional variables were available.

The results of our analysis show that in order to properly understand the climate risk metrics being used in corporate disclosures, financial supervision and academia, users need to properly justify why which metric has been chosen, and which assumptions are driving the results. With regards to using climate risk metrics to enhance information availability in financial markets and to reduce the current information asymmetry between firms and investors, our results suggest two main implications. First, given that climate transition risk rankings tend to converge for most and least exposed firms, the metrics are expected to translate into financial market price signals if applied by many actors. Second, in order to decrease information asymmetry between firms, tool providers and investors, financial supervisory authorities should define a joint baseline approach to ensure basic comparability of disclosed metrics, and should ask for detailed assumption documentations alongside the metrics to enable third party users to better understand the disclosures. For academia, it should become standard to justify the selection of a specific climate risk metric, instead of just using any metric which is available. This also implies that all findings should be interpreted in the light of the metric assumptions. This enables to correctly understand the implications and limitations of the findings.

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A Appendix

A.1 Frequency plots

In order to get more intuition on the individual metric distributions, we display as an example plots for the metrics of the comparable subsample with a 2°C temperature target and time horizon of 2050 in Figures 9 - 11. The plots indicate that the various providers' risk assessments for the same sample of firms follow very different distributions, even if employing comparable temperature target and time horizon specifications.

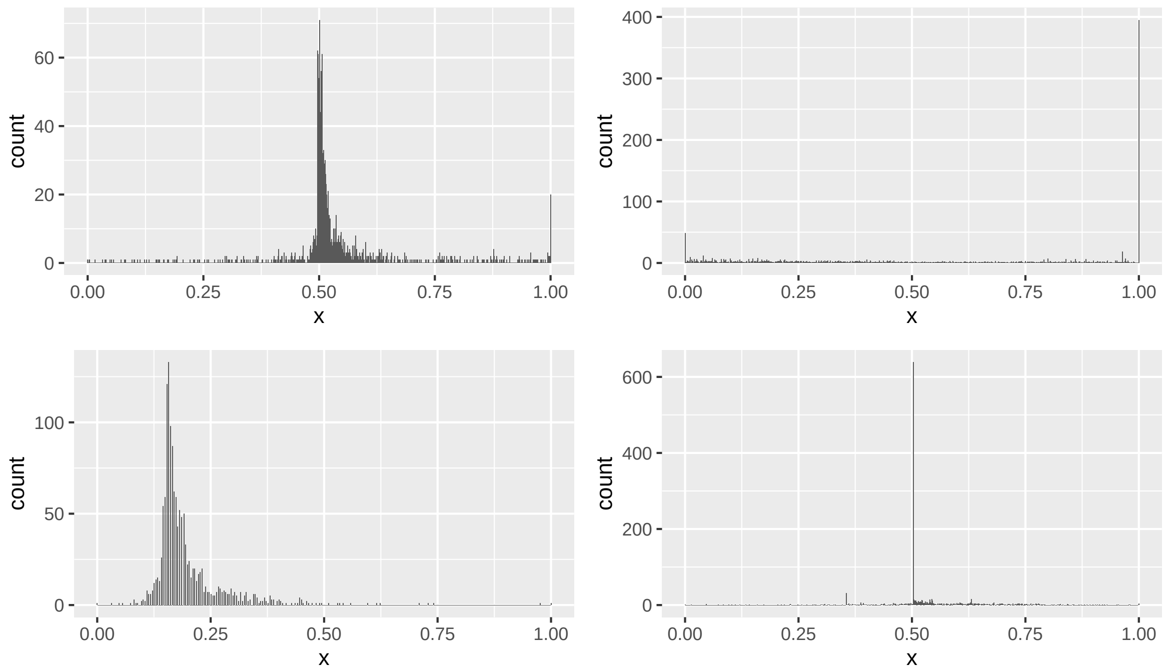


Figure 9: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050 (1/3)

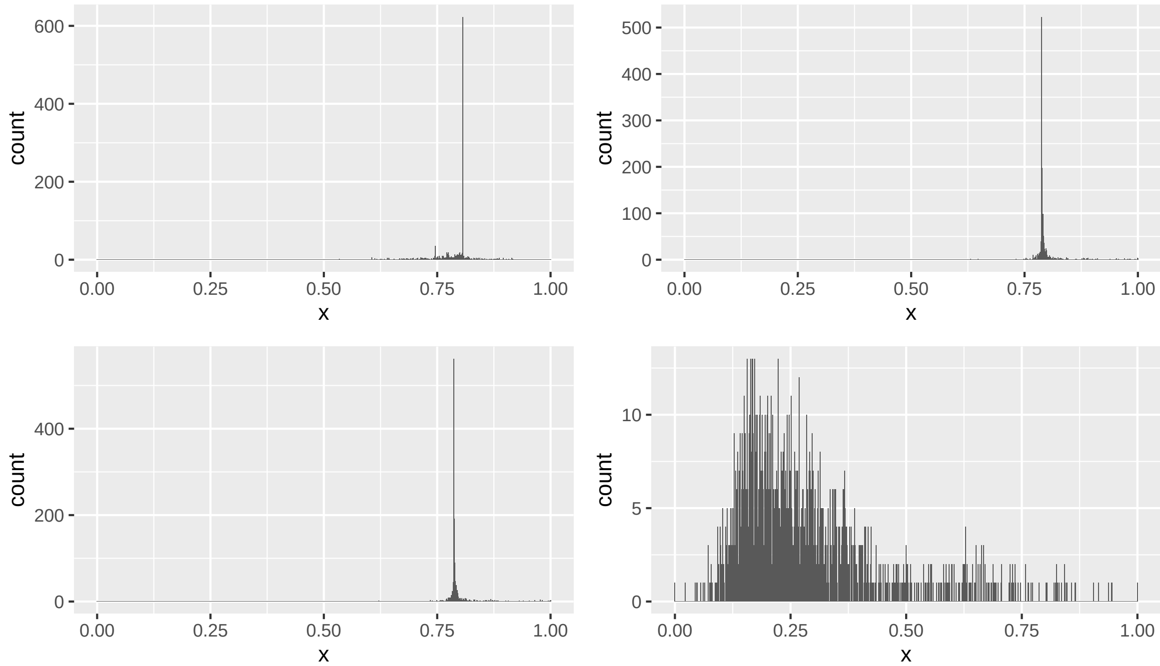


Figure 10: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050 (2/3)

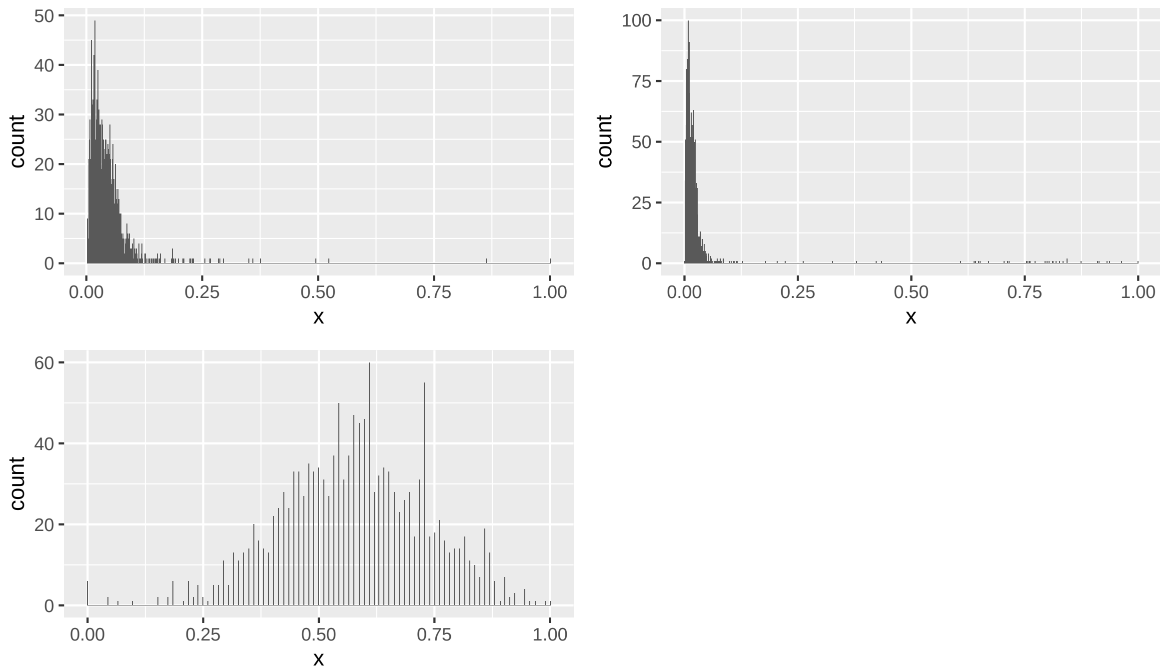


Figure 11: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050 (3/3)

A.2 Frequency plots by sector

Some tools, but not all, exhibit considerable differences in the sectoral distributions: For some, certain sectors seem to be associated with a specific level of risk, as can be seen for those providers where the distribution exhibits considerable peaks, associated with specific sectors. For Metric 26 the peak in the Energy and to a lower extent in the Utilities sector are more to the right than for the other sectors. Similarly, this effect is clear for Metric 34 (also for Utilities and Materials), 42 (also for Utilities) 56 (also for Industrials and to a lower extent for Materials), 69 (also for Utilities) 73 (also for utilities) and 76 (here the effect is also evident for Materials and Utilities).

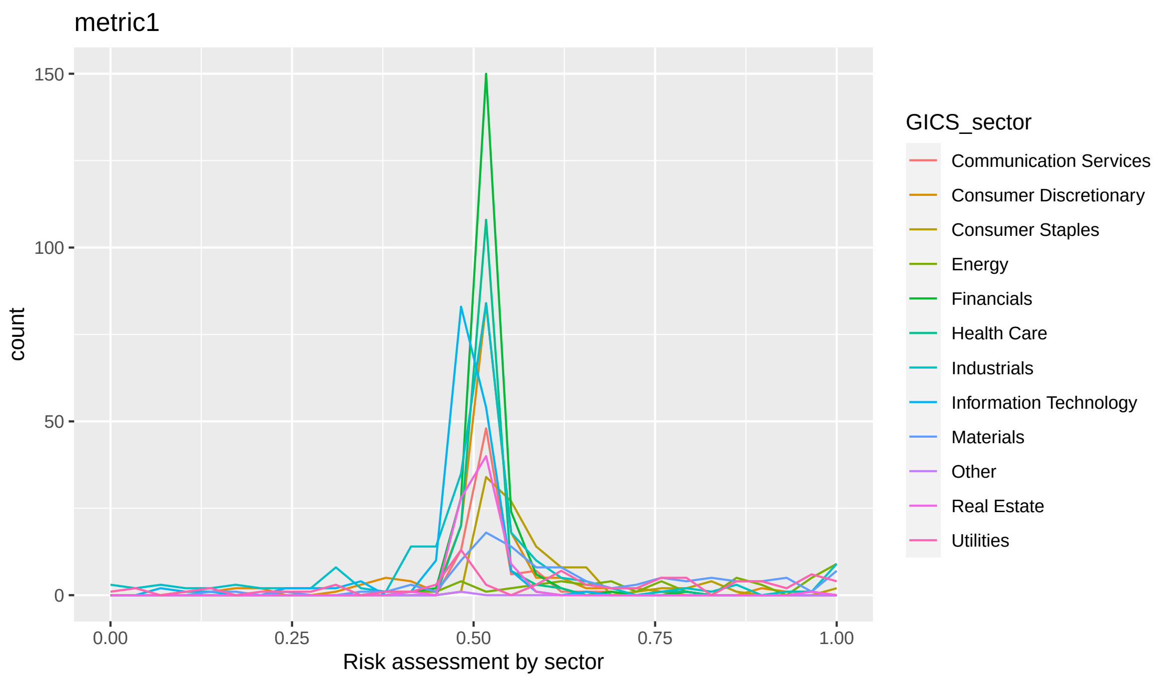


Figure 12: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (1/11)

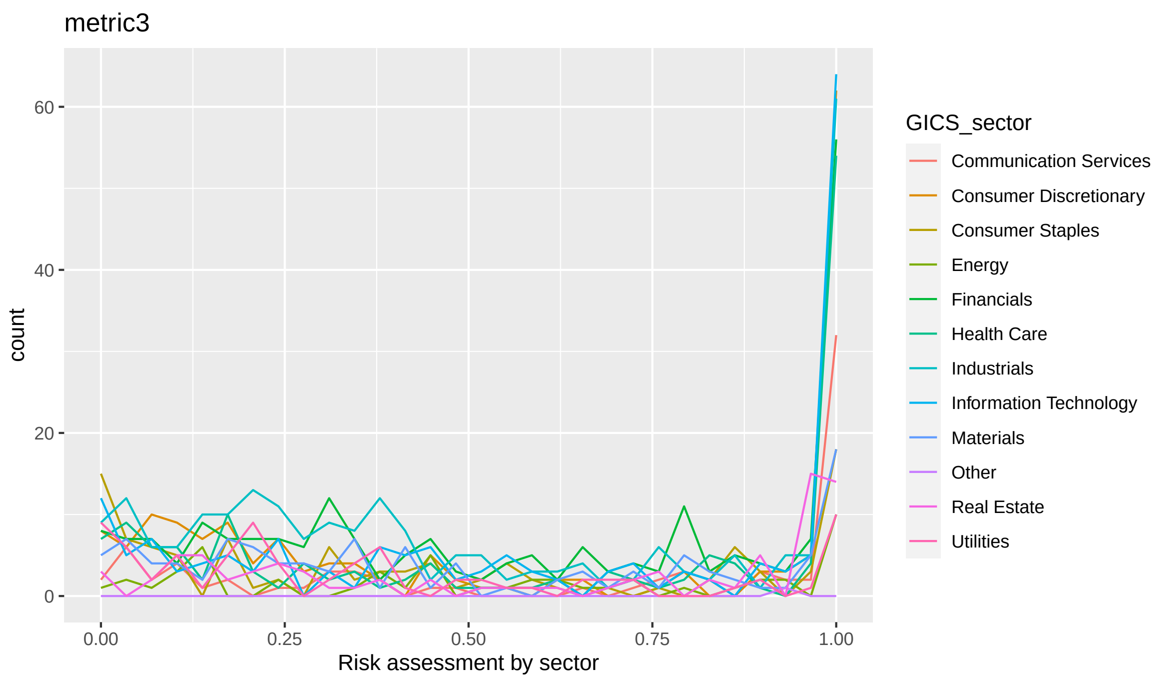


Figure 13: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (2/11)

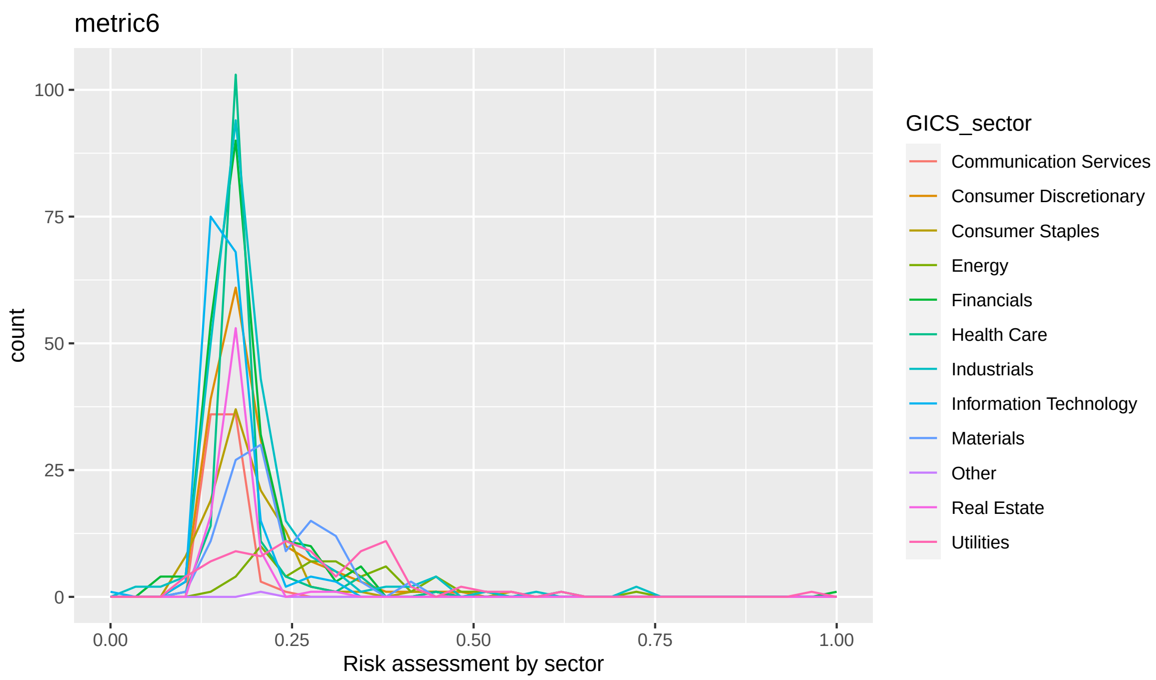


Figure 14: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (3/11)

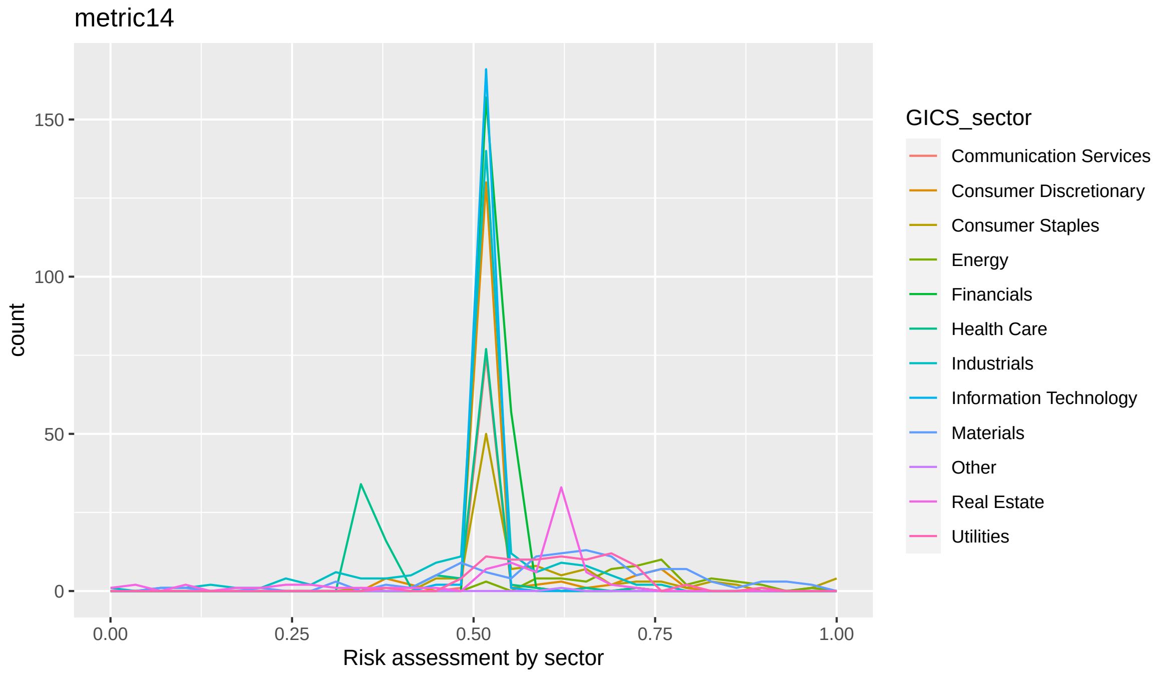


Figure 15: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (4/11)

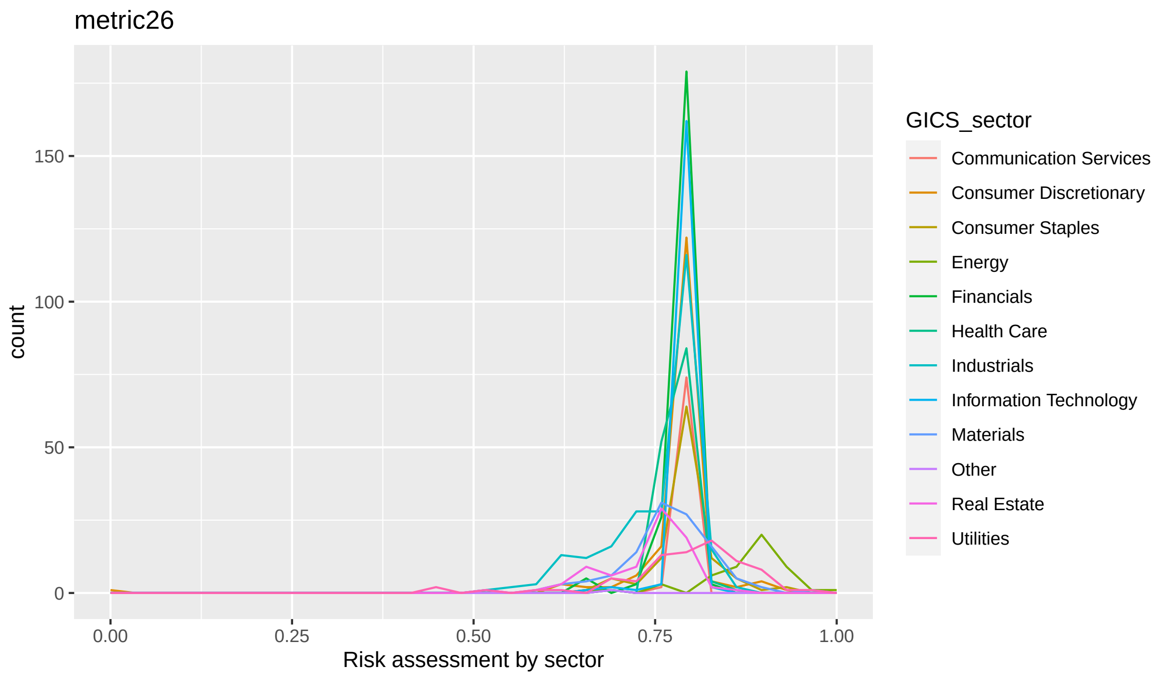


Figure 16: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (5/11)

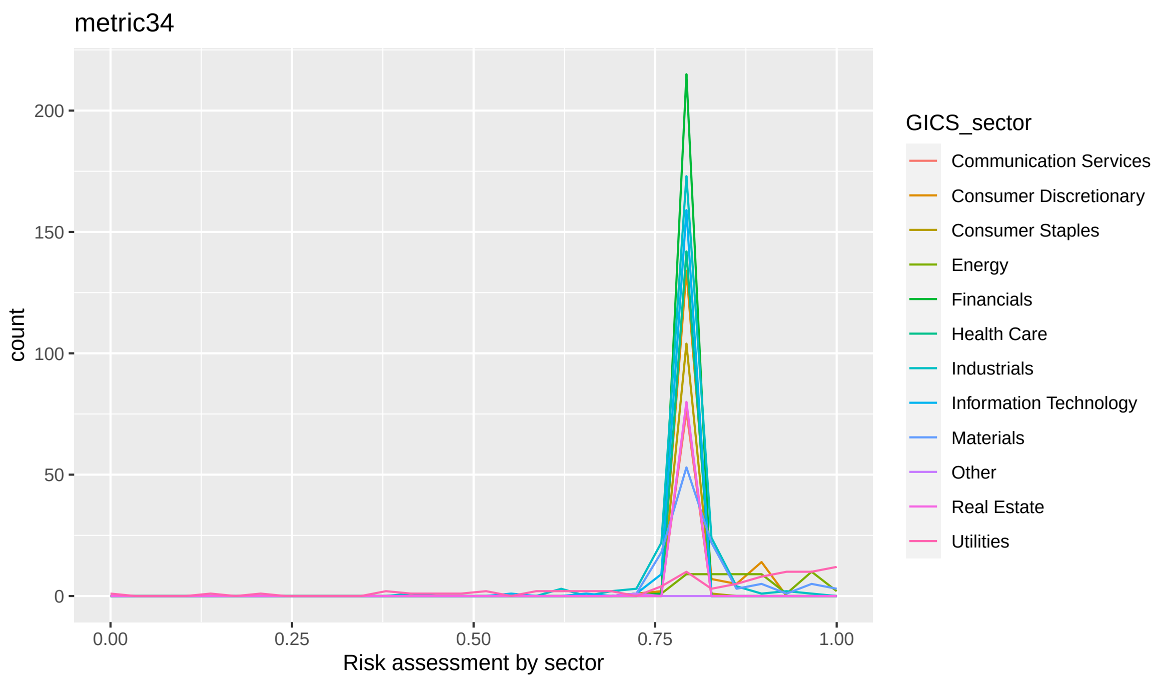


Figure 17: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (6/11)

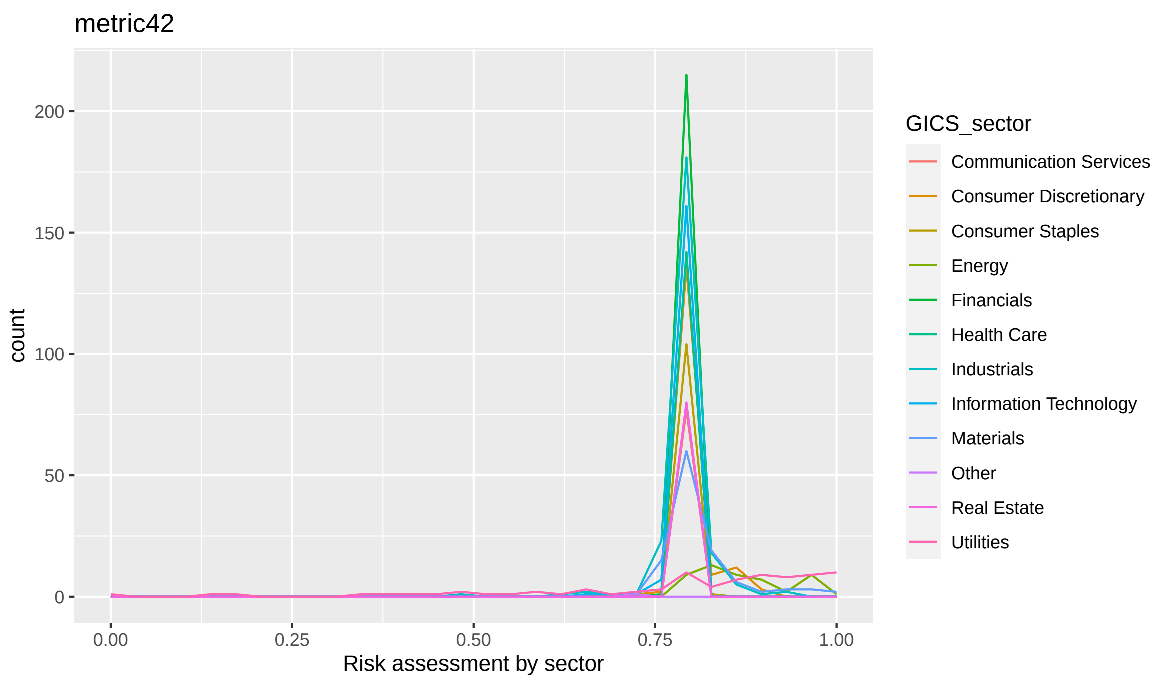


Figure 18: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (7/11)

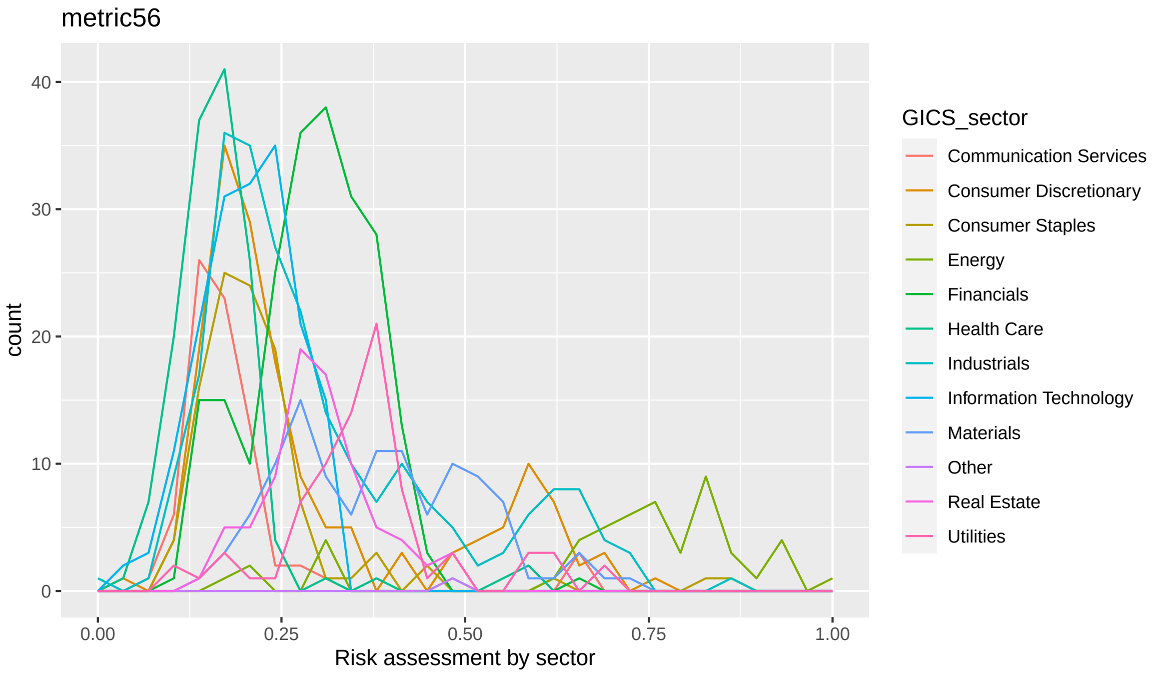


Figure 19: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (8/11)

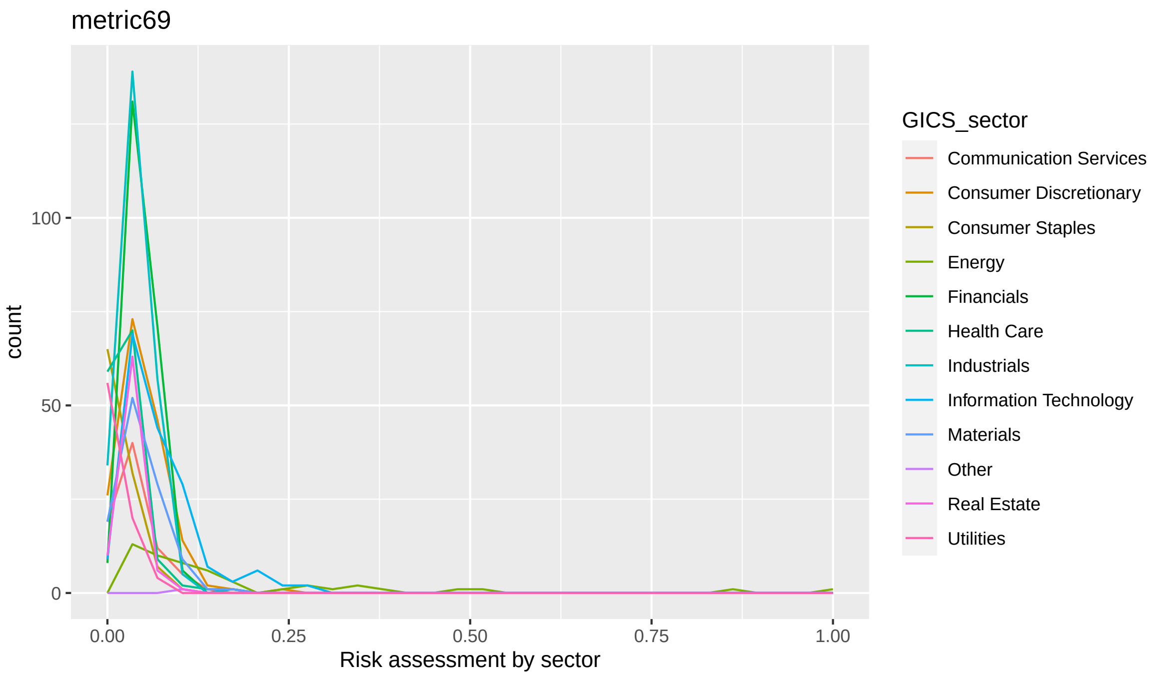


Figure 20: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (9/11)

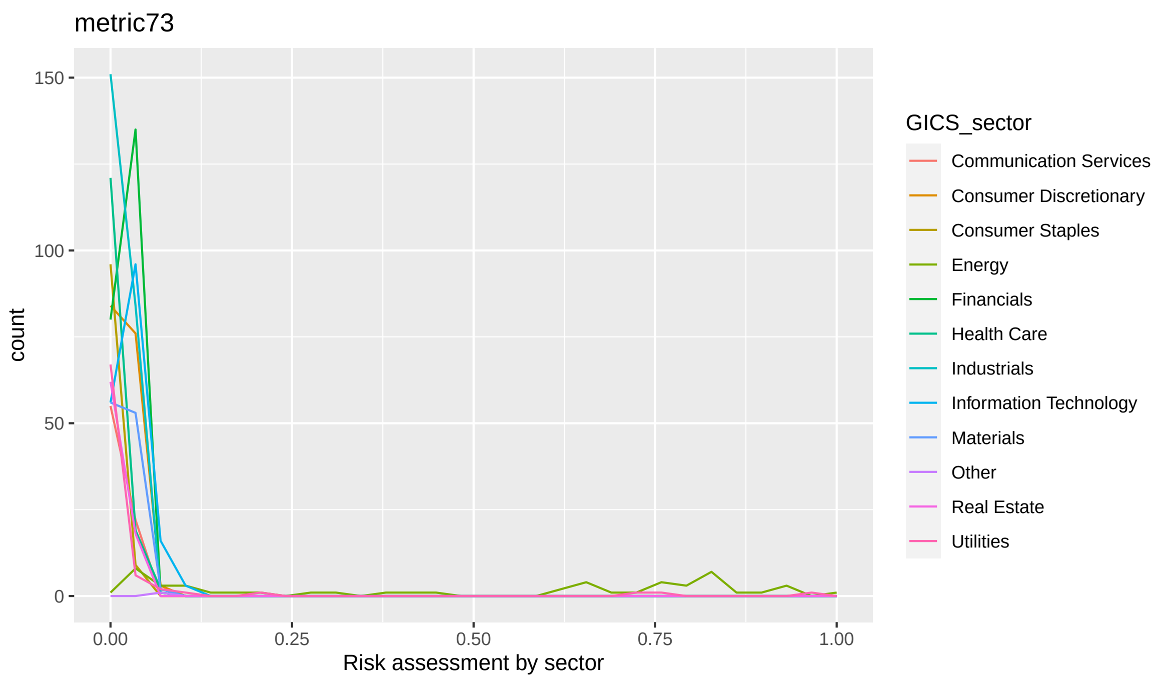


Figure 21: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (10/11)

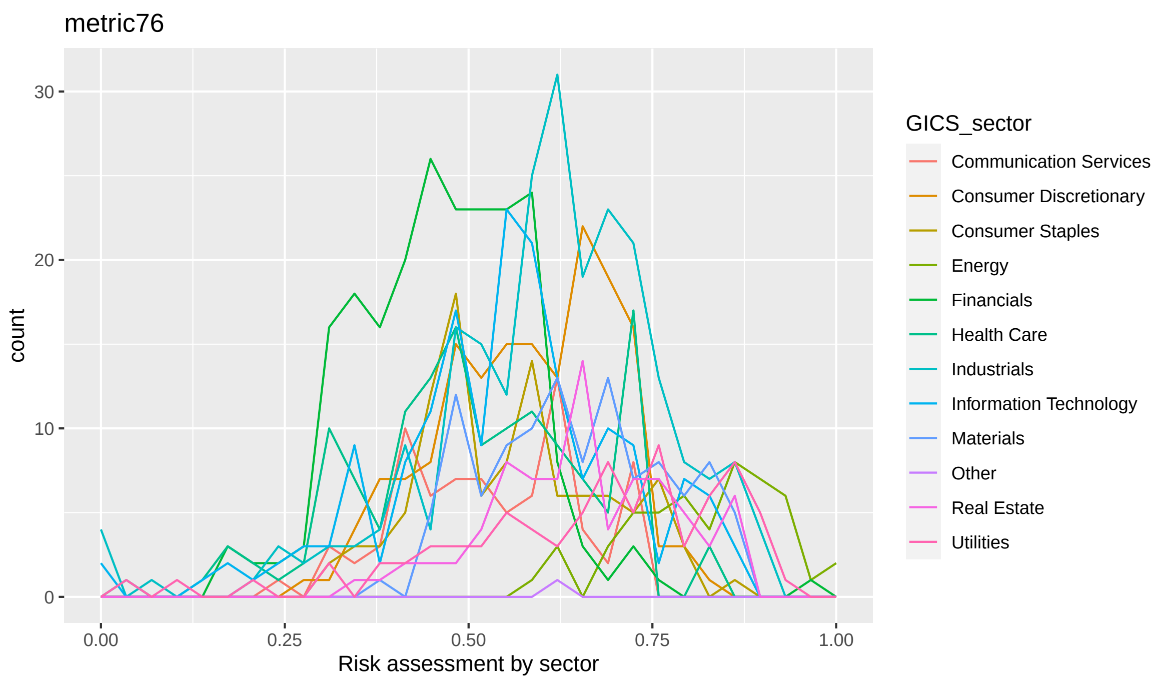


Figure 22: Frequency plot of risk assessment for metrics with 2°C temperature target and time horizon 2050, differentiated by sector (11/11)

A.3 Pairwise scatterplots by sector

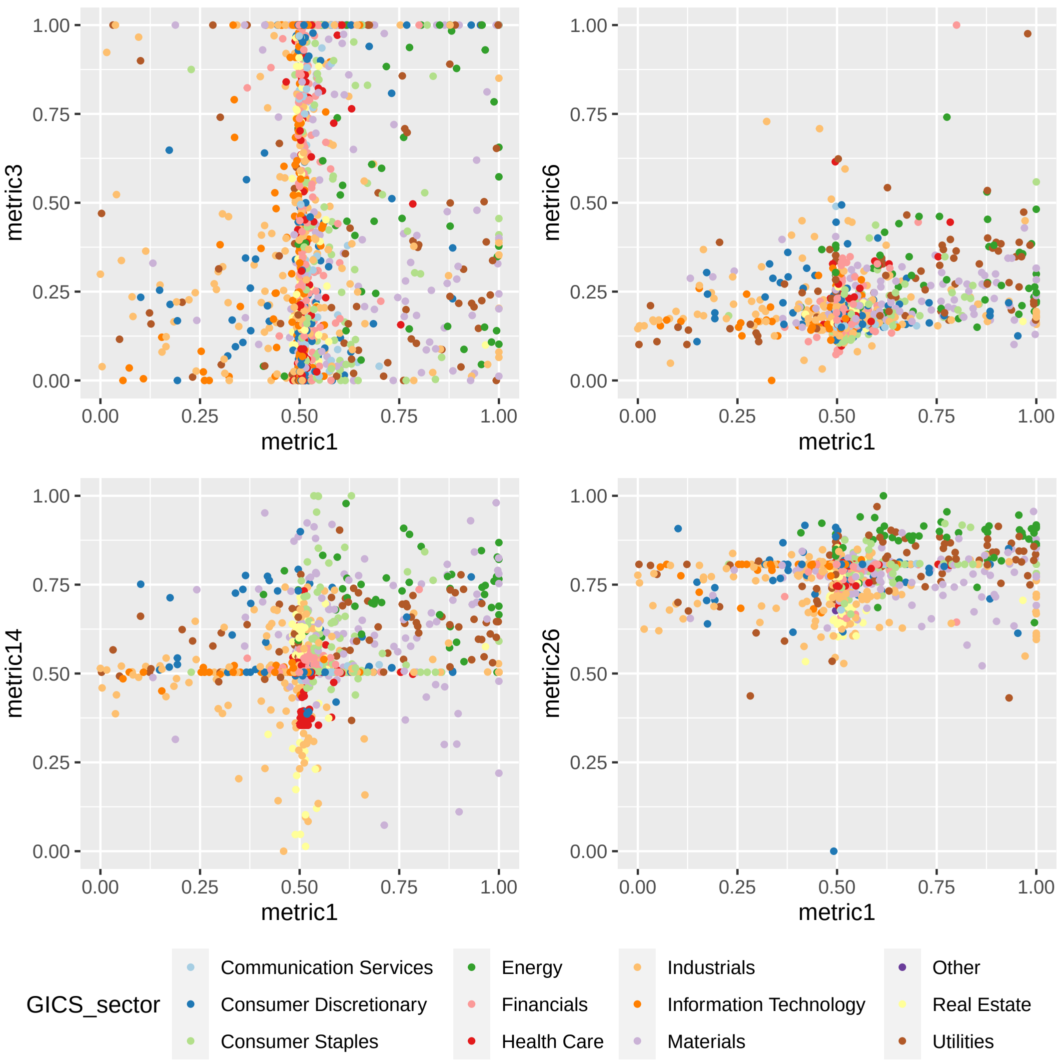


Figure 23: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (1/14)

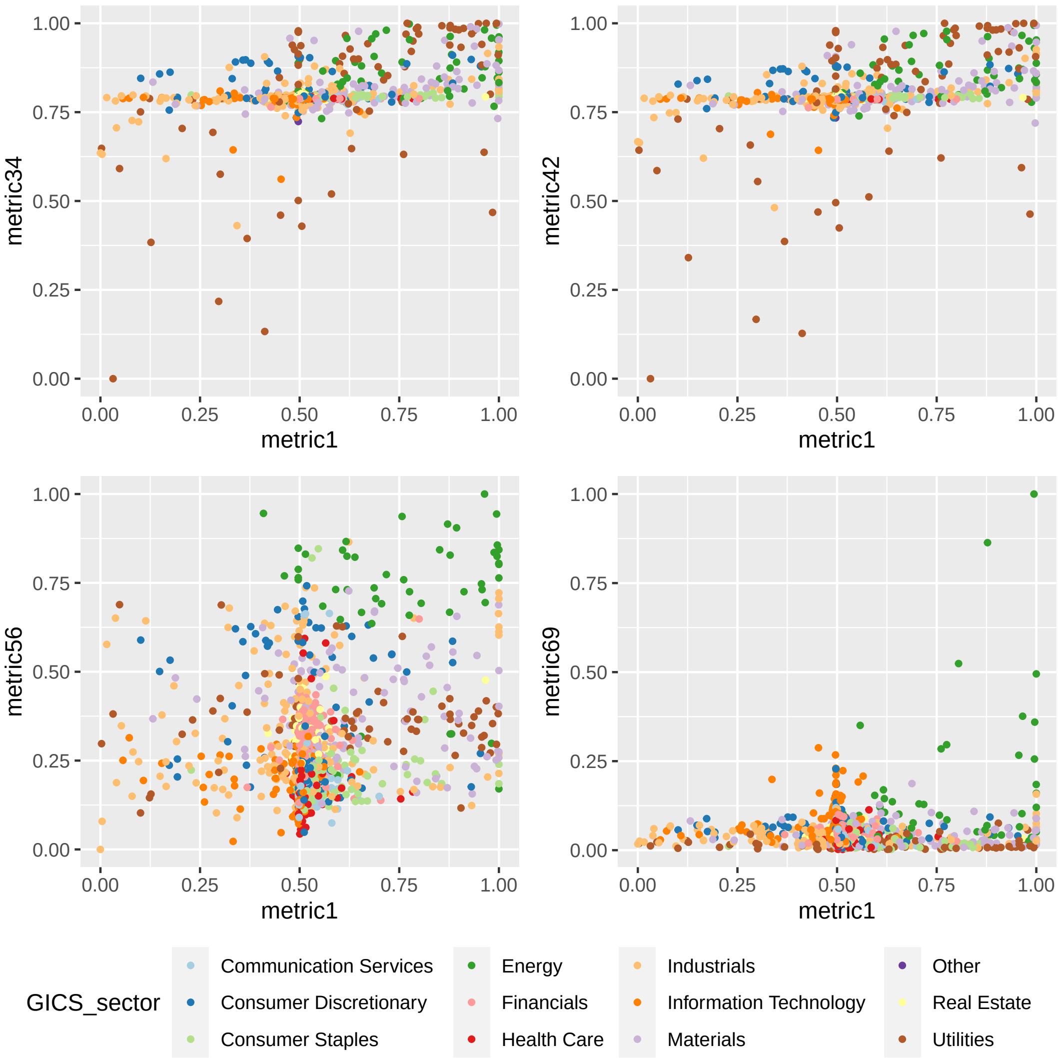


Figure 24: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (2/14)

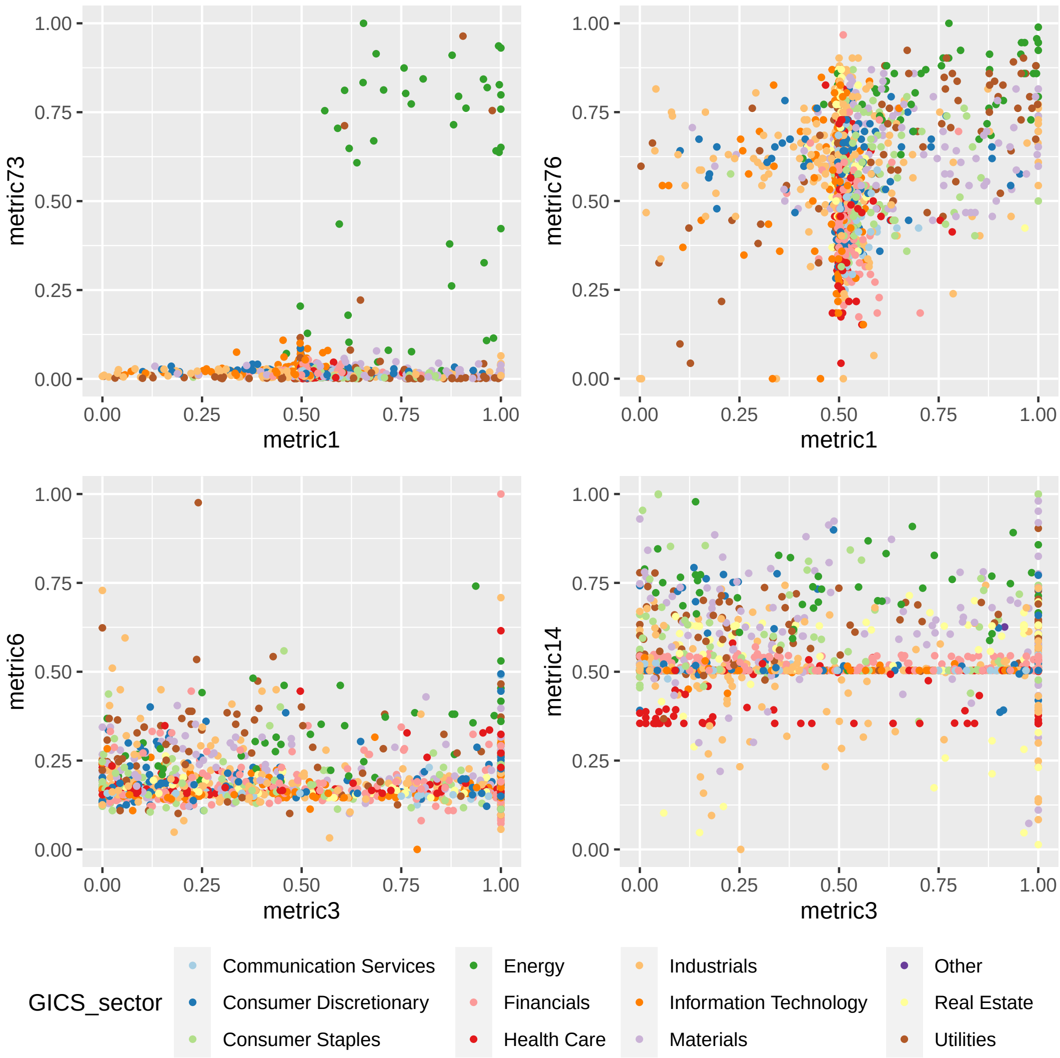


Figure 25: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (3/14)

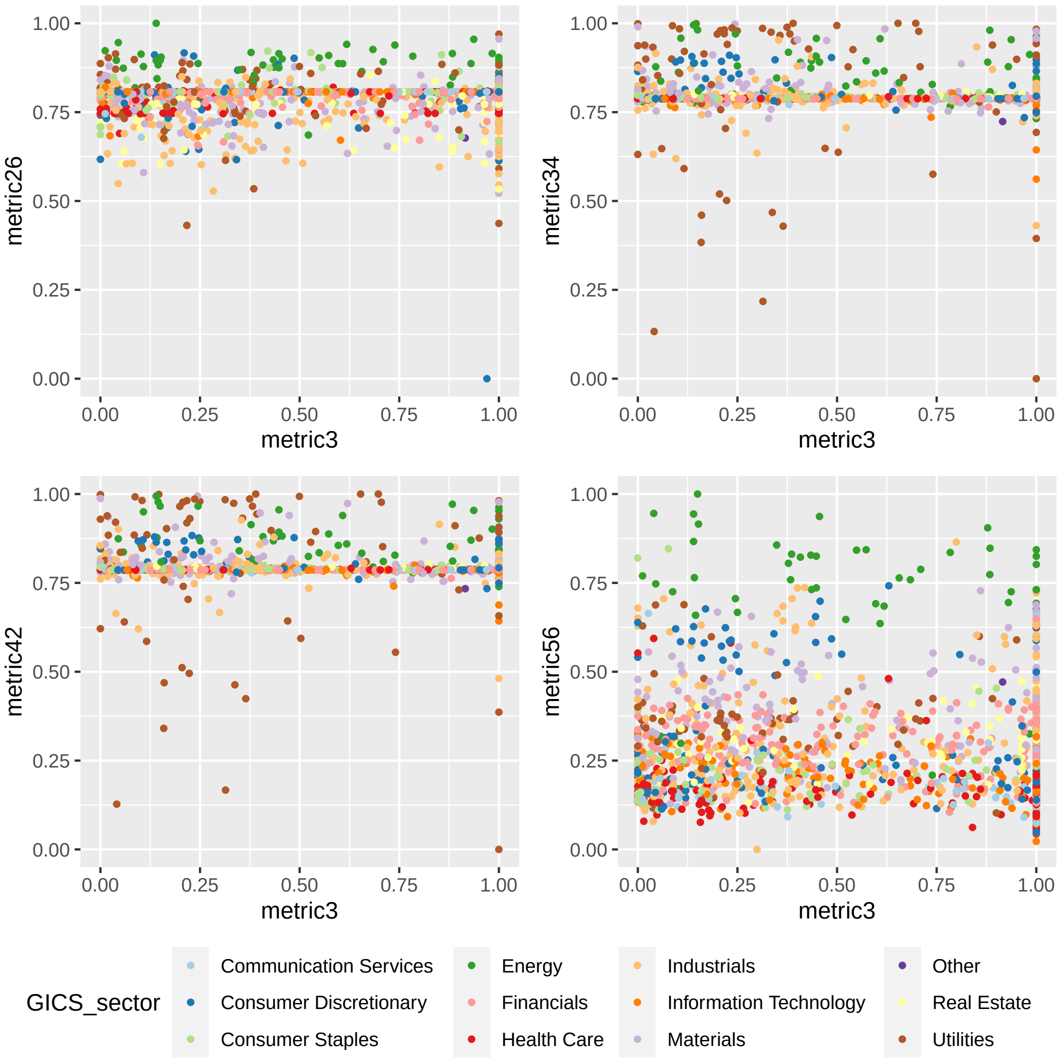


Figure 26: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (4/14)

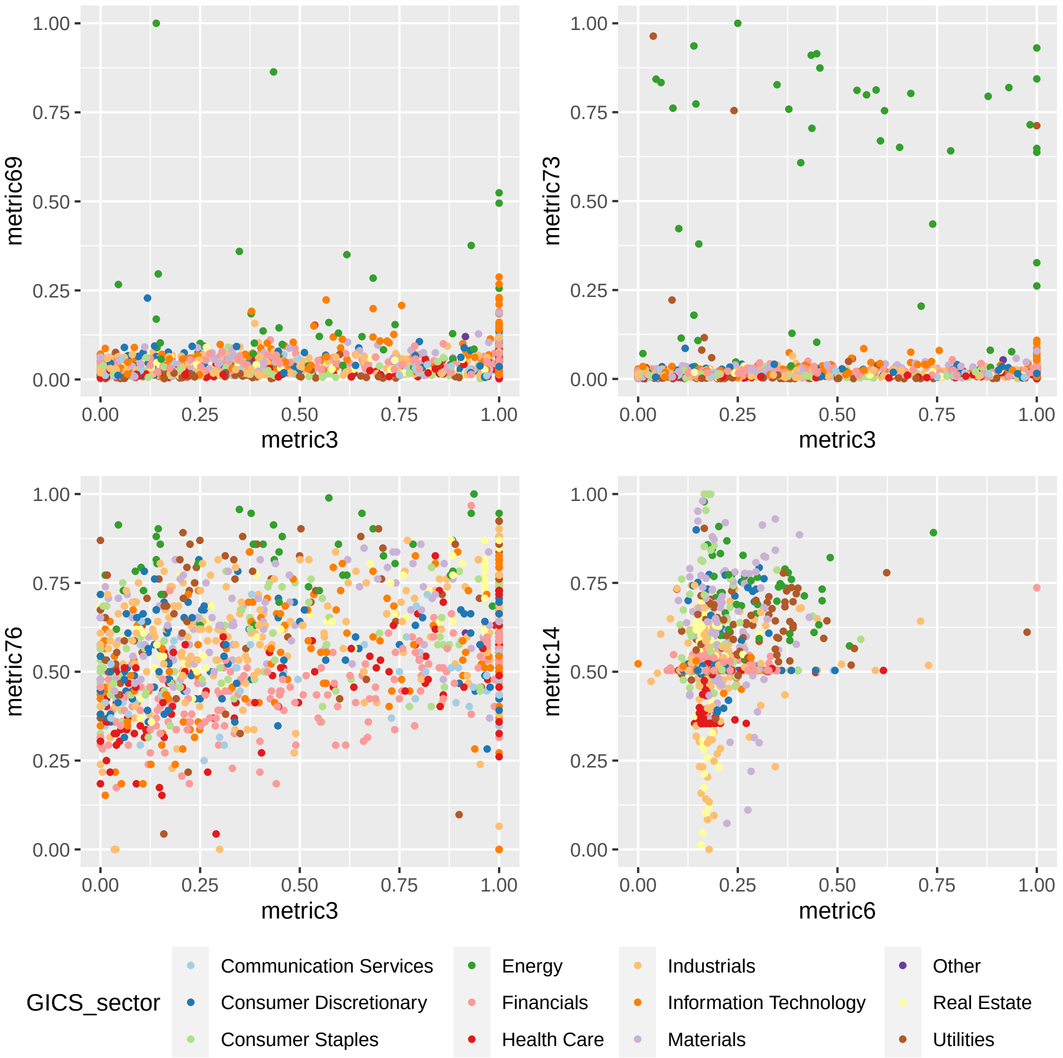


Figure 27: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (5/14)

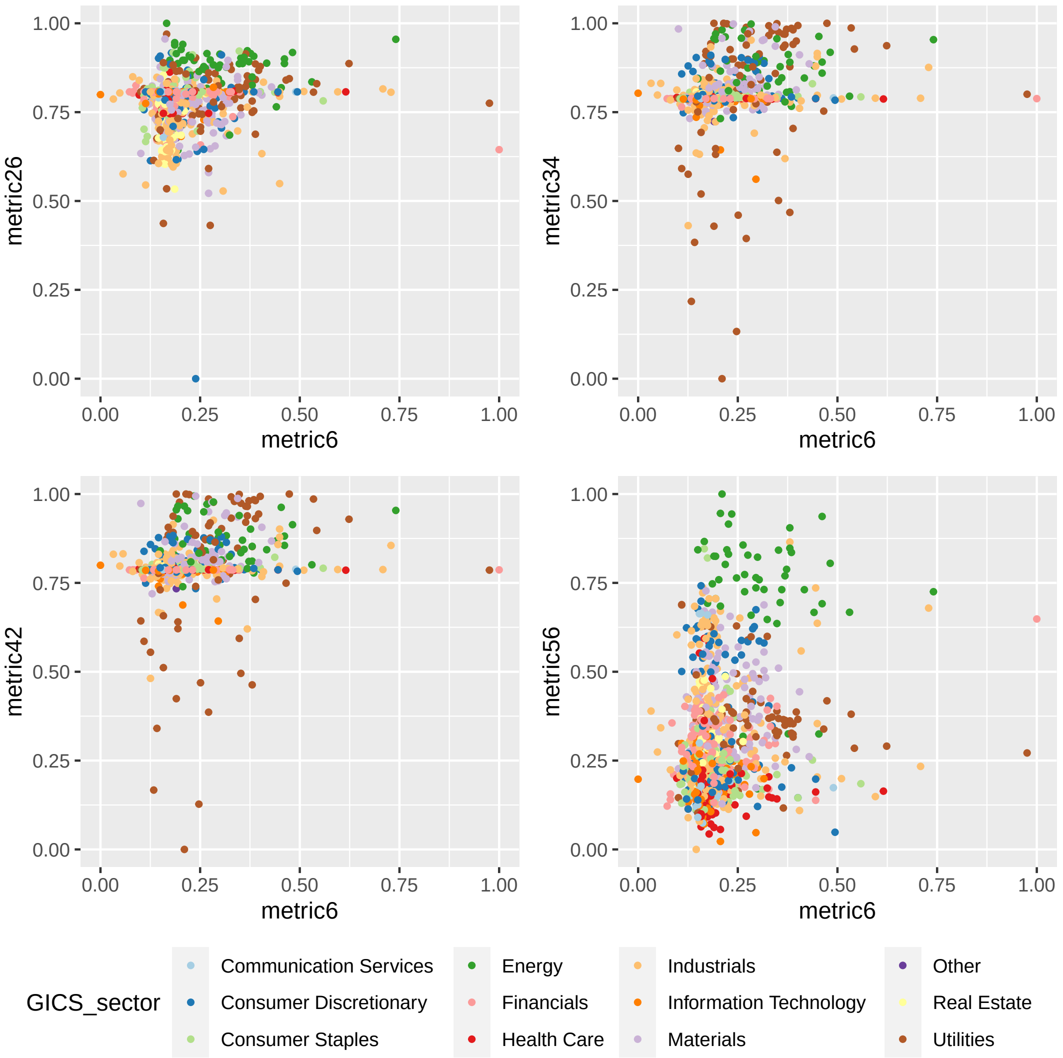


Figure 28: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (6/14)

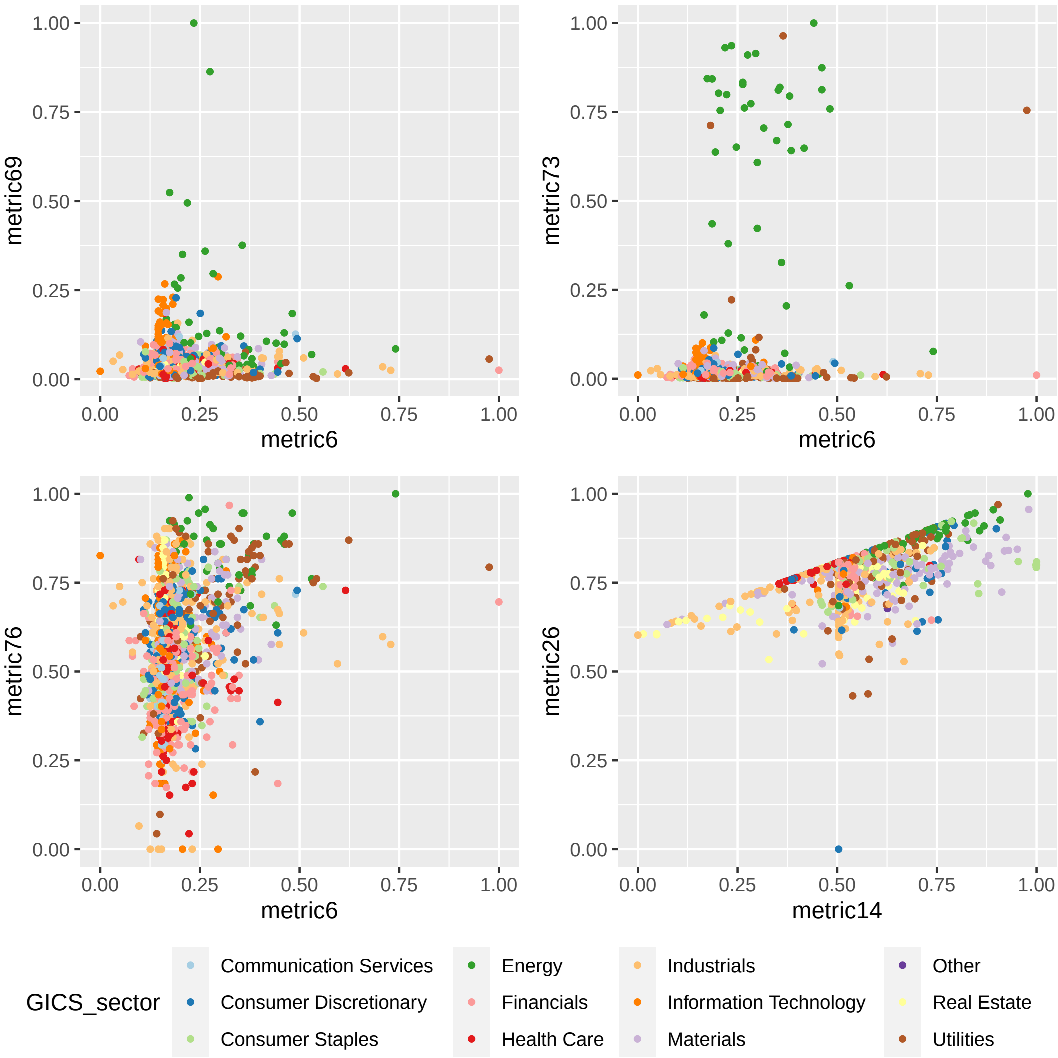


Figure 29: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (7/14)

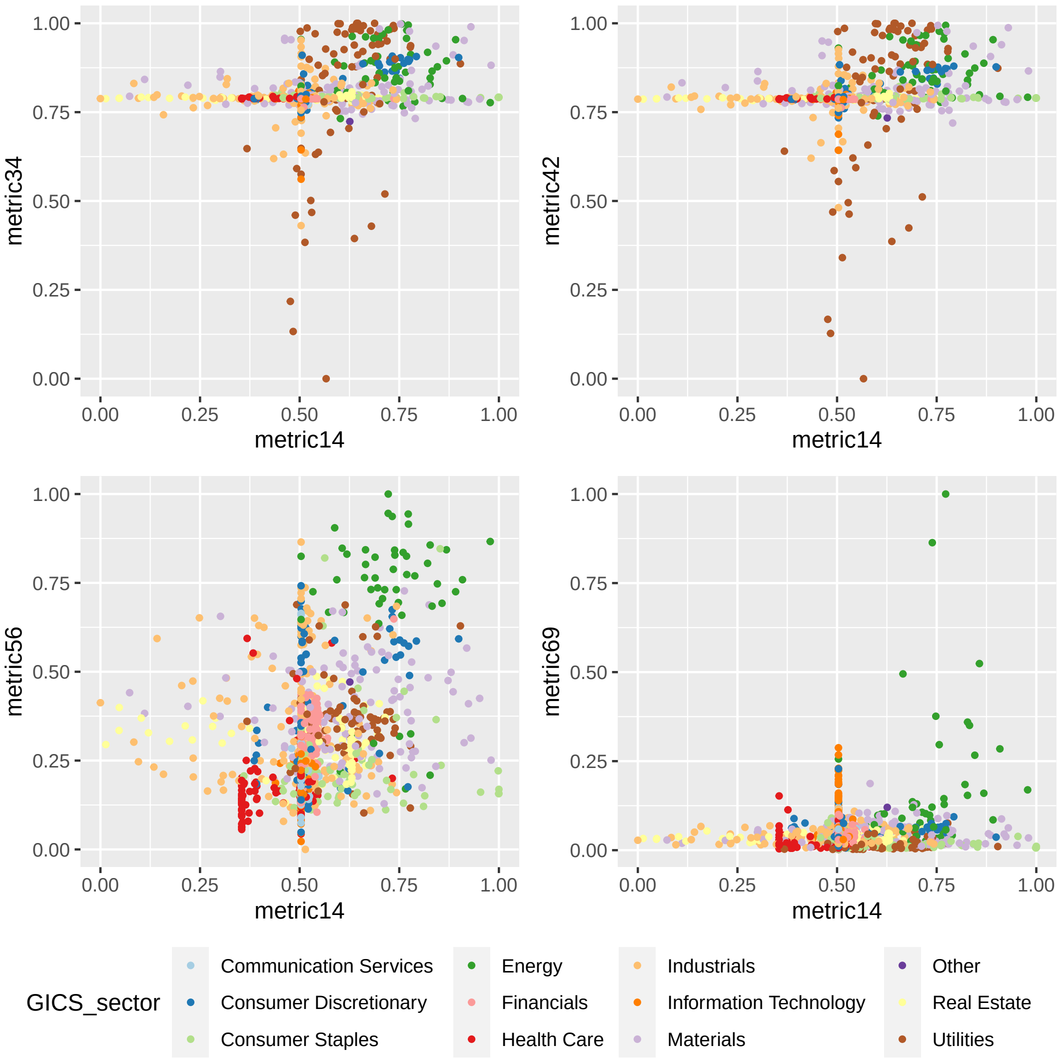


Figure 30: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (8/14)

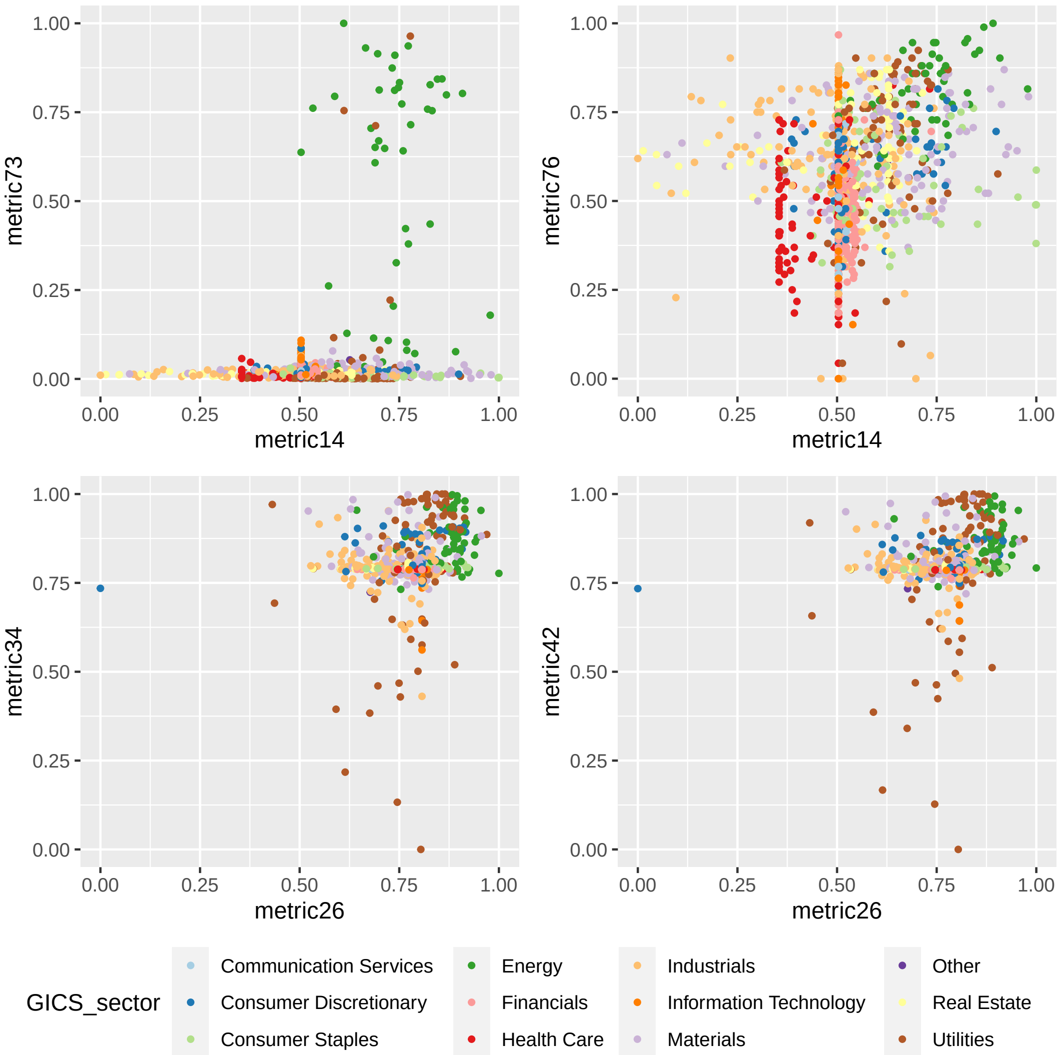


Figure 31: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (9/14)

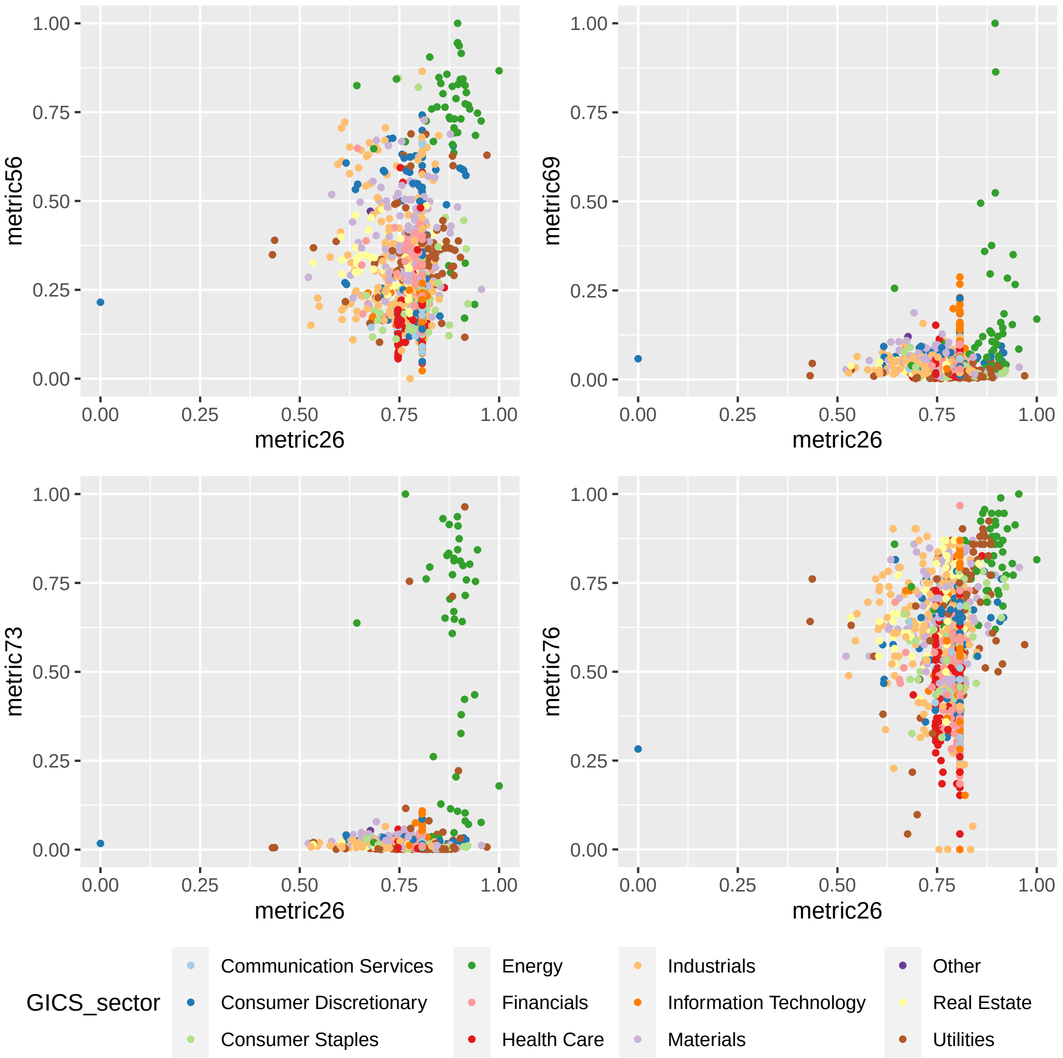


Figure 32: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (10/14)

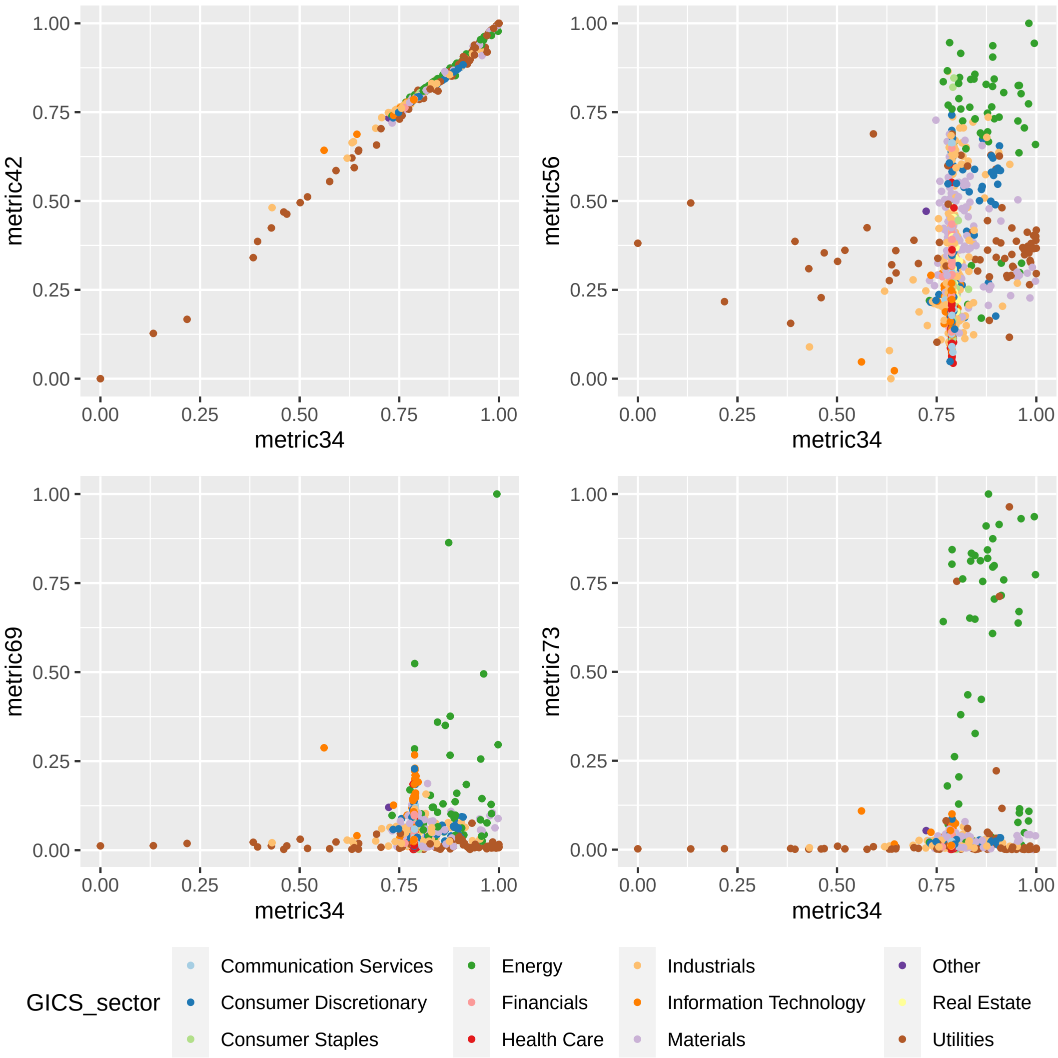


Figure 33: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (11/14)

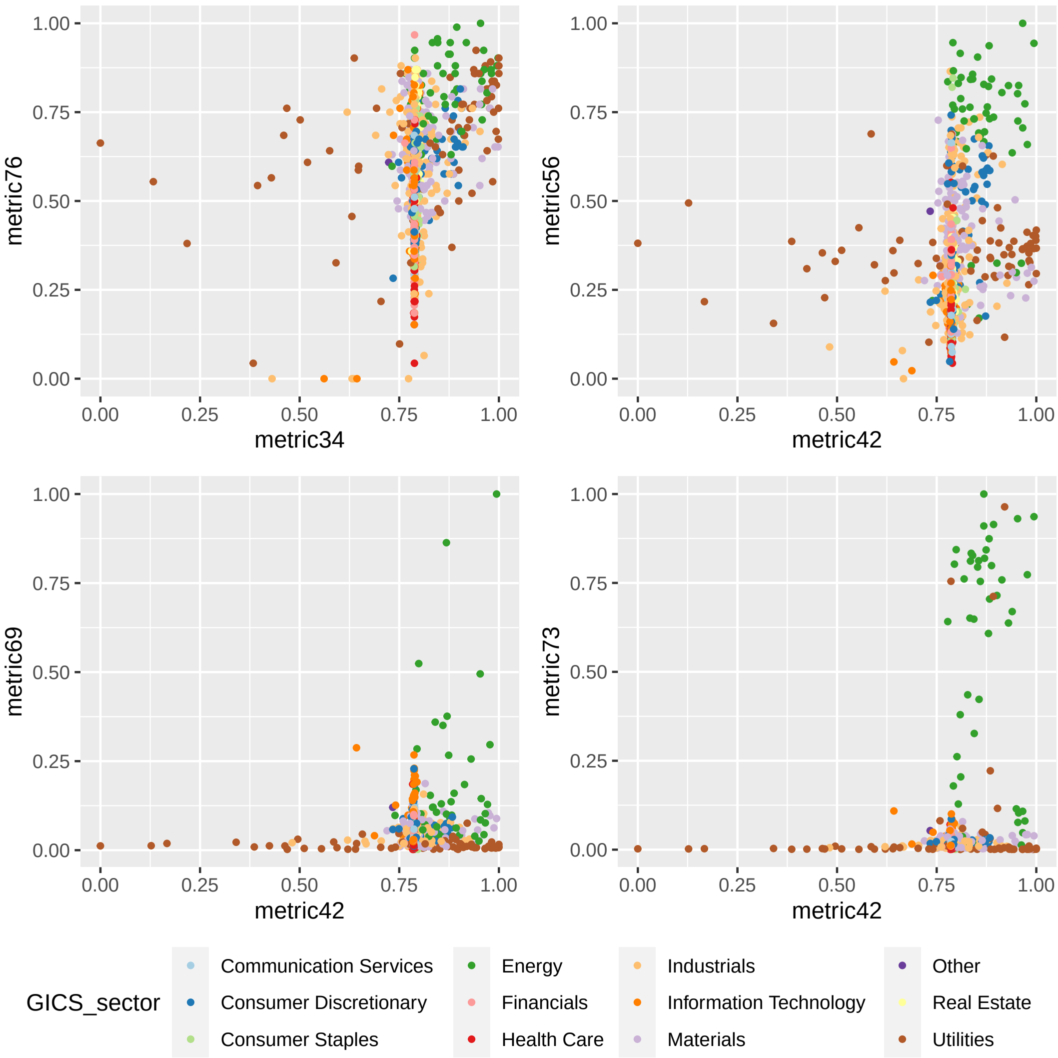


Figure 34: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (12/14)

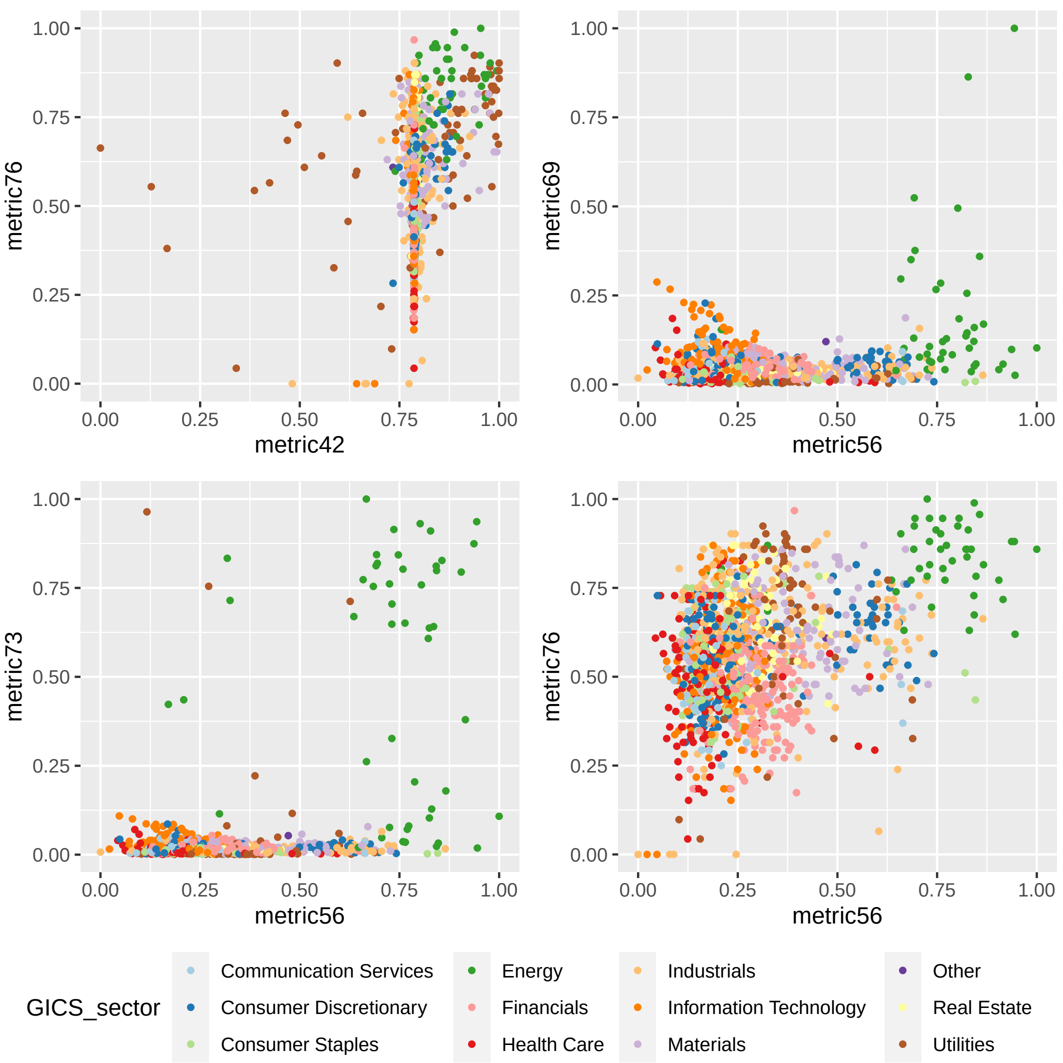


Figure 35: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (13/14)

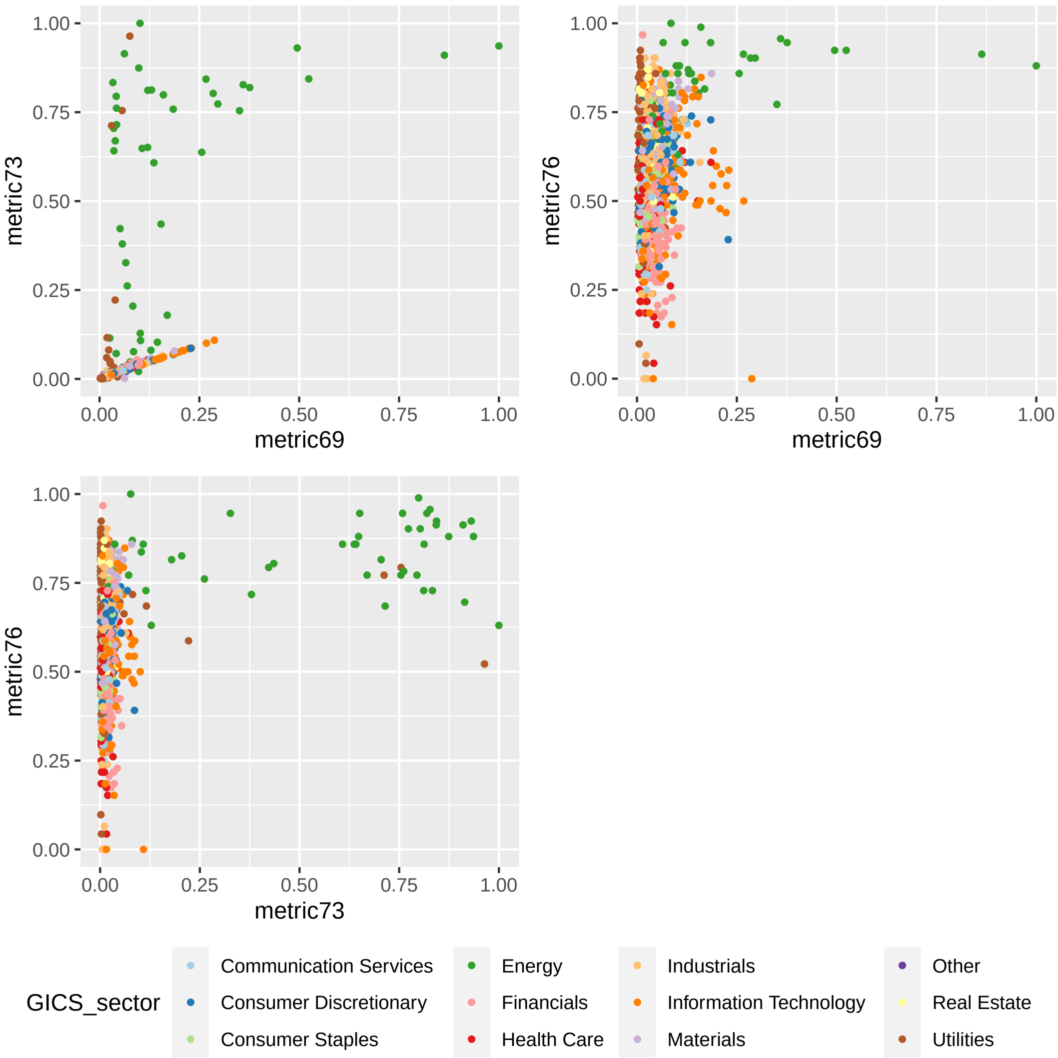


Figure 36: Pairwise scatterplots of risk metrics with 2°C temperature target and time horizon 2050, differentiated by sector (14/14)

A.4 Within sector analysis

The companies in our sample belong to 11 sectors according to the GICS classification (Consumer Discretionary, Industrials, Information Technology, Financials, Materials, Consumer Staples, Health Care, Energy, Real Estate, Utilities and Communication Services), plus a residual category, which only includes 3 companies (Others). To investigate whether the impact of metrics' characteristics varies across sectors, we run within-sector robust OLS and LASSO regressions, with heteroskedasticity- and cluster-robust standard errors. We specify a different model for each sector, except for the residual category as the number of observations is too low to obtain reliable results for the OLS and the LASSO regression. We first start with the standard robust linear regression results, as reported in tables 12 and 13.

Overall, we find that the statistical significance and the sign of most coefficients are consistent for all sectors and in line with the full sample linear regression results. Yet, some exceptions exist.

Adopting a higher temperature target of 3°C compared to 1.5°C is associated with lower risk, which is in line with what would be expected. Although this coefficient is not significant for the other sectors (similarly to what we obtained for the overall sample), for the Energy sector, the reduction in risk is clearly confirmed by a statistically significant coefficient at the 1% level (-0.286). Also not specifying a temperature target is highly significant in the case of the Energy sector and significant at the 10% confidence level for Materials, Consumer Staples and Utilities.

With regards to the time horizon, the coefficients for the time horizon 2030 and 2040, compared to a time horizon 2025 are in line with the full sample results. For the Materials sector, they are now statistically significant at the 5% level, whilst they were insignificant in the full sample case and for all other sectors. For the Energy sector, the time horizons 2040 and 2050 are statistically significant at the 10% and 5% level, and in line with expectations (0.130, 0.166). the time horizon 2040 is also significant for the Real Estate sector, although only at the 5% confidence level. For Energy, Real Estate, and Utilities, the time horizon 2100 is also statistically significant at the 1% and 5% level. The coefficients are again in line with expectations and with the previous full sample results (-0.398, -0.220, -0.280). However, given that the time horizon 2100 is assessed by few providers, only, these results could also capture the setup of the tool in general or any other modelling assumption, which is also associated with higher risk assessments for those sectors. The same holds when the time horizon is not available, given that few metrics do not use any time dimension in their analysis.

For the output variables, similar to the issues related to this variable in the robust OLS case, the results could also capture the general tool setup. Therefore, the following estimates have to be interpreted with caution. For the financial metric output, results diverge considerably across sectors in terms of statistical significance. Apart from the Energy sector, where the coefficient is insignificant, a gap output is associated across all sectors with a considerably higher risk, being statistically significant at the 1% level. Compared to the baseline of deploying a balance sheet change-related output, risk score metrics are associated with considerably higher risk values, with coefficients being statistically significant at the 1% level for all sectors.

As we already found in the full sample OLS, the inclusion of firm targets in the analysis

Table 12: Robust OLS regression by sector with heteroskedasticity- and cluster-robust standard errors (1/2)

	Dependent variable: Risk assessment					
	Consumer Discretionary	Industrials	Information Technology	Financials	Materials	Consumer Staples
temp_target_b2	−0.149 (0.202)	−0.145 (0.215)	−0.109 (0.298)	−0.110 (0.382)	−0.111 (0.178)	−0.132 (0.204)
temp_target_2	−0.139 (0.253)	−0.138 (0.274)	−0.093 (0.305)	−0.095 (0.393)	−0.116 (0.222)	−0.122 (0.258)
temp_target_3	−0.169 (0.153)	−0.154 (0.164)	−0.128 (0.350)	−0.131 (0.447)	−0.146 (0.166)	−0.141 (0.158)
temp_target_na	0.241 (0.222)	0.229 (0.236)	0.125 (0.283)	0.149 (0.363)	0.366* (0.195)	0.387* (0.223)
time_horizon_2030	0.044 (0.033)	0.039 (0.032)	0.039 (0.064)	0.041 (0.088)	0.047** (0.023)	0.045 (0.039)
time_horizon_2040	0.116 (0.073)	0.104 (0.076)	0.106 (0.125)	0.108 (0.159)	0.120** (0.050)	0.111* (0.060)
time_horizon_2050	0.127 (0.097)	0.112 (0.105)	0.118 (0.141)	0.121 (0.167)	0.133 (0.103)	0.122 (0.101)
time_horizon_2100	−0.054 (0.106)	−0.094 (0.117)	0.023 (0.144)	0.099 (0.176)	−0.177 (0.116)	−0.069 (0.111)
time_horizon_na	−0.413*** (0.121)	−0.433*** (0.135)	−0.397*** (0.105)	−0.341*** (0.123)	−0.398*** (0.131)	−0.497*** (0.122)
output_finmetric	0.590* (0.311)	0.534 (0.344)	0.694** (0.324)	0.605 (0.386)	0.392 (0.278)	0.595* (0.328)
output_gap	0.680*** (0.132)	0.517*** (0.151)	0.711*** (0.092)	0.554*** (0.103)	0.402** (0.161)	0.607*** (0.142)
output_riskscore	0.335*** (0.055)	0.254*** (0.061)	0.443*** (0.034)	0.250*** (0.038)	0.183*** (0.068)	0.207*** (0.056)
firm_target_1	0.316*** (0.077)	0.308*** (0.087)	0.354*** (0.059)	0.334*** (0.063)	0.241** (0.096)	0.284*** (0.088)
capex_1	0.582*** (0.082)	0.535*** (0.091)	0.651*** (0.095)	0.575*** (0.110)	0.436*** (0.095)	0.629*** (0.085)
approach_comb	−0.407*** (0.050)	−0.262*** (0.057)	−0.372*** (0.047)	−0.288*** (0.053)	−0.286*** (0.057)	−0.315*** (0.056)
approach_topdown	0.058 (0.138)	0.145 (0.151)	−0.025 (0.143)	0.018 (0.162)	0.164 (0.156)	0.198 (0.166)
Constant	−0.071 (0.237)	−0.039 (0.254)	−0.198 (0.216)	−0.109 (0.276)	0.086 (0.198)	−0.102 (0.235)

*p<0.1; **p<0.05; ***p<0.01

Table 13: Robust OLS regression by sector with heteroskedasticity- and cluster-robust standard errors (2/2)

	Dependent variable: Risk assessment				
	Health Care	Energy	Real Estate	Utilities	Communication Services
temp_target_b2	−0.118	−0.112	−0.085	−0.117	−0.117
	(0.196)	(0.092)	(0.195)	(0.219)	(0.289)
temp_target_2	−0.123	−0.158	−0.101	−0.109	−0.101
	(0.235)	(0.123)	(0.249)	(0.264)	(0.294)
temp_target_3	−0.154	−0.286***	−0.152	−0.093	−0.137
	(0.178)	(0.075)	(0.192)	(0.243)	(0.344)
temp_target_na	0.057	0.286***	0.198	0.411*	0.027
	(0.208)	(0.094)	(0.210)	(0.219)	(0.274)
time_horizon_2030	0.040	0.051	0.044	0.033	0.037
	(0.033)	(0.038)	(0.037)	(0.035)	(0.068)
time_horizon_2040	0.102	0.130**	0.104*	0.081	0.103
	(0.075)	(0.065)	(0.061)	(0.068)	(0.128)
time_horizon_2050	0.111	0.166*	0.109	0.079	0.116
	(0.116)	(0.085)	(0.137)	(0.094)	(0.133)
time_horizon_2100	0.005	−0.398***	−0.220**	−0.280***	0.009
	(0.104)	(0.078)	(0.108)	(0.106)	(0.147)
time_horizon_na	−0.321***	−0.046	−0.286**	−0.607***	−0.335***
	(0.117)	(0.092)	(0.141)	(0.120)	(0.097)
output_finmetric	0.738**	0.052	0.505	0.341	0.724**
	(0.304)	(0.122)	(0.340)	(0.388)	(0.328)
output_gap	0.799***	−0.071	0.600***	0.438***	0.791***
	(0.110)	(0.078)	(0.144)	(0.146)	(0.086)
output_riskscore	0.432***	−0.175***	0.369***	0.225***	0.500***
	(0.057)	(0.035)	(0.079)	(0.050)	(0.028)
firm_target_1	0.359***	0.216***	0.241***	0.222**	0.357***
	(0.067)	(0.040)	(0.086)	(0.086)	(0.056)
capex_1	0.680***	0.059	0.537***	0.476***	0.678***
	(0.072)	(0.046)	(0.093)	(0.096)	(0.090)
approach_comb	−0.399***	−0.249***	−0.441***	−0.235***	−0.431***
	(0.045)	(0.025)	(0.055)	(0.054)	(0.045)
approach_topdown	0.010	0.347***	0.113	0.138	−0.068
	(0.147)	(0.053)	(0.203)	(0.161)	(0.131)
Constant	−0.220	0.589***	−0.014	0.104	−0.215
	(0.210)	(0.070)	(0.214)	(0.197)	(0.209)

*p<0.1; **p<0.05; ***p<0.01

matters for the risk assessment. The coefficient is statistically significant for all sectors at the high 1% level, and, as in the full sample cases, is associated with higher risk values. The same holds for the CAPEX variable for all sectors, with considerably higher risk values except for the Energy sector. In this case, the coefficient is relatively low (0.059), compared to the strong effect for all other sectors, and not statistically significant.

Like in the OLS full sample case, applying a combined top-down and bottom-up approach is associated with lower risk values, compared to the baseline case of applying a pure bottom-up approach. The estimated coefficients are again statistically significant for all sectors at the 1% level. Finally, as before, the coefficients for applying the top down approach, compared to the bottom-up approach, is not statistically significant, except for the Energy sector. This is the only sector, where the top down approach is associated with considerably higher risks (0.347), compared to the bottom-up approach, at the 1% significance level.

Again, we then run the combined LASSO-reduced linear regression to better account for the potential out of sample explanatory power of the variables. The results are reported in tables 14 and 15. The results show that the above linear regression findings for the temperature target variables are confirmed. The time horizon variables 2030 and 2040, in contrast to the standard linear regression, turns out to be statistically significant for most of the sectors. This endorses the results for some of the sectors of the standard model, and suggests that, depending on the sector, risk analyses might be more or less affected by the selected time horizon. This is an important finding - in contrast to what we have seen in the full sample and the sector-differentiated standard linear regression analysis, the time horizon might matter more than previously identified.

This aspect needs further out of sample analysis. In addition, for some sectors, the time horizon 2100 variable has been dropped, whilst it is statistically significant for the same sectors like in the previous model. For all other variables, the findings from the standard linear regression by sector are confirmed. They have been in most cases kept by the model, and signs and magnitude of the coefficients are generally in line with the previous results. The LASSO coefficients are, as would be expected, larger for the statistically significant variables, given that the model is by construction biased, reflecting the explanatory power of the individual variables. Overall, statistical significance of the variables is similar, just that the firm target consideration is now statistically insignificant for most sectors. This variable has been significant at the 1% level for all sectors in the standard linear regression model.

Table 14: LASSO regression by sector with heteroskedasticity- and cluster-robust standard errors (1/2)

	Dependent variable: Risk assessment					
	Consumer Discretionary	Industrials	Information Technology	Financials	Materials	Consumer Staples
temp_target_b2	−0.158 (0.157)	−0.156 (0.159)	−0.168 (0.157)	−0.152 (0.162)	−0.122 (0.154)	−0.170 (0.159)
temp_target_2	−0.126 (0.166)	−0.124 (0.168)	−0.117 (0.157)	−0.109 (0.169)	−0.122 (0.175)	−0.140 (0.168)
temp_target_3	−0.123 (0.153)	−0.117 (0.155)	−0.109 (0.150)	−0.104 (0.160)	−0.135 (0.153)	−0.121 (0.153)
temp_target_na	0.170 (0.184)	0.135 (0.185)	0.089 (0.177)	0.080 (0.188)	0.279 (0.170)	0.236 (0.182)
time_horizon_2030	0.043** (0.019)	0.038** (0.018)	0.047*** (0.017)	0.042** (0.018)	0.045** (0.020)	0.042** (0.018)
time_horizon_2040	0.096** (0.040)	0.088** (0.038)	0.101*** (0.034)	0.088** (0.038)	0.104** (0.045)	0.098** (0.039)
time_horizon_2050	0.086 (0.058)	0.079 (0.055)	0.085* (0.049)	0.076 (0.056)	0.105* (0.062)	0.095* (0.054)
time_horizon_2100	−0.123 (0.141)	−0.134 (0.137)	— — —	— — —	−0.201* (0.115)	−0.128 (0.139)
time_horizon_na	−0.289* (0.152)	−0.328** (0.152)	−0.302 (0.189)	−0.258* (0.150)	−0.309*** (0.114)	−0.355** (0.144)
output_finmetric	0.377* (0.208)	0.359* (0.206)	0.446** (0.223)	0.391* (0.205)	0.309* (0.175)	0.402* (0.206)
output_gap	0.488** (0.199)	0.401** (0.198)	0.481* (0.257)	0.422** (0.193)	0.346** (0.148)	0.476** (0.193)
output_riskscore	0.260*** (0.041)	0.266*** (0.041)	0.332*** (0.097)	0.232*** (0.039)	0.163*** (0.036)	0.201*** (0.038)
firm_target_1	0.223* (0.133)	0.233* (0.131)	0.233 (0.148)	0.233* (0.130)	0.206** (0.099)	0.201 (0.129)
capex_1	0.462*** (0.112)	0.434*** (0.110)	0.530*** (0.124)	0.473*** (0.111)	0.397*** (0.085)	0.537*** (0.108)
approach_comb	−0.325*** (0.074)	−0.234*** (0.073)	−0.261** (0.111)	−0.243*** (0.072)	−0.256*** (0.055)	−0.272*** (0.072)
approach_topdown	0.048 (0.073)	0.050 (0.074)	— — —	−0.015 (0.118)	0.158** (0.067)	0.133* (0.072)
Constant	−0.371* (0.202)	−0.352* (0.200)	−0.438** (0.214)	−0.389* (0.202)	−0.324* (0.171)	−0.395** (0.198)

*p<0.1; **p<0.05; ***p<0.01
— indicates that the variable has been dropped by LASSO.

Table 15: LASSO regression by sector with heteroskedasticity- and cluster-robust standard errors (2/2)

	Dependent variable: Risk assessment				
	Health Care	Energy	Real Estate	Utilities	Communication Services
temp_target_b2	−0.173 (0.152)	−0.118 (0.094)	−0.125 (0.154)	−0.149 (0.164)	−0.177 (0.157)
temp_target_2	−0.143 (0.158)	−0.166 (0.122)	−0.121 (0.172)	−0.127 (0.182)	−0.130 (0.160)
temp_target_3	−0.126 (0.147)	−0.274*** (0.092)	−0.133 (0.152)	−0.111 (0.160)	−0.113 (0.152)
temp_target_na	0.074 (0.191)	0.235* (0.143)	0.194 (0.182)	0.288 (0.177)	0.040 (0.189)
time_horizon_2030	0.041** (0.017)	0.046 (0.031)	0.040** (0.019)	0.035* (0.020)	0.044*** (0.017)
time_horizon_2040	0.091** (0.037)	0.123** (0.056)	0.086** (0.039)	0.083** (0.038)	0.099*** (0.035)
time_horizon_2050	0.075 (0.055)	0.148** (0.070)	0.075 (0.054)	0.076 (0.048)	0.083 (0.052)
time_horizon_2100	−0.072 (0.162)	−0.432*** (0.082)	−0.275** (0.133)	−0.271** (0.108)	— — —
time_horizon_na	−0.300* (0.176)	−0.065 (0.089)	−0.264* (0.148)	−0.475*** (0.118)	−0.270* (0.163)
output_finmetric	0.481** (0.234)	— — —	0.334 (0.204)	0.291 (0.184)	0.461** (0.222)
output_gap	0.574** (0.233)	— — —	0.450** (0.190)	0.382** (0.155)	0.548*** (0.211)
output_riskscore	0.334*** (0.044)	−0.112** (0.052)	0.279*** (0.039)	0.204*** (0.032)	0.347*** (0.038)
firm_target_1	0.242 (0.155)	0.184*** (0.070)	0.175 (0.126)	0.183* (0.101)	0.239* (0.141)
capex_1	0.553*** (0.130)	0.078 (0.070)	0.450*** (0.107)	0.436*** (0.087)	0.549*** (0.122)
approach_comb	−0.289*** (0.086)	−0.274*** (0.067)	−0.348*** (0.070)	−0.219*** (0.057)	−0.305*** (0.079)
approach_topdown	0.006 (0.077)	0.307*** (0.097)	0.135** (0.068)	0.128** (0.063)	−0.039 (0.122)
Constant	−0.442** (0.222)	−0.023 (0.098)	−0.334* (0.196)	−0.304* (0.174)	−0.443** (0.209)

*p<0.1; **p<0.05; ***p<0.01
— indicates that the variable has been dropped by LASSO.

A.5 Random Forest

To allow for the possibility that the relationship between the features and the response variable is non linear, we also run a random forest (RF) analysis on the moments of the distribution. Potential non-linearities in the relationships would indeed not be captured by OLS or LASSO regressions.

Tree-based methods generally rely on bagging (or bootstrap aggregation), which is a general-purpose procedure for reducing the variance of statistical learning methods. Bagging refers to random sampling with replacement, basically segmenting the predictor space into regions or nodes and constructing several training sets. The algorithm splits the predictor space into the regions that lead to the greatest possible reduction in the mean square error (MSE). At each split, a subset of $m \leq k$ regressors are tested for the split optimization rule, optimally choosing variables which separate observations and dividing each node into two daughter nodes. Note that a random sample of predictors is chosen in order to avoid that very strong predictors are always chosen at the top leading to similar trees and thus to highly correlated predictions. The process of splitting is the repeated within each region to further minimize the MSE and continues until a stopping criterion is reached, which defines the set of terminal (unsplit) nodes for the tree. The RF uses this set of B bootstrap samples to grow an independent tree model on different sub-sample of the population. As described above, each tree is grown by recursively partitioning the population based on the split optimization rule over the k-dimensional covariate space. Trees are then repeatedly fit to bootstrapped subsets of the observations, where each bagged tree makes use of around two-thirds of observations. The remaining one-third of observations which are not used to fit a given bagged tree are referred to as of bag observations. The response for the i-th observation can then be predicted using each of the trees in which that observation was OOB. This will yield around $B/3$ predictions for the i-th observation, where B is the number of training sets. In order to obtain a single prediction for the i-th observation the predicted responses are averaged. This way, an OOB prediction can be obtained for all the observations from which the overall OOB MSE can be computed.

The prediction error of the RF is measured through the out-of-bag (OOB) error or out-of-bag estimate, which is reported in Figure 37 for the four moments of the distribution. The figure demonstrates that it does not take a large number of trees to stabilize the forest prediction error estimate.

We then extract the OOB prediction estimates from the random forest and plot them as displayed in Figure 38. The plot shows the predicted mean, standard deviation skewness and kurtosis, where one point is one observation in the training set. The boxplot is shown to give an indication of the distribution of the prediction estimates.

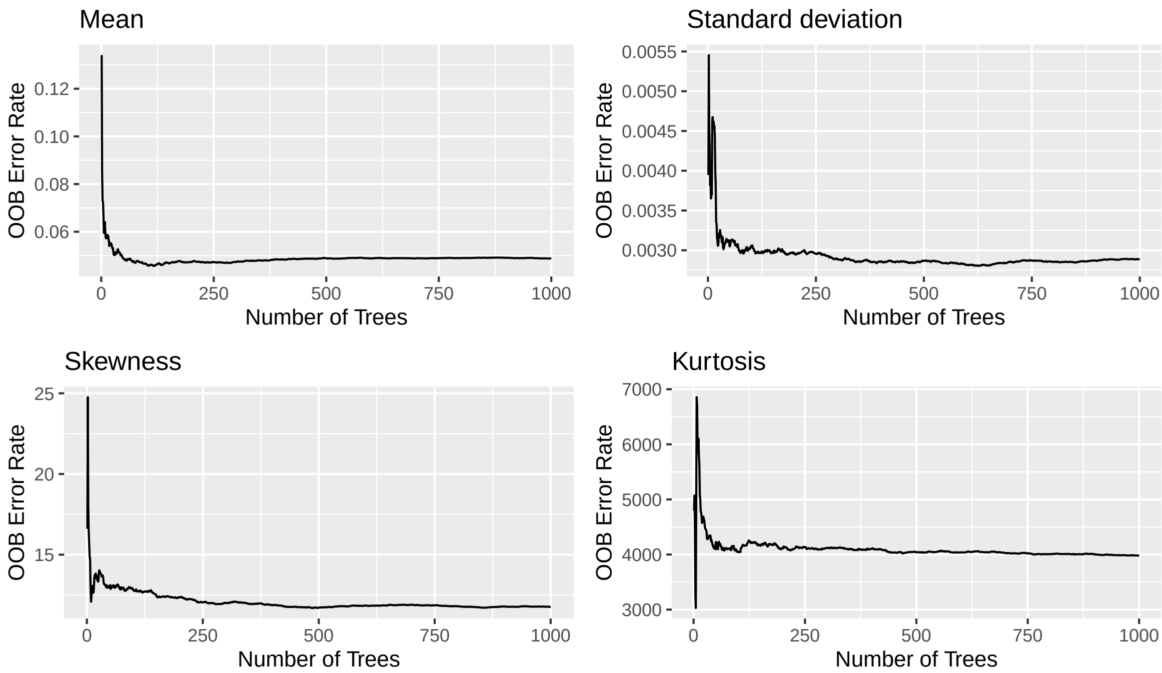


Figure 37: OOB error random forest for mean, standard deviation, skewness, kurtosis

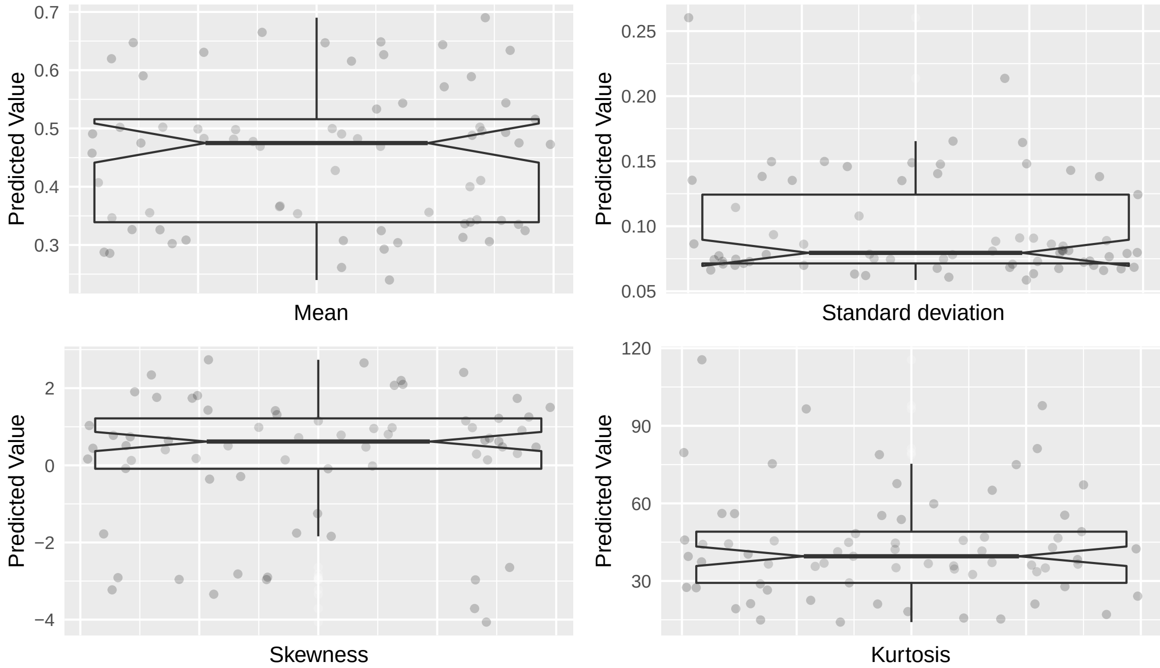


Figure 38: Predictions random forest for mean, standard deviation, skewness, kurtosis

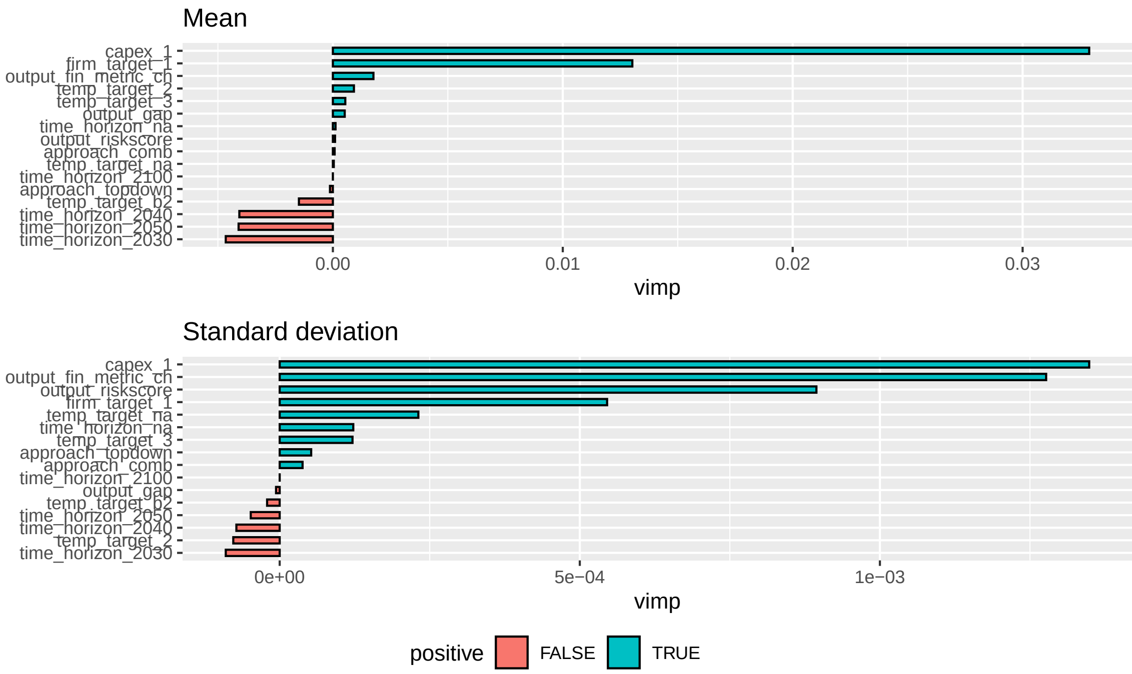


Figure 39: Variable importance for mean and standard deviation

Variable importance (VIMP). RF does not produce explicit p-value/significance test for variable selection. Instead, it ascertain which variables contribute to the prediction. The VIMP is the difference between the OOB prediction error under the observed values and under a random permutation of the values of a variable. Hence, a large VIMP value indicates that mis-specification detracts from the variable predictive accuracy in the forest. VIMP close to zero indicates the variable contributes nothing to predictive accuracy, and negative values indicate the predictive accuracy improves when the variable is mis-specified. In this case, noise is more informative than the true variable.

Figure 40 shows the VIMP plot for the mean of the distribution, which captures how the model performs without one of each variable. Specifically, it shows the percentage increase in the mean squared error (or the mean decrease in accuracy) if one variable is removed, where high values mean that these variables give a large contribution to accuracy. Figure 40 shows the variables in VIMP rank order, from the largest (inclusion of CAPEX plans) at the top, to smallest (time horizon of 2030 for the mean and standard deviation of the distribution, temperature target below 2°C for skewness and kurtosis) at the bottom. For our random forest, the top two variables have the largest VIMP, with a modest (for standard deviation and kurtosis) to sizable (for mean and skewness) difference to the remaining variables. Some VIMP measures are negative, which suggests that we should not rely on these variables to understand the predictive power of the forest.

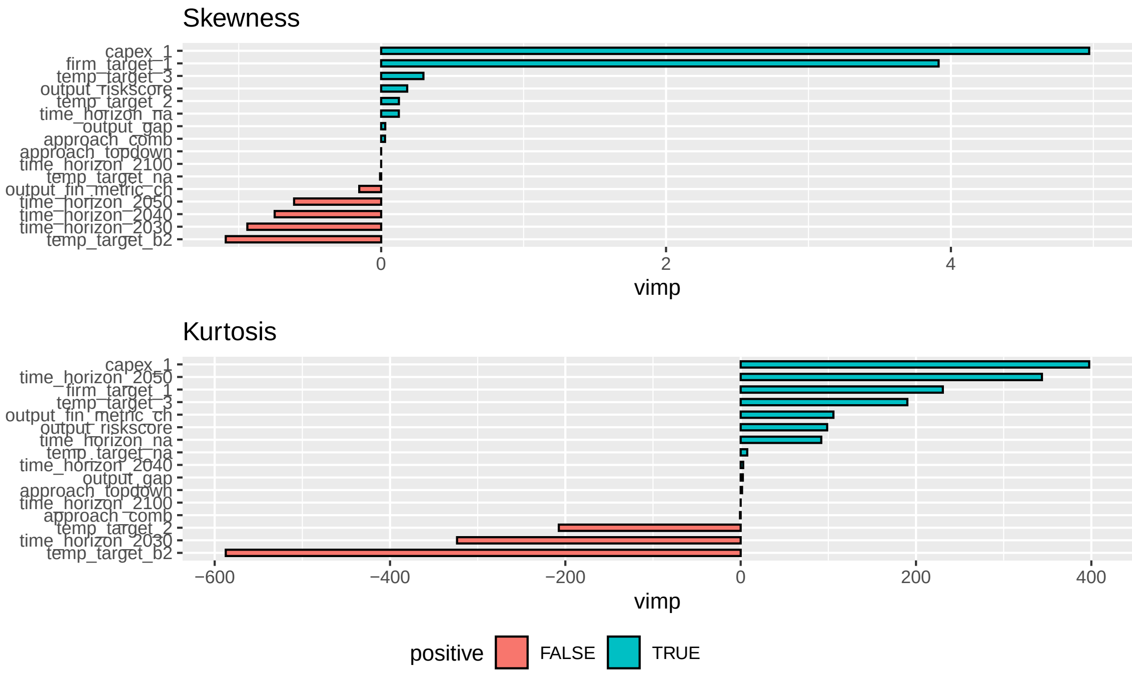


Figure 40: Variable importance for skewness and kurtosis

Since we originally had categorical variables that have been broken down into dummies further caution is needed when interpreting the VIMP plots. To obtain the overall importance of a variable in prediction, we first find the variable frequencies within each group and then computed the weighted average of the individual categories. The results are reported in Tables 16 - 19, which shows that the order of importance varies depending on the moment of the distribution considered, but the inclusion of CAPEX plans is always the variable with the largest value, whereas the type of approach used always the lowest.

Table 16: Mean

Variable	capex	firm_target	temp_target	output	time_horizon	approach
MSE decrease	0.88	0.47	0.14	0.12	0.11	0.03

Table 17: Standard deviation

Variable	capex	output	firm_target	temp_target	time_horizon	approach
MSE decrease	0.04	0.03	0.02	0.01	0.005	0.004

Table 18: Skewness

Variable	capex	firm_target	temp_target	time_horizon	output	approach
MSE decrease	172.38	148.1	32.86	28.8	20.85	4.1

Table 19: Kurtosis

Variable	capex	firm_target	time_horizon	temp_target	output	approach
MSE decrease	29731	27853.47	11600.5	9885.5	5493.4	494.64

Shapley values. To explain how much each feature value contribute to one prediction compared to the average prediction, we compute the Shapley values. For each possible combination of variables, the predicted distribution moment is computed with and without a specific feature value. The marginal contribution of this specific variable is then obtained by taking the difference between the predicted distribution moment with and without this feature value. The Shapley value is the (weighted) average of marginal contributions. In Figure 42, the y-axis indicates the variable name, in order of importance from the top to the bottom and the value next to the variable name is the Shapley value. The dots represent all the mean, standard deviation, skewness and kurtosis values of the 69 distributions. As an example, low value of the CAPEX feature, which means not including the CAPEX in our case since this is a dummy, is associated with a lower mean of the distribution, whereas a higher value of the CAPEX (1 in our case) is associated with higher average risk.

Overall, the results of the RF analysis confirm the importance of including the variables that we chose for our robust OLS and LASSO regressions.

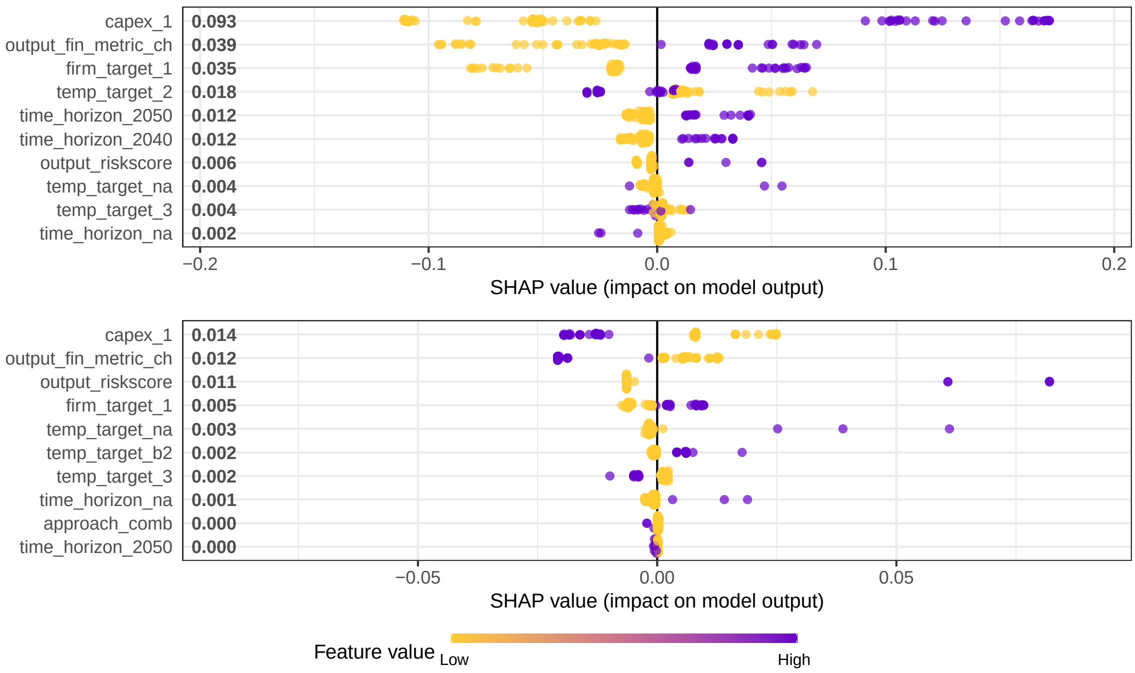


Figure 41: Shapley values for mean and standard deviation

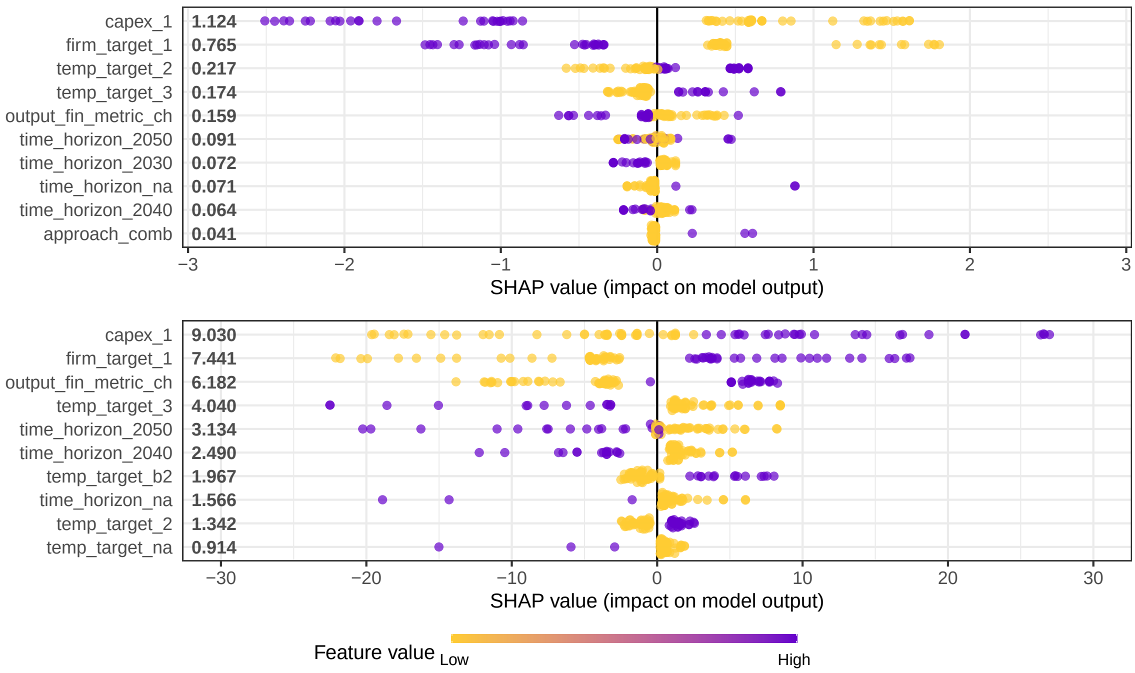


Figure 42: Shapley values for skewness and kurtosis

B Provider self-descriptions

Raw table

Tool name
Owner / Developer
Access
Documentation

Table 20: Summary PROVIDER

Description

Coverage

Sectors:

Countries / Regions:

Emission types:

Emission scopes:

Analysis horizon and time steps:

Financial asset classes:

- ☐ Stocks
- ☐ Bonds - corporate
- ☐ Bonds - sovereign
- ☐ Bonds - project
- ☐ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)

☐ Earnings / EBITDA (climate risk-adjusted)

☐ Climate financial risk score / factor

☐ Climate alignment / gap

☐ Other, namely:

Transition risk sources:

☐ Policy

☐ Market upstream (supply chain)

☐ Market downstream (demand)

☐ Technology

☐ Other / not applicable, because:

Transition trajectories:

☐ Orderly

☐ Disorderly

☐ Other / not applicable, because:

Temperature targets:

☐ 1.5°C (Paris Agreement compatible, 66% probability)

☐ < 2°C (Paris Agreement compatible, 66% probability)

☐ 2°C (Kyoto Protocol target, 66% probability)

☐ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))

☐ $> 3 - 4$°C (Current policies / Business as usual)

☐ Other / not applicable, because:

Model setup

Approach:

☐ Top-down

☐ Bottom-up

☐ Combined

Most granular unit of analysis:

☐ Physical asset

☐ Firm

☐ Sector

☐ Other, namely:

User data required as input:

Modelling options

Climate model options:

☐ IEA: ETP

☐ IEA: WEO

☐ PIK: REMIND

☐ PIK/IIASA: REMIND-MAgPIE

☐ IIASA: MESSAGEix-GLOBIUM

☐ JGCRI: GCAM

☐ Other models, namely:

☐ Own models, namely:

☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

☐ IPCC SSP1

☐ IPCC SSP2

☐ IPCC SSP3

☐ IPCC SSP4

☐ IPCC SSP5

☐ NGFS Net Zero 2050

☐ NGFS Below 2°C

☐ NGFS Divergent Net Zero

☐ NGFS Delayed Transition

☐ NGFS Nationally Determined Contributions

☐ NGFS Current Policies

☐ Not applicable / not identified

Firm-level modelling options:

☐ Cost pass-through

☐ Firms' own climate targets

☐ Capex plans

☐ Other, namely:

Figure 43: Schematic model overview NAME

B.1 2 Degrees Investing Initiative & Asset Resolution

Tool name	Paris Agreement Capital Transition Assessment (PACTA)
Owner	2 Degrees Investing Initiative, Asset Resolution
Developer	Consortium led by 2 Degrees Investing Initiative, supported by UNPRI
Access	Public, free access
Documentation	`https://www.transitionmonitor.com/resources/#background`

Table 21: Summary 2 Degrees Investing Initiative - PACTA

Description The PACTA tool covers listed equities, corporate bonds, and corporate loans. It is based on analysis of companies' asset-based investment and production plans in both high-emissions activities and low-carbon solutions across key climate sectors (fossil fuel extraction, power generation, automotive, steel and cement manufacturing and aviation). The production volume trajectory and technology mixes of the fossil fuel, power and automotive sector are then compared to technology road maps presented in climate change scenarios. In the case of steel, cement, and aviation – for which technology roadmaps are less well defined - a required emission intensity reduction is required based on the climate scenario. The output of the tool is a set of exposure metrics and a set of alignment metrics given at both the portfolio and individual client level. In particular, the tool helps answering three research questions:

1. What is the exposure to climate relevant sectors and technologies of a given portfolio?
2. How do the aggregated CAPEX plans (of the clients) align with climate scenarios in terms of production build out? (PACTA allows for a 5 year forward looking assessment of production build out)

The objective of the PACTA assessment framework is to measure the alignment of financial portfolios with climate goals e.g. 2°C, 1.5°C, net zero decarbonization pathways. Specifically, the framework quantifies a financial portfolio's exposure to a 2∘C benchmark in relation to various climate-related technologies. The result is thus a misalignment indicator that measures the extent to which current and planned assets purchases, production profiles, investments, and GHG emissions are aligned with a 2°C trajectory. The model used does not follow pre-defined macroeconomic trends or shocks, but rather creates a "translation software" that maps forecasted macroeconomic trends and shocks into financial portfolios impacts. Thus, it does not rely on developing these economic trends themselves and can be used to test any macroeconomic assumption. In the following the key modelling principles are briefly summarized:

- The model calculates the expected benchmark exposure for each technology in the specific asset class by taking the current exposure in the respective asset class and geography and adding the trend line as defined in the scenario (e.g. the IEAs 2°C compatible sustainable development scenario). The build-out percentages take a simple "market share principle" under which the companies in the investable universe are assumed to adjust production capacity in line with the scenario, consistent with their market share;
- The model assesses the scenario alignment of financial portfolios with a 5-year time horizon/forecast period. The time horizon is limited to the time horizon of capital expenditure planning for which data can be tracked at a meaningful level. While this time horizon may differ across sectors, a homogeneous time horizon is taken to allow for the comparability of results;
- The model applies traditional financial accounting principles such as a portfolio-weight approach to allocate company-level results to portfolio level. Notably the equity share principle can also be applied followed where possible (i.e. 1% ownership of a company implies 1% ownership of assets).

The Data: Asset Resolution (AR) is the data spin-off of 2DII and provides the asset-based company data that feeds in the PACTA tool. AR's vision is of a financial sector that empowers the global economy to take swift and decisive action in line with the Paris Agreement. AR believes that the financial sector has an instrumental role to play in empowering climate action. PAMS, our forward-looking database of Physical Assets Matched with Securities, covers 300,000 physical assets across climate critical sectors: oil and gas extraction (upstream), coal mining, power generation, automotive manufacturing, aviation and shipping industry, and cement and steel manufacturing. AR links these assets to over 55,000 companies/issuers — helping financial institutions look under the hood of their portfolios. AR links financial portfolios with the real economy with data that:

- Is based on a transparent bottom-up asset-based approach
- Includes over 50k private companies
- Captures asset-based, forward-looking CAPEX plans/production and emissions factors
- Provides a universal link to the company/issuer through a corporate ownership tree across sectors
- Is delivered in a consistent format across sectors and indicators

Coverage

Sectors: *Oil and gas extraction (upstream), coal mining, power generation, automotive manufacturing, aviation and shipping industry, and cement and steel manufacturing.*

Countries / Regions: *All*

Emission types: *All* CO_2*-eq*

Emission scopes: *Scope 1, 2, and 3*

Analysis horizon and time steps: *annual, 2020 to 2026*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☐ Bonds - sovereign
- ☐ Bonds - project
- ☒ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)

- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☐ Climate financial risk score / factor
- ☒ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ☐ Policy
- ☐ Market upstream (supply chain)
- ☐ Market downstream (demand)
- ☐ Technology
- ☒ Other / not applicable, because: *As determined in a given scenario, all sources play a role.*

Transition trajectories:

- ☐ Orderly
- ☐ Disorderly
- ☐ Other / not applicable, because: *As determined by the scenario, could be either.*

Temperature targets:

- ☒ 1.5°C (Paris Agreement compatible, 66% probability)
- ☒ < 2°C (Paris Agreement compatible, 66% probability)
- ☒ 2°C (Kyoto Protocol target, 66% probability)
- ☒ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☒ $> 3 - 4$°C (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☐ Top-down
- ☒ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☒ Physical asset
- ☐ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input: *List of ISINs*

Modelling options

Climate model options:

- ☒ IEA: ETP
- ☒ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely: *European Commission: POLES-JRC; One-Earth Climate Model*
- ☐ Own models, namely:
- ☐ Not applicable, because:

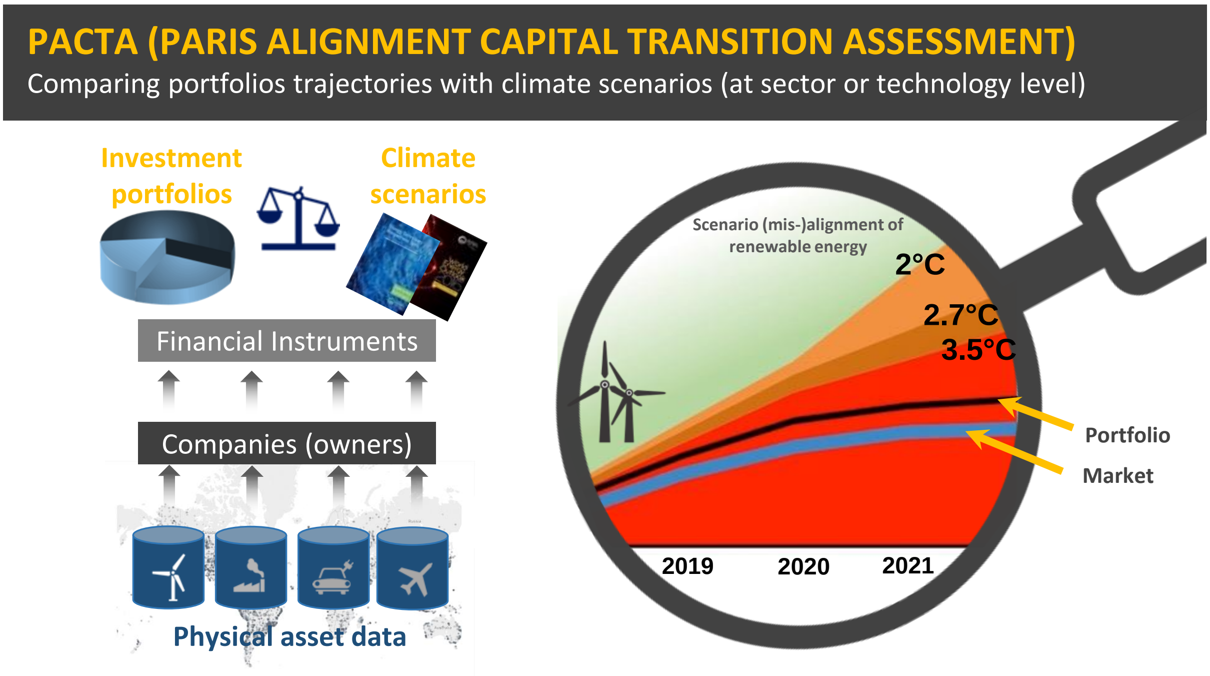
Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☒ Not applicable / not identified

Firm-level modelling options:

- ☐ Cost pass-through
- ☐ Firms' own climate targets
- ☒ Capex plans
- ☒ Other, namely: *Asset-level production forecasts*

Figure 44: Schematic model overview PACTA



B.2 Cambridge Institute for Sustainability Leadership

Tool name	ClimateWise Transition Risk Framework
Owner / Developer	ClimateWise/ University of Cambridge for Sustainability Leadership (CISL)
Access	Public, free access
Documentation	`https://www.cisl.cam.ac.uk/resources/sustainable-finance-publications/navigating-transition`

Table 22: Summary ClimateWise / CISL

Description The ClimateWise Transition Risk Framework is an open source methodology designed to help investors to:

1. Assess the breadth of asset types exposed to transition risk and opportunity across an investor's portfolio (across different subsectors, regions and time frames)
2. Define the potential financial impact from the low carbon transition down to an asset level
3. Incorporate transition impacts into their asset financial models.

The framework focuses on infrastructure investments and can be applied to an array of global infrastructure asset types. The tool follows the general scheme: Financial driver analysis → Transition scenario analysis → Portfolio risk and opportunity exposure → [optional: Asset impact identification] → [optional: Financial modeling analysis] → Tool output. The framework is set out in three steps, which can be used independently or combined to explore transition risks and opportunities (CISL, 2019). Each of the three steps highlights practical actions investors might take in order to manage risks and capture opportunities:[12]

- Step 1: Portfolio risk and opportunity exposure. This step allows investors to identify the material financial impacts from transition risks across a large portfolio, by applying the Infrastructure Risk Exposure Matrix. This step helps to assess potential exposure to transition risk across a breadth of asset types, geographies, climate scenarios and time frames.
- Step 2: Asset impact identification. This step allows investors to assess the financial impact from the low carbon transition at an asset-by-asset level, which provides insights on ways to improve asset resilience. Risks vary considerably between assets of the same type, depending on their geography, carbon intensity, technology (for example solar versus wind) and competitive positioning in the local market. Depending on an investor's portfolio size and risk appetite, the Asset Impact Identification Methodology can be re-applied asset-by-asset to an entire portfolio, or to the most exposed assets identified by overlaying Infrastructure Risk Exposure Matrix. Additionally, stress testing of the portfolio under different time frames and scenarios will produce a more holistic understanding of transition risk and opportunity.
- Step 3: Financial modeling analysis. This step allows investors to incorporate the potential impacts of transition risk directly into their own financial models. This is done by integrating the financial drivers identified in Steps 1 and 2 into investors' own in-house financial models.

Coverage

Sectors: *Power generation, fuel infrastructure, transport, social, water, telecommunications*

Countries / Regions: *US, the EU and India*

Emission types: *not applicable*

Emission scopes: *not applicable*

Analysis horizon and time steps: *2025, 2030, 2040*

[12] This description has been taken from Bingler and Colesanti Senni (2020)

Financial asset classes:

- ☐ Stocks
- ☐ Bonds - corporate
- ☐ Bonds - sovereign
- ☐ Bonds - project
- ☐ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☐ Options and derivatives
- ☒ Other, namely: *Infrastructure*

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☒ Climate financial risk score / factor
- ☐ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ☒ Policy
- ☒ Market upstream (supply chain)
- ☒ Market downstream (demand)
- ☒ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

- ☒ Orderly
- ☐ Disorderly
- ☐ Other / not applicable, because:

Temperature targets:

- ☐ 1.5°C (Paris Agreement compatible, 66% probability)

- ☐ $< 2°C$ (Paris Agreement compatible, 66% probability)
- ☒ 2°C (Kyoto Protocol target, 66% probability)
- ☒ $2 - 3°C$ (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☐ $> 3 - 4°C$ (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☒ Top-down
- ☐ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☐ Firm
- ☒ Sector
- ☐ Other, namely:

User data required as input: *Additional jurisdictional or asset-specific data could be incorporated to the Infrastructure Risk Exposure Matrix based on users' scope of analysis.*

Modelling options

Climate model options:

- ☒ IEA: ETP
- ☒ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

- ☒ IPCC SSP1
- ☒ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions

☐ NGFS Current Policies

☐ Not applicable / not identified

Firm-level modelling options:

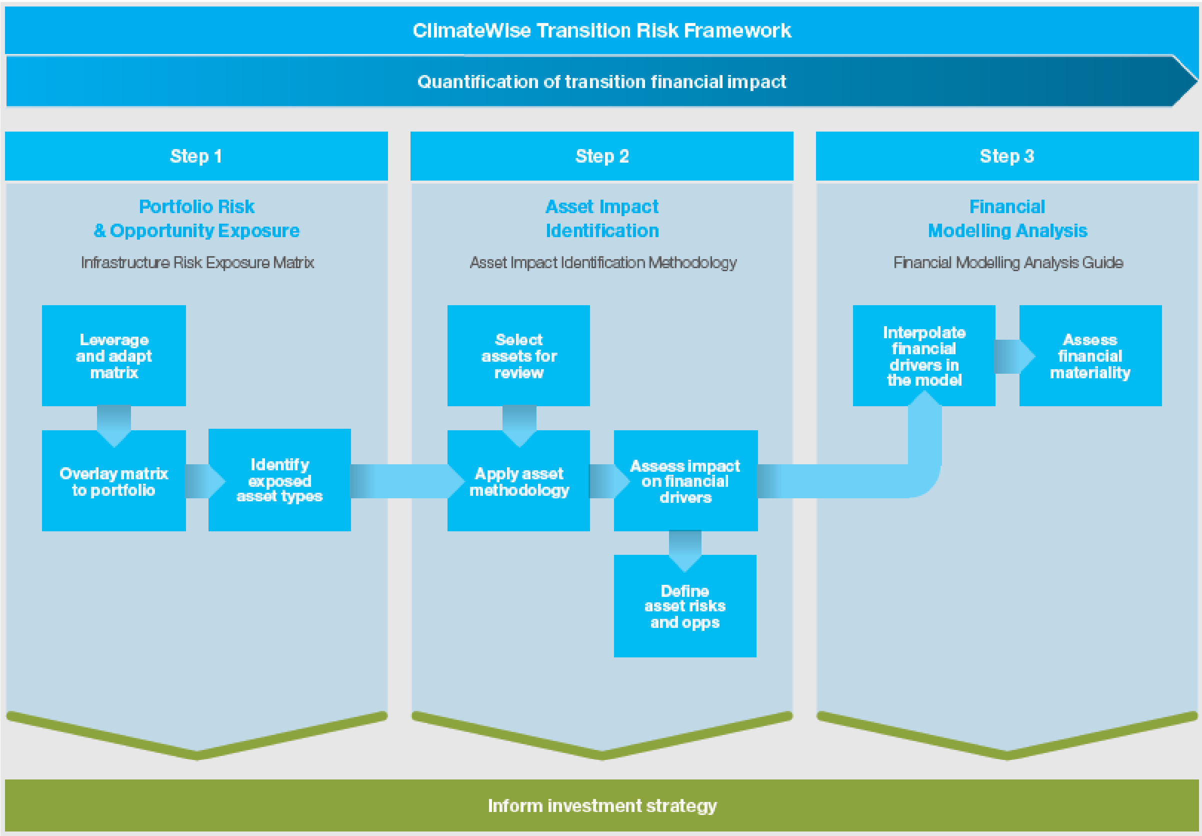
☒ Cost pass-through

☐ Firms' own climate targets

☐ Capex plans

☐ Other, namely:

Figure 45: Schematic model overview CISL



B.3 Entelligent

Tool name	Smart Climate® Technology
Owner / Developer	Entelligent
Access	Entelligent by FTP/Open: FactSet
Documentation	https://insight.factset.com/resources/at-a-glance-entelligent-smart-climate
	https://www.factset.com/marketplace/catalog/product/smart-climate-e-scores

Table 23: Summary Entelligent

Description Entelligent is a specialist quantitative data and analytics firm that assesses climate change transition risk for asset owners, asset managers, banks, and insurance companies. Entelligent's patented Smart Climate® process and E-Score® data suite provides climate-adjusted equity and fixed income risk metrics at the individual asset, geographic, portfolio, and fund level. These measures align investments with portfolio scenario analysis recommendations made by the Task Force on Climate-Related Financial Disclosures (TCFD). Smart Climate blends energy economics and climate forecasts with financial data to predict corporate vulnerability to climate transition risk under various scenarios. Rather than relying on backward-looking ESG data, Entelligent® uses integrated resource assessment models, financial modeling, and machine learning to create forward-looking, predictive E-Suite indicators. The E-Score data suite and accompanying analytics offer leading indicators for company performance and environmental impact that are rooted in science, and additive to investment strategies.

The Entelligent Smart Climate process and E-Score data suite have two primary use-cases:

1. The first is for the purpose of quantitative portfolio strategy construction. The E-Score data suite can be utilized in portfolio screening, tilting, and optimization processes to launch either active portfolios, to construct passive indices, or climate hedging solutions. Banks, insurance companies, asset owners, and asset managers can partner with Entelligent to license the Smart Climate technology for this purpose. These custom investment strategies meet TCFD recommendations for portfolio scenario analysis and can be integrated with additional Environmental, Social, Governance (ESG) factors and traditional financial objectives.
2. The second use case is to subscribe to the Smart Climate E-Score data suite for the purpose of meeting TCFD recommendations for scenario analysis at the organizational level. Asset owners and managers can measure and report TCFD recommendations for scenario analysis by isolating the relationship between energy transition pathways and their portfolios risks and opportunities by integrating the E-Score data suite into their governance, reporting, and investment processes. Organizations that subscribe to the E-Score data suite work with Entelligent to include scenario analysis into strategic planning and enterprise risk management and use scenario analysis to improve disclosures on strategy and metrics and targets.

For each scenario, Entelligent generates price and demand forecasts for nine major energy sources (oil, coal, gas, nuclear, biofuels, renewable fuel, renewable electricity, hydroelectricity, and new technologies, such as battery storage). Combining price and demand, it is possible to estimate future revenue for each energy source. Then, combining historical investment cost and the expected operating cost for each energy source, we determine the source's cash flow and profitability indicators, such as net present value (NPV), return on investment (ROI), debt coverage ratio (DCR) and internal rate of return (IRR). The Energy profitability Indicators as well as Energy prices that Entelligent is using, are capturing (proxy of) all type of risks as indicated above. Price and Demand of all energy sources are created considering multiple factors such as GDP, Population, Energy Efficiency electrification, Cost of carbon and others.

In addition to the E-score, the following metrics are available:

- Climate Resiliency/Fitness (Energy Mix Transition Risk (EMTR)) = Climate Sensitivity of a company to selected future climate scenarios. Entelligent scores companies quarterly based on the sensitivity of their share price (or total returns with dividends reinvested) to historical and forecast energy profitability indicators (from step 2). Self-reported policy commitments and other company-level initiatives are not considered. Scores are based purely on the historical price dependency of a company's performance indicators and energy profitability indicators, carefully captured over 20 quarters or more. Companies with higher sensitivity to energy prices are rated as having a higher Energy-Mix Transition Risk (EMTR). EMTR serves as the basis for Entelligent's E-Score®.

- Climate Alignment (Transition Risk (T-Risk)) = Directional climate risk matrix to improve financial and environment performance of equity investment portfolios. T-Risk measures the return spread from BAU scenario to scenario like a Paris aligned net zero. T- Risk is a directional climate matrix which indicates not only the climate sensitivity but also the direction. Negative T-Risk indicates superior adjustments in Paris Scenario relative to current BAU. T-Risks are based on the dependency of a company's historical performance and energy factors over 40-60 quarters. And T-Risk captures both cohort common estimation (cohort is defined as firms from the same industry group and region) and a company's own random effect.

Data subscriptions are available via Open:FactSet or directly from Entelligent by FTP.

Coverage

Sectors: *All 11 GICS economic sectors*

Countries / Regions: *Global (Entities in: Asia, North America, Europe, Latin America, Middle East, Pacific, Africa*

Emission types: *CO2 equivalent*

Emission scopes: *Scope 1 and Scope 2*

Analysis horizon and time steps:

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate *(prototype)*
- ☒ Bonds - sovereign *(prototype)*
- ☒ Bonds - project *(prototype)*
- ☐ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)

- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☒ Climate risk score / factor
- ☒ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ☒ Policy
- ☒ Market upstream (supply chain)
- ☒ Market downstream (demand)
- ☒ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

- ☒ Orderly
- ☒ Disorderly *(under development)*
- ☐ Other / not applicable, because:

Temperature targets:

- ☒ 1.5°C (Paris Agreement compatible, 66% probability)
- ☐ < 2°C (Paris Agreement compatible, 66% probability)
- ☐ 2°C (Kyoto Protocol target, 66% probability)
- ☒ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☒ $> 3 - 4$°C (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☒ Top-down
- ☐ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☒ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input: *We require users portfolio holding information including company identifiers (ISIN etc.) and investment amounts (weights)*

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☒ PIK/IIASA: REMIND-MAgPIE *(under development)*
- ☒ IIASA: MESSAGEix-GLOBIUM *(under development)*
- ☒ JGCRI: GCAM *(under development)*
- ☒ Other models, namely: *MIT: EN-ROADS*
- ☐ Own models, namely:
- ☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☒ NGFS Net Zero 2050 *(under development)*
- ☐ NGFS Below 2°C
- ☒ NGFS Divergent Net Zero *(under development)*
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☒ NGFS Current Policies *(under development)*
- ☒ Not applicable / not identified, because: *Own scenarios*

Firm-level modelling options:

- ☐ Cost pass-through
- ☐ Firms' own climate targets
- ☒ Capex plans *(under development)*
- ☐ Other, namely:

Figure 46: Schematic model overview Entelligent

B.4 ESG Plus

Tool name	CLEANVEST and ESG Model
Owner / Developer	ESG Plus GmbH
Access	
Documentation	https://www.cleanvest.org/de/about/ https://www.esgplus.com/leistungen-2/

Table 24: Summary ESG Plus

Description CLEANVEST is a platform by ESG Plus that provides free and easily accessible sustainability information of investment products. The platform currently rates the sustainability performance of around 4.000 securities and 12.000 investment products. With this tool ESG Plus aims to lead the way shifting the financial market towards more transparency when it comes to information on sustainability.

CLEANVEST allows users to verify the sustainability status of their investments or to identify new investment products that are in line with their individual preferences or values according to 10 sustainability criteria. The 10 sustainability criteria were developed in cooperation with a scientific advisory board and various Austrian as well as international NGOs such as Ashoka, Global 2000, He For She and many more. The criteria comprise social and ecological aspects of sustainability, namely child labor, weapons, oil and gas, health and education, green technology, nuclear power, coal, indigenous rights, protection of species and women's empowerment. The criteria can be clustered into negative criteria (such as "Free of Oil Gas" or "Free of nuclear power") and positive criteria (such as "Green technology" or "Health and Education). For the sustainability assessment of companies the following sources are used: publicly available data from company reports, online due-diligence databases, publications from international initiatives.

For the overall sustainability score of an investment product the respective companies are matched with the 10 criteria and assessed individually. Subsequently, the overall score is calculated using the mean of all individual scores. Thereby, each financial product receives a sustainability ranking which varies between 0 (not sustainable) and 10 (sustainable). In additional to the sustainability ranking, the platform displays key financial figures on the different products and offers a memory list.

The ESG Model combines ESG ratings for Corporate Stocks Bonds, Covered Bonds and Government Bonds measuring the sustainability level of investment portfolios or individual products. As the name ESG" suggests, it incorporates hot-spot indicators on environmental (E), social (S) and governance (G) topics to create a holistic score of sustainability performance ranging from 0 (not sustainable) to 100 (sustainable). In choosing the indicators, special emphasis was laid on materiality and transparency, meaning that the model strives to include as many indicators as needed using publicly available sources within the research process. The model currently comprises 150 sustainability indicators which were developed in a multi-stakeholder process with around 70 experts and 40 different scientific and non-governmental organizations.

In producing ESG Scores for corporate issuers the model uses a proprietary NGO-backed method which combines the sustainability rating of the industry sector the specific company operates in, the sustainability performance of the company in relation to its industry peers and the environmental, social and economic wrongdoings of the issuer as reported by media and NGOs. The ESG Model follows a very stringent definition of sustainability, which in turn differentiates it from widely used best-in-class" approaches in ESG screening and portfolio management. A simple example to elucidate this is the fact that in the ESG Model an Oil Gas company or a Coal Mining company cannot reach an ESG Score considered sustainable".

The ESG Model was developed to screen small to medium-sized investment portfolios. One of the major advantages of the ESG model is that it allows for comparability of ESG Scores across different industry sectors and types of assets (corporate stocks or bonds, government bonds, covered bonds) and therefore provides the possibility to generate a single metric quantifying the ESG performance of the overall portfolio. The model can be tailored according to the needs of asset managers. Additionally, to the ESG score it provides the possibility to investigate the different components of the portfolio, in order to find low hanging fruits, enhance ESG performance or examine problematic unsustainable investments.

Coverage

Sectors: *All*

Countries / Regions: *All*

Emission types:

Emission scopes: *Scope 1-2*

Analysis horizon and time steps: *Status quo company-reported information*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☒ Bonds - sovereign
- ☒ Bonds - project
- ☐ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☐ Climate financial risk score / factor
- ☐ Climate alignment / gap
- ☒ Other, namely: *climate-related indicator assessments, aggregated SDG score*

Transition risk sources:

- ☐ Policy
- ☐ Market upstream (supply chain)
- ☐ Market downstream (demand)
- ☐ Technology

- ☒ Other / not applicable, because: *We do not offer climate models, thus most questions in this form are not applicable to us.*

Transition trajectories:

- ☐ Orderly
- ☐ Disorderly
- ☒ Other / not applicable, because: *We do not offer climate models, thus most questions in this form are not applicable to us.*

Temperature targets:

- ☐ 1.5°C (Paris Agreement compatible, 66% probability)
- ☐ < 2°C (Paris Agreement compatible, 66% probability)
- ☐ 2°C (Kyoto Protocol target, 66% probability)
- ☐ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☐ $> 3 - 4$°C (Current policies / Business as usual)
- ☒ Other / not applicable, because: *Our data does not include specific temperature targets as we only provide an analysis of publicly available sustainability-related data of the companies status quo.*

Model setup

Approach:

- ☒ Top-down
- ☐ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☒ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input: *Portfolio*

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ☒ Not applicable, because: *We do not offer climate models, thus most questions in this form are not applicable to us.*

Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☒ Not applicable / not identified

Firm-level modelling options:

- ☐ Cost pass-through
- ☒ Firms' own climate targets
- ☐ Capex plans
- ☐ Other, namely:

B.5 ISS ESG

Tool name	ISS ESG's Climate Impact Report
Owner / Developer	ISS ESG
Access	Public, paywall, fixed price and customized options
Documentation	`https://insights.issgovernance.com/topics/environmental-social-governance/` `https://www.issgovernance.com/esg/`

Table 25: Summary ISS ESG

Description ISS ESG is one of the leading providers of data, analytics and advisory services on climate-related risks. ISS ESG's dedicated team of climate change experts provide financial market participants, governments and universities with market-leading carbon and climate data, actionable intelligence and state-of-the art portfolio analytics.

ISS ESG provides automated Carbon Footprint and Climate Impact Reports, including the underlying data, on a portfolio level for equity and fixed income corporate bonds via the client Portfolio Analytics tool on the DataDesk platform. This includes scenario analysis, transition risks and physical risks. Additionally, ISS ESG provides sovereign bond carbon footprint, transitional and physical risk data upon request and plans include this asset class in the automated Portfolio Analytics platform tool in 2021. On a bespoke basis ISS ESG can further provide carbon footprint data for private equity, loans private debt, listed and unlisted infrastructure, real estate, real assets (forestry, etc.), hedge funds and commodities or even specific projects such as an investment in a desalination plant.

Regarding transition risks, ISS ESG offers an analysis of the portfolio's transition climate risks in order to better understand how a client's investment universe is contributing to a transition towards a green economy. This analysis combines various indicators and aggregates company specific information on the fossil fuel exposure of client's holdings in the oil gas, coal and utilities sectors. The Transition Risk Analysis contains the following elements:

- Power Generation - Green/Brown Share and Overall Exposure
- Fossil Fuel Reserves and Potential Emissions
- Controversial Business Practices
- Portfolio Carbon Risk Rating

Through its Carbon Risk Rating, ISS ESG offers a forward-looking indicator informing investors about the future evolution of issuers' carbon emissions. The Carbon Risk Rating provides a sophisticated metric to evaluate:

- In how far a company is exposed to climate/carbon risks and opportunities, and
- Whether these are managed in a way to seize opportunities, and to avoid or mitigate risks

Thereby, the Carbon Risk Rating assesses to what extent a company will be able to cope with future challenges related to ongoing climate change and also seize opportunities arising from a transition to a low-carbon economy, in order to gain a competitive advantage in a world undergoing major transformation processes.

ISS ESG is developing a Transition Risk Model which aims to evaluate how climate transition opportunities and risks, including carbon pricing, impact investees and portfolio valuations. The release will feature a Transition Value at Risk leveraging ISS ESG's EVA (Economic Value Added) financial valuation model. Additionally, ISS ESG offers detailed scenario analyses to enable clients to assess the potential business implications of climate change, as suggested by the Task Force on Climate-related Financial Disclosures ("TCFD"). Historical emission intensities for the past five years are used to estimate future emission trajectories. The average emission intensities for both direct (scope 1) and indirect (scope 2) emissions are then compared to what is required under three scenarios provided by the International Energy Agency ("IEA") in their report World Energy Outlook 2020.

Coverage

Sectors: *All*

Countries / Regions: *Global coverage, including revenue distribution and specific asset location data*

Emission types: *All in CO_2 equivalent*

Emission scopes: *Scopes 1-3, quality checked reported and approximated emissions*

Analysis horizon and time steps: *Until 2050, annual breakdown available for most outputs*

Financial asset classes:

- ☒ Stocks *(all asset classes offed on bespoke basis)*
- ☒ Bonds - corporate *(all asset classes offed on bespoke basis)*
- ☒ Bonds - sovereign *(all asset classes offed on bespoke basis)*
- ☒ Bonds - project *(all asset classes offed on bespoke basis)*
- ☒ Loans - corporate *(all asset classes offed on bespoke basis)*
- ☒ Loans - project *(all asset classes offed on bespoke basis)*
- ☒ Credits (personal loans, consumption credits, e.g. for cars) *(all asset classes offed on bespoke basis)*
- ☒ Mortgages - commercial *(all asset classes offed on bespoke basis)*
- ☒ Mortgages - private housing *(all asset classes offed on bespoke basis)*
- ☒ Real estate - commercial *(all asset classes offed on bespoke basis)*
- ☒ Real estate - private housing *(all asset classes offed on bespoke basis)*
- ☒ Options and derivatives *(all asset classes offed on bespoke basis)*
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☒ Value at Risk *change* (due to climate risk)
- ☒ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☒ Climate financial risk score / factor
- ☐ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ☒ Policy
- ☒ Market upstream (supply chain)
- ☒ Market downstream (demand)
- ☒ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

☐ Orderly

☐ Disorderly

☒ Other / not applicable, because: *: Scenarios from a variety of providers are used, e.g. IEA, IPCC, etc.*

Temperature targets:

☐ 1.5°C (Paris Agreement compatible, 66% probability)

☐ < 2°C (Paris Agreement compatible, 66% probability)

☒ 2°C (Kyoto Protocol target, 66% probability)

☒ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))

☒ $> 3 - 4$°C (Current policies / Business as usual)

☒ Other / not applicable, because: *IEA: SDS, STEPS, CPS; Net Zero Scenario, NGFS Scenario*

Model setup

Approach:

☒ Top-down

☒ Bottom-up

☐ Combined

Most granular unit of analysis:

☐ Physical asset

☒ Firm

☐ Sector

☐ Other, namely:

User data required as input: *Company identifiers portfolio weight*

Modelling options

Climate model options:

☒ IEA: ETP

☒ IEA: WEO

☐ PIK: REMIND

☐ PIK/IIASA: REMIND-MAgPIE

☐ IIASA: MESSAGEix-GLOBIUM

☒ JGCRI: GCAM

☐ Other models, namely:

☐ Own models, namely:

☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

☐ IPCC SSP1

☐ IPCC SSP2

☐ IPCC SSP3

☐ IPCC SSP4

- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☒ Not applicable / not identified *(See above)*

Firm-level modelling options:

- ☐ Cost pass-through
- ☒ Firms' own climate targets
- ☐ Capex plans
- ☐ Other, namely:

B.6 Moody's

Tool name	Moody's Climate Solutions - Temperature Alignment and Climate EDF® Solution
Owner / Developer	Moody's ESG Solutions and Moody's Analytics
Access	
Documentation	`https://esg.moodys.io/climate-solutions` `https://www.moodysanalytics.com/-/media/whitepaper/2021/assessing-the-credit-impact-of-climate-risk-for-corporates.pdf`

Table 26: Summary Moody's

Description

Moody's offer a holistic framework that spans across the overall risk management framework offers climate data analytics across both physical and transition risks, climate scenario analysis and stress testing, integration to credit risk modelling, broader financial metrics and tools to support Climate related financial disclosures, namely TCFD, regulatory climate stress testing and portfolio temperature alignment. Moody's Analytics' forward looking probability of default model is a structural model measuring an Expected Default Frequency (EDF) for individual companies by incorporating the impact of both transition and physical risk. It leverages data at the company level to generate a PD term structure of 30+ years for each companies, under several scenarios. This allows users to:

1. define appropriate climate scenarios
2. link the climate scenarios to the climate risk impact channels
3. translate risk into financial and economic scenarios
4. estimate the climate adjusted risk metrics

Furthermore, to assess the temperature alignment of companies and portfolios, several approaches based on mathematical measures can be used. The framework considered by the Moody's ESG Solutions, powered by V.E is based on extensive literature review on existing approaches developed by academic, non-profit and private institutions. As outlined by the technical review of existing temperature alignment methodologies (Raynaud et al. 2020), Moody's framework for assessing temperature alignment is composed of 4 main steps:

1. **Measure the climate performance of companies and portfolios.** The focus is on current and future performance.
2. **Choose scenarios.** A scenario models a specific world, that can be obtained if assumptions and construction rules defining temperature trajectories are met.
3. **Construct benchmarks.** Decarbonization trajectories described in scenarios need to be converted from macro to micro level temperature alignment benchmarks.
4. **Compare.** Compare companies' and portfolios' climate performance (step 1) with decarbonization trajectories calculated as benchmark (step 3) to assess temperature alignment.

Each step will require some model choices and key assumptions. For example, for those companies in homogenous carbon intensive sectors for which technological projections are available to meet final demand for industry, transport and building services, Sector Decarbonization Approach(SDA) is utilized and for more heterogenous sectors, Absolute Reduction Approach (ARA) is used.

Coverage

Sectors: *50+ sectors for financial (credit) risk analysis – both higher transition and lower transition sectors. As to transition risk assessments and alignment, 40 key sectors are covered.*

Countries / Regions: *Global coverage across many countries and regions.*

Emission types: *In line with the Greenhouse Gas (GHG) Protocol, the Intergovernmental Panel on Climate Change (IPCC) guidelines, and other recognized international standards, Moody's carbon footprint methodology takes into account all relevant GHG emissions (CO2, CH4, N20, HFCs, PFCs, SF6, NF3) reported as tonnes of carbon dioxide equivalent (CO2 eq), based on accepted global warming potential (GWP) data. Source can be company reported (verified and not verified) as well as estimated using in-house methodologies.*

Emission scopes: *Scope 1, 2 and 3 are all covered. Company reported (as per the purpose of carbon footprint and energy transition score, alignment) Estimated (as per the purpose of credit risk modelling and scenario analysis, both reported and estimated) Moody's leverages both point in time emissions data as well as trend based (for temperature alignment, forward looking for 10 years ahead for financial (credit) analysis, allowing mean regression to industry averages in relative emission rates and for the industry average to fall based on technology shifts.)*

Analysis horizon and time steps: *Time horizon analysis is flexible for financial (credit) risk analysis and valuation, annual values until the year 2100. For temperature alignment, horizon is considered 2030.*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☒ Bonds - sovereign
- ☐ Bonds - project
- ☒ Loans - corporate
- ☐ Loans - project
- ☒ Credits (personal loans, consumption credits, e.g. for cars) *(US, UK only)*
- ☒ Mortgages - commercial *(US only)*
- ☒ Mortgages - private housing *(US, UK only)*
- ☒ Real estate - commercial *(US only)*
- ☒ Real estate - private housing *(US, UK only)*
- ☐ Options and derivatives
- ☒ Other, namely: *Structured Credit*

Tool output:

- ☒ Stock price *change* (due to climate risk)
- ☒ Stock price (climate risk-adjusted)
- ☒ Value at Risk *change* (due to climate risk)
- ☒ Value at Risk (climate risk-adjusted)
- ☒ Probability of Default *change* (due to climate risk)
- ☒ Probability of Default (climate risk-adjusted)
- ☒ Credit Rating *change* (due to climate risk)
- ☒ Credit Rating (climate risk-adjusted)
- ☒ Earnings / EBITDA *change* (due to climate risk)
- ☒ Earnings / EBITDA (climate risk-adjusted)
- ☒ Climate financial risk score / factor *(Moody's ESG Solutions carbon emission data, and Physical Risk scores are used as inputs within the credit risk models.)*
- ☒ Climate alignment / gap

☐ Other, namely: *Re-valuation of Credit risky Instruments issued by firm, e.g. climate conditioned credit spreads.*
Output estimates for financial (credit) risk analysis can be "expected" (e.g. mean estimate – high probability, estimated impact) and "extreme" values (e.g. tail estimate – low probability, high impact)

Transition risk sources:

☒ Policy

☒ Market upstream (supply chain)

☒ Market downstream (demand)

☒ Technology

☐ Other / not applicable, because:

Transition trajectories:

☒ Orderly

☒ Disorderly

☐ Other / not applicable, because:

Temperature targets:

☒ 1.5°C (Paris Agreement compatible, 66% probability)

☒ <2°C (Paris Agreement compatible, 66% probability)

☒ 2°C (Kyoto Protocol target, 66% probability)

☒ $2-3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))

☒ $>3-4$°C (Current policies / Business as usual)

☐ Other / not applicable, because:

Model setup

Approach:

☐ Top-down

☐ Bottom-up

☒ Combined

Most granular unit of analysis:

☐ Physical asset

☒ Firm

☒ Sector

☐ Other, namely:

User data required as input: *There may be different data input requirements, depending on the asset classes, risk metrics and portfolios under consideration. In summary:*

1. *Fixed Income Equities, Corporate (listed): ISINs are enough to perform the complete analysis on the entities*
2. *SME and Corporate (private firms): location specification (if available) or country/region, sector-level (NACE or SIC codes), baseline rating (PD) and size of firm by total sales (if available)*
3. *Real estate, Consumer Credit (e.g. mortgages, auto loans etc.): location specification or population weighted (by state, urban area, city etc.)*
4. *Specifically for temperature alignment, ISINs were sufficient to carry out the analysis.*

Modelling options

Climate model options:

- ✗ IEA: ETP
- ✗ IEA: WEO
- ☐ PIK: REMIND
- ✗ PIK/IIASA: REMIND-MAgPIE
- ✗ IIASA: MESSAGEix-GLOBIUM
- ✗ JGCRI: GCAM
- ☐ Other models, namely:
- ✗ Own models, namely: *Moody's also has its own Macro Climate scenario analysis capability, where the standard IAMs are extended, in terms of macro financial impacts.*
- ☐ Not applicable, because:

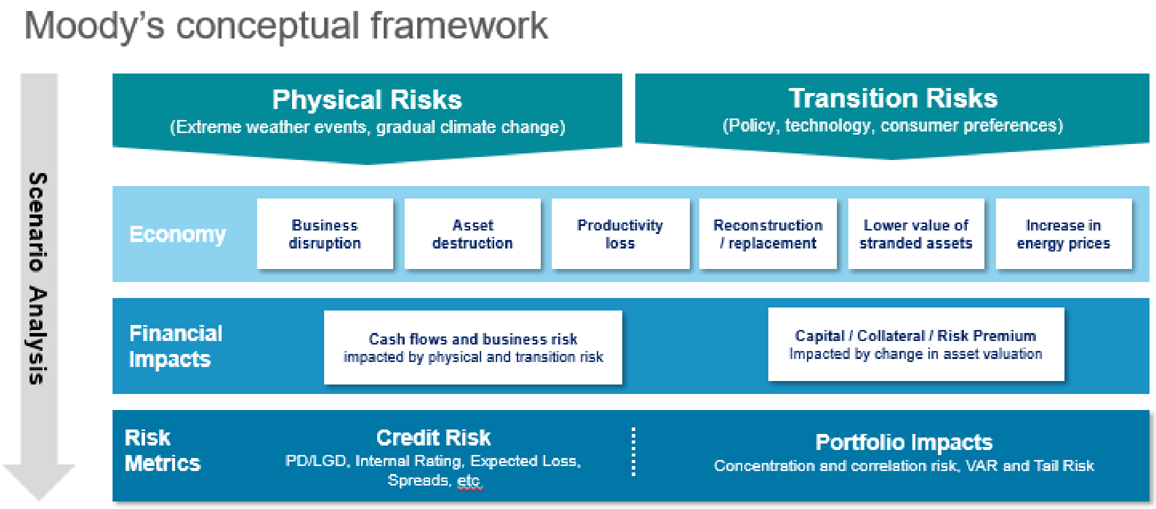
Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ✗ NGFS Net Zero 2050
- ✗ NGFS Below 2°C
- ✗ NGFS Divergent Net Zero
- ✗ NGFS Delayed Transition
- ✗ NGFS Nationally Determined Contributions
- ✗ NGFS Current Policies
- ☐ Not applicable / not identified

Firm-level modelling options:

- ✗ Cost pass-through
- ✗ Firms' own climate targets *(for temperature alignment, not for credit risk analysis)*
- ☐ Capex plans
- ☐ Other, namely:

Figure 47: Schematic model overview Moodys



B.7 MSCI

Tool name	MSCI Climate Value-at-Risk Tool (Climate VaR)
Owner / Developer	MSCI/ Carbon Delta AG (Switzerland)
Access	Public, paywall, fixed price and customized options
Documentation	https://www.msci.com/climate-solutions

Table 27: Summary MSCI

Description MSCI's Climate Value-at-Risk (Climate VaR) model provides investors with a quantitative, forward-looking analysis on how climate change may affect the investment return in portfolios. The metric allows investors to assess and mitigate future risks from climate change, while at the same time identifying new investment opportunities.

Climate VaR is closely aligned with the recommendations of the Taskforce on Climate-related Financial Disclosures (TCFD) in that it quantifies both transition and physical impacts in a climate scenario context. On the transition side, the model identifies future policy-related costs and future green profits linked to specific emission scenario pathways. The entirety of country emission reduction pledges (Nationally Determined Contributions, NDCs) have been quantified and normalised to align with a 3°C scenario. Based on the UNEP GAP report, the model further quantifies additional emission reduction requirements necessary to achieve the goals of the Paris Agreement which is to limit global temperatures to 2°C or less by the end of the century. In addition, on the policy side, the model incorporates a Scope 2 Electricity Use and a Scope 3 Value Chain model to capture the company's ability to pass-through the cost of electricity as well as factoring in upstream and downstream impacts, for example for the automobile and oil gas sectors. On the opportunity side, the model assesses Clean Technology revenue market shares of companies in combination with a low carbon patent scoring methodology. Finally, on the physical side, an extensive asset location database comprising of over 400,000 company facilities has been overlaid with hazards maps. Based on sector-based vulnerabilities, each location's climate-related revenue loss for 8 extreme weather hazards is computed with the help of damage and business interruption functions.

The net present value of all future climate-related costs and green profits is finally related to the current valuation of the asset to provide users with a climate stressed market valuation, assuming that climate change impacts are currently not priced in.

Features of Climate Value-at-Risk:

- The framework provides a broad number of scenarios which incorporate different scenario pathways to help assess the climate impact of investment portfolios - a total of 10 transition and 2 physical climate scenarios are available.
- The Climate Value-at-Risk has quantified the entirety of national emission reduction pledges that countries have committed to under the goals of the Paris Agreement to limit the global temperature increase to 2°Celsius or lower. Apart from factoring in direct emission impacts, the model also incorporates indirect transition impacts via an Electricity Use model (Scope 2) and a Value Chain Model incorporating both upstream and downstream impacts (Scope 3).
- On the opportunity side, Climate Value-at-Risk combines low carbon patent scoring and EU-taxonomy-aligned green activities to identify the longer-term future "green" innovation potential of companies in the transition to a low carbon economy.
- The model moreover calculates climate-related costs and green profits on issuer level and apportions them to the equity and liability side of the business based on the Merton model, a credit risk framework. In this way, climate risk can be computed at security-level, linking Climate VaR on the issuer to the equities and corporate bonds issued by same issuer. In addition, the Climate VaR for corporate bonds also considers the maturity date of individual bonds.

Implied temperature metric: Although not the focus of this analysis, based on the Climate VaR methodology described in more detail above, the model also provides an Implied Temperature Rise metric (ITR) which provides investors with an indication of how companies and investors are aligned with global climate targets (i.e. the Paris Agreement). The ITR, expressed in degrees Celsius (°C), estimates the global implied temperature rise (in the year 2100 or later) if the whole economy had the same carbon budget over-/undershoot level as the company/portfolio analyzed, based on its projected Scope 1, 2 and 3 emissions. The metric compares the company's projected GHG emissions against its carbon budget. The total estimated carbon budget over-/undershoot is then converted to a degree of temperature rise using the science-based ratio approach of Transient Climate Response to Cumulative Carbon Emissions (TCRE).

Coverage

Sectors: *All sectors*

Countries / Regions: *All countries and regions*

Emission types: *CO2 equivalent*

Emission scopes: *Scopes 1, 2 and 3 (All categories)*

Analysis horizon and time steps: *Until 2100, time steps analysis under development*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☒ Bonds - sovereign *(under development)*
- ☐ Bonds - project
- ☒ Loans - corporate *(under development)*
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☒ Mortgages - commercial *(in case underlying property info is available)*
- ☒ Mortgages - private housing *(in case underlying property info is available)*
- ☒ Real estate - commercial
- ☒ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☒ Value at Risk *change* (due to climate risk)
- ☒ Value at Risk (climate risk-adjusted)
- ☒ Probability of Default *change* (due to climate risk) *(under development for banks)*
- ☒ Probability of Default (climate risk-adjusted) *(under development for banks)*
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☒ Earnings / EBITDA *change* (due to climate risk) *(leveraging MSCI's climate-related transition costs, users could compute this)*
- ☒ Earnings / EBITDA (climate risk-adjusted) *(leveraging MSCI's climate-related transition costs, users could compute this)*
- ☐ Climate financial risk score / factor

☒ Climate alignment / gap *(via Implied Temperature Rise metric)*

☐ Other, namely:

Transition risk sources:

☒ Policy

☒ Market upstream (supply chain)

☒ Market downstream (demand)

☒ Technology *(Focus on opportunities: The model assesses Clean Technology revenue market shares of companies in combination with a low carbon patent scoring methodology.)*

☐ Other / not applicable, because:

Transition trajectories:

☒ Orderly

☒ Disorderly

☐ Other / not applicable, because:

Temperature targets:

☒ 1.5°C (Paris Agreement compatible, 66% probability)

☒ < 2°C (Paris Agreement compatible, 66% probability)

☒ 2°C (Kyoto Protocol target, 66% probability)

☒ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))

☐ $> 3 - 4$°C (Current policies / Business as usual)

☐ Other / not applicable, because:

Model setup

Approach:

☐ Top-down

☐ Bottom-up

☒ Combined

Most granular unit of analysis:

☐ Physical asset

☒ Firm

☐ Sector

☐ Other, namely:

User data required as input:

Modelling options

Climate model options:

☐ IEA: ETP

☐ IEA: WEO

☐ PIK: REMIND

☒ PIK/IIASA: REMIND-MAgPIE

☐ IIASA: MESSAGEix-GLOBIUM

- ☒ JGCRI: GCAM
- ☒ Other models, namely: *IMAGE, AIM/CGE*
- ☐ Own models, namely:
- ☐ Not applicable, because:

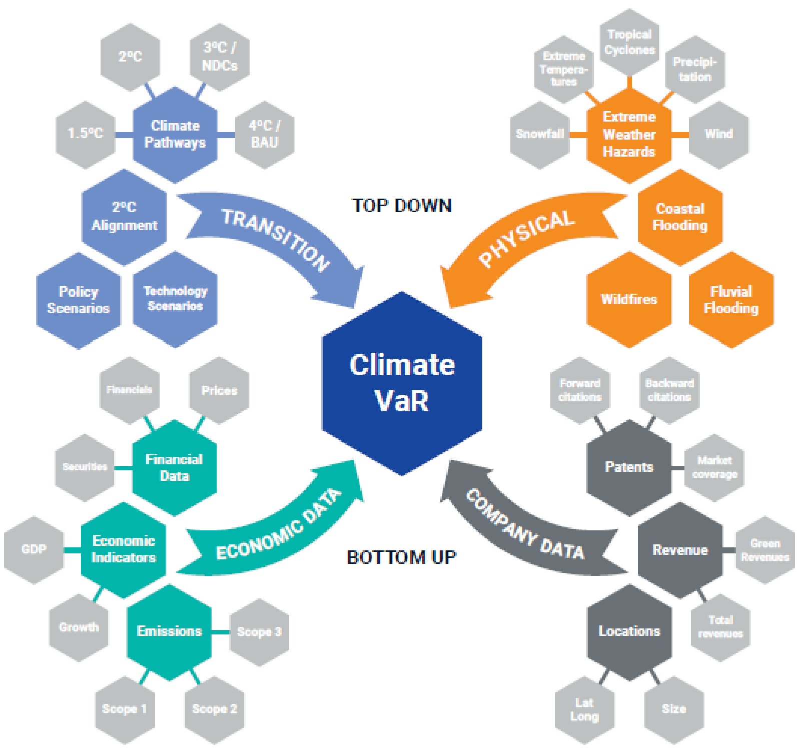
Modelled reference scenarios / scenario equivalents:

- ☒ IPCC SSP1
- ☒ IPCC SSP2
- ☐ IPCC SSP3
- ☒ IPCC SSP4
- ☒ IPCC SSP5
- ☒ NGFS Net Zero 2050
- ☒ NGFS Below 2°C
- ☒ NGFS Divergent Net Zero
- ☒ NGFS Delayed Transition
- ☒ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☐ Not applicable / not identified

Firm-level modelling options:

- ☒ Cost pass-through
- ☒ Firms' own climate targets
- ☐ Capex plans *MSCI has started collecting this data point for electric utilities and oil & gas companies. However, Capex is currently not integrated and assessed in the Climate VaR model.)*
- ☐ Other, namely:

Figure 48: Schematic model overview MSCI



B.8 Planetrics

Tool name	The Planetrics model
Owner / Developer	Planetrics
Access	
Documentation	https://www.parisalignedinvestment.org/media/2021/03/Portfolio-Testing-Report-IIGCC-Net-Zero-Investment-Framework-1.pdf

Table 28: Summary Planetrics

Description The Planetrics model uses scenario analysis, microeconomic and macroeconomic modelling to quantify transition and physical risk impacts on financial assets and markets. Results can be provided as part of bespoke data solutions, model integration exercises, or through our platform, PlanetView. PlanetView provides transition risk and physical risk climate risk impacts for 5 asset classes: listed equities, corporate bonds, sovereign bonds, real estate, and private equity. Temperature alignment analysis is also provided using the model. For corporates (listed equities and corporate bonds), the starting point of the analysis is bottom-up, with asset level data used when possible and otherwise entity-level.

- Climate scenarios can be tailored to a client's view of future climate policy, or based on existing scenarios (e.g. NGFS, IPCC 1.5SR or IEA).
- The model incorporates various exposure channels including changes in fossil fuel and mineral demand, cleantech deployment, carbon prices, labour and agricultural productivity changes due to temperature change, and changes in the frequency and severity of extreme weather events.
- Next, economic responses (emissions abatement and adaptation to physical risks) to cost increases from policy and physical risks are factored in
- Finally, competitiveness impacts at the sector-region level are estimated based on a microeconomic model of firm competitiveness. This captures effects such as cost pass through (market and firm-level), price changes, and changes in market share.
- Together, these channels produce a detailed picture of climate risk impacts at the security, sector, region, and asset class level

Corporate credit risk modelling is based on a ratings-based scorecard model and captures issuer-level impacts wherever issuer-level data is available (>75% of included corporate bonds). Outputs include credit rating changes, PD changes, bond valuation changes, and Z-spread changes.

For sovereign bonds, Planetrics make use of the NiGEM, a global macroeconomic model, run and maintained by the National Institute of Economic and Social Research (NIESR). NiGEM is used to model macroeconomic shocks (including fiscal and monetary policy responses) from climate scenarios. These shocks are then used by Planetrics to model changes in sovereign bond valuations.

Coverage

Sectors: *All*

Countries / Regions: *World, and specific countries (analysis can be broken out for all individual countries)*

Emission types: *Kyoto Protocol gases*

Emission scopes: *Scope 1-3*

Analysis horizon and time steps: *Model runs until 2050*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate

- ✗ Bonds - sovereign
- ✗ Bonds - project
- ✗ Loans - corporate
- ✗ Loans - project
- ✗ Credits (personal loans, consumption credits, e.g. for cars)
- ✗ Mortgages - commercial
- ✗ Mortgages - private housing
- ✗ Real estate - commercial
- ✗ Real estate - private housing
- ☐ Options and derivatives
- ✗ Other, namely: *Private Equity*

Tool output:

- ✗ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ✗ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ✗ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ✗ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ✗ Climate financial risk score / factor
- ✗ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ✗ Policy
- ✗ Market upstream (supply chain)
- ✗ Market downstream (demand)
- ✗ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

- ✗ Orderly
- ✗ Disorderly
- ☐ Other / not applicable, because:

Temperature targets:

- ✗ 1.5°C (Paris Agreement compatible, 66% probability)
- ✗ < 2°C (Paris Agreement compatible, 66% probability)
- ✗ 2°C (Kyoto Protocol target, 66% probability)
- ✗ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ✗ $> 3 - 4$°C (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☐ Top-down
- ✗ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ✗ Physical asset
- ✗ Firm
- ✗ Sector *(most analysis takes pace at the asset, or company business-unit level. There are some elements of the analysis that are less granular depending on data availability, so we have marked the other boxes too)*
- ☐ Other, namely:

User data required as input: *For listed asset classes (listed equities, corporate bonds, sovereign bonds), ISIN or other common security identifier (e.g. CUSIP), and portfolio holdings. For alternative asset classes (real estate, listed equity), sector/real estate type, region, and portfolio holdings*

Modelling options

Climate model options:

- ☐ IEA: ETP
- ✗ IEA: WEO
- ✗ PIK: REMIND
- ✗ PIK/IIASA: REMIND-MAgPIE
- ✗ IIASA: MESSAGEix-GLOBIUM
- ✗ JGCRI: GCAM
- ✗ Other models, namely: *any publicly available scenario can be used*
- ✗ Own models, namely: *bespoke scenarios in collaboration with academics and other modelling institutions*
- ☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

- ✗ IPCC SSP1
- ✗ IPCC SSP2
- ✗ IPCC SSP3
- ✗ IPCC SSP4
- ✗ IPCC SSP5
- ✗ NGFS Net Zero 2050
- ✗ NGFS Below 2°C
- ✗ NGFS Divergent Net Zero
- ✗ NGFS Delayed Transition
- ✗ NGFS Nationally Determined Contributions
- ✗ NGFS Current Policies
- ☐ Not applicable / not identified

Firm-level modelling options:

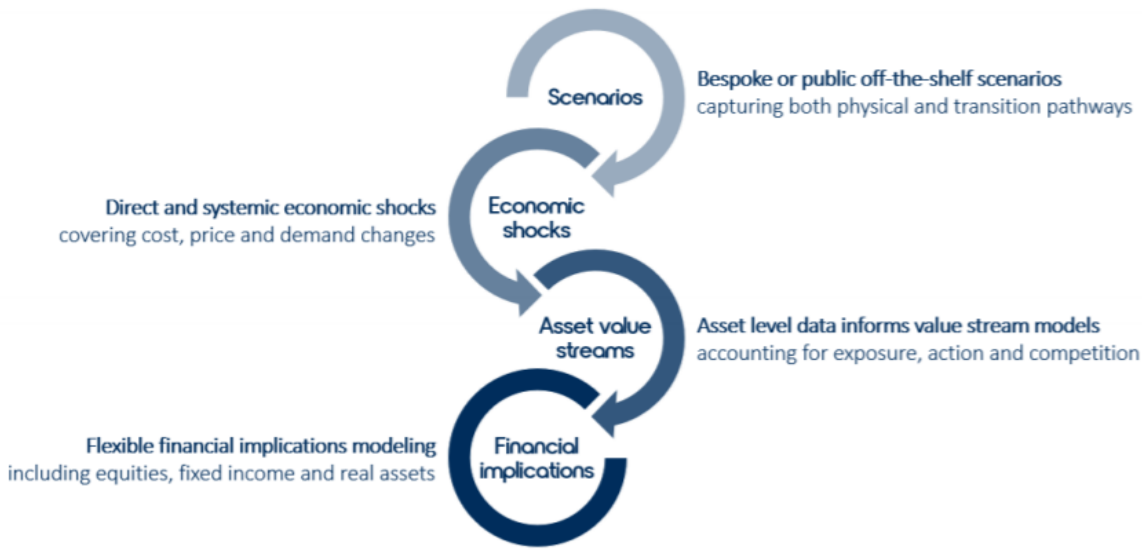
- ✗ Cost pass-through

☐ Firms' own climate targets

☐ Capex plans *(Not directly considered, but form part of breakeven costs in sectors such as oil gas where forward-looking cost curve analysis is conducted.)*

☐ Other, namely:

Figure 49: Schematic model overview Planetrics



B.9 PwC / The CO-Firm

Tool name	Climate Excellence
Owner / Developer	The CO-Firm Climate Excellence now part of PwC / PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft
Access	Public, customized pricing
Documentation	`https://www.pwc.de/de/nachhaltigkeit/climate-excellence-unternehmen-fit-machen-fuer-den-klimawandel.html` `https://et-risk.eu/publications`

Table 29: Summary PwC / The CO-Firm

Description Climate Excellence provides a forward-looking financial assessment (in terms of relative EBITDA and revenue change) of climate related risks and opportunities with the general flexibility to build upon any scientific scenario and cover any level of detail for assets with real economy underlying.

Climate Excellence modules overview (further modules, e.g. underwriting under development):

- Asset management covers up to 40,000 listed securities in over 50 countries
- Banking covers up to 40,000 listed companies, additional 30,000 unlisted companies as well as more than 50,000 sector-country combinations
- Real Estate covers all building types (residential, office, hotel, retail, health, logistic, other) in the EU27 countries plus the United Kingdom and the United States

Transition risks: it helps deriving and understanding key risk and opportunity drivers along the TCFD categories technology, policy and market which comprises demand and price changes.

- The tool builds on fundamental analysis, enabling the assessment of risks also from market and competitive dynamics, technological advancements, and regulations that also extend beyond carbon prices (quotas, energy efficiency requirements, energy subsidies)
- A bottom-up asset-level modeling, allowing integrated insights on a plant, technology, company, country, and sector level
- View on the specific risk position of the real economy counterparty, as the tool provides insights on the impact of strategic choices of companies (adaptive capacity).
- Builds on renowned and accepted scenarios that are well understood.

Physical risks: it helps assessing the impact of acute and chronic physical hazards, such as convective storms, flooding and sea level rise and the vulnerability of a business's value chain to them.

Coverage

Sectors: *All*

Countries / Regions: *Worldwide coverage, regional and country granularity*

Emission types: *Sector-dependent*

Emission scopes: *Sector-dependent*

Analysis horizon and time steps: *2025, 2030, 2040, 2050*

Financial asset classes:

☒ Stocks

☒ Bonds - corporate

- ☐ Bonds - sovereign
- ✗ Bonds - project
- ✗ Loans - corporate
- ✗ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ✗ Real estate - commercial
- ✗ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ✗ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☐ Climate financial risk score / factor
- ☐ Climate alignment / gap
- ✗ Other, namely: *sales change (due to climate risk)*

Transition risk sources:

- ✗ Policy
- ✗ Market upstream (supply chain)
- ✗ Market downstream (demand)
- ✗ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

- ✗ Orderly
- ☐ Disorderly
- ☐ Other / not applicable, because:

Temperature targets:

- ☐ 1.5°C (Paris Agreement compatible, 66% probability)
- ✗ < 2°C (Paris Agreement compatible, 66% probability)
- ✗ 2°C (Kyoto Protocol target, 66% probability)
- ✗ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☐ $> 3 - 4$°C (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☐ Top-down
- ☒ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☒ Physical asset *(sector-dependent)*
- ☒ Firm *(sector-dependent)*
- ☐ Sector
- ☐ Other, namely:

User data required as input: *Asset management: company identifiers (ISIN, company name), exposure (investment exposure); Banking: company identifiers (ISIN or LEI or company name), allocation (geography, sector code), exposure (loan exposure); Real Estate: identifier (address, construction year, building size), allocation (geography, building type), exposure (count of buildings, size, building value)*

Modelling options

Climate model options:

- ☒ IEA: ETP *(key model)*
- ☒ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☒ IPCC SSP2 *(for macroeconomic factors; source: IEA WEO 2020)*
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☐ Not applicable / not identified

Firm-level modelling options:

- ☒ Cost pass-through

- ✗ Firms' own climate targets
- ✗ Capex plans
- ✗ Other, namely: *Adaptive Capacity pathways allow for different company pathways based on strategic positioning*

Figure 50: Schematic model overview PwC / The CO-Firm (1/2)

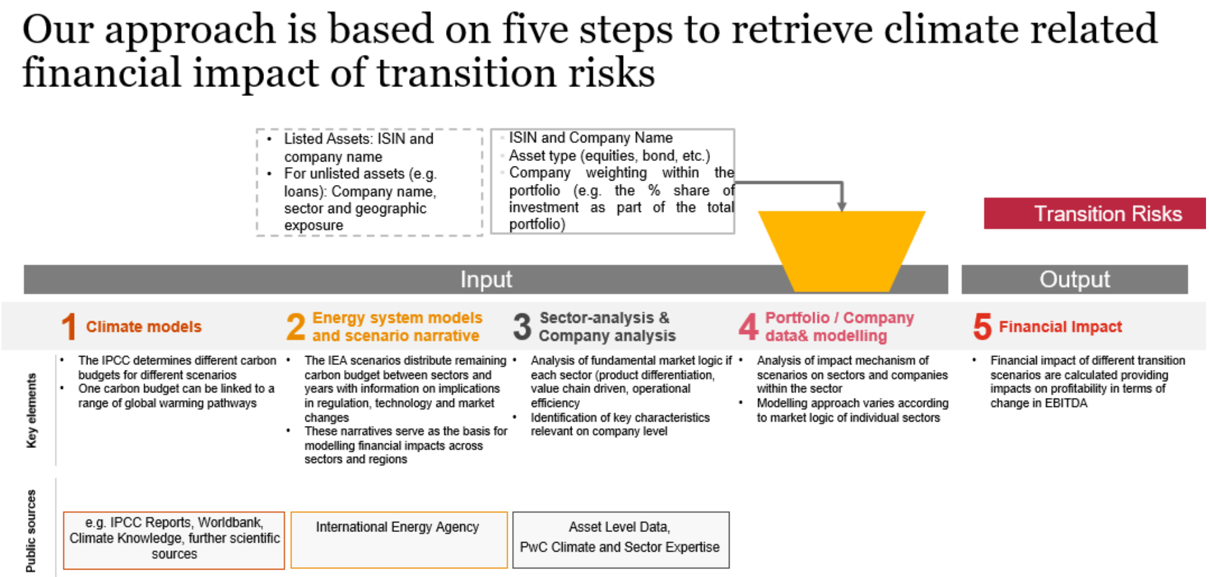
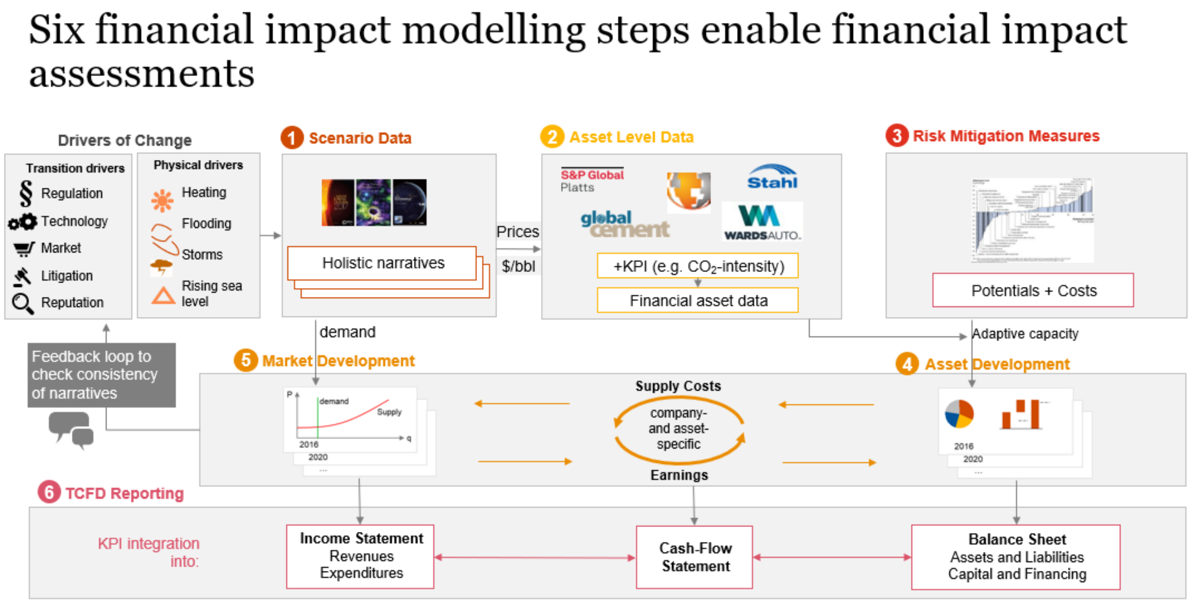


Figure 51: Schematic model overview PwC / The CO-Firm (2/2)



B.10 right. based on science

Tool name	X-Degree Compatibility Model (XDC Model)
Owner / Developer	right. based on science
Access	
Documentation	https://www.right-basedonscience.de/en/xdc-model/

Table 30: Summary right. based on science

Description The X-Degree Compatibility (XDC) Model calculates the contributions of a company, portfolio or any other economic entity to climate change, answering the question: How much global warming could we expect, if the entire world operated at the same economic emission intensity as the entity in question? Results are expressed in a tangible degree Celsius number: the XDC. This science-based temperature alignment metric offers unprecedented transparency to companies, banks, investors, and the public on climate risk and climate alpha. Thus, enabling the transition to a $< 2°C$ economy and to fulfilling the Paris Climate Agreement (Paris Alignment).

The XDC Model was developed by right. based on science and is the 'engine' powering their software products for companies, asset managers, banks, and others to: conduct climate impact, climate risk and portfolio temperature analysis; manage their temperature alignment / Paris Alignment; simplify sustainability reporting; set emission reduction targets; conduct forward-looking scenario analysis (e.g. following TCFD guidelines); identify transition companies and best-in-class climate performers to make better ESG investment and engagement decisions; and communicate with stakeholders.

The XDC Model is the only methodology of its kind to integrate a climate model (the FaIR Model, also used by the UN Intergovernmental Panel on Climate Change (IPCC)). The XDC Model is science-based, peer-reviewed, forward-looking, scenario-agnostic, transparent and will be made available as an Open Source application at the end of 2021 (already accessible for academic research).

Coverage

Sectors: *All NACE 1-digit and 2-digit*

Countries / Regions: *(almost all) Countries economic growth rates are taken into account*

Emission types: *Our database and companies data are in CO2eq, however the model is in multi-gas mode and can cover different gases when data are available.*

Emission scopes: *Scope 1, Scope 2, Scope 3*

Analysis horizon and time steps: *It depends on the scenario. Depending on data availability, simulation run up to 2100 is possible.*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☒ Bonds - sovereign
- ☒ Bonds - project
- ☒ Loans - corporate
- ☒ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing

- ✗ Real estate - commercial
- ✗ Real estate - private housing
- ✗ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☐ Climate financial risk score / factor
- ✗ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ☐ Policy
- ☐ Market upstream (supply chain)
- ☐ Market downstream (demand)
- ☐ Technology
- ✗ Other / not applicable, because: *Alignment tool*

Transition trajectories:

- ✗ Orderly
- ☐ Disorderly
- ☐ Other / not applicable, because:

Temperature targets:

- ✗ 1.5°C (Paris Agreement compatible, 66% probability)
- ✗ <2°C (Paris Agreement compatible, 66% probability)
- ✗ 2°C (Kyoto Protocol target, 66% probability)
- ☐ $2-3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ✗ $>3-4$°C (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☐ Top-down
- ☐ Bottom-up
- ☒ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☒ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input: *For companies: Scope emissions, EBITDA, Personnel costs, Country, NACE code, base year; For real estate: base year emissions and area, base year; For portfolios: isin, security weight, base year*

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☒ Other models, namely: *Finite Amplitude Impulse Response (FaIR)*
- ☐ Own models, namely:
- ☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

- ☒ IPCC SSP1
- ☒ IPCC SSP2
- ☒ IPCC SSP3
- ☒ IPCC SSP4
- ☒ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☐ Not applicable / not identified

Firm-level modelling options:

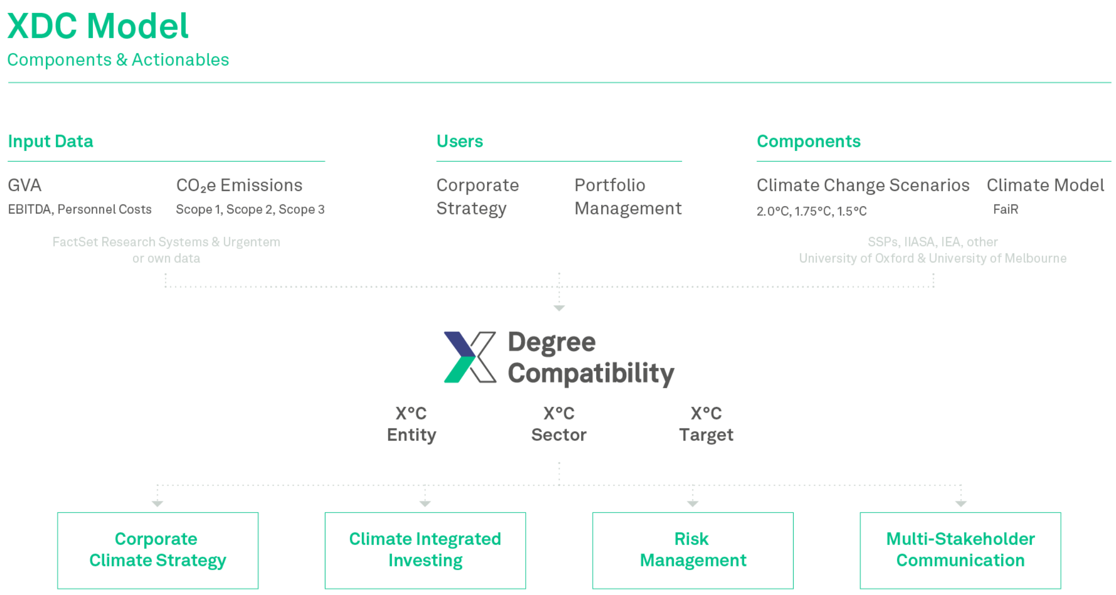
- ☐ Cost pass-through

☒ Firms’ own climate targets

☐ Capex plans

☐ Other, namely:

Figure 52: Schematic model overview right. based on science



B.11 S&P Global

Tool name	S&P Global Corporate Sustainability Assessment – Climate Strategy Metric
Owner / Developer	S&P Global Inc.
Access	
Documentation	https://portal.csa.spglobal.com/survey/documents/DJSI_CSA_Measuring_Intangibles.pdf https://portal.csa.spglobal.com/survey/documents/CSA_CorporateSustainabilityAssessment_factsheet.pdf

Table 31: Summary S&P Global

Description The Climate Strategy Criterion is part of the annual S&P Global Corporate Sustainability Assessment. Depending on the materiality of the topic, a different set of underlying questions are used to assess companies across 61 different industries. The questions aim to assess both physical and transition risk exposure as well as companies' understanding of the opportunities arising from climate change. The Climate Strategy Metric also captures management incentives, the understanding of Scope 3 emissions and the quality of climate change governance and target setting. The resulting question scores are aggregated to a Climate Strategy Score ranging from 0 to 100, 100 representing the best score.

Coverage

Sectors: *All sectors, 61 different industries*

Countries / Regions: *All*

Emission types:

Emission scopes: *Scope 1-3*

Analysis horizon and time steps: -

Financial asset classes:

- ☒ Stocks
- ☐ Bonds - corporate
- ☐ Bonds - sovereign
- ☐ Bonds - project
- ☐ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☐ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)

- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☐ Climate financial risk score / factor
- ☐ Climate alignment / gap
- ☒ Other, namely: *Companies are assessed in terms of physical and regulatory (transition) climate risks and the financial implications with a focus on EBITDA changes. The Climate Strategy Metric also includes management incentives and climate strategy governance aspects.*

Transition risk sources:

- ☒ Policy
- ☒ Market upstream (supply chain)
- ☒ Market downstream (demand)
- ☒ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

- ☐ Orderly
- ☐ Disorderly
- ☒ Other / not applicable, because: *We assess if a company's targets are science-based.*

Temperature targets:

- ☐ 1.5°C (Paris Agreement compatible, 66% probability)
- ☐ < 2°C (Paris Agreement compatible, 66% probability)
- ☐ 2°C (Kyoto Protocol target, 66% probability)
- ☐ $2 - 3$°C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☐ $> 3 - 4$°C (Current policies / Business as usual)
- ☒ Other / not applicable, because: *RCP 2.6 was explicitly mentioned in the 2020 assessment. However, companies could also indicate other scenarios. In 2021, the questions will explicitly refer to all these targets.*

Model setup

Approach:

- ☐ Top-down
- ☒ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☒ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input:

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ☒ Not applicable, because: *Companies are assessed in terms of scenario analysis. The different options include some of the ones above (IEA 450, IEA B2DS, IEA Sustainable Development).*

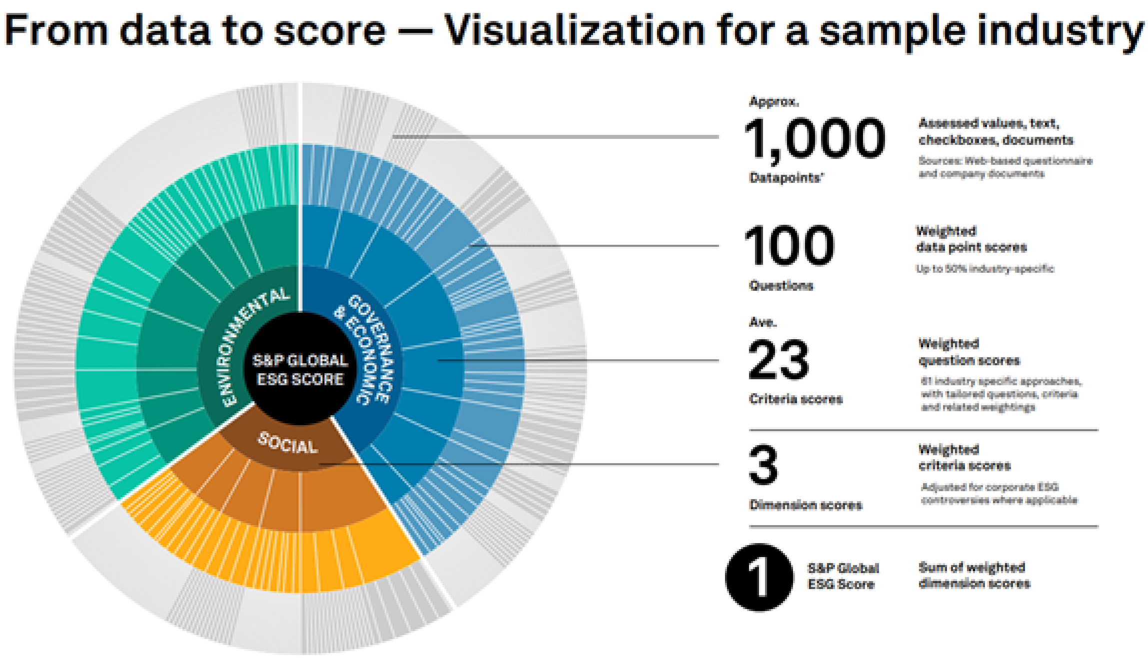
Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☒ Not applicable / not identified

Firm-level modelling options:

- ☒ Cost pass-through
- ☒ Firms' own climate targets
- ☒ Capex plans *(We analyze CAPEX options for emission reduction of companies, but do not have access to actual CAPEX plans of companies)*
- ☐ Other, namely:

Figure 53: Schematic model overview S&P Global



B.12 Sustainaccount

Tool name	Sustainaccount ESG Enterprise Suite
Owner / Developer	Sustainaccount
Access	
Documentation	www.sustainaccount.com

Table 32: Summary Sustainaccount

Description As an initial comment, our approach is projecting cash flows from climate-induced cost and revenue changes at a company or asset level. We restrain from converting these cash flows into financial metrics (such as VaR, PoD etc.) as we believe that each financial institution has their own calculation approaches and we want to deliver as "pure" numbers / metrics as possible. Thus, also, for bonds in the ISIN list we just analyzed the emitting company up to 2050, irrespective of the maturity of the bond. Numbers are relative changes in cash flows discounted to 2019 currencies, base year is 2019 (last pre-COVID year).

Our goal is to help financial institutions to integrate climate risk into their financial and economic decision-making tools. Sustainaccount focusses on both, granular ESG data acquisition from companies (particularly SME), and climate risk analysis based on such data. Our main approach to climate risk is the question: which technological and business model abatement options does a company have, at which price? We built our approach around two hypotheses:

- Companies will realize an abatement option, if the life-cycle NPV, including reputational impact of targets etc., is positive.
- Future projections, such as development of prices and particular abatement path of a company are subject to uncertainties and thus should be modelled probabilistically.

Sustainaccount uses stochastic modelling for all future projections. Using the NGFS scenarios as a baseline, we create multiple realizations of these scenarios, varying the forecasts in a plausible manner. We then focus on the abatement options of a company at a given time, based on technology and price projections. On this company level, the tool uses Monte Carlo analysis to simulate if and when abatement options are realized by the company. This approach yields in a set of climate induced projected cash flow pathways of any company. The tool outputs probability distributions of these cash flows at any future time. Sustainaccount builds on a large and growing dataset of abatement options that reach beyond the development of renewable energy as in conventional scenarios (e.g. IEA). In ESG data acquisition, we specialize on SME counterparties as a large blind spot in coprporate financing and investment. In principle, any financial instrument that derives from a fundamental can be analysed. We are focusing on generating forecasts on costs and revenues of a company, real asset or project. Based on this data, analysts can derive the financial implications, such as market values, probabilities of default, etc., of the counterparties, using their own financial risk approaches.

Coverage

Sectors: *All*

Countries / Regions: *All countries, with varying depth of data available per country*

Emission types: *CO2e*

Emission scopes: *Scope 1-3*

Analysis horizon and time steps: *2050*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate

☐ Bonds - sovereign

☒ Bonds - project

☒ Loans - corporate

☒ Loans - project

☐ Credits (personal loans, consumption credits, e.g. for cars)

☒ Mortgages - commercial

☒ Mortgages - private housing

☒ Real estate - commercial

☒ Real estate - private housing

☐ Options and derivatives

☒ Other, namely: *SME financing (equity or debt)*

Tool output:

☐ Stock price *change* (due to climate risk)

☐ Stock price (climate risk-adjusted)

☐ Value at Risk *change* (due to climate risk)

☐ Value at Risk (climate risk-adjusted)

☐ Probability of Default *change* (due to climate risk)

☐ Probability of Default (climate risk-adjusted)

☐ Credit Rating *change* (due to climate risk)

☐ Credit Rating (climate risk-adjusted)

☒ Earnings / EBITDA *change* (due to climate risk)

☐ Earnings / EBITDA (climate risk-adjusted)

☒ Climate financial risk score / factor

☐ Climate alignment / gap

☒ Other, namely: *Climate induced change in expected cash flows, derived from revenue and cost changes.*

Transition risk sources:

☒ Policy

☒ Market upstream (supply chain)

☒ Market downstream (demand)

☒ Technology

☐ Other / not applicable, because:

Transition trajectories:

☒ Orderly

☐ Disorderly

☐ Other / not applicable, because:

Temperature targets:

☒ 1.5°C (Paris Agreement compatible, 66% probability)

☒ $<2°$C (Paris Agreement compatible, 66% probability)

☒ 2°C (Kyoto Protocol target, 66% probability)

☐ $2-3°$C (Stated policies / UNFCCC's nationally determined contributions (NDCs))

☐ $>3-4°$C (Current policies / Business as usual)

☐ Other / not applicable, because:

Model setup

Approach:

- ☐ Top-down
- ☒ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☒ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input:

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☒ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ☐ Not applicable, because:

Modelled reference scenarios / scenario equivalents:

- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☐ Not applicable / not identified

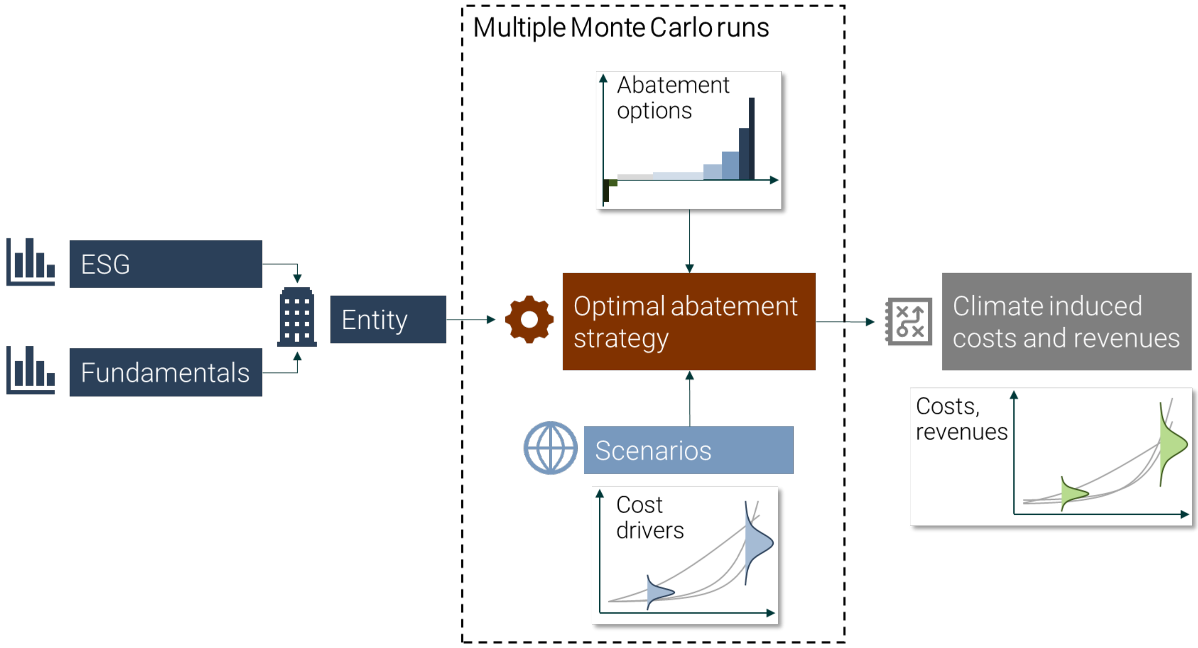
Firm-level modelling options:

- ☐ Cost pass-through
- ☒ Firms' own climate targets

☒ Capex plans *(We analyze CAPEX options for emission reduction of companies, but do not have access to actual CAPEX plans of companies)*

☐ Other, namely:

Figure 54: Schematic model overview Sustainaccount



B.13 University of Augsburg

Tool name	Carbon Risk Management (CARIMA)
Owner / Developer	Prof. Dr. Marco Wilkens, Chair of Finance and Banking, University of Augsburg
Access	Public, free access
Documentation	https://assets.uni-augsburg.de/media/filer_public/ad/69/ad6906c0-cad0-493d-ba3d-1ec7fee5fb72/carima_manual_english.pdf

Table 33: Summary CARIMA

Description Görgen et al. (2019) quantify the "carbon risk" via a "Brown-Minus-Green (BMG) factor". To construct BMG, the author use detailed carbon and transition-related information for over 1,600 globally listed firms filtered from four major ESG databases and categorize these firms as brown or green using an annual "Brown-Green-Score" (BGS). The BGS is a composite measure of three indicators designed to separately capture the sensitivity of firms' "value chains" (e.g., current emissions), of their "public perception" (e.g., response to perceived emissions), and of their "adaptability" (e.g., mitigation strategies) to carbon risk. The BMG can be added to all traditional factor models (e.g., CAPM, Carhart Model etc.) and tests show that the BMG significantly increases the explanatory power of common asset pricing models, suggesting that it is equally important in explaining variation in global equity prices as the size factor. The BGS allows estimating an applicable measure of carbon risk: "Carbon beta", which measures the stock value decrease or increase in comparison to other stocks if the transition process is unexpectedly changing. The author compute carbon betas for 39,000 firms and report them for countries and sectors. To measure the carbon risk of firms without primary carbon or transition-related information, Görgen et al. (2019) run time-series regressions explaining firms' excess returns using an extended Carhart model. The Carbon beta is thus a capital market-based measure of carbon risk that captures the sensitivity of a firm to carbon risk. Positive values represent "brown" firms, which are likely to be affected by carbon risk in the transition process towards a Green Economy. They also report average Carbon betas by country and industry. Carbon betas are high and positive in countries like South Africa, Brazil, and Canada, which means they are likely to be negatively affected if the world speeds up the transition to a low-carbon economy. Contrarily, average carbon betas are negative in European countries and Japan. On the industry level, tech firms have carbon betas near zero on average, while basic material and energy firms have the highest positive carbon betas as expected. There are, however, significant differences in Carbon betas within industries. Finally, the authors show that carbon risk is related to firm characteristics independent of their industry. Firms investing in innovation and clean technology, proxied by RD expenditures, have lower Carbon betas while firms with dirty or "stranded" assets, proxied by property plant and equipment (PPE) assets, have higher carbon betas.

Coverage

Sectors: *All*

Countries / Regions: *World*

Emission types: *CO2, CH4, N2O, O3, CFCs, HCFCs, HFCs*

Emission scopes: *Scope 1 and 2 directly, Scope 3 indirectly*

Analysis horizon and time steps: *In the CARIMA approach, the time horizon priced in by the capital market is used. However, this time horizon is not directly observable.*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☐ Bonds - sovereign
- ☐ Bonds - project
- ☒ Loans - corporate
- ☐ Loans - project

- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☒ Options and derivatives
- ☐ Other, namely:

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☒ Climate financial risk score / factor *(Carbon Beta)*
- ☐ Climate alignment / gap
- ☐ Other, namely:

Transition risk sources:

- ☒ Policy
- ☒ Market upstream (supply chain)
- ☒ Market downstream (demand)
- ☒ Technology
- ☐ Other / not applicable, because:

Transition trajectories:

- ☐ Orderly
- ☐ Disorderly
- ☒ Other / not applicable, because: *In the CARIMA approach, the reduction trajectory priced in by the capital market is used. A wide variety of definitions of the reduction trajectory is used by capital market participants.*

Temperature targets:

- ☐ 1.5°C (Paris Agreement compatible, 66% probability)
- ☐ $< 2°$C (Paris Agreement compatible, 66% probability)
- ☐ 2°C (Kyoto Protocol target, 66% probability)
- ☒ $2 - 3°$C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☐ $> 3 - 4°$C (Current policies / Business as usual)
- ☒ Other / not applicable, because: *In the CARIMA approach, the temperature target priced in by the capital market is used. However, this target is not directly observable.*

Model setup

Approach:

- ☐ Top-down
- ✗ Bottom-up *(Uses financial markets' current climate risk assessment and pricing in)*
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ✗ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input: *Asset returns, factor time series (free available)*

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ✗ Not applicable, because: *In the CARIMA approach, the models priced in by the capital market are used. A wide variety of models are used by capital market participants, including the models mentioned above.*

Modelled reference scenarios / scenario equivalents:

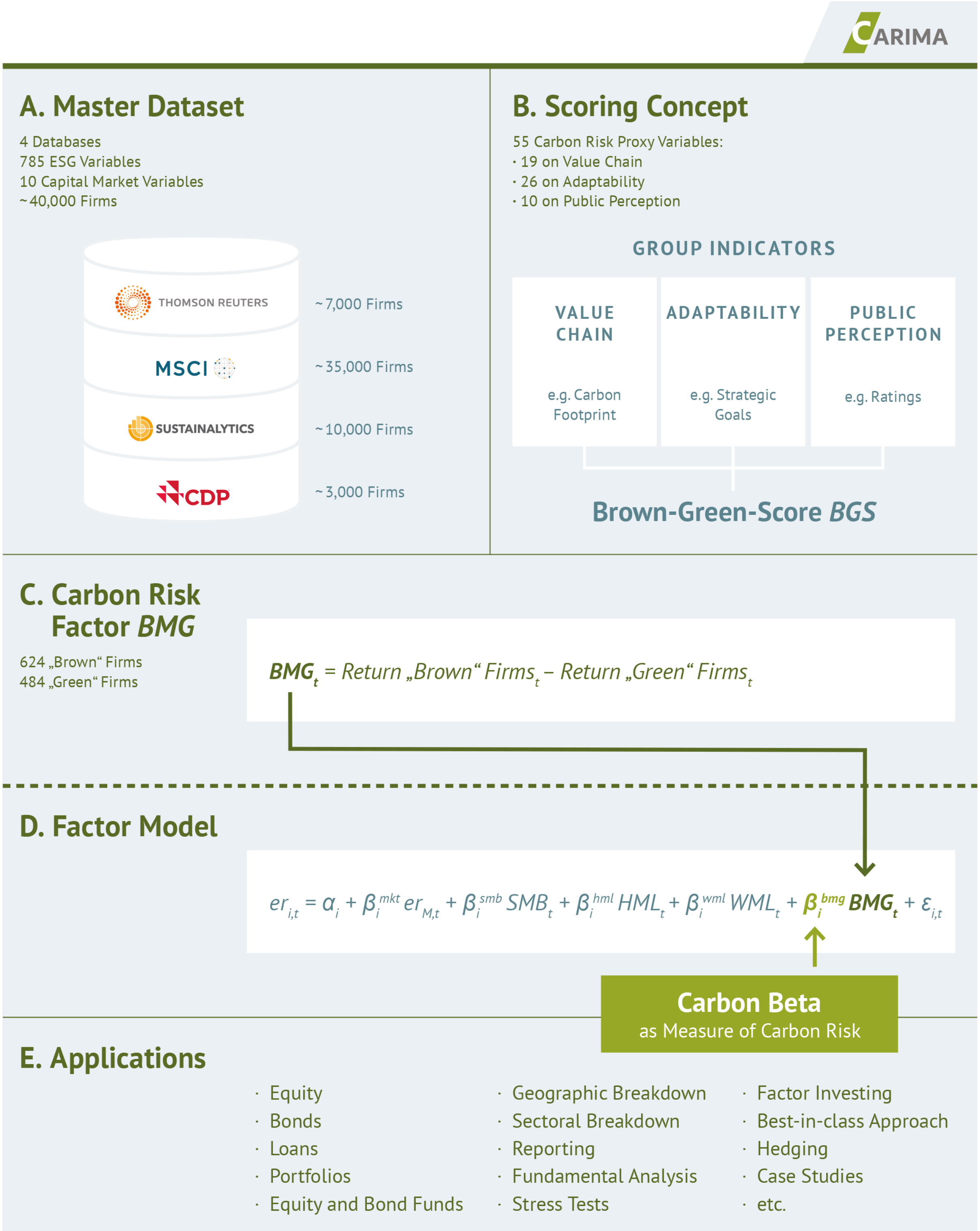
- ☐ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ✗ Not applicable / not identified

Firm-level modelling options:

- ✗ Cost pass-through
- ✗ Firms' own climate targets

- ☒ Capex plans
- ☒ Other, namely: *(no specific firm modelling options, but considered in the analysis to the extent to which financial market participants consider these aspects / to which these aspects are reflected in financial market pricing)*

Figure 55: Schematic model overview CARIMA



B.14 Zero Carbon 2030

Tool name	zero-carbon 2030 Carbon Rating
Owner / Developer	zero-carbon 2030 Trust
Access	
Documentation	

Table 34: Summary Zero Carbon 2030

Description Key characteristics: zero-carbon 2030's Carbon Ratings assess a company's actions and commitments on climate with the objective to encourage transition to a 1.5 °C temperature target. Parameters assessed are similar to those adopted by Climate Action 100+, and include:

- Carbon disclosure, reporting emissions (Scope 1-3, full value chain) and Carbon labelling of products and services.
- Climate governance, management, and compliance with TCFD.
- Net-zero target-setting across Scope 1-3 (full value chain emissions).
- Adoption / Commitment to adopt 100% renewable energy.
- Climate mechanisms, including use of offsets and use of carbon pricing in investment decision-making.
- Use of climate influence.
- For the financial sector, exposure to fossil fuels.

Coverage

Sectors: *All*

Countries / Regions: *All*

Emission types: *All, reported in tC02e*

Emission scopes: *Scope 1-3, full value chain emissions (supply chain mandatory)*

Analysis horizon and time steps: *As noted, we are not assessing a particular transition scenario, rather we assess a company's actions and commitments on climate with the objective to encourage a(n orderly) transition to a* $1.5^{\circ}CC$ *temperature target irrespective of when this occurs.*

Financial asset classes:

- ☒ Stocks
- ☒ Bonds - corporate
- ☐ Bonds - sovereign
- ☐ Bonds - project
- ☒ Loans - corporate
- ☐ Loans - project
- ☐ Credits (personal loans, consumption credits, e.g. for cars)
- ☐ Mortgages - commercial
- ☐ Mortgages - private housing
- ☐ Real estate - commercial
- ☐ Real estate - private housing
- ☒ Options and derivatives

- ☐ Other, namely: *(Our Carbon Ratings cover group entities. Ratings flow to subsidiaries and brand (consumer focused) of the rated entity. Carbon Ratings are relevant to all financial instruments issued by an entity, and counterparty relationships e.g. derivative instruments, supply chain relationship etc.)*

Tool output:

- ☐ Stock price *change* (due to climate risk)
- ☐ Stock price (climate risk-adjusted)
- ☐ Value at Risk *change* (due to climate risk)
- ☐ Value at Risk (climate risk-adjusted)
- ☐ Probability of Default *change* (due to climate risk)
- ☐ Probability of Default (climate risk-adjusted)
- ☐ Credit Rating *change* (due to climate risk)
- ☐ Credit Rating (climate risk-adjusted)
- ☐ Earnings / EBITDA *change* (due to climate risk)
- ☐ Earnings / EBITDA (climate risk-adjusted)
- ☐ Climate financial risk score / factor
- ☒ Climate alignment / gap *(Carbon Rating, calibration of an entity's actions and commitments on climate change.)*
- ☐ Other, namely:

Transition risk sources:

- ☐ Policy
- ☐ Market upstream (supply chain)
- ☐ Market downstream (demand)
- ☐ Technology
- ☒ Other / not applicable, because: *We consider that all risks may play a role in either delaying or bringing forward the transition. And there is inherent trade-off between transition and physical risk – a faster orderly transition will subject companies to greater transition risk but likely avoids the worst impacts of physical risk.*

Transition trajectories:

- ☒ Orderly *(zero-carbon 2030's Carbon Ratings are not assessing a particular transition scenario, rather we assess a company's actions and commitments on climate with the objective to encourage an (orderly) transition to a* $1.5^{\circ}C$ *temperature target.)*
- ☐ Disorderly
- ☒ Other / not applicable, because:

Temperature targets:

- ☒ 1.5°C (Paris Agreement compatible, 66% probability) *(Note: zero-carbon 2030's Carbon Ratings assess a company's actions and commitments on climate with the objective to encourage transition to a* $1.5^{\circ}C$ *temperature target.)*
- ☐ $< 2^{\circ}$C (Paris Agreement compatible, 66% probability)
- ☐ 2°C (Kyoto Protocol target, 66% probability)
- ☐ $2 - 3^{\circ}$C (Stated policies / UNFCCC's nationally determined contributions (NDCs))
- ☐ $> 3 - 4^{\circ}$C (Current policies / Business as usual)
- ☐ Other / not applicable, because:

Model setup

Approach:

- ☐ Top-down
- ☒ Bottom-up
- ☐ Combined

Most granular unit of analysis:

- ☐ Physical asset
- ☒ Firm
- ☐ Sector
- ☐ Other, namely:

User data required as input: *n/a*

Modelling options

Climate model options:

- ☐ IEA: ETP
- ☐ IEA: WEO
- ☐ PIK: REMIND
- ☐ PIK/IIASA: REMIND-MAgPIE
- ☐ IIASA: MESSAGEix-GLOBIUM
- ☐ JGCRI: GCAM
- ☐ Other models, namely:
- ☐ Own models, namely:
- ☒ Not applicable, because: *zero carbon 2030 does not presently use a specific climate model.*

Modelled reference scenarios / scenario equivalents:

- ☒ IPCC SSP1
- ☐ IPCC SSP2
- ☐ IPCC SSP3
- ☐ IPCC SSP4
- ☐ IPCC SSP5
- ☐ NGFS Net Zero 2050
- ☐ NGFS Below 2°C
- ☐ NGFS Divergent Net Zero
- ☐ NGFS Delayed Transition
- ☐ NGFS Nationally Determined Contributions
- ☐ NGFS Current Policies
- ☐ Not applicable / not identified

Firm-level modelling options:

- ☒ Cost pass-through *(Not specifically considered but we anticipate for companies to achieve transition they will be obliged to pass through incremental costs.)*
- ☒ Firms' own climate targets
- ☒ Capex plans *(Our Carbon Ratings include a parameter as to whether companies are using carbon pricing / shadow carbon pricing in their investment decision-making processes.)*
- ☐ Other, namely:

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