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Climate Transition Risk Metrics – Investigating Convergence and Estimation Drivers[1]

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Climate Transition Risk Metrics

Investigating Convergence and Estimation Drivers

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Abstract

Climate risks are now fully recognized as financial risks. Against this background, a rapidly growing number of market participants and financial authorities are exploring which metrics to use to capture climate risks, to what extent the use of different metrics delivers heterogeneous results, and which factors impact the assessment of risk. To shed a light on these questions, we analyse a sample of 69 transition risk metrics, delivered by nine providers, and covering about 1,500 firms worldwide. Our findings show that firms' risk assessments across metrics are relatively heterogeneous but display some degree of convergence. Convergence between metrics is significantly higher for the firms most exposed to transition risk. Our results also highlight that metrics' characteristics – the scenario and methodology they rely on – have an impact on the estimated risks. These findings bear important insight for the practical use of climate risk metrics: they suggest that available metrics provide useful information to risk managers to address high climate risk exposures and that risk managers must understand how metrics are built to choose those most appropriate to their needs.

Keywords: climate risk metrics, transition risk, panel OLS, scenario analysis, risk management

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

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1. Introduction

Climate risks are financial risks. As such, they must be duly assessed and managed by investors, asset managers and other financial institutions.[1] Financial supervisors and central banks must also diligently monitor and mitigate them to safeguard the stability of individual financial institutions and the financial system as a whole. However, although the materiality of climate-related financial risks is uncontested,[2] there is currently no agreement on how to measure these risks. There is a consensus, however, that traditional backward-looking methods, based on historical data and fitted distributions, are not suited to assess the unprecedented risks of climate change.[3] Against this background, various risk metrics providers have started to develop new forward-looking approaches that can be used by financial market participants to assess and manage climate-related financial risks.

Yet, the methodologies, data and assumptions underpinning these new risk assessment approaches can vary substantially from one metric to another (Bingler and Colesanti Senni 2020). This does not come as a surprise: it reflects the significant complexity and uncertainty in the analysis of climate risks. This heterogeneity can generate divergence in climate risk assessments across metrics and thus requires conscious decisions on which metrics to use by investors and financial institutions, as well as by central banks and financial supervisors.

In this context, previous research shows that forward-looking transition risk metrics display much less heterogeneity for the firms that are most and, to a lesser extent, least exposed to transition risks (Bingler et al., 2020, 2021a). This feature can be used by investors, asset managers, central banks, and financial supervisors to mitigate exposures to high climate-related financial risks. The same research also shows that understanding how metrics characteristics affect their risk assessments is key.

Against this background, in this study, we first check whether the convergence of metrics on firms most exposed to transition risk observed by Bingler et al. (2020, 2021a) for a European sample of firms is also observed globally. For that, we replicate Bingler et al.'s study with additional transition risk metrics and for a larger portfolio that is also covering non-European firms. Second, we explore which metric characteristics are associated with changes in the estimated transition risk exposures. For that, we empirically assess which sub-elements of the metric characteristics (i.e. underlying scenario elements and methodology elements) significantly affect transition risk estimates.

Our results confirm the earlier findings of Binger et al. (2020, 2021a), that is: 1) climate risk metrics display a significant degree of heterogeneity, which reflects the complexity of assessing climate risks, as well as the different methodologies and data

[1] See Monnin (2020).

[2] Central banks and financial supervisors acknowledge the materiality of climate-related financial risks (NGFS, 2018; BCBS, 2020; Bolton et al., 2020; FSOC, 2021), and the scientific literature back this assessment (Caldecott et al., 2016; Gros et al., 2016; Battiston et al., 2017; Stolbova et al., 2018; Roncoroni et al., 2019; Bretschger and Karydas, 2019).

[3] There is also a general recognition that non-linearity, non-stationarity, path-dependencies and endogeneity render climate-related financial risks more challenging to assess than traditional risks (Weitzman, 2011; Chenet et al., 2019; Battiston et al., 2019; Karydas and Xepapadeas, 2019).

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 assumptions underlying metrics affect the convergence between them: metrics sharing similar transition scenarios tend to have a higher degree of convergence than when they diverge in these dimensions.

We also find strong evidence that the scenario and the methodology underlying a metric affect the estimated transition risk. Our analysis shows that 1) the individual model characteristics are an important driver of the estimated risk. In particular, metrics that include information on firms' climate plans are associated with higher risk estimates than metrics, which do not include such information. Furthermore, we find 2) that the scenario on which a metric is based impacts its estimated risk: lower temperature targets increase risk estimates, longer time horizons also increase the estimated risk, and an orderly transition scenario delivers lower risk estimates than a disorderly transition scenario. Finally, our analysis shows that the majority of metric characteristics are not statistically significantly associated with the shape of the distributions of estimated risks, i.e. the distributions' standard deviation, skewness and kurtosis.

These findings provide important insights for the practical use of climate risk metrics. First, despite the heterogeneity observed across metrics, we find that metrics tend to converge on which firms are the most exposed to transition risks. They thus provide decision-useful information to risk managers to address high transition risk exposures. Second, the scenario and methodology underlying metrics do impact the estimated risk. It is therefore important for risk managers to understand well how metrics are built to choose the ones that are the most appropriate to their needs. Third, firms, which disclose climate risks should also report the underlying methods, data sources and scenario assumptions in addition to the metrics' values.

2. Data

In this study, we focus on the companies included in the MSCI World Index as of 31 January 2021. Moreover, we only consider forward-looking risk metrics that provide an assessment of transition risk at the firm level.

We contacted 25 providers of transition risk metrics and invited them to share with us their estimates of transition risk for the companies in our portfolio. Out of 25 providers, 14 agreed to send us their estimates, of which we removed 5 because their metrics were not providing estimates at the firm level, were not covering at least half of our portfolio, or were not based on forward-looking analysis (e.g., were based on current CO2 emissions only).[4]

Several providers delivered estimates for various temperature targets, time horizons and assumptions about the transition path. We treated each combination of temperature target, time horizon and transition path from the same provider as one specific metric. Overall, this gave us 69 different transition risk metrics from nine

[4] For a detailed description of our data and sample procedure see Bingler et al. (2021b).

providers, all based on different methodologies, horizons, and transition scenarios.[5] This sums up to a dataset of 105'000 transition risk point estimates for the individual firms in our sample.[6]

For metric characteristics, we distinguish between features of the scenario underlying the risk estimation (temperature target, time horizon and shape of transition path) and features related to the methodology underlying the metrics (type of metric delivered, inclusion of information about firms' climate plans, bottom-up vs top-down approach[7]). These characteristics are detailed in Table 1.

Metrics characteristics

Description Table 1

	Possible values
Scenario	
Temperature target	1.5°C, below 2°C, 2°C, 3°C, NA
Time horizon	2025, 2030, 2040, 2050, 2100, NA
Transition path	Orderly, Disorderly, NA
Methodology	
Type of metric[8]	Income statement, Asset price, Risk score, Alignment
Information on firms' climate plans	CAPEX, Target, None
Approach	Bottom-up, Top-down, Combination, NA

3. Assessing convergence across risk metrics

To assess the convergence between metrics, we first rank the firms according to their estimated risk exposure for each metric. 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 two metrics, we use two indicators:

5 The metrics included in the final sample for the analysis in this paper are from the following providers: ISS ESG, Moody's Corporation, MSCI ESG Research, PwC / The CO-Firm, Planetrics, right. based on science, S&P Global Market Intelligence, Sustainaccount, University of Augsburg.

6 Keeping in mind that some metrics are not available for all the firms in our sample.

7 Top-down approaches are macro-oriented (e.g. overall reduction needed in a sector translated at the firm level), bottom-up approaches have firm level data as starting point.

8 The types of metrics are characterised as follows:

(1) Income statement: metric shows the estimate of climate transition risks as an estimated impact on firms' costs, revenues or overall profits for a specific timeframe.

(2) Asset price: metric shows the estimated effect of climate transition risks on the equity or bond price of the individual firm.

(3) Risk score: metric assigns a specific climate transition risk score to the individual firm or provides a climate transition risk-adjusted credit risk rating for the individual firm.

(4) Alignment: metric assesses the degree of global climate targets alignment/misalignment of a firms' operations and climate-related performance.

1. The average difference for a firm's risk category between the two metrics (*Absolute Distance*). The lower the Absolute Distance, the higher the convergence 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.

Convergence within providers

Our findings indicate a high degree of convergence between risk assessments when they are delivered by the same provider. However, we observe a significant degree of heterogeneity when the risk assessments are delivered by different providers.

As shown in Table 2 (Specification 1), the degree of convergence increases when two metrics are delivered by the same provider. The degree of convergence, however, differs between providers: it is almost perfect for some and lower for others (see Table 2, Specification 2). This suggests that, for some providers, the ranking of firms is not significantly influenced by the scenario and methodology underlying the different metrics of the provider. For other providers, these dimensions have an impact on firms' ranking.

Convergence within providers

OLS regression

Table 2

	Specification 1		Specification 2	
	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**

* (**) means statistically significant with a 5% (1%) confidence interval.

Convergence across providers

Our results in Table 2 also indicate that, when two metrics are delivered by two different providers, a significantly lower degree of convergence is observed between them. This result confirms the heterogeneity in risk assessments delivered by different providers that we observed in our previous study (Bingler *et al*. 2020, 2021a). The heterogeneity in risk assessments that we find does not come as a surprise: it reflects the significant complexity and uncertainty in the analysis of climate risks.

However, some degree of convergence exists between providers. Our regression results in Table 2 show that the Agreement Rate between two metrics stemming from two different providers is about 25%, that is 20% more frequently than if the two metrics were perfectly heterogeneous.

To highlight the drivers of the convergence between two metrics from different providers, we assess whether the characteristics of each provider's methodology impact the convergence between two metrics. To this end, we assess whether the convergence between two metrics increases when they are based on similar scenarios,[9] metric type, and methodologies.[10] The results are presented in Table 3.

Convergence by similar metrics features

OLS Regression Table 3

	Absolute Distance	Agreement Rate
Intercept	1.56**	0.208**
Same Time Horizon	-0.02	0.007*
Same Temperature Target	-0.07**	0.012**
Same Transition Path	-0.06**	0.018**
Same Metric Type[1]	-0.03	0.010
Same Approach[2]	0.02	0.005
Both with information on firms' climate plans	-0.02*	-0.001

[1] Impact on income statement, impact on asset price, risk score or alignment with transition.

[2] Top-down, bottom-up or combined approach.

* (**) means statistically significant with a 5% (1%) confidence interval.

Our results show that metrics sharing similar scenario characteristics like similar horizon, temperature target and assumptions on the path of the transition display higher convergence, both when measured by the Absolute Distance (decrease in the Absolute Distance) and the Agreement Rate (increase in the Agreement Rate). Evidence on the impact of the type of methodology is less univocal: delivering the same metric type or being both based on information including firms' climate plans significantly increases convergence only according to one of our two statistics: The Agreement Rate when metrics have the same type of metric, and the Absolute Distance when metrics are both based on information including firms' climate plans. Note, however, that, although statistically significant, the impact of similar scenarios

[9] 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 between metrics that model an orderly or a disorderly transition.

[10] We distinguish between types of output delivered by the metrics – financial indicators (e.g. future earnings, value-at-risk, stock price change) vs. other indicators (e.g. risk score, alignment measure) – and whether metrics include information of firms' climate plans (CAPEX or climate targets).

and methodologies only moderately improves the convergence between two metrics: the heterogeneity between them remains pronounced even when two metrics are based on similar scenarios and methodologies.

Convergence on firms with high exposure

We confirm another important result of Bingler et al. (2020, 2021a): metrics from different providers tend to converge more for firms that are assessed as 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 assessments were fully heterogeneous. To reflect the fact that characteristics of metrics might impact the convergence between metrics (see previous section), we only compare the pairs of assessments for metrics that have similar horizons, temperature targets, assumptions on the path of the transition and output indicators. The results are presented in Table 4.

Convergence between firm's risk assessment pairs

Observed excess frequency (in %) Table 4

Difference between risk assessments in the pair	
0	30
1	6
2	-8
3	-27
4	-20

A positive (negative) number indicates that the difference between two risk assessments for the same firm is observed more (less) frequently than if the two metrics where not correlated

Table 5 shows that pairs of assessments in which two metrics agree – i.e., two metrics rank a firm in the same quintile – occur more often than with an independent distribution. This indicates that risk metrics tend to agree relatively more often than they disagree on the risk exposure of the same firm.

We find that the highest excess frequency is observed for the pairs where both assessments fall into the fifth quintile. This indicates that convergence in assessments between metrics is more pronounced for firms with the highest estimated exposure to transition risks. Bingler *et al.* (2020, 2021a) find the same results on a sample of European firms.

Convergence between firm's risk assessment pairs per quintiles

Observed excess frequency (in %) Table 5

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

A positive (negative) number indicates that the difference between two risk assessments for the same firm is observed more (less) frequently than if the two metrics where not correlated

4. Understanding the drivers of risk assessments

In order to better understand the individual risk assessments, we explore which characteristics of a metric can be associated with the estimated value of firms' transition risk. Unfortunately, the providers in our dataset deliver estimated transition risks in different units (e.g., change in stock price, value-at-risk, credit score, etc.), which makes a direct comparison between metric values impossible. To cope with this issue, we use two different rescaling methods for the metrics for our analyses across firms and providers, each presented in the next two subsections. In addition, in a third subsection, we explore whether the characteristics of a metric impact how estimated risks are distributed across firms – i.e., whether metrics' characteristics modify the shape of the metrics' estimated risk distribution.

Impact of metrics characteristics on firms' risk assessments

We first rescale each 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 $y_{i,j}$ is the estimated transition risk exposure for firm i with metric j. The rescaling produces a new vector of risk assessments for each metric, with values ranging between 0 and 1. Clearly, with this rescaling, we lose information about the level and the range of the estimated transition risk for a metric compared to other metrics. However, we keep important information on the level of transition risks for a firm relative to other firms provided by one metric.

We use this rescaling to assess whether metric characteristics are associated with changes in the estimated relative level of transition risk for a firm across all metrics. For that, we estimate a heteroskedasticity-robust panel OLS regression with firm-fixed effects to control for unobservable variables at the firm level. We choose an estimation method which is robust to outliers[11] and we compute our model for cluster-robust standard errors, where the clustering is given by the provider.

The results are presented in Table 6. The coefficients are our estimation of the impact of using different temperature targets, time horizons, metric types, climate plan considerations and metric approach, all compared to our baseline. The baseline is a metric using a 1.5°C temperature target, a time horizon of 2025, estimating transition risks for firms' income statement, not including any information about firms' climate plans and using a bottom-up approach.

Impact of metrics characteristics on firm's risk assessment

Robust Panel OLS Regression — Table 6

	Estimated coefficient	Standard error
Intercept		
Scenario		
Temperature target (Baseline: 1.5°C)		
Below 2°C	-0.129	0.199
2°C	-0.124	0.241
3°C	-0.149	0.176
Not applicable	0.228	0.215
Time horizon (Baseline: 2025)		
2030	0.042	0.032
2040	0.109	0.064
2050	0.019	0.107
2100	-0.060	0.109
Not applicable	-0.400**	0.123
Methodology		
Type of metrics (Baseline: Income statement)		
Asset price	0.559	0.315
Alignment	0.578**	0.139
Risk score	0.281**	0.057
Information on firm's climate plans (baseline: no information)		
Firm's targets	0.303**	0.085
Firm's CAPEX	0.565**	0.089
Approach (baseline: Bottom-up)		
Combined	-0.322**	0.054
Top-down	0.096	0.155

* (**) means statistically significant with a 5% (1%) confidence interval.

Panel with fixed effects for firms.

[11] We use the iterated re-weighted least squares (IRLS). There are several weighting functions that can be used for IRLS. In our specification we use Huber weights.

We find that the type of metric used, the inclusion of a firm's climate plans and the approach underlying the metric are associated with a significant change in the estimated level of transition risk for a firm, relative to how this firm is assessed by a metric when using the baseline specification. On average, using an alignment indicator or a risk score produces higher relative estimated risks for a firm than using an income statement indicator. Similarly, including information on a firm's climate plans, either by considering a firm's climate targets or its CAPEX, induce a higher relative estimated transition risk than when the metric does not include information about a firm's climate plans. This could suggest that metrics reflect that there are only a few companies with climate plans aligned with the transition requirements and global or national climate targets, and most companies with climate plan not aligned with it. In such a situation, relative risk assessments for metrics that consider climate plans could be higher than risk assessments for metrics that do not take information about plans into account. Finally, we find that metrics based on a combination of top-down and bottom-up approach produce different relative estimated risks than metrics based solely on a top-down or a bottom-up approach. This result, however, should be interpreted with caution, as our dataset only contains a limited number of metrics using a combination of top-down and bottom-up approach.

Finally, we do not find that different temperature targets and time horizons affect the relative estimated risk for a firm. This, however, does not mean that scenarios have no impact on estimated risks. It might rather show that the average level of risk is influenced by scenarios, but that through our rescaling, we lose information about this level for a metric compared to other metrics. In the next subsection, we take advantage of the fact that some providers delivered several metrics in the same unit, but with different temperature targets and time horizons, to assess this case.

Impact of scenarios on risk level assessments

In this subsection, we take advantage of the fact that five providers deliver risk estimations for several scenarios, to assess whether different scenarios impact the level of transition risks estimated by a specific metric. For that, we use a slightly different rescaling, i.e.

$$y_{i,j}^{+} = \frac{y_{i,j} - \min_{i,j \in P}(y_{i,j})}{\max_{i,j \in P}(y_{i,j}) - \min_{i,j \in P}(y_{i,j})}$$

where P is the set of all metrics delivered by a specific provider. Since all the metrics provided by a specific provider are expressed in the same unit, we can rescale them all on the interval between the lowest and the highest value observed in the different scenarios delivered by the provider. This allows us to assess how scenario characteristics impact the estimated level of transition risks.[12]

12 Note that using this rescaling, we lose the information contained in metrics delivered by providers that do not estimate transition risks for multiple temperature targets and time horizons. Therefore, it was not a useful approach to assess the impact of the metrics' method on the estimated risks.

For each provider, we perform a heteroskedasticity-robust panel OLS regression with firm fixed effects. Note that the number of metrics and of explanatory variables varies across providers. Our results are reported in Table 7. Each column represents one provider, with the regression results for the metrics from this specific provider.

Our results, presented in Table 7, show that both, temperature targets and time horizon, have an impact on the estimated transition risk level. The impact of temperature targets is significant for all our providers. As expected, the lower the temperature target, the higher the estimated transition risk – i.e., a transition to 1.5°C is associated with higher risk estimates for firms than a transition to 3°C (which is commonly considered as business as usual). Results for different time horizons are similar: with the exception of Provider 2, for which the time horizon does not impact the risk level, increasing the horizon significantly increases the estimated risks. Finally, results for Provider 2 show that risks decrease when firms adapt to the transition, compared to the case in which they are inactive facing the transition. Results for Provider 5 indicate that an immediate transition entails less risk than a delayed transition, whereas Provider 3 does not find a significant difference for these two transition pathways.

Impact of temperature targets and time horizon on risk assessment

Robust OLS Regression — Table 7

	Provider 1	Provider 2	Provider 3	Provider 4	Provider 5
Intercept	-0.355**	0.269**	0.289**	-0.467**	-0.525**
Temperature target					
1.5°C			Baseline	Baseline	
Below 2°C	0.006**	0.004**		-0.021**	
2°C	Baseline	Baseline	-0.001**	-0.026**	
3°C		-0.002**	-0.003**		
Time horizon (baseline: 2025)					
2030		-0.001	0.000	0.006**	0.003**
2040		0.000	0.002**	0.008**	0.007**
2050		0.000	0.003**	0.011**	0.009**
Specific metrics assumption					
Firms adapt to transition		-0.011**			
Immediate transition			0.000		-0.002**

* (**) means statistically significant with a 5% (1%) confidence interval.

Impact of metrics characteristics on the shape of distributions

Finally, we assess whether metrics' characteristics significantly impact the shape of the distribution of the estimated risk, beyond their impact on the estimated mean, as shown in the previous sections. For that, for each metric, we compute three statistics summarizing the shape of the distribution of firms' estimated risks: the standard deviation, the skewness, and the kurtosis. The standard deviation shows how close estimated risks are from the metrics' average estimated risk.[13] The skewness is a measure of the symmetry of a distribution.[14] The kurtosis indicates how flat a distribution is.[15]

We then regress these statistics on provider characteristics. Note that since we compute each statistic per metric, we get 69 observations to regress on 17 metrics characteristics. This is potentially not enough observations to get robust estimated coefficients. To cope with this problem, we use a LASSO-reduced OLS regression. The LASSO methodology selects only the variables that have the most impact on the dependent variables, and then estimate a regression with this restricted set of regressors, to obtain a more robust estimation. Our results are presented in Table 8.

Overall, our results show that metrics' characteristics do not significantly alter the shape of the distribution of the estimated risks for firms beyond the metric distributions' means, i.e. the distributions' standard deviation, skewness and kurtosis. Some of them – metrics assessing risk in terms of impact on firms' asset prices, considering firms' climate plans by using information about firms' CAPEX, or adopting a combined bottom-up and top-down approach – reduce the spread of risks around the average (shown via the standard deviation estimates), while metrics assessing a risk score increase it. None of them affect the symmetry of the distribution (shown via the skewness estimates), while metrics assessing risk scores flatten the distribution (shown via the kurtosis estimates).

13 A high standard deviation indicates that the estimated risks are spread out over a large range of values.

14 A positive value means that the right tail of the distribution is longer than the left, a negative value that the left tail is longer than the right.

15 A negative kurtosis indicates that the distribution is flatter than a normal distribution – i.e. with "fat tails".

Impact of metrics characteristics on shape of distribution

LASSO-Reduced OLS Regression Table 8

	Standard deviation	Skewness	Kurtosis
Intercept	0.163**	2.084	45.475**
Temperature target (Baseline: 1.5°C)			
Below 2°C	--	--	--
2°C	-0.017	--	--
3°C	-0.041	--	-17.049
Not applicable	--	--	--
Time horizon (Baseline: 2025)			
2030	--	--	--
2040	--	--	--
2050	--	--	--
2100	--	--	--
Not applicable	--	--	--
Type of metrics (Baseline: Income statement)			
Asset price	-0.073**	--	--
Alignment	--	--	--
Risk score	0.128**	--	-31.986**
Information on firm's climate plans (baseline: no information)			
Firm's targets	--	-2.001	--
Firm's CAPEX	-0.063**	-2.689	--
Approach (baseline: Bottom-up)			
Combined	-0.108**	--	--
Top-down	--	--	--

* (**) means statistically significant with a 5% (1%) confidence interval.

-- indicates that the variable is not selected by the LASSO procedure

5. Conclusion

Our results confirm the early findings of Binger et al (2020, 2021a), that is: 1) climate risk metrics display a significant degree of heterogeneity, 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 1) metrics from the same provider but based on different scenarios display a higher degree of homogeneity than metrics from different providers, and 2) the scenarios and the methodology underlying a metric affect the convergence between two metrics from different providers: metrics sharing similar time horizons, temperature targets and assumptions 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.

Turning to the drivers of the risk estimates, we find strong evidence that metric characteristics impact the estimated level of transition risk. Our results show that both the methodology underlying a metric and the scenario it relies on significantly affect the estimated risk for a firm. The across-tools analysis shows 1) that the individual model characteristics are an important driver of the estimated risk relative to another metric. In particular, metrics that include information on firms' climate plans seem to deliver higher relative risk estimates than metrics which do not include such information. Furthermore, our within-tool analysis shows that 2) the scenario on which a metric is based impacts the estimated risks: lower temperature targets increase risk estimates, longer time horizons also increase the estimated risk, and an orderly transition scenario delivers lower risk estimates than a disorderly transition scenario. Finally, our analysis shows that metrics' characteristics do not significantly impact the shape of the distribution of estimated risks beyond the metric distributions' means, i.e. do not impact the standard deviation, skewness and kurtosis.

These findings provide important insights for the practical use of climate risk metrics. First, despite the heterogeneity observed across metrics, we find that metrics tend to converge on which firms are assessed as most exposed to transition risks. They thus provide useful information to risk managers to address high transition risk exposures. Second, the scenario and methodology underlying the metrics impact the estimated risk. It is therefore important for risk managers to understand well how metrics are built and to choose the ones that are the most appropriate to their needs. Third, firms, which disclose climate risks should also report the underlying methods, data sources and scenario assumptions in addition to the metrics' values.

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Climate risk metrics: Convergence, divergence and metrics characteristics

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Contribution

- Climate risks are financial risks
  - assessed, monitored and controlled
  - integrated in financial supervision and monetary policy operations

(1) Do different climate risk metrics lead to a different risk assessment for the same firm?

(2) Do the scenario and the methodology underlying a metrics impact on the estimation of transition risk?

Data and variables

- 1543 firms, components of MSCI World Index as of 31 January 2020
- 9 providers of forward-looking climate risk or alignment metrics
- More than 105'000 observations from 69 transition risk metrics
- For each metric, 6 variables describing the underlying scenario and methodology

Convergence analysis

- For each metric, firms are classified in 5 risk categories (1 = lowest risk, 5 = highest risk)

- Two indicators of coherence between metrics:
  (1) **Absolute distance**: average risk category difference across firms
  (2) **Agreement rate**: percentage of firms in same risk category

- Coherence within providers

	Specification 1		*Specification 2*	
	Absolute Distance	Agreement Rate	Absolute Distance	Agreement rate
Intercept	1.45***	0.245***	1.45***	0.245***
Same Provider	-1.07***	0.478***		
Provider 1			-1.35***	0.655***
Provider 2			-0.88***	0.352***
Provider 3			-0.77***	0.305***
Provider 4			-1.34***	0.689***
Provider 5			-1.12***	0.445***
Provider 6			-0.94***	0.354***

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

Convergence across providers

- Scenario and methodology matter for coherence across providers

	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

- Higher coherence for firms highly exposed to transition risk

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

(a) Difference in pairs

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

(b) Per quintile pairs

Highest quintile \ Lowest 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

Metrics characteristics

- Indep. variable: Risk assessments (min-max normalization)
  (1) Across-metrics panel OLS
    - Dep. variables: Temperature target, time horizon, output type, firm targets, CAPEX, approach
    - Heteroskedasticity- and cluster-robust SE
  (2) Within-metric OLS
    - Dep. variables: Temperature target, time horizon, transition path
    - Heteroskedasticity-robust SE
- Robust to outliers specification

Across-metrics panel OLS

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

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

Across-metrics panel OLS

modelling approach

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

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

Across-metrics panel OLS

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

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

Within-metric analysis

- 5 providers: different assumptions about temperature target, time horizon and transition path
- Robust to outliers, but no panel dimension, no cluster-robust SE and different normalization
- Temperature target, time horizon and transition path matter for the risk assessment

Conclusion

- Metrics based on similar scenario and methodology deliver more similar risk assessments
- Metrics converge more for firms highly exposed to transition risk
- Metrics methodology is associated with changes in the estimation of transition risk
- Scenarios are also associated with changes in the level of risk within tools

Thank you!

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Appendix

Data providers

Table: 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			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 / Vigeo Eiris	Financial services			financial metric
MSCI / CarbonDelta	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	Think tank			risk score

Explanatory variables

Table: 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

Double LASSO - Risk assessments I

- Prediction: LASSO + robust OLS on reduced model
- 16 dummified variables, only 1 dropped (bottom-up approach)
- Same direction of impacts but different significance
  - Non significance of the type of output
  - Non significance of including of firm targets

Double LASSO - Risk assessments II

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

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

Within-metric OLS

	Dependent variable: risk assessment				
	Metrics 5-6	Metrics 7-30	Metrics 31-46	Metrics 53-64	Metrics 66-73
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_mainstream		-0.011***			
		(0.0002)			
ass_immediate			0.00004		-0.002***
			(0.0003)		(0.0004)
Constant	-0.355***	0.296***	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

Within-metric double LASSO

	Dependent variable: Risk assessment				
	Metrics 5-6	Metrics 6-30	Metrics 31-46	Metrics 53-64	Metrics 66-73
time_horizon_2030				0.010*** (0.001)	
temp_target_2			-0.002** (0.001)	-0.056*** (0.001)	
temp_target_3		-0.005*** (0.001)	-0.004*** (0.001)		
temp_target_b2	0.007*** (0.003)	0.005*** (0.0005)		-0.049*** (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_mainstream		-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

Moments of the distribution

- Mean, standard deviation, skewness and kurtosis
- Higher temperature target associated with lower kurtosis
- Financial/gap/risk scores metrics associated with higher mean, lower skewness, mixed standard deviation
- CAPEX/firm targets associated with larger mean and lower skewness
- Combined/top-down approach associated with lower standard deviation

Moments of the distributions OLS

	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

Moments of the distributions double LASSO

	Dependent variable: Distribution of risk assessment			
	Mean	Standard deviation	Skewness	Kurtosis
temp_target_2		-0.017 (0.013)		
temp_target_3		-0.041 (0.025)		-17.049 (18.737)
output_finmetric		-0.073*** (0.020)		
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)		
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