Climate Financial Risks: Assessing Convergence, Exploring Diversity

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Abstract

Climate risks are now fully recognized as financial risks by asset managers, investors, central banks, and financial supervisors. As a result, the integration of climate risk metrics into risk management processes is moving up agendas worldwide. In that context, a rapidly growing number of market participants and financial authorities are exploring which metrics to use to capture climate risks, and to what extent the use of different metrics delivers heterogeneous results. This discussion note takes a first step in analyzing the convergence in assessments of climate-related transition risks across metrics providers, based on the ECB corporate bond portfolio. Our findings show that firms' risk assessments across metrics are fairly heterogeneous but tend to converge on which firms are most and least exposed to transition risks. We also show that the temperature targets and time horizons underlying the metrics matter, although moderately, for the assessment of firms' risk exposure and that providers using similar methodologies tend to deliver more convergent assessments. Our findings contribute to the growing recognition that asset managers, investors, central banks and financial supervisors can and should use available metrics to better integrate climate risks into risk management and financial supervision.

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Uncertainty and lack of data is not an excuse.”

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Governor of the Bank of England

INTRODUCTION

Climate risks are financial risks. Academics have highlighted this fact extensively (see, e.g., Caldecott et al., 2016; Gros et al. 2017; Battiston et al., 2017; Stolbova et al., 2018; Roncoroni et al., 2019; Bretschger and Karydas, 2019). It is also widely acknowledged by the financial community, from central banks and financial supervisors (NGFS, 2018; BCBS, 2020; Bolton et al., 2020), to key financial market participants (see, e.g., BlackRock 2020).

Climate financial risks, as any other source of risk, must be diligently assessed, monitored and controlled by asset managers, both in private and public institutions, like central banks (see Monnin, 2020). They should also be comprehensively integrated in financial supervision and regulation.

Against this background, a rapidly growing number of market participants and financial authorities are exploring which metrics to use to capture climate risks, and to what extent the use of different metrics and scenarios deliver heterogeneous results. A key question on their agenda zooms in on whether different climate risk metrics give a drastically different risk assessment for the same firm, and if so, why.

Research on metrics covering environmental, social and governance (ESG) criteria, e.g. Berg et al. (2019), shows considerable heterogeneity among ESG ratings delivered by different providers. Yet, ESG ratings are different from metrics for climate risks. Whilst the latter focus solely on climate-related risks, the former usually cover a composite of various environmental, social and governance-related factors. An assessment of the convergence of climate risk metrics, to our knowledge, does not exist yet.

This paper aims at taking a first step to fill this gap, focusing on transition risks. Specifically, we give a preliminary assessment of the convergence of various transition risk metrics delivered by different providers. We use our findings to provide initial recommendations to asset managers, investors, central banks, and financial supervisors regarding the use of climate risk metrics. Our conclusions are preliminary, and we hope will contribute to further research in the field.

The aim of the study is to give initial answers to the following questions:

(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?)

(2) Do we see a higher convergence in assessment when providers rely on similar methodologies?

(3) What are the consequences of heterogeneous climate risk assessments for the same firm for asset managers, investors, central banks, and financial supervisors?

(4) What are the recommendations for asset managers, investors, central banks, and financial supervisors, stemming from the results of the study?

Our findings show that while there exists a significant degree of heterogeneity in the risk assessments delivered by different providers across the entire universe of firms, risk metrics tend to converge for firms that are most and least exposed to transition risks.

Our analysis also indicates that part of the observed heterogeneity in risk assessments is associated with differences in the methodologies used by the different providers. However, we also observe heterogeneity in risk assessments among providers using similar methodologies. In that context, we find that the temperature target chosen for the assessment, as well as the time horizon considered, matter for the conclusions about the transition risk of firms.

The heterogeneity in risk assessments that we find reflects the significant complexity and uncertainty in the analysis of climate risks. In this context, we believe that calls for a single standard of climate risk metrics are misconceived. To advance the field of climate risk metrics, different perspectives and views are needed to drive a dynamic process that constantly questions prevailing judgement. This requires an open market architecture that allows for constant entries of new players who bring new knowledge and insights to the field. However, defining common transparency principles about the methodologies used by providers would be useful for metrics users to better compare the risk metrics available to them.

Moreover, the risk metrics currently available can and should be applied by asset managers, investors, central banks and financial supervisors to better integrate climate risks in risk management and financial regulation. To that end, and given the complexity and uncertainty in the field, we recommend them to rely on a set of metrics, rather than only a single one, to assess the transition risk of their portfolio or of their supervised institutions. To select this set, they should carefully understand the underlying methodology of the selected metrics, as well as the different assumptions regarding the scenario adopted, and to choose those that best fit their needs and beliefs.

Finally, to the extent that users of climate risk metrics are concerned about the heterogeneity in assessments across the entire universe of firms, we contend that this is not a reason for inaction and that they should in any case start integrating climate risk metrics for firms that are the most and the least exposed to transition risks, where metrics are converging.

Asset managers can and should use the information delivered by a set of climate risk metrics to better manage the overall risk profile of their portfolio. Central banks and supervisors may choose to focus on identifying firms that are the most exposed to transition risk, since they are mostly concerned about not including high-risk assets in their balance sheets and about identifying risky investments undertaken by their supervised institutions, respectively. The available risk metrics are particularly useful to these goals as they tend to converge on the firms that are the most exposed to transition risk.

In what follows, we first describe the data used and the methodology adopted in this study. Second, we report our main findings and results. Finally, we conclude with policy recommendations for asset managers, investors, central banks and financial supervisors.

DATA AND METHODOLOGY

We base our analysis on the European Central Bank's (ECB's) corporate bond portfolio stemming from its Corporate Sector Purchase Program (CSPP). This portfolio gives us a sample of firms for which we asked various providers of risk metrics to assess their exposure to transition risk. To make the results of different providers comparable, we homogenize the data as explained at the end of this section.

Firm sample

Our sample includes 287 firms from 10 sectors (see Table 1). The sample is based on the list of bonds owned by the ECB in its CSPP portfolio as of 28 August 2020. Our sample of firms corresponds to the list of firms that have issued these bonds. Note that sometimes, the issuer of the bonds is not its guarantor. For example, Volkswagen Financial Services AG is guaranteed by Volkswagen AG. In these cases, the guarantor is backing the repayment of the bond and is thus the relevant entity for assessing the exposure to climate risk of that bond. For such cases, we replace the issuer of a bond by its guarantor in our sample of firms.

TABLE 1: NUMBER OF FIRMS IN SAMPLE, BY SECTORS

Sector	# of firms
Basic materials	26
Consumer Cyclicals	32
Consumer Non-Cyclicals	21
Energy	18
Financials	26
Healthcare	10
Industrials	57
Real Estate	28
Technology	25
Utilities	44

TABLE 2: RISK METRICS PROVIDERS PARTICIPATING IN THE STUDY

Provider	Metrics	Name used in the study	Sector
Carbone 4	Carbon Impact Metrics	Carbone4	Think Tank
University of Augsburg	CARIMA	CARIMA	Academia
Cambridge Institute for Sustainability Leadership	ClimateWise Transition Risk Framework	CISL	Academia
Data Ahead	ESG Enterprise Suite	DAA	Financial Services
ISS ESG	Portfolio Climate Impact Report and Raw Data	ISS	Financial Services
MSCI CarbonDelta	Climate VaR	MSCI	Financial Services
PWC / The CO-Firm	Climate Excellence	PWC	Financial Services
right. based on science	XDC model	right	Think Tank
S&P Global Market Intelligence	Climate Strategy Metric	SP	Financial Services
Vivid economics	Climate Risk Metric Toolkit	VIVID	Financial Services

Providers

We contacted 13 providers of climate risk metrics and asked them to provide us with an assessment of the transition risk exposure for each firm in our sample. The 10 providers who participated are listed in Table 2.

Risk metrics

The list of metrics used in this study, as well as their provider and description are presented in Table 3. Note that most of the metrics used do not assess all firms in our sample. The coverage range is also indicated in the table. For more detailed information about the methodologies by the different providers, we refer the reader to the official documentation from each provider and the working paper by Bingler and Colesanti Senni (2020).

TABLE 3: TRANSITION RISK ASSESSMENTS USED IN THE STUDY

Provider	Assessment Output	Description	Coverage
Carbone4	Overall rating	The overall rating is a combination of total emissions produced by a company, its emission savings and a qualitative rating. The qualitative rating is based, for instance, on CAPEX plans.	196/287
CARIMA	Carbon Beta	The Carbon Beta measures how financial markets value the risk associated with a firm's exposure to the transition to a low-carbon economy. The market-based metric builds on the CAPM model.	136/287
CISL	Risk score	The risk score is the ratio of current cost/revenue to expected future cost/revenue in transition scenarios. It is provided for different time horizons (2025, 2030 and 2040) and temperature targets (Paris Agreement and 2°C).	106/287
DAA	Risk score	The risk score reflects the discounted impact of the transition on both costs and revenues of a firm over different time horizons (2025, 2030, 2040 and 2050) compared to their level in 2020.	286/287
ISS ESG	Carbon Risk Rating (CRR)	The CRR is a firm-specific score based on an assessment of over 100 industry-specific indicators and a carbon risk classification at the industry and sub-industry levels.	190/287
ISS ESG	Climate VaR	The Climate VaR measures the difference between the current share price and the transition risk adjusted share price.	132/287
ISS ESG	Climate Margin	The Climate Margin measures the profit margin after adjustment for transition risk.	158/287

MSCI	Climate VaR	Climate Value-at-Risk is designed to provide a forward-looking and return-based valuation assessment to measure climate-related risks and opportunities in an investment portfolio across asset classes. Climate VaR maps scenarios to individual issuers and then calculates the valuation impacts that such scenarios would represent for issuers and their securities. By expressing everything in terms of valuation impacts, Climate VaR provides a measure of risk that makes different components of climate risks (e.g. transition and physical risks) comparable with each other and makes climate risks comparable with other types of financial risks.	191/287
PWC	EBITDA change	The metric is the change in yearly earnings of a firm due to the transition, relative to its current earnings. This change is assessed for different time horizons (2025, 2030, 2040 and 2050) and temperature scenarios (1.8°C, 2.0°C and 2.7°C). In addition, each scenario can be supplemented by simulations of a company's adaptive capacity, i.e. their ability to adapt to a low-carbon transition. Thereby, both firms' downside risks and upside opportunities from the transition are assessed.	282/287
Right	Gap	The Gap measures the misalignment of the current emissions produced by a company with the ones that the company should emit in order to be in line with a given climate scenario.	206/287
SP	Climate Strategy Criterion Score	The Score captures the extent to which companies integrate both short- and longer-term climate change impacts, risks and opportunities into their management and other strategic planning activities.	165/287
VIVID	Profit impairment	The metric captures the profit impairment in percent (relative to current values) under the NGFS REMIND-MAgPIE climate scenarios relative to a business-as-usual scenario (i.e. 3.6°C degree of warming in 2100). Results are provided for three different temperature targets (1.5°C, 2°C, NDCs) and four time horizons (2025, 2030, 2040, 2050). For non-listed bond issuers sectoral proxy results are provided.	275/287

Some providers deliver metrics for various transition scenarios, which differ in terms of temperature targets and time horizons (four providers use multiple temperature targets, and four providers use different time horizons). We use these providers to study the impact of different temperature targets and time horizons on firms' relative risk exposure within a metric.

Metrics homogenization

Climate risk metrics are expressed in different units and scales, depending on each provider's methodology. To be able to compare them, we translate the assessment outputs into the same unit: the ranking of each firm in terms of risk exposure within each provider's specific sample. Concretely, for each of the metrics, we rank the firms according to their exposure to transition risk (i.e., for each of the metrics, the firm with the lowest risk exposure gets rank one, the firm with the highest risk exposure gets rank *N(i)*, with *N(i)* being the number of firms analysed for metric *i*). We then divide the individual ranks by *N(i)* to express each firm's exposure with a score between 0 and 1 (i.e., for each of the metrics, the firm with the lowest exposure to transition risk gets a score of 0 and the one with the highest exposure gets a score of 1).

Using ranks instead of initial assessments has the advantage to keep the ranking of the firms within an assessment, and thus to make metrics comparable with each other. The downside of our approach is, however, that we lose information about the scale of the difference in risk exposures between firms across the different metrics as well as about the absolute levels of risk they identify.

In addition to the individual firm ranks within each metrics, we also use an alternative risk categorization, which attributes a score from 1 to 5 – from low- to high-risk exposure – to each firm according to the quintile of their rank within one assessment.

Convergence analysis

Our analysis of the overall convergence of rankings obtained by the providers is structured along two lines: *across-metrics* and *within-metrics* analysis. The across-metrics analysis investigates the convergence of the rankings across different metrics, that is, their agreement on exposure to climate risk of the companies in the sample. The within-metrics analysis aims instead at assessing the convergence of the rankings produced by the same metric under different transition scenarios in terms of temperature targets and time horizons.

Across-metrics analysis

In this section, we assess the degree of convergence in assessments across the transition risk metrics delivered by different providers. For that, we use two different samples: the *core sample* and the *extended sample*. The core sample includes eight risk metrics and considers only firms for which we have at least four assessments available (191 in total).

The extended sample includes 12 risk metrics[1] and considers all firms which were ranked by at least two providers.

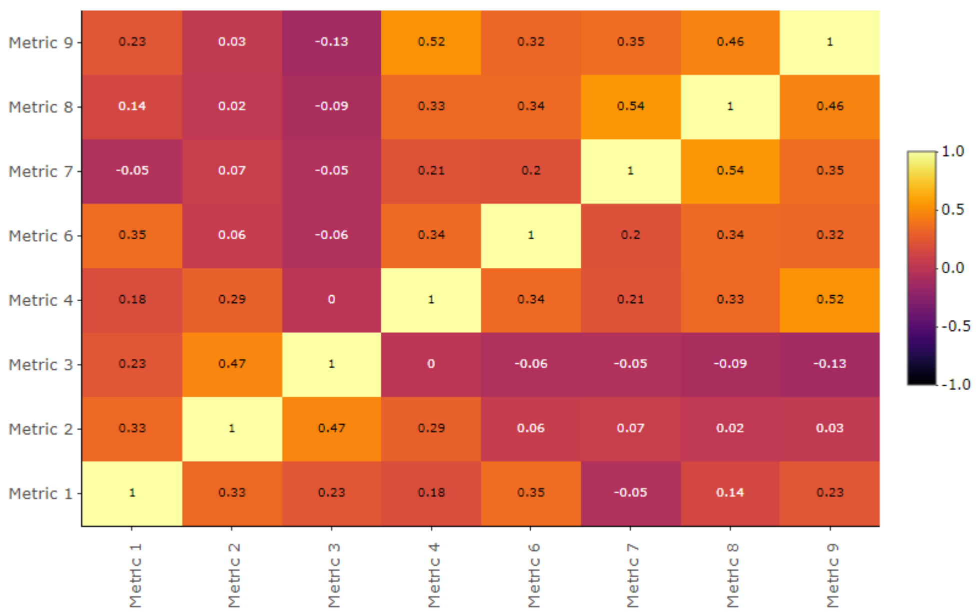
Furthermore, for the core sample, we focus on metrics that cover a sufficient range of firms in our portfolio and that are based on a clear forward-looking approach and firm-level data (see Monnin 2018). When several time horizons and temperature scenarios were available for one metric, we took the value corresponding to a 2°C scenario and to the longest horizon available (usually until the year 2040 or 2050), which corresponds to the baseline specification used by providers delivering only one metric.

Convergence in risk assessments – General picture

The general picture shows that the convergence in firms' risk assessments between different metrics across the entire sample is heterogeneous. Two different risk metrics can give significantly different assessments of the transition risk exposure of the same firms. At the same time, risk metrics do display convergence. In particular, the degree of convergence grows notably for firms that are assessed as most and least exposed to transition risk.

Figure 1 gives a first illustration. It shows the correlation in firms' rank – i.e., the Spearman correlation – between two metrics for the core sample. A higher correlation indicates more convergence between the rankings of two metrics.

Figure 1: Correlation of ranks between metrics



[1] We could analyze the results from 12 metrics because one provider calculates three different types of metrics.

Correlations across the entire core sample are relatively low, with the highest value of 0.54 and even negative correlation values. However, some correlations (17 out of 28) are significantly different from zero, which means that convergence exists between the respective pairs of risk metrics. Correlations in the extended sample show a similar picture (see Annex A, Figure A.1).

Figure 2 sheds more light on these findings. It plots all possible pairs of ranks for each firm produced by two metrics (4221 observed pairs in total for the core sample). On the horizontal axis, the higher value of the two assessments in each pair is reported, on the vertical axis, the lower. When a pair is close to the diagonal, the convergence between the assessments of one specific firm's risk exposure between two metrics is high.

FIGURE 2: PAIRWISE RANK ANALYSIS OF CONVERGENCE

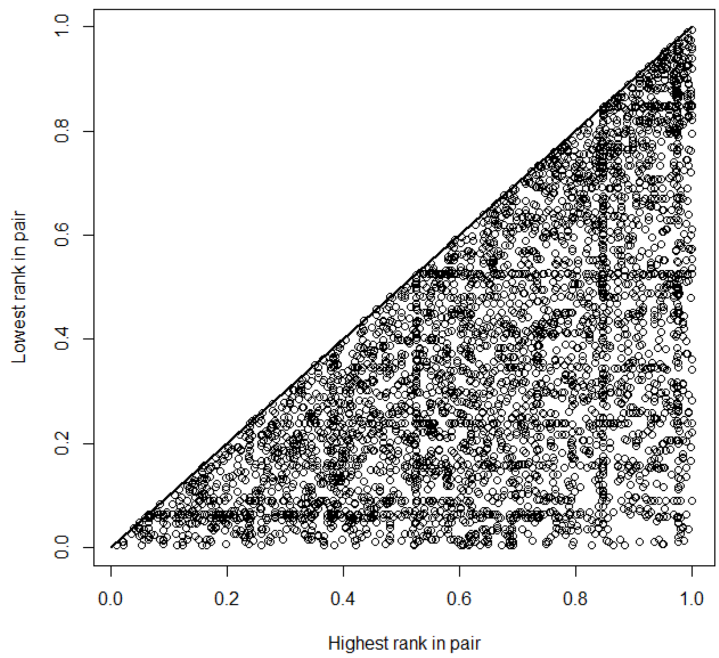


Figure 2 highlights the heterogeneity between risk assessments across the full core sample. Divergence in risk assessments for the same firm is frequent between two metrics – i.e. there is a significant number of pairs not on or close to the diagonal. However, there is also a significant amount of convergence and thus agreement on risk exposures – in particular for those companies that are most risk-exposed. A similar pattern can be observed in the extended sample (see Annex A, Figure A.2).

A further statistical analysis highlights the degree of convergence between metrics in the assessment of firms' risk exposure. We tested the hypothesis of total independence between metrics – i.e. no correlation at all between them, meaning that ranks are randomly distributed – with a Chi-square test. This hypothesis is rejected at a 0.1% level in both the reference and the extended samples. This indicates that the distribution of risk assessment between metrics is not random, and convergence is present in the data.

Table 4 sheds more light on the shape of this convergence. It presents the differences between the number of pairs observed in our core sample and the theoretical number of pairs that we should observe if the metrics were independent from each other – i.e. would not be correlated. In panel (a), a positive number (in green) indicates that the number of pairs observed for a quintile combination in our sample is higher than what we would observe if metrics were independent. For example, pairs of metrics for which both assessments agree on a firm's' very high risk exposure– i.e. quantile (5,5), up-right corner of the table – are 75% more frequent than if metrics were uncorrelated. In panel (b) a positive number indicates that a given quintile difference between two metrics is observed more often than if the metrics would be independent from each other.

TABLE 4: DIFFERENCE IN PAIRS FREQUENCIES BETWEEN OBSERVED AND INDEPENDENT METRICS (IN %)

(a) Quintile combination

Lowest quintile in pair	1	2	3	4	5
5					75
4				18	4
3			8	-4	-9
2		18	7	-10	-21
1	21	12	-3	-7	-40

Highest quintile in pair (columns)

(b) Quintile difference

0	28
1	5
2	-8
3	-14
4	-40

Panel (a) shows that pairs in similar quintile – i.e. close to the diagonal in Figure 2 – are observed much more frequently in our sample than if metrics were unrelated. In contrast, pairs of firms' risk assessments for which metrics totally diverge are observed much more rarely than they should be under an independent distribution of ranks. Panel (b) gives a similar picture: pairs of assessments in which two metrics converge – a difference of 0 in quintile – are much more frequent than in the case of an independent distribution. The "excess" frequency is highest for cases in which both assessments agree and decreases with the degree of disagreement between metrics.

These results indicate that metrics tend to converge more than they diverge. The analysis of the extended sample yields similar conclusion, even if it indicates less convergence between metrics than in the core sample (see Annex A, Table A.1). This is in line with our intuition, since the extended sample includes all metrics and not only those which we considered as being structurally relatively similar.

Convergence in risk assessments across risk levels – Taking a closer look

We analyze further the convergence of risk assessments by looking more closely at how convergence changes across different firms' exposure levels. Our findings confirm our previous observation: there is more convergence in risk assessments for firms that are most and least exposed to transition risk.

Table 5 presents the excess frequency of assessment pairs compared to an independent distribution, decomposed by the level of firms' exposure. The first column gives the quintiles in which at least one of the assessments in the pair is located. The next five columns indicate the excess frequency in percent observed in the core sample for the respective difference in pair's assessments – 0 means that the assessments are in the same quintile, 1 that they are in the same quintile or one quintile away from each other, etc. A high value indicates that the difference between assessments in a pair is observed more frequently than in an independent distribution.

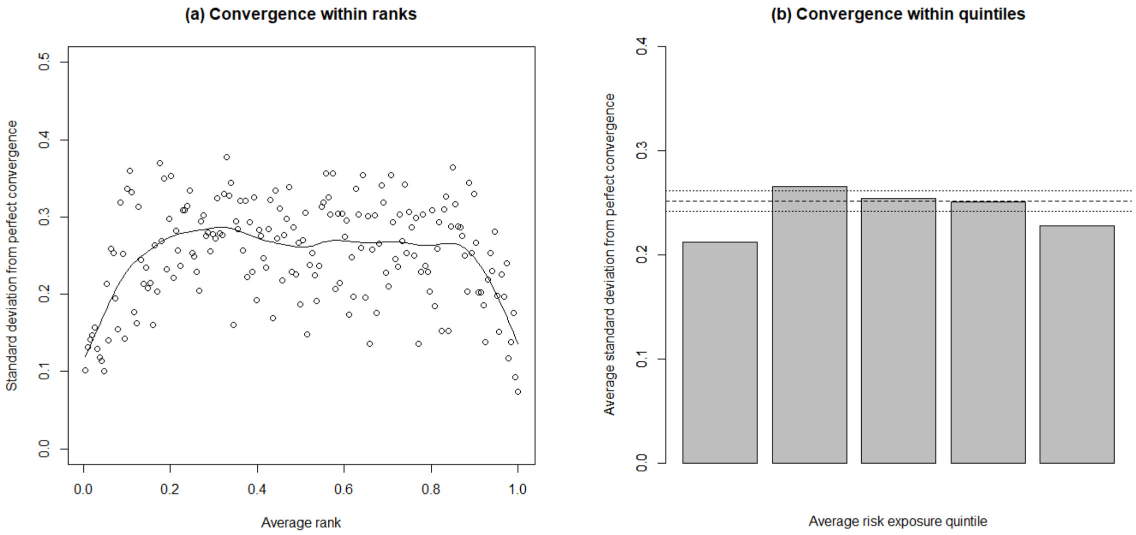
TABLE 5: EXCESS FREQUENCY RELATIVE TO INDEPENDENT DISTRIBUTION, PER QUINTILE (IN %)

Quintile in pair	Maximum difference in pair				
	0	1	2	3	4
1	21	15	8	4	-6
2	18	11	5	0	
3	8	3	-1		
4	18	3	0	-2	
5	75	28	13	3	-6

The results show that for all degrees of convergence, understood as pairs in which the two assessments are a maximum of one quintile away from each other, we observe a higher excess frequency for the fifth quintile – i.e. firms for which at least one assessment in a pair is in the fifth quintile. This indicates a higher degree of convergence between metrics for firms most exposed to transition risks. We also observe higher convergence between metrics for firms that are less exposed to transition risks – i.e. firms for which at least one metric in a pair is in the first quintile.

Figure 3 presents other statistics corroborating our findings so far. Panel (a) indicates the variance – in terms of standard deviation – of the assessments that we observe for each firm (y-axis) once firms are ranked according to their average rank across metrics (x-axis). The inverted U-shape found in this figure indicates a lower variance – and thus a higher convergence - in the case of most and least risk exposed companies (in terms of average rank across metrics). Panel (b) gives similar statistics aggregated by quintiles.[2,3]

FIGURE 3: VARIANCE OF ASSESSEMENTS ACROSS RISK EXPOSURE LEVELS



We observe again less dispersion for firms with a high or a low level of assessed risk exposure – i.e. those with a high or low average rank. This is an additional indication that metrics are more convergent for firms most and least exposed to transition risk. In contrast to what we find in table 5, the level of convergence is relatively higher for firms least exposed to transition risks than for the most exposed ones. Notwithstanding this difference, the findings in both table 5 and figure 3 point to more convergence for firms that are most and least exposed to transition risks.

Convergence across types of metrics – A first exploration

Finally, we explore whether we can attribute part of the heterogeneity observed in risk assessments between metrics to methodological differences between them. For that we first perform a cluster analysis of the metrics in our extended sample (Figure 4).[4] A cluster analysis allows to assess the convergence between two metrics and to automatically and statistically group them according to their degree of convergence. The y-axis displays the value of the

[2] The dashed line represents the average variance across the whole core sample and the dotted line its confidence interval at the 95% confidence level.

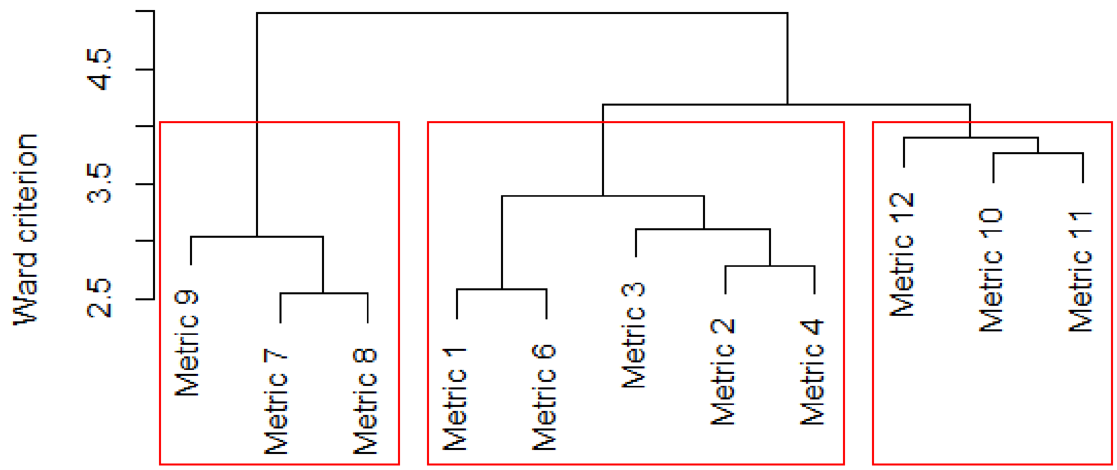
[3] Note that the variance across average rank levels is inverted-U-shaped by construction since our values are constrained between 0 and 1, and due to the use of the average rank for the x-axis. However, we find that the inverted-U-shape that we observe in both panels of Figure 3 is significantly more concave than for the case in which risk metrics are not correlated.

[4] Apart from one metric which we excluded because its inclusion would excessively reduce the number of firms inour sample.

Ward criterion between two metrics – a measure of their degree of convergence. The lower this criterion, the higher the convergence between two metrics.

The cluster analysis shows that we can distinguish three groups in which metrics are more convergent with each other – i.e. are giving more similar assessments for firms. These groups can be characterized by the methodologies that providers use to estimate them. The first group (on the left-hand side of the dendrogram, composed of three metrics) comprises metrics that aggregate several indicators of exposure to transition risks to form a rating indicator. The second group (in the middle of the dendrogram, composed of five metrics) comprises metrics that rely on the estimation of specific financial indicators (e.g. future earnings, value-at-risk, stock price change) for a transition scenario. The last group is less homogeneous and comprises metrics that are not based on forward-looking methodologies and/or on a firm-level analysis.

FIGURE 4: CLUSTER ANALYSIS



The average correlations (see Figure 1) between metrics in the first group – score metrics – and of the second group – financial metrics – are 0.45 and 0.22, respectively. The average correlation between metrics of the last group with the very different metrics is only 0.10. These results support the findings from the cluster analysis: they indicate that metrics are more convergent within a group than with metrics from the other group. It appears that part of the heterogeneity observed in our samples (see Figure 2) is thus associated with differences in the methodologies used by metrics providers.

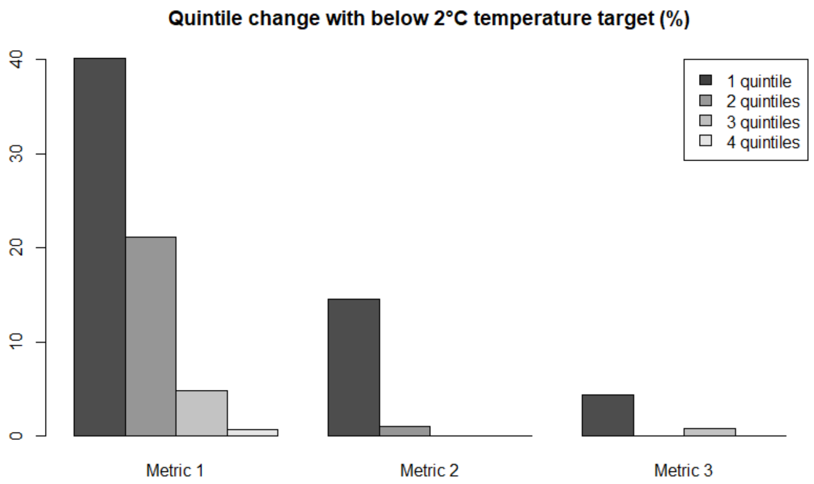
Within-metrics analysis

As already outlined above, many factors can potentially lead to differences in assessment, such as the climate scenario adopted, the macroeconomic assumptions made, and the scopes of emissions included. In this section, we seize the opportunity that a few providers produce their assessments for different temperature targets and time horizons to show differences within metrics based on these variables. This way, we can illustrate to what extent these two different scenario assumptions can drive heterogeneity in assessments.

Convergence across temperature targets

The convergence across different temperature targets within the same metrics can be analyzed for three out of the 12 metrics, as these three provide multiple temperature targets.[5] We focus on the impact on the assessed exposure to climate risk of companies, when using a below 2°C temperature target instead of a 2°C target. Moreover, we focus on quintile changes, not on rank changes. This implies that we focus on significant changes in the exposure to climate risk of a company and we disregard small changes in the assessed risk exposure.

FIGURE 7: QUINTILE CHANGE FOR LOWER TEMPERATURE TARGET (IN % OF FIRMS)



[5] Note that for one of the metrics considered we only use firm-specific assessments and disregard assessments obtained using a sector-based approach only.

Our analysis shows that the temperature target adopted matters for the ranking of firms, as the ranking is affected when different temperature targets are considered. For the providers considered, the rank changes induced by a lower temperature target are mostly by one quintile up or downwards (40%, 15% and 4%, respectively). We also observe, quintile changes of order two (21% and 1%), three (5% and 1%) and four (1%). The results are displayed in Figure 7, where the percentage of firms that changed their position by one quintile or more (both up- or downwards) is depicted.

Overall, metrics are heterogeneous with respect to which companies experience the largest rank change when adopting a different temperature target. The potential reasons here are manyfold: Providers differ in their sectoral and firm coverage, and in their modelling approach (top-down or bottom-up, choice of climate scenario, assumptions about how the outcomes of the climate scenario affect the economy at the macroeconomic or sectoral level, etc.). Based on our data availability, we cannot identify the exact reasons for the variety in assessments. Our results also show that there is no sectoral pattern among the companies experiencing the largest change in their position. This implies that metrics, which are solely based on a sectoral approach, might miss the heterogeneity in exposure of the individual companies within that sector.

We also find that for all the metrics considered, when a lower temperature target is imposed, the percentage of firms being assessed as more risk exposed is larger than the percentage of the firms becoming less risk exposed. For the providers considered, the firms which were assessed as more risk exposed are 55%, 53% and 73%. On the opposite, 42%, 36% and 21% of the companies were considered as less risk exposed.[6] Our finding is in line with the hypothesis that a lower temperature target increases the exposure to transition risk of firms.

Convergence across time horizons

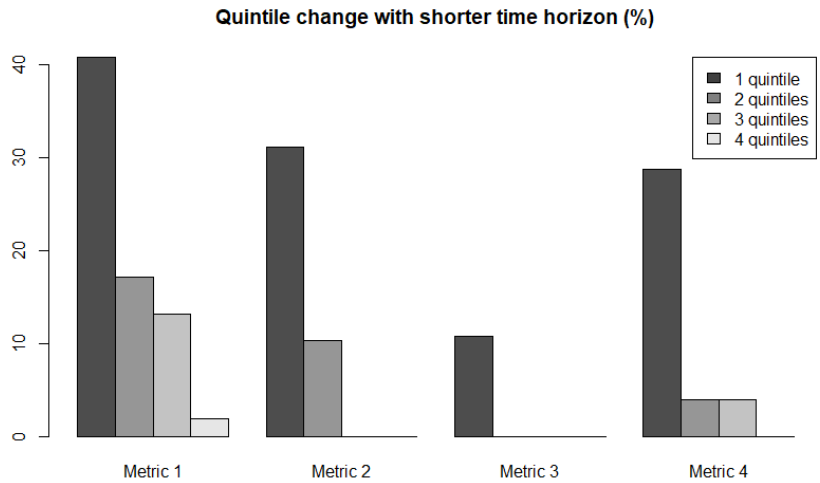
The convergence across different time horizons for the same metric can be assessed for four out of the 12 metrics, as these metrics provide multiple time horizons. In our analysis, we focus on the impact on the risk exposure of companies when using the longest time horizon available compared to the shortest. As in the case of different temperature targets, we do not focus on individual rank position changes, but rather on quintile changes in the ranking.

Our analysis shows that the time horizon matters for the assessment of risk exposures. Rankings are affected when different time horizons are considered. For all the providers considered, quintile changes induced by imposing a shorter time horizon are mostly by one quintile up or downwards (41%, 31%, 11% and 29%, respectively). However, we also observe quintile changes of order two (17%, 10%, and 4% in three out of the four metrics), three (13% and 4% for two providers) and four (2% in the case of one metric). This shows that although

[6] Note that the assessment of the exposure to climate risk did not change for some firms.

there are changes in the assessments of risk exposure, these are not drastic, as the majority of the companies change their rank by either no or just one quintile. The results are displayed in Figure 8, where the percentage of firms that changed their position by one quintile or more (both up- or downwards) is depicted.

FIGURE 8: QUINTILE CHANGE FOR SHORTER TIME HORIZON (IN % OF FIRMS)



We also find that for two out of the four metrics considered, when a shorter time horizon is imposed, the percentage of firms being assessed as more risk exposed is larger than the percentage of the firms becoming less risk exposed. Specifically, the companies the companies increasing their exposure to climate risk are 50%, 46%, 49% and 28%, whereas the companies reducing their exposure to climate are risk are 49%, 52%, 48% and 69%, respectively. We can thus not make a clear statement of the impact of imposing a longer time horizon on climate risk exposures.

CONCLUSION AND RECOMMENDATIONS

This discussion note is a first step to evaluate the convergence of the assessments of firms' exposure to climate risk provided by existing metrics. We study this convergence on a sample of firms based on the issuers, respectively the guarantors, of bonds held by the ECB in its CSPP portfolio as of August 2020. To perform our analysis, we compare the assessments of 12 risk metrics from 10 providers on the exposure to climate risk of the companies in the sample.

We find significant heterogeneity between different metrics across the sample. This finding, in our view, is not as surprising as many would think: it reflects the fact that risk metrics very much differ in terms of the methodology adopted and the assumptions made, as well as the data inputs used. We believe that a certain level of such diversity is key to contribute to a more comprehensive assessment of exposure to climate risk and to capture different dimensions of such exposures.

Crucially, assessments tend to converge on which companies are most and least exposed to climate risks.

We also find that convergence is higher for metrics based on similar methodologies, and that temperature targets and the time horizon of the scenario matter, although moderately, for the assessment of the relative risk exposure of companies.

With the present study, we also take a first step in exploring why risk assessments differ across metrics providers. More research is warranted to identify more clearly the reasons explaining the differences in assessments of exposure to climate risk by different providers.

To conclude, even if users of climate risk metrics might be concerned about the heterogeneity in climate risk metrics across the entire universe of firms, our results assert that there is no reason for inaction and that asset managers, investors, central banks and financial supervisors should in any case start integrating climate risk metrics for firms that are the most and the least exposed to transition risks, where metrics are converging.

Recommendations for asset managers and investors

Given the heterogeneity in risk assessments across risk metrics, we recommend asset managers and investors to rely on a set of metrics, rather than only on a single one, to assess the exposure to transition risk of their investments. Making use of and aggregating the information from several risk metrics increases the probability of having a comprehensive assessment of such exposures. For each of the metrics adopted, a deep understanding of the drivers and assumptions of the metrics is required to properly understand and manage the identified risk.

If asset managers and investors choose to focus on a single approach, they are even more advised to carefully understand the underlying methodology, as well as the scenario assumptions adopted. Different methodologies, temperature targets and time horizons might result in different risk assessments. Users should thus understand the assumptions implied by each methodology and choose the one that best fits their needs and beliefs.

Finally, we recommend asset managers, who are concerned about heterogeneity, to use a set of risk metrics to identify firms that are most and least exposed to transition risks, as risk metrics tend to give a more convergent assessment for these firms. Asset managers and investors can use this information to better manage the risk profile of their portfolio.

Recommendations for central banks and supervisors

Central banks and financial supervisors face similar challenges as asset managers and investors in dealing with climate risks. The recommendations made above thus also apply for them.

In addition, central banks are usually more concerned about excluding high-risk assets from the universe of eligible securities for monetary policy operations, than about picking the lowest-risk assets. In such a context, using risk metrics to identify firms that are most exposed to transition risk should be seen as the most urgent step for them to take. Using a set of transition risk metrics is particularly useful in targeting this goal as risk metrics tend to converge on the firms that are the most exposed to transition risk.

Similarly, financial supervisors are more concerned about spotting high risks in the portfolio of their supervised institutions than about identifying low-risk investments. Here again, using a set of transition risk metrics is an urgent step to take given the convergence that we observed across metrics, when it comes to highly exposed firms.

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Annex A: Results for the extended sample

Figure A.1: Correlation of ranks between metrics

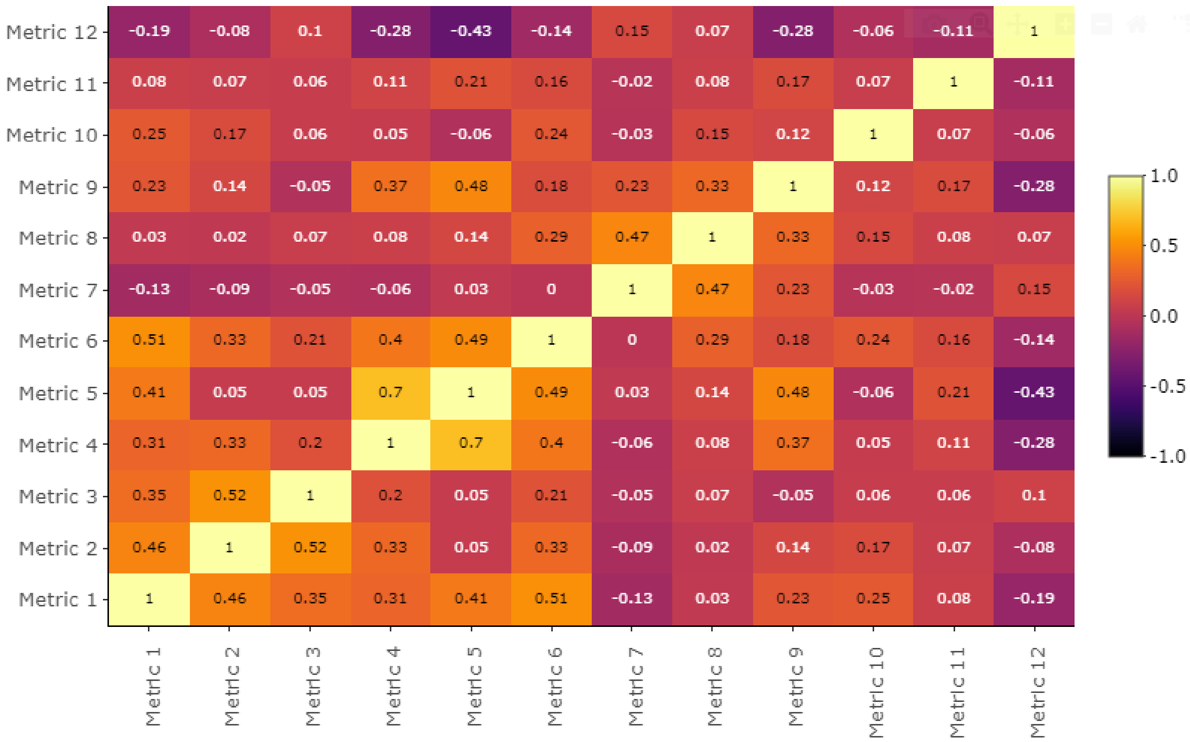

Figure A.2: Pairwise analysis of convergence

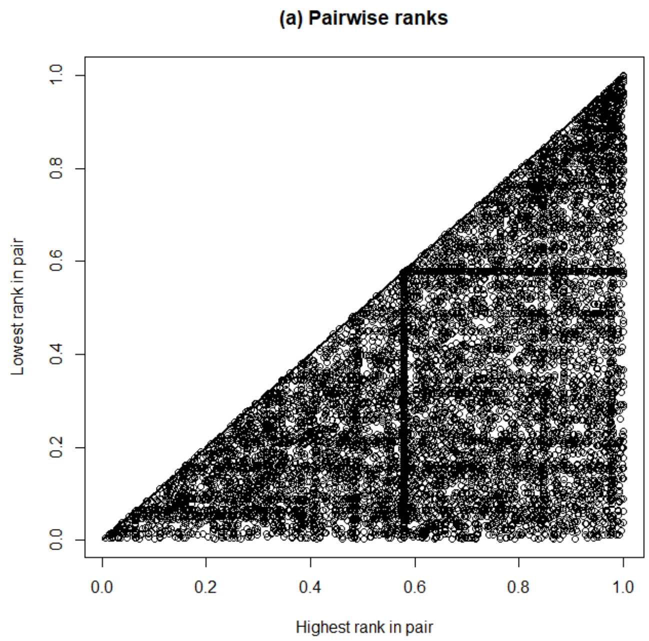

TABLE A.1: DIFFERENCE IN PAIRS FREQUENCIES BETWEEN OBSERVED AND INDEPENDENT METRICS

(a) Quintile combination

Lowest quintile in pair \ Highest quintile in pair	1	2	3	4	5
5					59
4				-12	-10
3			19	-9	-6
2		7	13	-17	-21
1	15	11	19	-4	-19

(b) Quintile difference

0	18
1	1
2	-1
3	-12
4	-19