# **How you measure transition risk matters:**
Comparing and evaluating climate transition risk metrics

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**Abstract**

A fundamental and seemingly easy question in climate finance remains unanswered: how to best measure companies' climate transition risk. Most authors do not critically discuss this first order question, however, as we show in this paper, choosing different transition risk metrics can lead to significantly different results. We employ a new dataset containing for the first-time *reported* EU taxonomy alignment of both capex and revenues as a proxy for companies transition risk. We compare taxonomy alignment to commonly used CO2 emission data and E scores from Refinitiv and MSCI. We also utilize TRBC codes as a granular sector/technology classification as well as text-based approaches to measure transition risk. We find a strong divergence in transition risk metrics for similar companies. Next, we also evaluate the different transition risk proxies. Our empirical approach uses the return sensitivity of 9 transition risk metric based Brown Minus Green portfolios against news indices which track unexpected shocks to transition risk. Thereby, we are able to show which transition risk metric is more/less sensitive to transition risk shocks and therefore better suited to measure climate transition risk of firms. We find that green taxonomy, text based and TRBC based portfolios react strongest to climate transition risk shocks. Popular emission or MSCI E-score based portfolios do not react significantly to climate transition risk shocks, indicating that they are no valid transition risk measures. Interestingly, no chosen risk metric is able to create a brown portfolio, which is significantly related to transition risk shocks. Our findings are relevant for all stakeholders on global financial markets who want to accurately measure the brown- and greenness of their portfolios.

**Keywords:** Climate transition risk, EU taxonomy, CO2 emissions, ESG scores, sector/technology classification, climate transition risk metrics

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# 1 Introduction

Climate transition risks are unanticipated gains or losses due to a faster than previously expected transition towards net zero. An unexpected acceleration of the transition can be driven by different factors. Most notably, technological shocks to the costs of green technologies or policy shocks in the form of higher than expected CO2 prices or green subsidies can cause transition risks. Furthermore, legal drivers or changing expectations of both market participants or consumers can drive transition risk. Firms with high transition risk are usually called brown firms, whereas firms facing opportunities from the low carbon transition are referred to as green. Whether a given enterprise is positively, negatively or neutrally exposed to climate transition risk depends mostly on two things, the economic sector(s) the company is operating in and the technology used in the production process. For instance, a company operating in the energy sector is naturally more exposed to climate transition risk than a health care company, thus sectoral differences are key. However, whether the company might profit in a transition (e.g. a utility using wind power) or is at high risk (a utility using coal power) depends on the utilized technology.

In order to track, price and manage companies' climate transition risk, it is key to accurately measure transition risk over time. Interestingly, there is substantial heterogeneity in proposed measuring approaches reaching from different E scores (Pástor et al., 2022; van der Beck, 2021), emission levels (Bolton & Kacperczyk, 2021; Bolton & Kacperczyk, 2023), emission intensities (Ardia et al., 2022; Aswani et al., 2024), estimated taxonomy alignments (Bassen et al., 2022; Sautner et al., 2022), text learning based measures (Sautner et al., 2023a, 2023b) to sector classifications which focus on technology information (Fliegel, 2023; Jourde & Stalla-Bourdillon, 2023).

Most empirical studies do not address in detail why a particular metric is chosen. It is thus a critical research gap to evaluate the different options available in order to provide rigorous advice which metrics should (not) be used when measuring companies` climate transition risk. We therefore want to answer the question: *How can firms climate transition risk be best measured?*

We answer this question in a two-step approach. First, we investigate whether different popular transition risk metrics diverge for a given firm. Second, we evaluate the transition risk metrics available, by comparing their sensitivities to unexpected transition risk shocks.

We operationalize our research question into testable hypotheses:

Concerning step 1, we expect:

H1: *There is no significant correlation between climate transition risk metrics but significant correlation within transition risk proxies.*

H1 is based on previous findings in the literature of a substantial divergence between transition risk metrics and a low correlation within most transition risk metrics (Berg et al., 2022; Busch et al., 2022; Wilkens et al., 2023).

Moving toward evaluating different transition risk metrics, we develop and test hypotheses for the different transition risk metrics employed. The hypotheses are either based on previous research or logically developed considering the special characteristics of the respective transition risk metric.

The Refinitiv Business Classification (TRBC) as a sector/technology classification takes sectoral differences into account and can differentiate Paris aligned as well as not aligned production technologies within climate sensitive sectors (Fliegel, 2023; Jourde & Stalla-Bourdillon, 2023), therefore we expect:

H2: *TRBC based transition risk metrics are valid in measuring both brown and green companies' climate transition risk.*

The EU Taxonomy is developed to measure the climate mitigation objective aligned portion of the revenues/capex, based on certain sector specific technical screening criteria. Therefore, it can be thought of as a highly granular sector/technology classification. As financial markets are forward looking, we would further expect that the capex-based risk measure performs better than the revenue-based risk measure since only the capex alignment provides insights into the forward-looking technological profile of a firm. Given that the taxonomy, to date, does not offer technical screening criteria for brown business activities, we expect:

H3: *Taxonomy alignment-based transition risk metrics are better in measuring green firm's climate transition risk than in correctly classifying brown business activities.*

Carbon emission data suffers predominantly from low availability, particularly for reliable scope 3 emissions (Busch et al., 2022; Kalesnik et al., 2020). The common practice of excluding scope 3 emissions in empirical studies might however wrongly classify firms with high scope 3 but low scope 1-2 emissions as green. Generally, firms with low emissions are not necessarily green, but might also be transition risk neutral. However, high emission intensity firms should be brown, therefore, we develop the following hypotheses.

H4: *Scope 1-2 emission intensity is a valid measure for brown firm's climate transition risk in case they do not have high value chain emissions. However, the proxy cannot reliably measure green firms transition risk.*

H5: *Scope 1-3 emission intensity is a valid measure for all brown firms' climate transition risk, but fails to reliable measure green firms transition risk.*

ESG scores are criticized for having many biases and shortcomings. Missing comparability (Gibson Brandon et al., 2021), measurement and scope divergence (Berg et al., 2022) as well as size bias (Drempetic et al., 2020) being some of the most severe problems. Moreover, environmental pillar scores are not even supposed to measure climate transition risk, as they are designed as a broad environmental score. Therefore, we put the lowest trust in E-scores scores to accurately measure companies' climate transition risk:

H6: *E-scores from both Refinitiv and MSCI are no valid measure for either brown or green companies' climate transition risk.*

Concerning the text-based measures for firm's climate transition risk, Sautner et al. (2023a) find a significant correlation of their climate change exposure measure to the media-based climate change attention index by Engle et al. (2020). We therefore expect:

H7: *Text based measures are valid in measuring both brown and green companies' climate transition risk.*

Finally, we want to test whether a sector/technology classification such as TRBC can be mixed with either emission data or taxonomy alignment data in order to enhance the overall performance of the risk metric. The intuition is straightforward, a business/technology classification can reliably categorize the core business activity and utilized technology of a firm into brown/green/neutral, but fails to granularly differentiate between different shades of brown or green. However, taxonomy alignment for green firms and/or emission data for brown firms could add this missing granularity in order to create a more reliable overall risk metric.

H8: *Mixed transition risk metrics, which exploit strengths in singular transition risk metrics while reducing weaknesses, are a highly valid measure for both brown and green company's climate transition risk.*

In order to test the hypotheses and answer the research question, we follow a twostep research approach. First, we collect the most comprehensive and up to date dataset on available transition risk metrics that we are aware of. We are able to collect 9 different transition risk metrics for European firms featuring the most utilized metrics (emission intensities as well as two different E scores) as well as promising metrics (TRBC, text-based approaches, as well as taxonomy alignment of revenues and capex). We also test three novel risk metrics, which are created by mixing climate transition risk proxies. By means of rank correlations we can show that the climate transition risk metrics are highly uncorrelated, in other words, depending on which risk metric chosen, one will reach significantly different results for a firm's climate transition risk. Most notably, firms with higher taxonomy alignments show higher emission intensities indicating that emission data alone is not sufficient to identify green companies. Taxonomy alignments are also largely uncorrelated to E-scores and TRBC, but strongly correlated to text-based measures. Moreover, we find that firms with higher $CO_2$ emissions have higher Refinitiv E-scores.

The results from step 1 warrant a second step inquiry into evaluating the different transition risk proxies available. Thereby, we go beyond simply documenting a divergence to also provide advice on what is a valid transition risk metric under which circumstances. To this end, we rely on a nascent stream of empirical literature developing transition risk shock indices which capture unexpected increases in public transition risk awareness. The first climate change risk index was developed by Engle et al. (2020) on a monthly basis. Subsequent research also provided weekly (Apel et al., 2023) as well as daily (Ardia et al., 2022) transition risk shock indices. Our identification strategy exploits transition risk shocks to analyze the sensitivity of Brown Minus Green (BMG) portfolio stock returns to transition shocks. In the baseline analysis we create 9 different BMG portfolios, one based for each transition risk metric available, and argue that the more sensitive the stock prices of a BMG portfolio react to unexpected transition risk shocks, the better the risk proxy is able to detect and classify firm's climate transition risk. In the language of our hypotheses, the more valid the proxy is. We find that only few of the transition risk metric based portfolio returns systematically react to transition risk shocks, indicating that scholars should be extremely cautious when picking a transition risk proxy.

Most notably, neither the commonly used scope 1-2 emission intensity, total emission intensity or MSCI E-scores react to unexpected transition risk shocks, putting large question marks behind their validity as transition risk proxies. BMG portfolios based on either taxonomy alignment of revenues or Refinitiv E-scores show the expected signs. Zooming into the brown and green component, we find that no transition risk metric is able to produce portfolios that react significantly to climate transition risk shocks. However, text-based approaches, TRBC, taxonomy-based metrics as well as Refinitiv E-scores are all consistently able to measure green companies transition risk. Our findings show that the two most popular transition risk metrics, CO2 emissions and E-scores from MSCI do not accurately measure climate transition risk and scholars should explore alternative metrics. We therefore propose to also consider using newly available transition risk proxies such as EU taxonomy alignment, sector/technology classifications or text-based approaches. Moreover, we find that mixing existing metrics can improve the performance of singular climate transition risk metrics.

By looking into the sectoral split of each portfolio, we are also able to explain why certain portfolios are not reacting to transition risk shocks. Most notably, green emission-based portfolio feature many heavily weighted companies in the service and technology sectors, which are neutral sectors not directly affected by transition risk shocks. Brown and green E-score portfolios from Refinitiv on the other hand, follow a best in class approach and therefore have a more even split across sectors. Thus, even the green E-score portfolio is invested in fossil fuel companies, whereas the brown E-score portfolio is invested in some renewable energy producers. TRBC and taxonomy-based portfolios on the other hand are more concentrated in energy, utility or transportation related companies, which are heavily affected by climate policies and therefore are more likely to react significantly to unexpected climate transition risk shocks.

There is a large gap in the literature on how to best measure climate transition risk of firms. By highlighting a divergence between transition risk metrics and by evaluating transition risk metrics, we add to multiple strands of literature. First, there is a limited literature investigating the divergence both within and across transition risk metrics. Berg et al. (2022) famously coined the term "aggregate confusion" for the divergence between ESG ratings from different providers for firms. Relatedly, Busch et al. (2022) also show substantial emission data differences, particularly concerning scope 3 as well as estimated emission data. There is less work assessing and explaining the divergence across different transition risk metrics. One exception is Dumrose et al. (2022), who study the relation of ESG scores and estimated EU taxonomy alignments of revenues. Bassen et al. (2022) also conduct research on the relation of ESG scores and estimated EU taxonomy alignment. They find a negative relation between the 2 variables. Bingler, Colesanti Senni, et al. (2022) show how different forward-looking scenario-based climate transition risk metrics diverge for similar companies. Wilkens et al. (2023) note that the inverted CO2 intensity (scope 1-2) of a company is negatively correlated to the environmental pillar score. Our study extends the aforementioned papers by offering an extensive comparison of all widely used transition risk metrics, including, for the first-time, *reported* taxonomy alignment, including the forward-looking data on capital expenditures as well as text-based approaches. Previous studies only rely on estimated taxonomy alignments due to a lack of reported data. We also offer new insights into emission data by analyzing scope 1-2 as well as scope 1-3 emission intensities separately.

Second, we add to a small literature on the evaluation of transition risk metrics. Ardia et al. (2022) study the emission intensity of sorted portfolios and show that brown stocks underperform green stocks on days with unexpected increases in climate risks. However, Apel et al. (2023) construct a different climate transition risk shock index and find conflicting evidence. Most closely related to our study, Bua et al. (2024) construct a physical and a transition risk index. They test the sensitivity of these indices and find mostly insignificant results. Only E-score and emission intensity based green portfolios react marginally significant to transition risk shocks after the Paris Agreement, whereas brown portfolios did not. While our empirical strategy is comparable to the aforementioned studies, our objective is different since we want to evaluate different proxies for climate transition risk while the aforementioned authors want to validate their transition risk shock indices. Moreover, we employ a wider range of transition risk metrics including EU taxonomy alignments, 0text-based transition risk measures as well as a granular technology information.

A third strand of literature analyzes unexpected climate relevant events and their impact on company's asset prices. Since all of these studies use some form of brown/green categorization, this strand of literature indirectly also validates transition risk metrics. Kruse et al. (2023), for example, use the estimated share of sustainable business activities to investigate the stock market effect of the Paris Agreement. Other event studies include Rudebusch et al. (2023) who focus on the introduction of the US inflation reduction act or Ramelli et al. (2021) who analyze the effect of the first global climate strike on stock prices of carbon intensive firms.

Fourth, there is quickly expanding literature on the pricing implications of transition risk. While some authors investigate bond market pricing with inconclusive findings (Duan et al., 2023; Zerbib, 2019), a major debate has evolved around the pricing of climate transition risk on equity markets. Some authors found a brown or carbon premium mostly using emission data (Alessi et al., 2021; Bolton & Kacperczyk, 2021; Bolton & Kacperczyk, 2023; Hsu et al., 2023). Other scholars found a green premium using a variety of transition risk metrics including emissions data, E scores, estimated taxonomy alignment and sector/technology classifications (Bassen et al., 2022; Bauer et al., 2022; Enders et al., 2023; Fliegel, 2023; Pástor et al., 2022; van der Beck, 2021). Some scholars also found inconclusive or neutral pricing results (Aswani et al., 2024; Görgen et al., 2020). Different results might be due to different time frames, different empirical methodologies, or different transition risk metrics. By showing that only few transition risk metrics actually respond systematically to transition shocks and thus are actually suited to measure transition risk, we contribute to this debate by explaining that a large part of the divergent findings is actually due to the choice of the underlying climate transition risk metric. We further proof this claim by showing that we can produce positive as well as a negative brown premia, when we rely on a similar pool of companies but on different transition risk metrics.

By giving recommendations on which transition risk metric to use in which circumstance we finally also add to the ever-increasing large empirical literature on climate finance and environmental economics since accurately measuring transition risk of firms is a first order empirical question in both disciplines.

We thus make several key contributions. We offer the, to date, most comprehensive and most up to date comparison of widely used different risk metrics. Moreover, to the best of our knowledge, we are first in utilizing reported EU taxonomy alignment data of revenue and capex as a proxy for climate transition risk. Previous studies relied on estimated taxonomy data, and did not use taxonomy alignment as a comprehensive transition risk metric covering brown, green and neutral business activities. We can thereby also for the first time exploit the forward-looking taxonomy aligned capex share. Going beyond previous studies we not only show a divergence in risk metrics, but also develop and test hypotheses about the suitability of different transition risk metrics to proxy climate transition risk. By evaluating transition risk metrics, we can empirically show the inability of most common transition risk metrics to correctly identify companies which are highly sensitive to transition risk. Thereby, we can provide recommendations on which metrics should (not) be utilized under which circumstances. We are also able to explain why TRBC or taxonomy-based portfolios are more reactive to climate transition shocks than E-score or emission-based portfolios, namely because only TRBC and taxonomy-based portfolios identify companies in business sectors which are highly affected by transition risk, whereas both emission and E-score based portfolios have high exposure in not climate policy sensitive sectors. Most notably, we therefore recommend to not rely of either emission intensities or E-scores in isolation. There might be however, the case to mix different transition risk metrics. Additionally, scholars should test the application of promising new transition risk metrics such as EU taxonomy alignments, text-based approaches or sector/technology classifications.

The remainder of this paper is organized as follows. Section 2 introduces the different data sources as well as the empirical strategy. Section 3 presents key findings. Section 4 critically discusses the findings against the related literature. The final section 5 sums up and provides an outlook for further research.

## 2 Methods

We will first present the different data sources utilized in this paper to then explain our empirical approach.

### 2.1 Data

For this study we rely on different large financial and environmental datasets.

#### A. Financial data

Data on firm financials such as revenues or market capitalizations is from Refinitiv EIKON. Stock returns are from Compustat. Our final sample only includes active and listed firms with above 50million $ in annual sales, as this is the official threshold for EU taxonomy eligibility. Furthermore, we exclude all financial institutions, all firms without ISIN and companies without return information, which yields a final sample of 23,509 unique global firms, of which 3,079 are located in Europe. We winsorize returns and all emission data at the 1% level in order to reduce the effect of frequent databank specific errors and outliers. Additionally, we rely on widely used asset pricing factors. For the baseline specification we use the European factors from Kenneth French's Online Data Library[3]. For the global dataset we use the developed factors, since most of the companies in the dataset are located in developed economies.

#### B. Data on climate metrics

Based on ISINs we match data on climate metrics to the financial data. First, we rely on Bloomberg for EU taxonomy data for the year 2022, Second, we use ESG, TRBC as well as emission data from Refinitiv EIKON. Third, we use the text based firm level climate change exposure data from Sautner et al. (2023a, 2023b). We winsorize taxonomy eligibility and alignments at 100%. E scores are also trimmed above 100 and below 0.

*Table 1| Availability of climate transition risk metrics globally as well as in Europe.*

| Climate Transition Risk Metric | Global | Europe |
|---|---|---|
| E - scores (Refinitiv) | 7,962 | 1,690 |
| Scope 1 emissions | 5,310 | 1,450 |
| Scope 2 emissions | 5,320 | 1,456 |
| Scope 3 emissions | 3,062 | 1,101 |
| TRBC | 23,509 | 3,038[4] |
| CC Exposure opportunity | 4,519 | 1,084 |
| CC Exposure regulation | 4,519 | 1,084 |
| Climate Change exposure | 4,519 | 1,084 |
| Taxonomy revenue risk | - | 1,179 |
| Taxonomy capex risk | - | 1,098 |

As depicted in table 1, the overall data availability varies significantly depending on the transition risk metric. TRBC is most available with almost all firms in the dataset having a sector/technology classification. Roughly a third of companies has an E-score from Refinitiv. The availability of emission data, depends on

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[4] Some firms in the European dataset do not have a TRBC because some Bloomberg ISINs couldn't be matched to Refinitiv EIKON.

the respective scope, with scope 3 emission data being most scarce. Text based climate transition risk metrics are roughly equally available compared to emission data. The newly disclosed taxonomy information is already available for roughly one third of European firms.

In order to track unexpected shocks to climate transition risk expectations, we use the transition risk shock index by Apel et al. (2023). The shock index is derived through an Auto Regressive-Moving Average (ARMA) model of their transition risk index TRI. The TRI innovation index then captures the unexpected element of the TRI index by the residuals from the ARMA model.

## 2.2 Empirical Strategy

To answer the research question, we adapt a two-step empirical strategy. First, we compare the correlation of all transition risk metrics by means of comparing their rank correlations. Since, reported taxonomy alignment data is yet only available for the fiscal year 2022, we focus on transition risk metrics for the fiscal year 2022. Most notably, we utilize the following 8 climate transition risk metrics: Discretized TRBC sector/technology classification, scope 1-2 emission intensities, scope 1-3 emissions intensities, Refinitiv environmental pillar scores, taxonomy alignment of revenues and capital expenditures as well as two text-based measures from Sautner et al. (2023a). As we only possess aggregated data for the MSCI E-score portfolio returns, we cannot include MSCI E-score into the step 1 analysis.

Second, we rely on recent advances in the literature in measuring climate risk shocks by means of news-based risk indices. Our empirical strategy exploits these indices as exogenous shocks to the climate transition risk expectations of financial market participants in order to then test how different portfolios react to those shocks. Another way to look at the identification strategy is by thinking of climate transition risk in terms of exposure and expectations. The exposure to transition risk is measured by the transition risk metrics (e.g. the emission level) and is usually known and priced by the market. However, once an unexpected transition risk shocks shifts the expectations about the speed of the transition, heavily exposed firms will be repriced. Thus, the measures capturing the transition risk exposure best, will react most to such shocks.

Overall, we construct 9 BMG portfolios, one for each of the aforementioned transition risk metrics. Each BMG portfolio is long brown stocks and short green stocks. More formally, the return of the BMG factor can be written as:

$$\mathrm{BMG_{jt}} = (\mathrm{RB_{jt}} - \mathrm{RF_t}) - (\mathrm{RG_{jt}} - \mathrm{RF_t}) \tag{2.1}$$

Where $\mathrm{BMG_{jt}}$ is the monthly return of a BMG portfolio j. $\mathrm{RF_t}$ is the risk-free rate of return. $\mathrm{RB_{jt}}$ and $(\mathrm{RG_{jt}}$are the brown and green returns of portfolio j over time. We value weight all portfolio returns. The return is calculated by subtracting the excess return of a green portfolio g from the return of a brown portfolio b. Additional to the BMG portfolios we also create green and brown long only portfolios to account for the possibility that some risk metrics might better be better able to recognize either brown or green companies.

Our empirical approach is inspired by Ardia et al. (2022) who use their climate concern shock index as the independent variable of interest and an emission based Green Minus Brown portfolio as the dependent variable while controlling for different risk factors. We adopt the right-hand side of the equation but instead of only focusing on the pricing of one emission-based BMG portfolio, we compare the coefficient estimates of the transition risk shock index for each of the BMG portfolios in order to better understand which transition risk proxies react significantly to exogenous transition risk shocks. More formally, we estimate the following model on a monthly frequency:

$$\mathrm{BMG_{jt}} - \mathrm{RF_t} = \alpha_j + \beta_{1j}(\mathrm{RM_t} - \mathrm{RF_t}) + \beta_{2j}\mathrm{SMB}_t + \beta_{3j}\mathrm{HML}_t + \beta_{4j}\mathrm{RMW}_t + \beta_{5j}\mathrm{CMA}_t + \beta_{6j}\mathrm{TRI\_Innovation}_t + \epsilon_{it} \tag{2.2}$$

$\mathrm{RM_t}$ is the return of the market factor at time t. Additional to the market factor, the model also features the High Minus Low (HML) value- and Small Minus Big (SMB) size factors. We also control for the profitability factor Robust Minus Weak (RMW) as well as the investment factor Conservative Minus Aggressive (CMA). $\alpha_j$ is the constant, indicating whether a portfolio outperforms the market, even when controlling for risk factors. Our main variable of interest is $\beta_{6j}$ as the coefficient indicates whether transition risk shocks significantly explain the returns of our portfolios. Our time frame for the factor regressions starts in January 2010 and runs until August 2023, but as our baseline climate risk shock index has a shorter time frame, the bulk of the analysis is performed until the end of 2020.

In what follows we briefly present the rules for classifying firms into brown/green/neutral according to each of the transition risk metrics. First, in line with Jourde and Stalla-Bourdillon (2023) and Fliegel (2023) we use TRBC as a sector/technology classification. As opposed to the other metrics, TRBC is qualitative. Thus, we discretize the variable to differentiate green, brown and transition risk neutral firms. There are different ways of classifying TRBC codes into the brown/green/neutral categories. In our baseline analysis, we follow the most restrictive categorization in line with Fliegel (2023). The logic here is to only classify clearly fossil fuel related activities as brown and only renewable or no emission technologies as green. All other technologies are classified as neutral. Additionally, all technologies which to date do not have a commercially viable green alternative production technology are assumed to be transition risk neutral. This is rather restrictive as it classifies, for example, cement & concrete manufacturing as neutral since TRBC does not provide detailed information, whether the production process is performed in an emission neutral or emission intensive way. According to this categorization green companies are companies doing a majority of business in: electric vehicle manufacturing, battery technology, renewable utilities and manufacturing of renewable energy technologies. Brown companies are brown utilities, fossil fuel explorers/miners/refiners and internal combustion engine manufacturers. The different TRBC code categorizations are detailed in table A1 of Appendix 7.1.

Second, we use, for the first time, *reported* EU taxonomy alignment of revenues and capex in order to categorize firms into brown/green or neutral portfolios. Taxonomy aligned economic activities must substantially contribute to one of the 6 environmental objectives, fulfil the respective technical screening criteria, cannot significantly harm any of the other environmental objectives and finally must comply with minimum social safeguards (European Commission, 2020). In 2023, for the fiscal year 2022, large listed companies with more than 500 employees, for the first time, reported both the eligibility and alignment of their revenues, opex and capex with the climate change objectives. For this study, we will use revenue alignment as a backward-looking climate transition risk metric and capex alignment as a forward-looking climate transition risk proxy as investment decisions are usually made with a multi-year forward looking time horizon (Arnold et al., 2023). While taxonomy alignment per se is not a risk metric in the sense that it captures only the green part of transition risk, one can transform the variable, using both alignment and eligibility values, so that it also reflects the brown share of revenues or capex. We therefore build on Dumrose et al. (2022), who calculate the relative taxonomy alignment in order to control for firms which have different taxonomy eligibilities. They calculate:

$$(2.3) \qquad \text{Relative Taxonomy Alignment} = \frac{Taxonomy\ Alignment}{Taxonomy\ Eligibilty} \times 100$$

Thus, the higher this score the greener the company is. A low score on the other hand indicates that a lot of revenue/capex of a company would be eligible but fails to fulfill the technical screening criteria, therefore we classify a low score as brown. However, we extend the simple division in (2.3) by integrating a minimum eligibility criterion of 50% for revenue or capex. The reasoning can be easiest explained by an example of 2 companies. Company A has 10% eligibility and 10% alignment while company B, has 100% eligibility and 98% alignment. Company B is clearly a green pure play but would be treated as less green compared to company A which would receive the highest score albeit being not substantially exposed to the taxonomy regulation. By not setting a minimum eligibility criterion, one risks that the taxonomy as a transition risk metric fails to apply to large fractions of the company's business. Emissions and E scores on the other hand, assess the company as a whole. A second reason for setting the threshold is the weakness of the taxonomy regulation to only provide technical screening criteria for green economic activities. The aforementioned approach transforms the taxonomy into a risk metric by treating eligible but not aligned revenue/capex as brown. However, in some sectors without a green technology alternative, our approach of treating non-eligible revenue/capex as transition risk neutral does not hold, since these sectors are not covered at all by the taxonomy. The fossil fuel extraction sector is the most relevant example. The chosen 50% threshold excludes companies in such sectors and guarantees that fossil fuel companies with a small green business unit are not erroneously classified as transition risk neutral. For the highly exposed companies we calculate the 80% and 20% percentile of revenue/capex alignment. Companies which are above (below) the 80% (20%) percentile are classified as green (brown).

Third, in line with large parts of the empirical literature in climate finance (e.g. Ardia et al., 2022; Bauer et al., 2022; Bolton & Kacperczyk, 2021) we employ emission data for 2022 in order to create 2 distinct transition risk metrics. We use both scope 1-2- as well as scope 1-3 emission data scaled by annual revenues. We focus on intensities as opposed to emission levels as recent research (Aswani et al., 2024; Zhang, 2022) has shown that unscaled emissions rise linearly with revenue and might thus simply pick up firms' fundamentals as opposed to measuring companies' climate transition risk. We differentiate between scope 1-2 emission intensities and scope 1-3 data as Busch et al. (2022) have shown that cross databank correlation is significantly higher for scope 1 and 2. We therefore test whether excluding scope 3 emissions increases or decreases the quality of the transition risk measure. In order to classify companies based on emissions, we first invert the emission data. Thereby, the higher the emission number the greener the company, in line with the ordering logic of all other transition risk proxies in the dataset. Then we calculate the 80% and 20% percentiles of inverted scope 1-2 and scope 1-3 emissions and categorize the most (least) pollutant firms into the brown (green) portfolios.

Fourth, we utilize the widely used (e.g. Pástor et al., 2022; van der Beck, 2021) environmental pillar score of firms ESG score. We employ both E scores from Refinitiv EIKON and from MSCI for the fiscal year 2022. Again, we use percentiles to classify the top 20% of firms in terms of E-score as green and the bottom 20% as brown. As we do not have access to raw MSCI E-scores we only rely on the aggregate E-score portfolio returns from Pástor et al. (2022).

Fifths, we use the keyword discovery algorithm-based method of Sautner et al. (2023a) that estimates firm's climate change exposure as the attention of earning call participants attention to climate risk related topics. Most notably, we construct two different firm-specific climate transition risk metrics. First, we use the 80% (20%) percentiles of the overall climate change exposure score. Second, we construct a transition risk metric based on climate change opportunity and regulatory shock sub-indices. We treat the top 20% of opportunity companies as green and the top 20% regulatory shocks as brown. The data covers roughly 10,000 firms and is available until the end of 2022.

Finally, we construct novel mixed transition risk metrics. First, we combine TRBC with emission data in order to overcome the weakness of emission data to not being able to separate green firms from transition risk neutral firms. TRBC codes can exclude granularly, all non-climate sensitive economic sectors as well as technologies. For the remaining sectors and technologies emission data can add even more granularity in order to accurately measure brown and green firm's climate transition risk. Most notably, we exclude all emission data from companies which are from TRBC Business Sectors, which are not particularly climate sensitive, examples are the health, technology or service sector. Details can be obtained in table A2 of Appendix 7.1.

TRBC codes can also help overcoming a key weakness of taxonomy alignment-based risk metrics. Most notably, taxonomy-based metrics can only infer to brown parts of revenue/capex whenever there are green technical screening criteria. TRBC codes can help in rating the brown part of revenue/capex for all sectors which have no green technical screening criteria. This issue is foremost relevant in the fossil fuel TRBC business sector. An example would be a company which is 40% eligible and aligned (green) and 60% non-eligible (potentially neutral), but has the TRBC code `Oil & Gas Exploration and Production`. For all TRBC - fossil fuel companies, we drop the 50% taxonomy eligibility criteria and formulate a new taxonomy risk calculation rule:

$$\text{(2.4)} \qquad \text{Relative Taxonomy Alignment} = \frac{Taxonomy\ Alignment}{Taxonomy\ Eligibilty + 50} \times 100$$

We thus, increase the eligibility by 50% for all (74 companies in total) fossil fuel related companies in order to reflect their TRBC code, which is based on the most relevant (>50%) economic activity of the firm. All companies without taxonomy alignment data in the fossil fuel sector are automatically classified as 0% alignment.

There are several transition shock indices on different frequencies proposed in the literature. We rely on the Transition Risk Index (TRI) constructed by Apel et al. (2023) as the index can correctly differentiate between events, which increase transition risk for brown companies (e.g. Paris Agreement) and events that decrease transition risk (e.g. the US withdraw from the Paris Agreement) and thereby benefitted brown companies. All other transition risk shock indices usually come with the implicit assumption that the sheer amount of transition risk news increases transition risk, or vice versa, no transition risk news decreases transition risk. This however, fails to recognize that high impact transition risk events can have both positive and negative implications for brown companies (Apel et al., 2023).

Table 2 depicts the summary statistics for the monthly value weighted returns.

***Table 2|Summary statistics for the time series of monthly European value weighted returns.*** *The Table depicts descriptive statistics for the monthly excess returns of several constructed portfolios, the European market factor, the TRI monthly innovation climate shock index, as well as asset pricing factors. All returns are in percentages.*

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Brown TRBC | 132 | .258 | 4.813 | -15.497 | 23.238 |
| Brown Tax. Revenue | 132 | .972 | 6.359 | -18.062 | 18.907 |
| Brown Tax. Capex | 132 | 1.011 | 5.409 | -16.677 | 15.681 |
| Brown Emission Intensity | 132 | .628 | 4.021 | -12.733 | 15.699 |
| Brown Scope 1-2 Intensity | 132 | .561 | 4.324 | -13.165 | 18.35 |
| Brown Refinitiv E Score | 132 | 1.429 | 4.144 | -14.224 | 14.155 |
| Brown CC Opp/ Reg | 132 | .673 | 4.726 | -18.122 | 18.733 |
| Brown Climate Change Exposure | 132 | .324 | 5.294 | -12.202 | 22.675 |
| Brown MSCI E-score | 132 | .351 | 5.11 | -14.33 | 20.77 |
| Brown Emission Intensity TRBC | 132 | .607 | 3.642 | -9.701 | 13.528 |
| Brown Tax. Revenue TRBC | 132 | 1.124 | 3.508 | -9.095 | 11.024 |
| Brown Tax. Capex TRBC | 132 | .793 | 4.532 | -18.932 | 14.273 |
| Green TRBC | 132 | 1.337 | 4.429 | -9.429 | 15.808 |
| Green Tax. Revenue | 132 | 1.078 | 3.731 | -12.651 | 10.878 |
| Green Tax. Capex | 132 | .641 | 4.119 | -11.199 | 11.559 |
| Green Emission Intensity | 132 | 1.011 | 3.865 | -12.297 | 13.014 |
| Green Scope 1-2 Intensity | 132 | 1.261 | 3.865 | -9.724 | 13.037 |
| Green Refinitiv E Score | 132 | .703 | 3.628 | -10.31 | 14.348 |
| Green CC Opp/ Reg | 132 | .717 | 4.444 | -19.563 | 16.201 |
| Green Climate Change Exposure | 132 | .89 | 3.983 | -12.478 | 12.712 |
| Green MSCI E-score | 132 | .603 | 4.238 | -13.236 | 13.328 |
| Green Emission Intensity TRBC | 132 | .669 | 5.11 | -16.709 | 21.694 |
| Green Tax. Revenue TRBC | 132 | .529 | 4.587 | -14.768 | 19.666 |
| Green Tax. Capex TRBC | 132 | 1.24 | 4.244 | -12.324 | 13.455 |
| Market Factor | 132 | .617 | 5.106 | -15.44 | 16.62 |
| SMB Factor | 132 | .252 | 1.712 | -5.06 | 4.72 |
| HML Factor | 132 | -.395 | 2.659 | -11.3 | 10.76 |
| RMW Factor | 132 | .389 | 1.57 | -3.85 | 3.52 |
| CMA Factor | 132 | -.203 | 1.28 | -4.39 | 2.96 |
| TRI Monthly Innovation | 132 | 0 | 0 | -.002 | .001 |

## 3 Results

We first present the results of the correlations across risk metrics to then evaluate the different climate transition risk metrics.

## 3.1 Divergence of transition risk metrics

Results in table 3 show a very large divergence. Within emission based, text based and taxonomy-based metrics, there is some divergence as well, however, the correlation is overall positive. It is the divergence between metrics that is striking. Most notably, *all* taxonomy-based transition risk proxies correlate negatively with inverted emissions. That indicates that greener firms, as measured by the EU taxonomy, are actually more polluting than brown firms. Taxonomy alignments are also largely uncorrelated to both TRBC codes as well as E-scores. Interestingly, taxonomy alignments are relatively strongly correlated with text-based measures. Refinitiv E- scores are also negatively related to emissions, that is, firms which score high in the environmental pillar have higher emissions, compared to low scoring firms. Overall the findings from the rank correlation indicate, as suspected in H1, a large divergence. In other words, simply choosing a different transition risk metric will lead to a completely different transition risk profile, thereby heavily impacting all subsequent calculations.

***Table 3|Results for Spearman's rank correlation coefficient.*** *The table shows the rank correlation with listwise deletion between all European transition risk metrics employed in this study as well as the opex alignment. TRBC codes are discretized with brown companies=1, neutral=2 and green=3 – details of the brown/green categorization in Appendix 7.1. All companies with above 0% taxonomy eligibility are included. Emissions are inverted. All data relates to the fiscal year 2022.*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) Tax. Revenue alignment | 1.000 | | | | | | | | | |
| (2) Tax. Capex alignment | 0.725 | 1.000 | | | | | | | | |
| (3) Tax. Opex alignment | 0.770 | 0.797 | 1.000 | | | | | | | |
| (4) Total Emission Intensity | -0.256 | -0.284 | -0.324 | 1.000 | | | | | | |
| (5) Scope 1-2 Emission Intensity | -0.303 | -0.310 | -0.352 | 0.600 | 1.000 | | | | | |
| (6) TRBC | -0.086 | -0.147 | -0.124 | 0.244 | 0.223 | 1.000 | | | | |
| (7) E Score | 0.167 | 0.244 | 0.192 | -0.266 | -0.225 | -0.085 | 1.000 | | | |
| (8) CC exposure regulation | 0.253 | 0.271 | 0.247 | -0.275 | -0.299 | -0.078 | 0.236 | 1.000 | | |
| (9) CC exposure opportunity | 0.466 | 0.454 | 0.461 | -0.404 | -0.450 | -0.240 | 0.221 | 0.417 | 1.000 | |
| (10) CC exposure | 0.497 | 0.488 | 0.473 | -0.445 | -0.517 | -0.257 | 0.228 | 0.603 | 0.888 | 1.000 |

In order to increase the external validity of results, we also repeat the analysis with the global dataset for 2022. Table 4 shows the results, which are highly comparable to the European risk metric correlations.

***Table 4|Results for Spearman's rank correlation coefficient.*** *The table shows the rank correlation with listwise deletion between all global transition risk metrics. TRBC codes are discretized with brown companies=1, neutral=2 and green=3 – details of the brown/green categorization in Appendix 7.1. Emissions are inverted. All data relates to the fiscal year 2022.*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) Total Emission Intensity | 1.000 | | | | | | |
| (2) Scope 1-2 Emission Intensity | 0.630 | 1.000 | | | | | |
| (3) TRBC | 0.234 | 0.160 | 1.000 | | | | |
| (4) E Score | -0.184 | -0.165 | -0.000 | 1.000 | | | |
| (5) CC exposure regulation | -0.310 | -0.309 | -0.119 | 0.131 | 1.000 | | |
| (6) CC exposure opportunity | -0.349 | -0.337 | -0.121 | 0.165 | 0.447 | 1.000 | |
| (7) CC exposure | -0.411 | -0.407 | -0.146 | 0.154 | 0.650 | 0.852 | 1.000 |

## 3.2 Evaluating different transition risk metrics – European data

The high divergence in in transition risk results, as highlighted in the previous section, makes it unlikely that all transition risk metrics are accurately able to classify firms' climate transition risk. After all, they are oftentimes *negatively* correlated. Therefore, we now want to evaluate the different measurement options available in order to establish which transition risk metrics are better in classifying brown/green firms climate transition risk.

We start the evaluation of the transition risk metrics by employing monthly data and by using BMG portfolios as the dependent variable. As depicted in table 5, we find that only taxonomy alignment of revenues and Refinitiv E-scores can produces portfolios which show significantly the expected (negative) sign of the TRI innovation coefficient. The negative coefficient can be interpreted in the following manner, in month with unexpected transition risk shocks, green firms tend to outperform brown firms. While the coefficient estimates for both the TRBC and the taxonomy capex portfolio are large and negative, they are not significant. Varying other pricing factors can sometimes significantly explain the returns of some portfolios.

***Table 5|Monthly BMG factor model regressions results.*** *The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| **VARIABLES** | **(1) BMG TRBC** | **(2) BMG Tax. Revenue** | **(3) BMG Tax. Capex** | **(4) BMG Emission Intensity** | **(5) BMG Scope 1-2 Emission Intensity** | **(6) BMG E-Score** | **(7) BMG CC Opp/ Reg** | **(8) BMG CC Exposure** | **(9) BMG MSCI E-score** |
|---|---|---|---|---|---|---|---|---|---|
| Market | 0.16* | 0.42*** | 0.29*** | 0.01 | 0.03 | 0.01 | -0.15*** | -0.09** | 0.01 |
| | (1.91) | (3.37) | (3.28) | (0.26) | (0.66) | (0.46) | (-4.26) | (-2.32) | (0.22) |
| SMB | -0.90*** | -0.19 | 0.38* | -0.32*** | -0.04 | 0.90*** | -0.03 | 0.25* | -0.06 |
| | (-3.99) | (-0.75) | (1.98) | (-4.70) | (-0.38) | (16.25) | (-0.38) | (1.82) | (-0.58) |
| HML | 0.64** | 0.13 | -0.14 | 0.33*** | 0.55*** | 0.11 | -0.50*** | -0.78*** | 0.53*** |
| | (2.37) | (0.44) | (-0.48) | (2.95) | (2.93) | (0.98) | (-5.77) | (-4.53) | (3.90) |
| RMW | 0.34 | -0.50 | -0.36 | 0.04 | 0.21 | -0.24** | -0.21 | -0.34 | 0.89*** |
| | (1.07) | (-1.33) | (-0.95) | (0.31) | (0.92) | (-2.01) | (-1.63) | (-1.39) | (4.92) |
| CMA | 0.28 | -0.96** | -0.59 | 0.05 | 0.09 | -0.68*** | 0.28* | 0.22 | -0.05 |
| | (0.65) | (-2.11) | (-1.24) | (0.30) | (0.46) | (-5.17) | (1.97) | (0.95) | (-0.22) |
| TRI Inn. | -1486.33 | -2523.43** | -898.22 | 225.05 | 695.49 | -702.98** | -434.35 | -497.29 | 408.66 |
| | (-1.46) | (-2.37) | (-1.17) | (0.61) | (1.25) | (-2.01) | (-1.20) | (-0.82) | (0.87) |
| Constant | -0.86* | -0.37 | -0.01 | -0.22 | -0.57*** | 0.43*** | -0.08 | 0.40* | -0.62*** |
| | (-1.97) | (-0.75) | (-0.03) | (-1.56) | (-2.84) | (4.54) | (-0.63) | (1.72) | (-3.10) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.316 | 0.272 | 0.192 | 0.342 | 0.376 | 0.677 | 0.511 | 0.455 | 0.212 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The reasons why so few BMG portfolio are significantly related to the TRI can be found in the long brown portfolios, which are highlighted in table 6. Results show that no portfolio is significantly negatively exposed to the TRI innovation factor. Only the coefficient of the taxonomy revenue portfolio as well as the E-score portfolios are negative, indicating that negative transition news reduce stock returns of brown firms. This is unexpected and shows that either no risk metric is able to correctly classify brown companies transition risk or that high transition risk (firms brownness) is not priced in financial markets.

*Table 6/Monthly brown factor model regressions results. The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) Brown TRBC | (2) Brown Tax. Revenue | (3) Brown Tax. Capex | (4) Brown Emission Intensity | (5) Brown Scope 1-2 Emission Intensity | (6) Brown E-Score | (7) Brown CC Opp/ Reg | (8) Brown CC Exposure | (9) Brown MSCI E-score |
|---|---|---|---|---|---|---|---|---|---|
| Market | 0.66*** | 0.92*** | 0.83*** | 0.69*** | 0.70*** | 0.66*** | 0.63*** | 0.62*** | 0.75*** |
| | (12.87) | (8.96) | (10.33) | (15.91) | (17.81) | (11.57) | (14.93) | (13.31) | (10.30) |
| SMB | -0.50*** | -0.15 | -0.01 | -0.23** | -0.24** | 0.48*** | -0.31*** | -0.08 | 0.14 |
| | (-3.92) | (-0.74) | (-0.04) | (-2.27) | (-2.58) | (4.16) | (-3.57) | (-0.57) | (0.78) |
| HML | 0.91*** | 0.34 | 0.27 | 0.27** | 0.47*** | 0.25 | 0.23** | -0.16 | 0.30 |
| | (5.07) | (1.31) | (1.23) | (2.50) | (3.88) | (1.53) | (2.09) | (-0.83) | (1.57) |
| RMW | 1.01*** | 0.05 | 0.20 | 0.42*** | 0.46*** | 0.34 | 0.46*** | 0.26 | 0.92*** |
| | (5.25) | (0.16) | (0.67) | (2.97) | (3.27) | (1.65) | (3.11) | (1.07) | (3.53) |
| CMA | -0.12 | -1.16*** | -0.64** | -0.14 | -0.18 | -0.65*** | -0.12 | -0.04 | 0.13 |
| | (-0.48) | (-3.72) | (-2.10) | (-1.01) | (-0.98) | (-3.49) | (-0.76) | (-0.22) | (0.55) |
| TRI Inn. | 1142.86*** | -439.52 | 748.55 | 448.99 | 909.43*** | -118.59 | 550.11* | 464.27 | -775.22 |
| | (2.89) | (-0.58) | (1.29) | (1.50) | (2.95) | (-0.25) | (1.89) | (0.90) | (-1.07) |
| Constant | -0.05 | 0.31 | 0.42 | 0.18 | 0.19 | 0.74*** | 0.20 | 0.60*** | 0.06 |
| | (-0.21) | (0.77) | (1.33) | (1.07) | (1.01) | (4.18) | (1.20) | (2.96) | (0.24) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.782 | 0.655 | 0.687 | 0.830 | 0.849 | 0.789 | 0.811 | 0.674 | 0.712 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Turning to the green portfolios in table 7, both taxonomy portfolios as well as the TRBC portfolio are significantly positively exposed to the TRI factor and show large coefficient estimates. In other words, these portfolio returns increase when climate concern increases, which is in line with our expectation. The text-based measures are also showing positive and significant coefficient estimates. Finally, the Refinitiv E-score portfolio shows a significant albeit small estimate. No emission-based risk metric reacts significantly to transition shocks and the green MSCI E-score based portfolio even underperforms in high transition risk months.

*Table 7|Monthly green factor model regressions results. The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) Green TRBC | (2) Green Tax. Revenue | (3) Green Tax. Capex | (4) Green Emission Intensity | (5) Green Scope 1-2 Emission Intensity | (6) Green E-Score | (7) Green CC Opp/ Reg | (8) Green CC Exposure | (9) Green MSCI E-score |
|---|---|---|---|---|---|---|---|---|---|
| Market | 0.51*** | 0.51*** | 0.54*** | 0.69*** | 0.68*** | 0.65*** | 0.77*** | 0.71*** | 0.75*** |
| | (6.74) | (8.26) | (10.03) | (12.82) | (12.39) | (13.87) | (15.70) | (17.19) | (12.40) |
| SMB | 0.40* | 0.05 | -0.38** | 0.10 | -0.19 | -0.41*** | -0.27* | -0.32*** | 0.21 |
| | (1.77) | (0.28) | (-2.54) | (0.83) | (-1.47) | (-4.13) | (-1.89) | (-2.71) | (1.40) |
| HML | 0.27 | 0.20 | 0.41** | -0.06 | -0.08 | 0.14 | 0.74*** | 0.63*** | -0.22 |
| | (1.20) | (1.18) | (2.24) | (-0.38) | (-0.37) | (0.99) | (5.57) | (5.13) | (-1.34) |
| RMW | 0.67*** | 0.56** | 0.57** | 0.39* | 0.26 | 0.58*** | 0.68*** | 0.62*** | 0.04 |
| | (2.67) | (2.32) | (2.01) | (1.81) | (1.08) | (3.51) | (3.48) | (3.96) | (0.16) |
| CMA | -0.39 | -0.19 | -0.04 | -0.18 | -0.26 | 0.04 | -0.39* | -0.25 | 0.19 |
| | (-1.03) | (-0.67) | (-0.13) | (-1.11) | (-1.44) | (0.34) | (-1.75) | (-1.14) | (0.76) |
| TRI Inn. | 2643.89*** | 2098.60*** | 1661.46** | 238.63 | 228.64 | 599.08** | 999.16** | 976.25*** | -1169.19* |
| | (3.08) | (3.27) | (2.43) | (0.53) | (0.45) | (2.02) | (2.37) | (2.69) | (-1.72) |
| Constant | 0.76** | 0.64** | 0.39 | 0.36* | 0.71*** | 0.26 | 0.24 | 0.16 | 0.63*** |
| | (2.39) | (2.35) | (1.43) | (1.67) | (3.22) | (1.65) | (1.12) | (0.77) | (2.88) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.434 | 0.517 | 0.573 | 0.725 | 0.707 | 0.807 | 0.818 | 0.833 | 0.706 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 3.3 Evaluating different transition risk metrics – Global Data

In order to increase the external validity of our European baseline results we repeat the analysis for global portfolios. This comes at the expense that we cannot report taxonomy-based portfolios anymore. As depicted in table 8, we have 7 transition risk metrics available for global companies. We only show the green portfolio results since no brown portfolio correlates significantly with the TRI factor in the expected direction, in line with the European results. Both the BMG and the brown portfolio can be obtained in Appendix 7.2. The global results largely reiterate our aforementioned findings. Most notably, the TRBC based portfolio as well as the text-based portfolios correlate significantly with the TRI factor with the expected positive signs. Neither emission- or E-score based portfolio react significantly or strongly to climate transition risk shocks.

*Table 8| Monthly green global factor model regressions results. The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) Green TRBC | (2) Green Emission Intensity | (3) Green Scope 1-2 Emission Intensity | (4) Green E-Score | (5) Green CC Opp/Reg | (6) Green CC Exposure | (7) Green MSCI E-score |
|---|---|---|---|---|---|---|---|
| Market | 0.61*** | 0.85*** | 0.91*** | 0.81*** | 1.00*** | 0.88*** | 0.94*** |
| | (9.78) | (23.47) | (21.60) | (25.45) | (17.26) | (22.65) | (23.75) |
| SMB | 0.18 | -0.06 | -0.20 | -0.31*** | 0.02 | -0.04 | -0.07 |
| | (0.92) | (-0.82) | (-1.45) | (-4.21) | (0.20) | (-0.45) | (-0.95) |
| HML | 0.09 | -0.22* | -0.23* | -0.05 | 0.41*** | 0.39*** | -0.06 |
| | (0.55) | (-1.94) | (-1.90) | (-0.85) | (4.64) | (6.22) | (-0.71) |
| RMW | 0.71** | 0.07 | 0.19 | 0.23*** | -0.11 | 0.07 | -0.08 |
| | (2.59) | (0.51) | (0.97) | (2.82) | (-0.54) | (0.53) | (-0.43) |
| CMA | 0.11 | -0.22 | -0.52** | 0.15 | -0.42** | -0.26 | 0.07 |
| | (0.43) | (-1.55) | (-2.32) | (1.27) | (-2.10) | (-1.54) | (0.44) |
| TRI Innovation | 2067.10** | -95.97 | -353.06 | 377.22* | 1215.64*** | 1136.93*** | -870.07* |
| | (2.59) | (-0.29) | (-0.53) | (1.90) | (3.45) | (4.40) | (-1.89) |
| Constant | 0.68** | 0.53*** | 0.65*** | 0.16* | 0.23 | 0.13 | 0.40*** |
| | (2.26) | (5.17) | (3.64) | (1.79) | (1.47) | (1.11) | (2.93) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.496 | 0.905 | 0.803 | 0.921 | 0.830 | 0.865 | 0.905 |

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 3.4 Novel measures mixing existing climate transition risk metrics

We also develop 3 novel risk metrics which are combining TRBC with either emission-based transition risk metrics or with taxonomy-based proxies. Table 9 highlights key results for the monthly value weighted specification. We see that both green taxonomy-based TRBC metrics are highly significantly related to the TRI factor and show the expected positive sign to the shock variable. Encouragingly, focusing the emission metrics only on TRBC climate sensitive sectors, doubles the emission-based coefficients. The TRBC-emission portfolio is now also significantly related to the TRI factor. Excluding many heavily weighted companies in non-climate sensitive sectors thus appears to substantially increase the ability of emission-based transition risk metrics to form green portfolios.

*Table 9|Monthly green factor model regressions results. The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) Green Emission Intensity TRBC | (2) Green Taxonomy Revenue TRBC | (3) Green Taxonomy Capex TRBC |
|---|---|---|---|
| Market | 0.63*** | 0.57*** | 0.56*** |
| | (9.54) | (11.28) | (10.23) |
| SMB | 0.31* | -0.08 | -0.40** |
| | (1.87) | (-0.49) | (-2.60) |
| HML | 0.46* | 0.30* | 0.51*** |
| | (1.95) | (1.95) | (3.05) |
| RMW | 0.45 | 0.54** | 0.65** |
| | (1.41) | (2.21) | (2.57) |
| CMA | -0.56** | -0.10 | -0.06 |
| | (-2.03) | (-0.36) | (-0.20) |
| TRI Inn. | 961.70** | 2210.84*** | 1724.18** |
| | (2.15) | (3.31) | (2.53) |
| Constant | 0.17 | 0.51** | 0.34 |
| | (0.58) | (2.07) | (1.36) |
| Observations | 132 | 132 | 132 |
| $R^2$ | 0.677 | 0.606 | 0.612 |

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 3.5 Explaining the divergence – looking into portfolio constituents

So far, we have shown that climate transition risk metrics diverge significantly for similar companies/portfolios. Moreover, we evaluate the different options available. Now, our objective is to explain the reason for the divergence as well as the evaluation. Therefore, we look into the portfolios in detail in order to better understand what kind of companies are considered green or brown when relying on which transition risk metric. We tabulate all portfolio splits by TRBC business sector, results can be obtained in Appendix section 7.3. Most notably, both the green and brown TRBC portfolios are (by construction) highly focused on highly climate sensitive industries: automotive, energy and utilities. Compared to other risk metrics TRBC excludes all other sectors which might not be particularly climate policy sensitive. It is therefore expectable that TRBC based green portfolios of pureplay climate transition risk sensitive companies show one of the strongest reactions to unexpected transition risk shocks.

Both taxonomy-based green portfolios show a high concentration in the utility sector with almost 50% of respective companies concentrated in that business sector. The other taxonomy based green companies are concentrated in different energy intensive business sectors such as industrial goods or Industrial & Commercial Services. The concentration of utilities in the taxonomy-based portfolios highlights that renewables are already relatively established in European electricity markets, whereas green energy intensive industrial companies are rare, examples would be firms which are predominantly producing green/low-CO2 steel, aluminum or cement. Taxonomy based brown companies are more dispersed across business sectors. Interestingly, many brown companies are in the software or IT sector. This is surprising given that the taxonomy does not offer technical screening criteria for these sectors. Measurement issues of certain company's taxonomy alignment might thus explain why we were not able to produce brown portfolios which react significantly to climate transition risk shocks. The bulk of the other companies is in more expectable brown sectors such as industrial goods, automobiles, or cyclical consumer products.

A closer look into the emission based green portfolios is valuable as it shows the previously discussed issues of emission based portfolios to differentiate between green and transition risk neutral companies. Most notably, most companies in the emission based green portfolios are in industrial and commercial services, and software/IT. Neither of those sectors is traditionally seen as green, since firms in these sectors are not actively enabling the green transition. We thus assess that emission-only portfolios mix up firms in neutral sectors with high revenues and low emissions as being green. We are therefore not surprised that neither scope 1-2 or scope 1-3 emissions based green portfolios are significantly reacting to transition risk shocks. Looking into the emission based brown portfolios we see more expectable sectors such as chemicals, fossil fuel, mineral resources, industrial goods, automotive, utilities and transportation. Thus, emission-based portfolios seem to better able to identify brown companies, however, not good enough to produce significant negative results to the TRI innovation coefficient.

Finally, E-scores show the largest dispersion across business sectors. This is in line with the construction principle of E-scores which assign a rating to every company relative to its industry peers (Kotsantonis & Serafeim, 2019). Thus, a portfolio of high/low E-score companies will always be a broad portfolio across many different industries without particular climate transition risk focus. It is therefore expectable that E-score based brown or green portfolios react not as strongly as pure play transition risk portfolios. However, the positive and significant coefficient of the Refinitiv E-score shows that picking the greenest companies in each sector actually produces a portfolio that reacts to climate news shocks.

### 3.6 Pricing of climate transition risk

Our results also provide interesting insights into the pricing of climate transition risk on global equity markets. By omitting the TRI factor, we can analyze the pricing of transition risk measured through different transition risk proxies.

***Table 10|Monthly BMG factor model regressions results.*** *The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) BMG TRBC | (2) BMG Tax. Revenue | (3) BMG Tax. Capex | (4) BMG Emission Intensity | (5) BMG Scope 1-2 Emission Intensity | (6) BMG E-Score | (7) BMG CC Opp/ Reg | (8) BMG CC Exposure | (9) BMG MSCI E-score |
|---|---|---|---|---|---|---|---|---|---|
| Market | 0.16* | 0.42*** | 0.29*** | 0.01 | 0.02 | 0.01 | -0.14*** | -0.09** | 0.01 |
| | (1.91) | (3.46) | (3.32) | (0.25) | (0.64) | (0.51) | (-4.20) | (-2.32) | (0.21) |
| SMB | -0.90*** | -0.18 | 0.38* | -0.32*** | -0.05 | 0.90*** | -0.03 | 0.25* | -0.06 |
| | (-3.91) | (-0.70) | (1.97) | (-4.70) | (-0.40) | (15.53) | (-0.37) | (1.84) | (-0.61) |
| HML | 0.61** | 0.09 | -0.16 | 0.34*** | 0.57*** | 0.10 | -0.51*** | -0.79*** | 0.53*** |
| | (2.26) | (0.28) | (-0.54) | (2.95) | (3.02) | (0.87) | (-5.91) | (-4.61) | (4.00) |
| RMW | 0.33 | -0.52 | -0.36 | 0.04 | 0.21 | -0.24** | -0.21* | -0.35 | 0.89*** |
| | (1.03) | (-1.37) | (-0.97) | (0.32) | (0.93) | (-2.00) | (-1.67) | (-1.40) | (4.93) |
| CMA | 0.31 | -0.91* | -0.58 | 0.04 | 0.08 | -0.67*** | 0.28** | 0.23 | -0.06 |
| | (0.72) | (-1.96) | (-1.19) | (0.27) | (0.39) | (-5.12) | (1.99) | (1.01) | (-0.25) |
| Constant | -0.82* | -0.31 | 0.01 | -0.23* | -0.59*** | 0.45*** | -0.07 | 0.41* | -0.63*** |
| | (-1.88) | (-0.65) | (0.03) | (-1.66) | (-3.04) | (4.91) | (-0.54) | (1.82) | (-3.19) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.306 | 0.251 | 0.188 | 0.341 | 0.368 | 0.668 | 0.507 | 0.452 | 0.208 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As depicted in table 10, there is a large variation in alpha coefficient estimates ranging from positive and highly significant estimates for the E-score and CC Exposure portfolios to negative coefficient estimates for the TRBC, MSCI E-score and emission-based portfolios. The taxonomy-based portfolios as well as the CC Opportunity/Regulation do not produce a significant alpha at all. Thus, depending on which climate transition risk metric chosen, we can "find" very different pricing results for climate transition risk. In table 11, we also, again, replicate our findings on a global scale. Results are comparable. The main take away is: how climate transition risk is priced, mainly depends on how you define and measure climate transition risk. As long as no universally accepted climate transition risk measure is found, it will be difficult to ultimately answer the questions whether a brown or green premium exists on global equity markets.

***Table 11| Monthly BMG global factor model regressions results.*** *The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) BMG TRBC | (2) BMG Emission Intensity | (3) BMG Scope 1-2 Emission Intensity | (4) BMG E-Score | (5) BMG CC Opp/Reg | (6) BMG CC Exposure | (7) BMG MSCI E-score |
|---|---|---|---|---|---|---|---|
| Market | 0.34*** | 0.01 | -0.05 | -0.03 | -0.24*** | -0.09** | 0.06 |
| | (4.98) | (0.12) | (-0.99) | (-0.97) | (-5.01) | (-2.07) | (1.28) |
| SMB | -0.17 | 0.05 | 0.29* | 0.60*** | -0.10 | -0.08 | 0.32*** |
| | (-0.76) | (0.70) | (1.76) | (6.39) | (-1.04) | (-0.80) | (2.67) |
| HML | 0.64*** | 0.52*** | 0.53*** | -0.10 | -0.16 | -0.64*** | 0.40*** |
| | (3.54) | (4.36) | (3.55) | (-1.05) | (-1.54) | (-4.79) | (3.12) |
| RMW | -0.47 | 0.16 | -0.03 | -0.13 | 0.35** | 0.28 | 0.70*** |
| | (-1.61) | (0.96) | (-0.15) | (-1.20) | (1.98) | (1.26) | (4.25) |
| CMA | -0.45 | 0.16 | 0.40 | -0.57*** | 0.32* | 0.40 | 0.08 |
| | (-1.61) | (0.86) | (1.21) | (-2.86) | (1.69) | (1.59) | (0.33) |
| Constant | -0.85*** | -0.56*** | -0.66*** | 0.50*** | -0.17 | 0.34* | -0.57*** |
| | (-2.66) | (-3.95) | (-2.97) | (4.55) | (-1.14) | (1.93) | (-3.08) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.386 | 0.375 | 0.317 | 0.442 | 0.430 | 0.418 | 0.202 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 3.7 Robustness Section

As another robustness test, we also want to make sure that our results are not only driven by some form of availability bias, as data availability varies widely between transition risk metrics. We therefore listwise delete all companies which have a missing value in any climate transition risk metric. After the deletions, 442 companies remain with full data availability. Results are reported in table 12 and show a high degree of comparability to the baseline results in table 7. Coefficient estimates for both emissions-based portfolios are insignificant. The coefficient of the Refinitiv E-score portfolio is only marginally significant putting some questions marks behind the stability of the previous results.

***Table 12|Monthly green factor model regressions results with listwise deletion.*** *The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) Green TRBC | (2) Green Tax. Revenue | (3) Green Tax. Capex | (4) Green Emission Intensity | (5) Green Scope 1-2 Emission Intensity | (6) Green E-Score | (7) Green CC Opp/ Reg | (8) Green CC Exposure |
|---|---|---|---|---|---|---|---|---|
| Market | 0.53*** | 0.48*** | 0.53*** | 0.75*** | 0.68*** | 0.72*** | 0.77*** | 0.70*** |
| | (4.00) | (7.36) | (9.36) | (9.43) | (11.52) | (13.21) | (14.14) | (16.23) |
| SMB | 0.32 | -0.12 | -0.52*** | 0.04 | -0.33** | -0.46*** | -0.32** | -0.38*** |
| | (0.90) | (-0.74) | (-3.30) | (0.22) | (-2.27) | (-3.61) | (-2.04) | (-3.14) |
| HML | 0.41 | 0.13 | 0.42** | -0.07 | 0.01 | 0.26* | 0.81*** | 0.61*** |
| | (1.07) | (0.72) | (2.08) | (-0.33) | (0.03) | (1.80) | (6.13) | (5.69) |
| RMW | -0.04 | 0.61** | 0.58* | 0.24 | 0.38 | 0.61*** | 0.65*** | 0.56*** |
| | (-0.08) | (2.31) | (1.91) | (0.75) | (1.53) | (3.31) | (3.27) | (3.71) |
| CMA | -0.98* | -0.01 | 0.04 | -0.58** | -0.18 | -0.15 | -0.73*** | -0.41*** |
| | (-1.83) | (-0.03) | (0.13) | (-2.39) | (-0.93) | (-1.14) | (-3.84) | (-2.77) |
| TRI Inn. | 2420.71 | 2122.97*** | 1822.12*** | 178.48 | 162.01 | 716.21* | 632.91 | 874.73*** |
| | (1.57) | (3.25) | (2.64) | (0.30) | (0.30) | (1.93) | (1.36) | (2.77) |
| Constant | 1.07* | 0.58** | 0.37 | 0.51* | 0.66*** | 0.26 | 0.35 | 0.17 |
| | (1.90) | (2.14) | (1.27) | (1.68) | (2.68) | (1.39) | (1.63) | (0.94) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.306 | 0.439 | 0.534 | 0.599 | 0.661 | 0.801 | 0.798 | 0.831 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 4 Discussion

The results for the transition risk divergence heavily support hypothesis 1 and are relevant since they show that scholars will reach very different transition risk results for companies depending on which risk metric is chosen. The second part of the analysis explains the large divergence by the finding that only some transition risk metrics are significantly exposed to transition risk shocks. Most notably, we find some support for hypothesis 2, at least for green firms, and we also find support for H3, since the taxonomy can measure green firms transition risk accurately. Both scope 1-2 and scope 1-3 emissions cannot reliably measure brown firms transition risk, therefore we must reject hypotheses 4-5. We further find mixed evidence for hypothesis 6 since only Refinitiv E-scores show a significant reaction to transition risk shocks, highlighting the strong divergence between E-scores, which is in line with Berg et al. (2022). Concerning text-based measures, we find support for hypothesis 7 as both text-based measures are significantly related to transition risk shocks.

Our results are partly at odds with previous findings in the literature by both Bua et al. (2022) for green portfolios based on emissions as well as Ardia et al. (2022), who find that emission intensity-based portfolios react to transition risk shocks. We cannot show that emission-based portfolios, be they brown or green, react to unexpected shocks in transition risk. Our results are therefore more in line with Apel et al. (2023) who also cannot find that emission-based indices react to transition risk shocks. Finally, there is some support for hypothesis 8, since the TRBC emission intensity metric improves the performance of the emission only measures when measuring green firms' climate transition risk. However, no mixed metric can form brown portfolios, which react negatively to positive transition risk shocks.

Differences in results are to some degree to be expected since Bua et al. (2022), Ardia et al. (2022) and Apel et al. (2023) all develop and use different transition risk shock indices. To date, there is not consensus in the literature which transition risk shock index is best able to actually measure unexpected climate transition risk shocks. However, we are inclined to follow the argument by Apel et al. (2023) that high attention to transition risk does not automatically imply higher transition risk for brown companies, it might also relate to a significant and unexpected decrease in transition risk. Examples are the election of Donald Trump or Trumps withdrawal from the Paris Agreement. Therefore, we utilize the index proposed by Apel et al. (2023) is best able to differentiate positive and negative transition risk shocks. Different calibration of transition shock indices might thus explain, to some degree, diverging results.

TRBC, taxonomy alignment of capex/revenues as well as text-based approaches appear to be best suited to detect green companies' climate transition risk. However, no tested transition risk proxy can form brown portfolios which are negatively exposed to transition risk shocks. There are different explanations for this striking finding. On the one hand, the tested transition risk metrics might simply have weaknesses in detecting brown firms. On the other hand, the chosen transition risk index might be flawed. Alternatively, financial markets might currently underestimate the climate transition risk of brown companies, while focusing on the opportunities in the transition for green firms. Investors might also expect that brown firms will successfully lobby against strong climate policy or that governments will bail out firms in case transition risk shocks lead to stranded assets (von Dulong et al., 2023). Turning to the green portfolio results, we can assess that financial market appear to price not the between industry transition risk, but actually look into the granular technologies utilized within one economic activity. As both TRBC and taxonomy alignment measure whether certain technologies are on a Paris-aligned pathway, financial market appear to differentiate the transition risk of technologies as opposed to simply look at low carbon intensities or high E-scores.

Our paper also holds important insights into the ongoing debate on the pricing of climate transition risk on financial markets as some scholars show a brown or carbon premium (Alessi et al., 2021; Bolton & Kacperczyk, 2021), while other authors find a green premium (Bauer et al., 2022; Fliegel, 2023; Pástor et al., 2022). We are able to demonstrate, based on our different BMG portfolios, that we could "find" a brown as well as a green premium of similar magnitudes than the aforementioned studies, simply by changing the employed transition risk metric. We can show, that within the same universe of companies, following the same portfolio construction rules, the performance results are diametrically opposed. Thus, we urge scholars to increasingly focus on the transition risk metric employed as this seemingly simply choice can substantially drive empirical results. Most notably, researchers should increasingly rely on robustness tests for climate transition risk metrics. Examples involve: using emissions from different vendors, including only scope 1-2 or scope 1-3 emissions, using different E-scores, or using alternative transition risk metrics such as TRBC, taxonomy or text-based transition risk metrics as robustness.

## 4.1 Real world relevance

Answering the question how to best measure companies' climate transition risk, is relevant for both financial markets and the green transition in general, since only what is correctly measured can be adequately reduced, managed and priced. Accurately, measuring transition risk is thus not only a technicality, but has real world implications: Most notably, investors are currently highly confused how-to best measure transition risk of companies (Berg et al., 2022). If investors erroneously categorized some brown high-risk companies as green, then the growing funds devoted to sustainable or ESG themed investing would be misallocated (Bams & van der Kroft, 2022; Chatterji et al., 2016). This can lead to large scale mispricing of transition risk on financial markets and can artificially reduce (increase) the costs of capital for brown (green) firms (Bams & van der Kroft, 2022). Another consequence of the transition risk metric confusion is the potential for firms to practice cheap talk in their earnings releases (Bingler, Kraus, et al., 2022) to greenwash their real impact on the global climate and to mitigate pressure from both consumers and policymakers (Drempetic et al., 2020). Thus, reducing the transition risk metric confusion might help to correctly price transition risk on financial markets and thereby create real impact on the green transition. At the same time, it enables policymakers to better track and manage transition risk of companies in the real economy.

## 4.2 Limitations

Our research is limited by several issues. First, the data on EU taxonomy alignment may not be 100% accurate, as reporting companies faced significant challenges in collecting granular alignment data with technical screening criteria for every business line, across all plants in multiple jurisdictions. This is particularly relevant as companies reported alignments for the first time ever, there is thus no experiences with this sort of data collection. Another limiting factor for the quality of taxonomy data is that assurance is not (yet) mandatory (Arnold et al., 2023). It is therefore particularly encouraging that we can already show that the taxonomy is highly useful in detecting green firms for the fiscal year 2022, the first year of data publication. We expect the data quality of the risk measure to increase in the coming years. Second, the main part of the analysis is limited to Europe, which reduces the sample size substantially. There are thus remaining questions about external validity of the results. We address these concerns by extending the analysis towards global companies at the expense of omitting taxonomy alignment data. Third, most available transition risk news indices are focused on US news data, while the focus of our paper is Europe. However, due to the heavy influence of US news and financial markets on Europe, it can be assumed that US news also heavily influence European stock prices. Again, we argue that the roughly comparable global results should reduce these concerns. Fourth, we can only construct all transition risk proxies once for the fiscal year 2022, as this is the first year when taxonomy alignment reporting became mandatory. A superior approach would feature a panel structure of the data, to also include time varying changes in the climate transition risk metrics. We see this limitation as being more problematic for the green portfolios since previously brown companies might end up in the green portfolio but previously green firms will hardly get substantially browner over time. Estimates for the green portfolios might thus represent a lower bound since green portfolios can be to some degree `diluted` by brown companies which only recently turned green. Fifth, the evaluation exercise on the quality of transition risk metrics rests on the identifying assumption that stock prices of transition risk exposed firms react to transition risk shocks. Logically, the transition risk proxy that can create a BMG portfolio which shows the strongest response to unexpected climate transition risk shocks is then best suited to measure transition risk. This argumentation is in line with the theoretical rational by Pástor et al. (2021) as well as the empirical setting by Ardia et al. (2022). However, only if the chosen transition risk index correctly captures actual transition risk shocks, the results can be causally interpreted.

## 5 Conclusion

Summing up, the results in this paper show that quality and availability of transition risk metrics are still key issues limiting a reliable measurement of firms' climate transition risk. The most utilized transition risk metrics, MSCI E-scores and emission data, fail to detect brown or green firms in a way that they systematically react to transition risk shocks. Taxonomy alignment metrics, text-based measures and sector/technology classifications are strong in measuring green firms' climate transition risk, but show weaknesses in measuring brown companies' climate transition risk. Moreover, to some degree Refinitiv E-scores seem to be able to identify best in class green companies. At the same time, taxonomy data has weaknesses in terms of availability, particularly outside of Europe as well as for smaller companies.

Going forward researchers should put increasing emphasis on how they measure firms' climate transition risk, as this paper shows that climate transition risk metrics significantly diverge and that only some metrics are actually able to capture firms' climate transition risk. We therefore propose to increasingly focus on stability/robustness tests for climate transition risk metrics. Another interesting future avenue is the replication of existing high impact papers on climate transition risk which are only based on either emission data or E-scores. One could for example, use all the metrics we used in the present study as robustness tests in published papers. Our hypothesis based on our results would be that most results are not robust to other measurements of climate transition risks. Finally, scholars should also try new transition risk metrics such as the EU taxonomy, business technology classifications, text-based approaches or innovative mixes of multiple transition risk measures.

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# 7 Appendix

## 7.1 TRBC Assignment

*Table A1| List of TRBC activity codes sorted into the respective TRBC based portfolio.*

| TRBC Brown | TRBC Green |
|---|---|
| Auto & Truck Manufacturers | Alternative Electric Utilities |
| Automobiles & Multi Utility Vehicles | Automotive Batteries |
| Light Trucks | Biodiesel |
| Motorcycle Parts & Accessories | Biomass & Biogas Fuels |
| Coal | Electrical (Alternative) Vehicles |
| Coal Wholesale | Ethanol Fuels |
| Fossil Fuel Electric Utilities | Geothermal Electric Utilities |
| Gasoline Stations | Geothermal Equipment |
| Integrated Oil & Gas | Hydroelectric & Tidal Utilities |
| LNG Transportation & Storage | Hydrogen Fuel |
| Motorcycles & Scooters | Photovoltaic Solar Systems & Equipment |
| Multiline Utilities | Pyrolytic & Synthetic Fuels |
| Natural Gas Distribution | Renewable Energy Equipment & Services |
| Natural Gas Exploration & Production - Onshore | Renewable Energy Services |
| Natural Gas Pipeline Transportation | Renewable IPPs |
| Natural Gas Utilities | Solar Electric Utilities |
| Oil & Gas Drilling | Stationary Fuel Cells |
| Oil & Gas Exploration and Production | Water & Related Utilities |
| Oil & Gas Refining and Marketing | Wind Electric Utilities |
| Oil & Gas Storage | Wind Systems & Equipment |
| Oil & Gas Transportation Services | Biomass & Waste to Energy Electric Utilities |
| Oil Drilling - Offshore | Renewable Fuels |
| Oil Exploration & Production - Offshore | Nuclear IPPs |
| Oil Exploration & Production - Onshore | Nuclear Utilities |
| Oil Pipeline Transportation | Power Charging Stations |
| Oil Related - Surveying & Mapping Services | Water Supply & Irrigation Systems |
| Oil Related Equipment | |
| Oil Related Services | |
| Oil Related Services and Equipment | |
| Petroleum Product Wholesale | |
| Petroleum Refining | |
| Sea-Borne Tankers | |
| Oil Drilling - Onshore | |
| Coal Mining Support | |
| Unconventional Oil & Gas Production | |
| Fossil Fuel IPPs | |
| Coke Coal Mining | |
| Natural Gas Exploration & Production - Offshore | |
| Fossil Fuel Electric Utilities | |
| Natural Gas Distribution | |
| Natural Gas Utilities | |
| Unconventional Oil & Gas Drilling | |

In line with the EU Taxonomy regulation, we classify uranium mining as neutral but nuclear power generation as green due to its zero emission technological profile.

For the TRBC-emission intensity mix transition risk metric, we classify business sectors based on TRBC as either being relevant or negligible from a climate transition risk perspective. This categorization is based on the climate policy relevant sector classification (Battiston et al., 2017; Battiston et al., 2022). They categorize 6 sectors (fossil fuel, utilities, energy intensive industry, buildings, transportation and agriculture) as being climate relevant as they: are high emitting sectors, are directly relevant for climate policy, exhibit an inelastic substitution away from fossil fuel and are relevant within the economic value chain. As highlighted in table A2, the overall TRBC business sectors in the climate sensitive column relate to the CPRS sectors. Only CPRS agriculture is not mapped onto TRBC climate sensitive as there is no clear agricultural sector in the TRBC business sectors. There is also one case when TRBC business sectors are not granular enough to separate climate (non-)sensitive business sectors, we therefore must go down one more level of granularity to TRBC industry names to separate the business sector Industrial & Commercial Services.

*Table A2| Economic sector classified as climate sensitive as well as all other sectors*

| **Climate Sensitive TRBC Business Sectors** | **Non Climate Sensitive TRBC Business Sectors** |
|---|---|
| Applied Resources<br>Automobiles & Auto Parts<br>Chemicals<br>Construction & Engineering<br>Energy - Fossil Fuels<br>Environmental Services & Equipment<br>Industrial Goods<br>Mineral Resources<br>Real Estate<br>Renewable Energy<br>Transportation<br>Utilities | Academic & Educational Services<br>Banking & Investment Services<br>Collective Investments<br>Consumer Goods Conglomerates<br>Cyclical Consumer Products<br>Cyclical Consumer Services<br>Financial Technology (Fintech) & Infrastructure<br>Food & Beverages<br>Food & Drug Retailing<br>Healthcare Services & Equipment<br>Holding Companies<br>Industrial & Commercial Services (without Environmental Services & Equipment & Construction & Engineering)<br>Insurance<br>Personal & Household Products & Services<br>Pharmaceuticals & Medical Research<br>Retailers<br>Software & IT Services<br>Technology Equipment<br>Telecommunications Services |

## 7.2 Global monthly value weighted regression results

***Table A3|Monthly BMG global factor model regressions results.*** *The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| VARIABLES | (1) BMG TRBC | (2) BMG Emission Intensity | (3) BMG Scope 1-2 Emission Intensity | (4) BMG E-Score | (5) BMG CC Opp/Reg | (6) BMG CC Exposure | (7) BMG MSCI E-score |
|---|---|---|---|---|---|---|---|
| Market | 0.34*** | 0.01 | -0.05 | -0.03 | -0.24*** | -0.09** | 0.06 |
| | (4.99) | (0.14) | (-0.94) | (-0.95) | (-5.00) | (-2.05) | (1.30) |
| SMB | -0.17 | 0.05 | 0.29* | 0.60*** | -0.10 | -0.09 | 0.32*** |
| | (-0.79) | (0.74) | (1.80) | (6.38) | (-1.06) | (-0.84) | (2.62) |
| HML | 0.63*** | 0.53*** | 0.54*** | -0.10 | -0.16 | -0.65*** | 0.41*** |
| | (3.49) | (4.37) | (3.63) | (-1.01) | (-1.58) | (-4.78) | (3.22) |
| RMW | -0.50* | 0.18 | -0.00 | -0.13 | 0.34* | 0.25 | 0.71*** |
| | (-1.66) | (1.09) | (-0.02) | (-1.13) | (1.97) | (1.19) | (4.48) |
| CMA | -0.45 | 0.16 | 0.39 | -0.57*** | 0.32* | 0.40 | 0.08 |
| | (-1.64) | (0.86) | (1.23) | (-2.90) | (1.73) | (1.61) | (0.33) |
| TRI Inn. | -1083.07 | 860.51** | 1182.47 | 397.93 | -442.29 | -1126.18*** | 710.04 |
| | (-1.07) | (2.10) | (1.55) | (1.05) | (-1.36) | (-3.04) | (1.62) |
| Constant | -0.88*** | -0.54*** | -0.63*** | 0.51*** | -0.18 | 0.31* | -0.55*** |
| | (-2.67) | (-3.78) | (-2.81) | (4.67) | (-1.19) | (1.78) | (-3.02) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.394 | 0.396 | 0.334 | 0.447 | 0.435 | 0.441 | 0.214 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table A4|Monthly brown global factor model regressions results.*** *The column headers highlight which monthly value weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Newey and West standard errors were employed for all models. Returns are in percent per month.*

| **VARIABLES** | **(1) Brown TRBC** | **(2) Brown Emission Intensity** | **(3) Brown Scope 1-2 Emission Intensity** | **(4) Brown E-Score** | **(5) Brown CC Opp/Reg** | **(6) Brown CC Exposure** | **(7) Brown MSCI E-score** |
|---|---|---|---|---|---|---|---|
| Market | 0.94*** | 0.86*** | 0.86*** | 0.78*** | 0.77*** | 0.79*** | 0.99*** |
| | (19.40) | (26.60) | (26.96) | (28.64) | (23.97) | (19.08) | (25.16) |
| SMB | -0.00 | -0.02 | 0.08 | 0.28*** | -0.09 | -0.14* | 0.23** |
| | (-0.01) | (-0.21) | (0.93) | (3.81) | (-1.12) | (-1.72) | (2.41) |
| HML | 0.71*** | 0.31*** | 0.31*** | -0.15* | 0.25*** | -0.26** | 0.34*** |
| | (8.96) | (5.67) | (4.15) | (-1.81) | (3.72) | (-2.45) | (3.29) |
| RMW | 0.21 | 0.24* | 0.18 | 0.10 | 0.22* | 0.31* | 0.62*** |
| | (1.50) | (1.97) | (1.40) | (0.87) | (1.96) | (1.84) | (4.02) |
| CMA | -0.34** | -0.08 | -0.13 | -0.43*** | -0.10 | 0.14 | 0.15 |
| | (-2.12) | (-0.62) | (-0.63) | (-3.19) | (-0.64) | (0.79) | (0.73) |
| TRI Inn. | 967.27*** | 747.78*** | 812.65*** | 758.39** | 756.58*** | -6.02 | -176.80 |
| | (2.64) | (3.94) | (2.63) | (2.09) | (3.54) | (-0.03) | (-0.37) |
| Constant | -0.15 | 0.03 | 0.06 | 0.71*** | 0.09 | 0.49*** | -0.11 |
| | (-0.96) | (0.26) | (0.45) | (7.25) | (0.84) | (4.29) | (-0.78) |
| Observations | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| $R^2$ | 0.884 | 0.935 | 0.901 | 0.910 | 0.900 | 0.884 | 0.887 |

Robust t-statistics are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 7.3 Explaining the divergence – sectoral split per portfolio

***Table A5|TRBC business sector split – TRBC green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Renewable Energy | 27 | 47.37 | 47.37 |
| Utilities | 30 | 52.63 | 100.00 |
| Total | 57 | 100.00 | |

***Table A6|TRBC business sector split – TRBC brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Automobiles & Auto Parts | 19 | 12.42 | 12.42 |
| Energy - Fossil Fuels | 10t9 | 71.24 | 83.66 |
| Utilities | 25 | 16.34 | 100.00 |
| Total | 153 | 100.00 | |

***Table A7|TRBC business sector split – Taxonomy revenue green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Cyclical Consumer Products | 1 | 2.13 | 2.13 |
| Cyclical Consumer Services | 1 | 2.13 | 4.26 |
| Healthcare Services & Equipment | 1 | 2.13 | 6.38 |
| Industrial & Commercial Services | 5 | 10.64 | 17.02 |
| Industrial Goods | 7 | 14.89 | 31.91 |
| Mineral Resources | 4 | 8.51 | 40.43 |
| Real Estate | 2 | 4.26 | 44.68 |
| Renewable Energy | 2 | 4.26 | 48.94 |
| Software & IT Services | 3 | 6.38 | 55.32 |
| Technology Equipment | 1 | 2.13 | 57.45 |
| Transportation | 3 | 6.38 | 63.83 |
| Utilities | 17 | 36.17 | 100.00 |
| Total | 47 | 100.00 | |

***Table A8|TRBC business sector split – Taxonomy revenue brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Automobiles & Auto Parts | 3 | 5.88 | 5.88 |
| Chemicals | 1 | 1.96 | 7.84 |
| Cyclical Consumer Products | 4 | 7.84 | 15.69 |
| Cyclical Consumer Services | 4 | 7.84 | 23.53 |
| Energy - Fossil Fuels | 2 | 3.92 | 27.45 |
| Food & Beverages | 1 | 1.96 | 29.41 |
| Industrial & Commercial Services | 6 | 11.76 | 41.18 |
| Industrial Goods | 6 | 11.76 | 52.94 |
| Mineral Resources | 3 | 5.88 | 58.82 |
| Real Estate | 2 | 3.92 | 62.75 |
| Renewable Energy | 1 | 1.96 | 64.71 |
| Software & IT Services | 8 | 15.69 | 80.39 |
| Technology Equipment | 2 | 3.92 | 84.31 |
| Telecommunications Services | 1 | 1.96 | 86.27 |
| Transportation | 6 | 11.76 | 98.04 |
| Utilities | 1 | 1.96 | 100.00 |
| Total | 51 | 100.00 | |

***Table A9|TRBC business sector split – Taxonomy capex green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 1 | 1.49 | 1.49 |
| Chemicals | 1 | 1.49 | 2.99 |
| Cyclical Consumer Products | 1 | 1.49 | 4.48 |
| Cyclical Consumer Services | 1 | 1.49 | 5.97 |
| Energy - Fossil Fuels | 3 | 4.48 | 10.45 |
| Food & Beverages | 1 | 1.49 | 11.94 |
| Healthcare Services & Equipment | 1 | 1.49 | 13.43 |
| Industrial & Commercial Services | 3 | 4.48 | 17.91 |
| Industrial Goods | 6 | 8.96 | 26.87 |
| Mineral Resources | 2 | 2.99 | 29.85 |
| Real Estate | 1 | 1.49 | 31.34 |
| Renewable Energy | 3 | 4.48 | 35.82 |
| Software & IT Services | 4 | 5.97 | 41.79 |
| Technology Equipment | 2 | 2.99 | 44.78 |
| Transportation | 3 | 4.48 | 49.25 |
| Utilities | 34 | 50.75 | 100.00 |
| Total | 67 | 100.00 | |

***Table A10|TRBC business sector split – Taxonomy capex brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Automobiles & Auto Parts | 3 | 3.85 | 3.85 |
| Chemicals | 1 | 1.28 | 5.13 |
| Consumer Goods Conglomerates | 2 | 2.56 | 7.69 |
| Cyclical Consumer Products | 5 | 6.41 | 14.10 |
| Cyclical Consumer Services | 7 | 8.97 | 23.08 |
| Energy - Fossil Fuels | 1 | 1.28 | 24.36 |
| Food & Beverages | 1 | 1.28 | 25.64 |
| Food & Drug Retailing | 1 | 1.28 | 26.92 |
| Healthcare Services & Equipment | 1 | 1.28 | 28.21 |
| Industrial & Commercial Services | 9 | 11.54 | 39.74 |
| Industrial Goods | 3 | 3.85 | 43.59 |
| Mineral Resources | 3 | 3.85 | 47.44 |
| Pharmaceuticals & Medical Research | 1 | 1.28 | 48.72 |
| Real Estate | 4 | 5.13 | 53.85 |
| Renewable Energy | 1 | 1.28 | 55.13 |
| Retailers | 7 | 8.97 | 64.10 |
| Software & IT Services | 15 | 19.23 | 83.33 |
| Technology Equipment | 2 | 2.56 | 85.90 |
| Telecommunications Services | 1 | 1.28 | 87.18 |
| Transportation | 8 | 10.26 | 97.44 |
| Utilities | 2 | 2.56 | 100.00 |
| Total | 78 | 100.00 | |

***Table A11|TRBC business sector split – Emission intensity green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Academic & Educational Services | 1 | 0.46 | 0.46 |
| Automobiles & Auto Parts | 4 | 1.84 | 2.30 |
| Consumer Goods Conglomerates | 6 | 2.76 | 5.07 |
| Cyclical Consumer Products | 5 | 2.30 | 7.37 |
| Cyclical Consumer Services | 23 | 10.60 | 17.97 |
| Energy - Fossil Fuels | 1 | 0.46 | 18.43 |
| Food & Beverages | 4 | 1.84 | 20.28 |
| Food & Drug Retailing | 5 | 2.30 | 22.58 |
| Healthcare Services & Equipment | 9 | 4.15 | 26.73 |
| Industrial & Commercial Services | 37 | 17.05 | 43.78 |
| Industrial Goods | 15 | 6.91 | 50.69 |
| Mineral Resources | 1 | 0.46 | 51.15 |
| Pharmaceuticals & Medical Research | 12 | 5.53 | 56.68 |
| Real Estate | 12 | 5.53 | 62.21 |
| Renewable Energy | 1 | 0.46 | 62.67 |
| Retailers | 7 | 3.23 | 65.90 |
| Software & IT Services | 45 | 20.74 | 86.64 |
| Technology Equipment | 16 | 7.37 | 94.01 |
| Telecommunications Services | 5 | 2.30 | 96.31 |
| Transportation | 3 | 1.38 | 97.70 |
| Utilities | 5 | 2.30 | 100.00 |
| Total | 217 | 100.00 | |

***Table A12|TRBC business sector split – Emission intensity brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 5 | 2.30 | 2.30 |
| Automobiles & Auto Parts | 14 | 6.45 | 8.76 |
| Chemicals | 23 | 10.60 | 19.35 |
| Consumer Goods Conglomerates | 1 | 0.46 | 19.82 |
| Cyclical Consumer Products | 9 | 4.15 | 23.96 |
| Cyclical Consumer Services | 2 | 0.92 | 24.88 |
| Energy - Fossil Fuels | 25 | 11.52 | 36.41 |
| Food & Beverages | 11 | 5.07 | 41.47 |
| Food & Drug Retailing | 3 | 1.38 | 42.86 |
| Industrial & Commercial Services | 6 | 2.76 | 45.62 |
| Industrial Goods | 37 | 17.05 | 62.67 |
| Mineral Resources | 26 | 11.98 | 74.65 |
| Personal & Household Products & Services | 3 | 1.38 | 76.04 |
| Real Estate | 6 | 2.76 | 78.80 |
| Renewable Energy | 3 | 1.38 | 80.18 |
| Retailers | 5 | 2.30 | 82.49 |
| Software & IT Services | 2 | 0.92 | 83.41 |
| Technology Equipment | 5 | 2.30 | 85.71 |
| Transportation | 13 | 5.99 | 91.71 |
| Utilities | 18 | 8.29 | 100.00 |
| Total | 217 | 100.00 | |

***Table A13|TRBC business sector split – Scope 1-2 emission intensity green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Academic & Educational Services | 1 | 0.35 | 0.35 |
| Automobiles & Auto Parts | 2 | 0.70 | 1.05 |
| Chemicals | 1 | 0.35 | 1.39 |
| Consumer Goods Conglomerates | 1 | 0.35 | 1.74 |
| Cyclical Consumer Products | 17 | 5.92 | 7.67 |
| Cyclical Consumer Services | 34 | 11.85 | 19.51 |
| Energy - Fossil Fuels | 3 | 1.05 | 20.56 |
| Food & Beverages | 1 | 0.35 | 20.91 |
| Food & Drug Retailing | 2 | 0.70 | 21.60 |
| Healthcare Services & Equipment | 8 | 2.79 | 24.39 |
| Industrial & Commercial Services | 38 | 13.24 | 37.63 |
| Industrial Goods | 14 | 4.88 | 42.51 |
| Mineral Resources | 2 | 0.70 | 43.21 |
| Personal & Household Products & Services | 2 | 0.70 | 43.90 |
| Pharmaceuticals & Medical Research | 14 | 4.88 | 48.78 |
| Real Estate | 24 | 8.36 | 57.14 |
| Renewable Energy | 1 | 0.35 | 57.49 |
| Retailers | 18 | 6.27 | 63.76 |
| Software & IT Services | 70 | 24.39 | 88.15 |
| Technology Equipment | 22 | 7.67 | 95.82 |
| Telecommunications Services | 3 | 1.05 | 96.86 |
| Transportation | 5 | 1.74 | 98.61 |
| Utilities | 4 | 1.39 | 100.00 |
| Total | 287 | 100.00 | |

***Table A14|TRBC business sector split – Scope 1-2 emission intensity brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 26 | 9.06 | 9.06 |
| Automobiles & Auto Parts | 8 | 2.79 | 11.85 |
| Chemicals | 22 | 7.67 | 19.51 |
| Consumer Goods Conglomerates | 1 | 0.35 | 19.86 |
| Cyclical Consumer Products | 10 | 3.48 | 23.34 |
| Cyclical Consumer Services | 6 | 2.09 | 25.44 |
| Energy - Fossil Fuels | 34 | 11.85 | 37.28 |
| Food & Beverages | 17 | 5.92 | 43.21 |
| Food & Drug Retailing | 2 | 0.70 | 43.90 |
| Healthcare Services & Equipment | 2 | 0.70 | 44.60 |
| Industrial & Commercial Services | 11 | 3.83 | 48.43 |
| Industrial Goods | 9 | 3.14 | 51.57 |
| Mineral Resources | 49 | 17.07 | 68.64 |
| Personal & Household Products & Services | 1 | 0.35 | 68.99 |
| Pharmaceuticals & Medical Research | 2 | 0.70 | 69.69 |
| Real Estate | 21 | 7.32 | 77.00 |
| Renewable Energy | 3 | 1.05 | 78.05 |
| Software & IT Services | 3 | 1.05 | 79.09 |
| Technology Equipment | 4 | 1.39 | 80.49 |
| Telecommunications Services | 3 | 1.05 | 81.53 |
| Transportation | 23 | 8.01 | 89.55 |
| Utilities | 30 | 10.45 | 100.00 |
| Total | 287 | 100.00 | |

***Table A15 | TRBC business sector split – E-Score green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 8 | 2.37 | 2.37 |
| Automobiles & Auto Parts | 10 | 2.96 | 5.33 |
| Chemicals | 14 | 4.14 | 9.47 |
| Cyclical Consumer Products | 25 | 7.40 | 16.86 |
| Cyclical Consumer Services | 20 | 5.92 | 22.78 |
| Energy - Fossil Fuels | 15 | 4.44 | 27.22 |
| Food & Beverages | 21 | 6.21 | 33.43 |
| Food & Drug Retailing | 9 | 2.66 | 36.09 |
| Healthcare Services & Equipment | 10 | 2.96 | 39.05 |
| Industrial & Commercial Services | 27 | 7.99 | 47.04 |
| Industrial Goods | 35 | 10.36 | 57.40 |
| Mineral Resources | 19 | 5.62 | 63.02 |
| Personal & Household Products & Services | 4 | 1.18 | 64.20 |
| Pharmaceuticals & Medical Research | 18 | 5.33 | 69.53 |
| Real Estate | 30 | 8.88 | 78.40 |
| Renewable Energy | 1 | 0.30 | 78.70 |
| Retailers | 14 | 4.14 | 82.84 |
| Software & IT Services | 9 | 2.66 | 85.50 |
| Technology Equipment | 7 | 2.07 | 87.57 |
| Telecommunications Services | 9 | 2.66 | 90.24 |
| Transportation | 14 | 4.14 | 94.38 |
| Utilities | 19 | 5.62 | 100.00 |
| Total | 338 | 100.00 | |

***Table A16 | TRBC business sector split – E-score brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 4 | 1.18 | 1.18 |
| Automobiles & Auto Parts | 6 | 1.78 | 2.96 |
| Chemicals | 5 | 1.48 | 4.44 |
| Consumer Goods Conglomerates | 6 | 1.78 | 6.21 |
| Cyclical Consumer Products | 20 | 5.92 | 12.13 |
| Cyclical Consumer Services | 17 | 5.03 | 17.16 |
| Energy - Fossil Fuels | 6 | 1.78 | 18.93 |
| Food & Beverages | 10 | 2.96 | 21.89 |
| Food & Drug Retailing | 3 | 0.89 | 22.78 |
| Healthcare Services & Equipment | 10 | 2.96 | 25.74 |
| Industrial & Commercial Services | 42 | 12.43 | 38.17 |
| Industrial Goods | 52 | 15.38 | 53.55 |
| Mineral Resources | 4 | 1.18 | 54.73 |
| Personal & Household Products & Services | 1 | 0.30 | 55.03 |
| Pharmaceuticals & Medical Research | 16 | 4.73 | 59.76 |
| Real Estate | 14 | 4.14 | 63.91 |
| Renewable Energy | 4 | 1.18 | 65.09 |
| Retailers | 9 | 2.66 | 67.75 |
| Software & IT Services | 64 | 18.93 | 86.69 |
| Technology Equipment | 21 | 6.21 | 92.90 |
| Telecommunications Services | 3 | 0.89 | 93.79 |
| Transportation | 13 | 3.85 | 97.63 |
| Utilities | 8 | 2.37 | 100.00 |
| Total | 338 | 100.00 | |

***Table A17|TRBC business sector split – Climate change exposure Opportunity/Regulation green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 5 | 4.13 | 4.13 |
| Automobiles & Auto Parts | 10 | 8.26 | 12.40 |
| Chemicals | 4 | 3.31 | 15.70 |
| Cyclical Consumer Products | 2 | 1.65 | 17.36 |
| Energy - Fossil Fuels | 14 | 11.57 | 28.93 |
| Food & Beverages | 2 | 1.65 | 30.58 |
| Food & Drug Retailing | 1 | 0.83 | 31.40 |
| Industrial & Commercial Services | 11 | 9.09 | 40.50 |
| Industrial Goods | 22 | 18.18 | 58.68 |
| Mineral Resources | 12 | 9.92 | 68.60 |
| Real Estate | 1 | 0.83 | 69.42 |
| Renewable Energy | 6 | 4.96 | 74.38 |
| Retailers | 5 | 4.13 | 78.51 |
| Software & IT Services | 2 | 1.65 | 80.17 |
| Technology Equipment | 7 | 5.79 | 85.95 |
| Telecommunications Services | 2 | 1.65 | 87.60 |
| Transportation | 3 | 2.48 | 90.08 |
| Utilities | 12 | 9.92 | 100.00 |
| Total | 121 | 100.00 | |

***Table A18|TRBC business sector split – Climate change exposure Opportunity/Regulation brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 9 | 4.15 | 4.15 |
| Automobiles & Auto Parts | 5 | 2.30 | 6.45 |
| Chemicals | 8 | 3.69 | 10.14 |
| Consumer Goods Conglomerates | 3 | 1.38 | 11.52 |
| Cyclical Consumer Products | 13 | 5.99 | 17.51 |
| Cyclical Consumer Services | 4 | 1.84 | 19.35 |
| Energy - Fossil Fuels | 22 | 10.14 | 29.49 |
| Food & Beverages | 8 | 3.69 | 33.18 |
| Healthcare Services & Equipment | 2 | 0.92 | 34.10 |
| Industrial & Commercial Services | 26 | 11.98 | 46.08 |
| Industrial Goods | 14 | 6.45 | 52.53 |
| Mineral Resources | 21 | 9.68 | 62.21 |
| Personal & Household Products & Services | 2 | 0.92 | 63.13 |
| Pharmaceuticals & Medical Research | 5 | 2.30 | 65.44 |
| Real Estate | 14 | 6.45 | 71.89 |
| Renewable Energy | 3 | 1.38 | 73.27 |
| Retailers | 5 | 2.30 | 75.58 |
| Software & IT Services | 9 | 4.15 | 79.72 |
| Technology Equipment | 12 | 5.53 | 85.25 |
| Telecommunications Services | 1 | 0.46 | 85.71 |
| Transportation | 9 | 4.15 | 89.86 |
| Utilities | 22 | 10.14 | 100.00 |
| Total | 217 | 100.00 | |

***Table A19|TRBC business sector split – Climate change exposure green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 8 | 3.69 | 3.69 |
| Automobiles & Auto Parts | 11 | 5.07 | 8.76 |
| Chemicals | 10 | 4.61 | 13.36 |
| Consumer Goods Conglomerates | 1 | 0.46 | 13.82 |
| Cyclical Consumer Products | 6 | 2.76 | 16.59 |
| Energy - Fossil Fuels | 29 | 13.36 | 29.95 |
| Food & Beverages | 1 | 0.46 | 30.41 |
| Industrial & Commercial Services | 23 | 10.60 | 41.01 |
| Industrial Goods | 28 | 12.90 | 53.92 |
| Mineral Resources | 27 | 12.44 | 66.36 |
| Real Estate | 5 | 2.30 | 68.66 |
| Renewable Energy | 9 | 4.15 | 72.81 |
| Retailers | 4 | 1.84 | 74.65 |
| Software & IT Services | 3 | 1.38 | 76.04 |
| Technology Equipment | 10 | 4.61 | 80.65 |
| Telecommunications Services | 1 | 0.46 | 81.11 |
| Transportation | 6 | 2.76 | 83.87 |
| Utilities | 35 | 16.13 | 100.00 |
| Total | 217 | 100.00 | |

***Table A20|TRBC business sector split – Climate change exposure brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC BUSI SEC NAME | Freq. | Percent | Cum. |
|---|---|---|---|
| Academic & Educational Services | 1 | 0.46 | 0.46 |
| Applied Resources | 1 | 0.46 | 0.92 |
| Chemicals | 1 | 0.46 | 1.38 |
| Consumer Goods Conglomerates | 1 | 0.46 | 1.84 |
| Cyclical Consumer Products | 7 | 3.23 | 5.07 |
| Cyclical Consumer Services | 28 | 12.90 | 17.97 |
| Food & Beverages | 5 | 2.30 | 20.28 |
| Food & Drug Retailing | 5 | 2.30 | 22.58 |
| Healthcare Services & Equipment | 27 | 12.44 | 35.02 |
| Industrial & Commercial Services | 16 | 7.37 | 42.40 |
| Industrial Goods | 7 | 3.23 | 45.62 |
| Mineral Resources | 1 | 0.46 | 46.08 |
| Personal & Household Products & Services | 1 | 0.46 | 46.54 |
| Pharmaceuticals & Medical Research | 26 | 11.98 | 58.53 |
| Real Estate | 9 | 4.15 | 62.67 |
| Retailers | 13 | 5.99 | 68.66 |
| Software & IT Services | 46 | 21.20 | 89.86 |
| Technology Equipment | 11 | 5.07 | 94.93 |
| Telecommunications Services | 3 | 1.38 | 96.31 |
| Transportation | 8 | 3.69 | 100.00 |
| Total | 217 | 100.00 | |