**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. We also utilize TRBC codes as a granular sector/technology classification to measure transition risk. We find a strong divergence in transition risk metrics for similar companies. Most notably, taxonomy-based risk measures are negatively correlated with inverted emissions and uncorrelated to E-scores. Next, we also evaluate the different transition risk proxies. Our empirical approach uses the return sensitivity of 6 transition risk metric based Brown Minus Green portfolios against news-based 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 ultimately measure climate transition risk of firms. We find that only taxonomy and TRBC based portfolios are able to measure green firms' climate transition risk. Interestingly, no chosen risk metric is able to create a brown portfolio, which is significantly related to transition risk shocks. We make 4 key contributions. First, we empirically compare different proxies for climate transition risk with the most comprehensive dataset available. Second, we provide recommendations on which transition risk metric performs better/worse and under which circumstances. Third, we propose an approach for evaluating the quality of transition risk measures, which can also be utilized for comparing other risk measures. Finally, we are also able to explain why certain portfolios do not react to climate transition risk shocks. Most notably, emission based green portfolios are highly invested in service, technology and finance, not typical green sectors enabling the transition. Our findings are relevant for all stakeholders on global financial markets who want to accurately measure the brown and green exposure 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, 2020), emission intensities (Ardia et al., 2022; Aswani et al., 2024), estimated taxonomy alignments (Bassen et al., 2022) 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 our step 1 exercise, 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.

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 develop:

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 are no valid measure for either brown or 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.

H7: *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. We are able to collect 6 different transition risk metrics for European firms featuring the most utilized metrics (scope 1-2- and scope 1-3 emission intensities as well as E scores) as well as promising metrics (TRBC codes 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 6 original 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. Moreover, we find that firms with higher $CO_2$ emissions have higher 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 that is able to capture firms' transition risk. 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 the data on transition risk shocks to analyze the sensitivity of Brown Minus Green (BMG) portfolio stock returns to transition shocks. In the baseline analysis we create 6 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 scope 1-2 emission intensity, total emission intensity or E-scores react to unexpected transition risk shocks in no specification, putting large question marks behind their reliability and validity as transition risk proxies. BMG portfolios based on either TRBC or taxonomy alignment of revenues/capex show the expected signs but fail to consistently produce significant estimates. This is largely due to their inability to produce brown portfolios which react systematically to transition risk shocks. However, they 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 do not accurately measure climate transition risk and scholars should explore alternative 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, both E-scores and emission-based portfolio feature many companies in the service, technology, and financial sectors, which are not actual green sectors highly affected by transition risk shocks. TRBC and taxonomy-based portfolios on the other hand are highly 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. We therefore propose to use newly available transition risk proxies such as EU taxonomy alignment or sector technology classifications. Moreover, we find that mixing existing metrics can improve the performance of singular climate transition risk metrics.

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. 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 climate transition risk shock index and find conflicting evidence. They validate their index with decarbonization- and sectoral GMB indices and find that only pure play sectoral, but not emission-based portfolios significantly react to transition risk shocks. Most closely related to our study, Bua et al. (2022) construct a physical and a transition risk index. They test the sensitivity of this index and find mostly insignificant results. Only E(SG) and emission intensity based green portfolios react marginally significant to transition risks 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 wanted to validate their transition risk shock indices. Moreover, we employ a wider range of transition risk metrics including EU taxonomy alignment 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 find a similar effect for the introduction of the US inflation reduction act or Ramelli et al. (2021) who show a negative 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 international equity markets. Some authors found a brown or carbon premium mostly using emission data (Alessi et al., 2021; Bolton & Kacperczyk, 2021; Bolton & Kacperczyk, 2020; 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 alignment-based risk metrics 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

We create and combine multiple large datasets. First, we download taxonomy related company information for European firms with more than 10 million $ in annual sales from Bloomberg for the fiscal year 2022, as the regulation only targets large, listed European firms. Based on ISINs we match data from Refinitiv EIKON to the Bloomberg dataset. Most notably, we add information on companies ESG scores, CO2 emissions, TRBC codes, weekly/monthly stock returns as well as financial information. The overall data availability varies significantly depending on the transition risk metric. Overall our combined dataset contains 5664 European companies. While all companies have TRBC codes, only 211 can be classified as brown and 100 as green. Concerning emission data, 1237 firms have information on scope 1 emission data, 1250 on scope 2 and 980 on scope 3. A roughly similar number of firms (1295) has information on taxonomy revenue risk, that is both eligibility and alignment data. However, of this relatively large number only 313 firms have more than 50% of their revenues exposed to economic activities covered by the taxonomy. 1209 enterprises have taxonomy capex risk data and 407 are more than 50% exposed. Finally, E-scores are available for 1575 firms.

To enlarge the sample size and increase the external validity of the results, we also extend the analysis to global companies. For the second dataset, we therefore drop the taxonomy data restriction and only download ESG scores, CO2 emissions, TRBC codes, stock returns and companies' financial information from Refinitiv EIKON. We limit the universe of companies to active, listed firms with ISIN, and at least 500 million USD in 2022 revenues. Thereby we can increase the sample size substantially to 14,856 ISINs.

Additional to the EIKON and Bloomberg download we also rely on widely used asset pricing factors. For the baseline specification we use the European factors from Kenneth French's Online Data Library[3] and combine them with weekly/monthly return information of the STOXX Europe 600 from EIKON. As there are no specific European weekly financial factors we must rely on the Fama French factors for the US. For the global dataset we use the developed factors, since most of the companies in the dataset are located in developed economies. Finally, we also use the climate 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.

In line with previous work, we winsorize all return data and all emission data at the 1% level in order to reduce the effect of frequent databank specific errors and outliers. As taxonomy eligibility and alignment cannot exceed 100%, we winsorize the taxonomy data at 0% and 100%. E scores are also trimmed above 100 and below 0. 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.

## 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 6 climate transition risk metrics: Discretized TRBC sector/technology classification, scope 1-2 emission intensities, scope 1-3 emissions intensities, environmental pillar scores, taxonomy alignment of revenues and finally taxonomy alignment of capital expenditures.

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

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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.

Overall, we construct 6 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:

$$(2.1) \qquad R_{jt} = (R_{bt} - RF_t) - (R_{gt} - RF_t)$$

Where $R_{jt}$ is the monthly or weekly return of a BMG portfolio j. $RF_t$ is the risk-free rate of return. We use both value- as well as equally weighted 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 able to recognize brown or green companies but are not an adequate risk metric for the other side of the transition risk spectrum.

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 both on a monthly and weekly frequency:

$$(2.2) \qquad R_{it} - RF_t = \alpha_i + \beta_{1i}(RM_{kt} - RF_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \beta_{6i}TRI\_Innovation_t + \epsilon_{it}$$

$RM_{kt}$ is the return of market portfolio k 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). $\alpha_i$ is the constant, indicating whether a portfolio outperforms the market, even when controlling for risk factors. Our main variable of interest is $\beta_{6i}$ as the coefficient indicates whether transition risk shocks significantly explain the returns of our portfolios.

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 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 more 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, whereas emissions and E scores are scoring 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 from Refinitiv EIKON. 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. The 60% in between are classified as neutral.

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 E scores from Refinitiv EIKON 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.

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 policy sensitive, examples are the health, technology or service sector. Details can be obtained in table A2 of the Appendix.

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 fossil fuel companies we drop the 50% taxonomy eligibility criteria and formulate a new taxonomy risk calculation rule:

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

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 1 depicts the summary statistics for the monthly value weighted returns. Table A2 in Appendix 7.2 shows the descriptive statistics for the weekly returns, our second empirical specification.

***Table 1|Summary statistics for the time series of monthly 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. Authors' own illustration with data from the Thomson Reuters Eikon database. All returns are in percentages.*

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Brown TRBC | 132 | .587 | 5.095 | -18.907 | 22.712 |
| Brown Tax. Revenue | 132 | 1.142 | 6.342 | -17.763 | 19.317 |
| Brown Tax. Capex | 132 | 1.207 | 5.623 | -17.824 | 16.679 |
| Brown Emission Intensity | 132 | .949 | 4.763 | -18.757 | 17.016 |
| Brown Scope 1-2 Intensity | 132 | .859 | 4.551 | -17.502 | 17.409 |
| Brown E Score | 132 | 1.902 | 5.198 | -17.206 | 27.638 |
| Brown Emission Intensity TRBC | 132 | 1.053 | 5.033 | -21.212 | 17.773 |
| Brown Tax. Revenue TRBC | 132 | .578 | 5.462 | -15.892 | 22.053 |
| Brown Tax. Capex TRBC | 132 | .598 | 5.267 | -17.273 | 20.428 |
| Green TRBC | 132 | 1.57 | 4.841 | -14.982 | 16.981 |
| Green Tax. Revenue | 132 | 1.378 | 3.9 | -13.099 | 10.017 |
| Green Tax. Capex | 132 | 1.019 | 4.456 | -15.642 | 12.159 |
| Green Emission Intensity | 132 | .833 | 5.448 | -23.019 | 21.633 |
| Green Scope 1-2 Intensity | 132 | 1.127 | 4.913 | -19.074 | 15.889 |
| Green E Score | 132 | .886 | 4.232 | -16.384 | 16.233 |
| Green Emission Intensity TRBC | 132 | .973 | 4.115 | -17.32 | 15.652 |
| Green Tax. Revenue TRBC | 132 | 1.308 | 4.007 | -15.167 | 10.721 |
| Green Tax. Capex TRBC | 132 | .992 | 4.631 | -17.319 | 13.23 |
| Market Factor | 132 | .66 | 3.92 | -14.545 | 13.844 |
| 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 | 0.0003 | -.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 2 show a very large divergence. Within emission based and taxonomy-based metrics, there is some divergence as well, however, the correlation is overall positive. The taxonomy-based risk metrics correlate with rank correlations above 0.5. The scope 1-2 and scope 1-3 emission intensities correlate strongly but the rank correlation of 0.6 also indicates that it plays a major role whether scope 3 emissions are included into the analysis. The between risk metric divergence is extreme. 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. 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 2|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. All taxonomy specific risk measures exclude companies with below with 50% taxonomy eligibility. TRBC codes are discretized with brown companies=1, neutral=2 and green=3 – details of the brown/green categorization in Appendix 7.1. All data relates to the fiscal year 2022.*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) Tax. Revenue alignment | 1.000 | | | | | | |
| (2) Tax. Capex alignment | 0.637 | 1.000 | | | | | |
| (3) Tax. Opex alignment | 0.773 | 0.698 | 1.000 | | | | |
| (4) Total Emission Intensity | -0.055 | -0.209 | -0.131 | 1.000 | | | |
| (5) Scope 1-2 Emission Intensity | -0.092 | -0.195 | -0.210 | 0.609 | 1.000 | | |
| (6) TRBC | 0.076 | -0.112 | -0.021 | 0.220 | 0.194 | 1.000 | |
| (7) E Score | 0.134 | 0.166 | 0.190 | -0.313 | -0.271 | -0.107 | 1.000 |

In the core specification we follow our rules from the portfolio construction and only calculate the taxonomy alignment-based transition risk measures when the taxonomy eligibility exceeds 50%, since the taxonomy risk metrics loose significant power for companies which are barely exposed to the taxonomy. In table A3 of the Appendix we also show results without the 50% threshold. Rank correlation results are roughly comparable. To increase the n per correlation, we also perform pairwise as opposed to listwise deletion and find roughly comparable results. We also compare the rank correlation with Pearson's correlation coefficient. Results can be obtained in table A4 and are once more aligned with the rank correlation results. In order to increase the external validity of results, we also repeat the analysis with the global dataset for 2022. Table 3 shows the results, which are highly comparable to the European risk metric correlations. Again, neither pairwise nor listwise deletion of missing data alters the results significantly

***Table 3|Results for Spearman's rank correlation coefficient.*** *The table shows the rank correlation with listwise deletion between 4 global transition risk metrics. All data relates to the fiscal year 2022.*

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| (1) Total Emission Intensity | 1.000 | | | |
| (2) Scope 1-2 Emission Intensity | 0.703 | 1.000 | | |
| (3) TRBC | 0.175 | 0.132 | 1.000 | |
| (4) E Score | -0.142 | -0.120 | -0.078 | 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 4, we find that only taxonomy alignment of revenues can produces portfolios which show significantly the expected (negative) sign of the TRI innovation coefficient. While the coefficient estimates for both the TRBC and the taxonomy capex portfolio are large and negative, they are not significant. Few other pricing factors can significantly explain the returns of the portfolios, the market factor as well as the RMW and CMA factor being the exception for some specifications.

*Table 4 | 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 |
|---|---|---|---|---|---|---|
| Market | 0.214** | 0.652*** | 0.497*** | 0.093* | -0.030 | 0.057 |
| | (0.095) | (0.111) | (0.106) | (0.054) | (0.049) | (0.055) |
| SMB | -0.750*** | -0.027 | 0.542** | 0.015 | -0.197** | 1.083*** |
| | (0.189) | (0.220) | (0.209) | (0.106) | (0.098) | (0.137) |
| HML | 0.434* | 0.148 | -0.171 | -0.283** | 0.170 | 0.079 |
| | (0.248) | (0.289) | (0.274) | (0.139) | (0.144) | (0.183) |
| RMW | 0.051 | -0.511 | -0.427 | 0.747*** | 0.918*** | -0.195 |
| | (0.328) | (0.383) | (0.363) | (0.184) | (0.187) | (0.196) |
| CMA | 0.418 | -0.749* | -0.516 | 0.248 | 0.454** | -0.752*** |
| | (0.344) | (0.402) | (0.381) | (0.193) | (0.218) | (0.233) |
| TRI Innovation | -1,515.787 | -2,471.687** | -1,310.963 | 190.503 | 845.472* | -402.247 |
| | (1,017.766) | (1,188.695) | (1,126.748) | (571.257) | (487.528) | (547.107) |
| Constant | -0.783** | -0.665* | -0.362 | -0.338* | -0.415** | 0.606*** |
| | (0.334) | (0.390) | (0.370) | (0.187) | (0.163) | (0.187) |
| #Companies | 144 | 80 | 114 | 374 | 484 | 628 |
| R-squared | 0.326 | 0.373 | 0.257 | 0.391 | 0.312 | 0.541 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The reasons why the TRBC and taxonomy capex portfolios cannot produce significantly negative coefficient estimates for the TRI climate transition risk shock coefficient can be found in the long brown portfolios, which are highlighted in table 5. Results show that no portfolio is significantly negatively exposed to the TRI innovation factor and only the taxonomy revenue portfolio has a negative coefficient, indicating that negative news on transition risk 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 is not priced in financial markets.

*Table 5|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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** |
|---|---|---|---|---|---|---|
| Market | 0.923*** | 1.231*** | 1.108*** | 1.024*** | 0.968*** | 0.986*** |
| | (0.059) | (0.101) | (0.075) | (0.044) | (0.041) | (0.064) |
| SMB | -0.219* | 0.211 | 0.328** | 0.151 | -0.020 | 0.964*** |
| | (0.119) | (0.193) | (0.143) | (0.098) | (0.105) | (0.155) |
| HML | 0.892*** | 0.502** | 0.403* | 0.402*** | 0.423*** | 0.411* |
| | (0.181) | (0.253) | (0.219) | (0.136) | (0.127) | (0.209) |
| RMW | 0.892*** | 0.070 | 0.134 | 0.271 | 0.466** | 0.075 |
| | (0.265) | (0.371) | (0.348) | (0.213) | (0.222) | (0.230) |
| CMA | -0.010 | -0.966*** | -0.600* | -0.322 | -0.050 | -0.873*** |
| | (0.288) | (0.336) | (0.327) | (0.212) | (0.215) | (0.312) |
| TRI Innovation | 1,131.590* | -54.915 | 915.253 | 735.558 | 1,349.352* | 462.321 |
| | (587.171) | (797.103) | (973.482) | (551.934) | (692.429) | (451.455) |
| Constant | 0.068 | 0.251 | 0.405 | 0.244 | 0.239 | 0.978*** |
| | (0.220) | (0.321) | (0.292) | (0.169) | (0.177) | (0.224) |
| #Companies | 103 | 40 | 58 | 187 | 242 | 314 |
| R-squared | 0.790 | 0.727 | 0.723 | 0.845 | 0.834 | 0.783 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Turning to the green portfolios in table 6, both taxonomy portfolios as well as the TRBC portfolio are significantly positively exposed to the TRI factor. In other words, these portfolio returns increase when climate concern increases, which is in line with our expectation. No emission-based risk metric reacts significantly to transition shocks and the E-score based portfolio only reacts in a marginally significant way.

*Table 6|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 |
|---|---|---|---|---|---|---|
| Market | 0.713*** | 0.582*** | 0.613*** | 0.934*** | 1.001*** | 0.932*** |
| | (0.098) | (0.063) | (0.072) | (0.059) | (0.055) | (0.037) |
| SMB | 0.541*** | 0.247 | -0.205 | 0.145 | 0.186* | -0.110 |
| | (0.193) | (0.169) | (0.185) | (0.152) | (0.108) | (0.093) |
| HML | 0.458* | 0.354* | 0.575** | 0.685*** | 0.253* | 0.332*** |
| | (0.254) | (0.190) | (0.231) | (0.169) | (0.142) | (0.104) |
| RMW | 0.850** | 0.590** | 0.570* | -0.467** | -0.443** | 0.279* |
| | (0.336) | (0.274) | (0.331) | (0.222) | (0.189) | (0.154) |
| CMA | -0.418 | -0.206 | -0.074 | -0.560** | -0.494** | -0.111 |
| | (0.353) | (0.312) | (0.352) | (0.226) | (0.198) | (0.158) |
| TRI Innovation | 2,661.966** | 2,431.360** | 2,240.804** | 559.644 | 518.469 | 879.156* |
| | (1,043.615) | (947.885) | (1,046.285) | (667.590) | (584.881) | (489.478) |
| Constant | 0.803** | 0.868*** | 0.719** | 0.535** | 0.607*** | 0.324** |
| | (0.342) | (0.273) | (0.305) | (0.225) | (0.192) | (0.143) |
| #Companies | 41 | 40 | 56 | 187 | 242 | 314 |
| R-squared | 0.459 | 0.455 | 0.478 | 0.837 | 0.835 | 0.880 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In tables A 6-8 of the Appendix, we repeat the analysis for weekly frequencies. The results are roughly comparable. Only the TRBC based BMG factor is significantly exposed to the TRI innovation factor. Focusing on the green portfolios, only the TRBC and the taxonomy revenue portfolio react significantly positively to transition risk shocks. All other portfolios show the expected positive sign but fail to produce significant and large coefficients.

### 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 7, we have 4 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. Both BMG and the long brown portfolio can be obtained in the Appendix. The global results largely reiterate our aforementioned findings that most transition risk metric-based portfolios do not react strongly to unexpected transition risk events. Solely the TRBC based portfolio correlate (marginally) significantly with the TRI factor with the expected positive signs. Neither emission- or E-score based portfolio react significantly to climate transition risk shocks.

***Table 7|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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** |
|---|---|---|---|---|
| Market | 0.912*** | 0.917*** | 0.869*** | 0.851*** |
| | (0.122) | (0.049) | (0.050) | (0.030) |
| SMB | 0.637** | -0.218* | -0.234* | -0.204** |
| | (0.295) | (0.122) | (0.125) | (0.089) |
| HML | -0.004 | 0.671*** | 0.462*** | 0.245*** |
| | (0.299) | (0.163) | (0.147) | (0.092) |
| RMW | -0.108 | -0.337* | -0.312* | 0.048 |
| | (0.441) | (0.201) | (0.182) | (0.136) |
| CMA | -1.010** | -0.698*** | -0.709*** | -0.369** |
| | (0.448) | (0.222) | (0.237) | (0.150) |
| TRI Innovation | 2,369.736* | 464.565 | 499.086 | 625.513 |
| | (1,297.080) | (394.112) | (353.130) | (391.873) |
| Constant | 1.000*** | 0.437*** | 0.532*** | 0.400*** |
| | (0.377) | (0.162) | (0.156) | (0.130) |
| #Companies | 211 | 212 | 336 | 1050 |
| R-squared | 0.549 | 0.876 | 0.856 | 0.886 |

(Robust) standard errors 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 8 highlights key results for the monthly value weighted specification. Again, the BMG and the brown results can be obtained in the Appendix. We see that both 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 marginally significantly related to the TRI factor. Excluding many heavily weighted companies in non-climate sensitive sectors thus appear to substantially increase the ability of emission-based transition risk metrics to form green portfolios.

*Table 8|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| VARIABLES | (1)<br>Green Emission Intensity TRBC | (2)<br>Green Taxonomy Revenue TRBC | (3)<br>Green Taxonomy Capex TRBC |
|---|---|---|---|
| Market | 0.894*** | 0.666*** | 0.648*** |
| | (0.052) | (0.075) | (0.073) |
| SMB | 0.445*** | 0.355** | -0.252 |
| | (0.103) | (0.149) | (0.199) |
| HML | 0.283** | 0.302 | 0.652*** |
| | (0.135) | (0.196) | (0.238) |
| RMW | 0.566*** | 0.514** | 0.660* |
| | (0.179) | (0.259) | (0.336) |
| CMA | -0.016 | -0.141 | -0.060 |
| | (0.187) | (0.272) | (0.369) |
| TRI Innovation | 996.372* | 2,501.157*** | 2,212.746** |
| | (553.820) | (804.822) | (1,068.495) |
| Constant | 0.187 | 0.741*** | 0.678** |
| | (0.182) | (0.264) | (0.306) |
| #Companies | 71 | 53 | 68 |
| R-squared | 0.789 | 0.531 | 0.508 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 3.5 Explaining the divergence – looking into portfolio constituents

So far, we showed that climate transition risk metrics diverge significantly for similar companies/portfolios. Moreover, we evaluated 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 portfolios split by TRBC business sector, results can be obtained in Appendix section 7.8. Most notably, both 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 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, mineral resources or chemicals. 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-$CO_2$ steel, aluminum or cement. Taxonomy based brown companies are more dispersed across business sectors. Interestingly, 15-20% of 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 companies 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 only transition risk metrics in differentiating between green and transition risk neutral companies. Most notably, most companies in the emission based green portfolios are in banking, insurance, 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. In other words, why should the stocks of Accenture or Allianz (some of the largest constituents of the emission based green portfolio) react significantly to climate related news events such as the Paris Agreement? 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 do not react to unexpected transition risk 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 9|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 |
|---|---|---|---|---|---|---|
| Market | 0.216** | 0.656*** | 0.499*** | 0.093* | -0.031 | 0.058 |
| | (0.096) | (0.113) | (0.106) | (0.054) | (0.049) | (0.055) |
| SMB | -0.745*** | -0.019 | 0.546** | 0.015 | -0.200** | 1.084*** |
| | (0.189) | (0.223) | (0.209) | (0.121) | (0.099) | (0.135) |
| HML | 0.408 | 0.106 | -0.194 | -0.280* | 0.185 | 0.072 |
| | (0.248) | (0.292) | (0.274) | (0.153) | (0.144) | (0.182) |
| RMW | 0.037 | -0.534 | -0.439 | 0.749*** | 0.926*** | -0.199 |
| | (0.330) | (0.388) | (0.364) | (0.199) | (0.191) | (0.195) |
| CMA | 0.446 | -0.705* | -0.493 | 0.244 | 0.438* | -0.745*** |
| | (0.345) | (0.406) | (0.381) | (0.213) | (0.222) | (0.233) |
| Constant | -0.742** | -0.599 | -0.327 | -0.343* | -0.438*** | 0.617*** |
| | (0.334) | (0.394) | (0.369) | (0.183) | (0.160) | (0.186) |
| #Companies | 144 | 80 | 114 | 374 | 484 | 628 |
| R-squared | 0.314 | 0.351 | 0.249 | 0.391 | 0.297 | 0.539 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As depicted in table 9, there is a large variation in alpha coefficient estimates ranging from positive and highly significant estimates for the E-score to negative coefficient estimates for the TRBC and emission-based portfolios. The taxonomy-based portfolios 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 10, we also, again, replicate our findings on a global scale. Results are comparable. The alpha estimates for the TRBC portfolio are even larger compared to the European dataset. The emission-based variables are also producing negative and significant alphas. The E-score BMG portfolio outperforms the market marginally while the mixed metric TRBC-emission portfolio is priced in line with the market, indicating that services or tech stocks potentially drive the negative alpha estimates in the emission only portfolios. Again, how climate transition risk is priced, mainly depends on how you define and measure climate transition risk.

***Table 10|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 Emission Intensity TRBC |
|---|---|---|---|---|---|
| Market | -0.038 | 0.019 | -0.049 | -0.057 | 0.019 |
| | (0.123) | (0.034) | (0.040) | (0.052) | (0.047) |
| SMB | -0.532* | 0.265*** | 0.344*** | 0.602*** | -0.069 |
| | (0.319) | (0.099) | (0.116) | (0.152) | (0.139) |
| HML | 0.607** | -0.170 | -0.041 | -0.098 | 0.259* |
| | (0.303) | (0.103) | (0.126) | (0.158) | (0.144) |
| RMW | 0.348 | 0.339** | 0.375** | -0.453* | -0.252 |
| | (0.457) | (0.151) | (0.157) | (0.232) | (0.212) |
| CMA | 0.752* | 0.229 | 0.149 | -0.483* | -0.454* |
| | (0.413) | (0.167) | (0.255) | (0.257) | (0.235) |
| Constant | -1.048*** | -0.299** | -0.352** | 0.386* | -0.080 |
| | (0.388) | (0.144) | (0.149) | (0.221) | (0.202) |
| #Companies | 942 | 424 | 672 | 2100 | 162 |
| R-squared | 0.172 | 0.124 | 0.118 | 0.199 | 0.079 |

(Robust) standard errors 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, 388 companies remain with full data availability. Results are reported in table 11 and show a high degree of comparability to the baseline results in table 4, if anything, TRI innovation estimates are substantially larger in magnitude for both taxonomy and TRBC based portfolios. Coefficient estimates for both emissions based as well as the E-score based portfolios are insignificant. Note, that the amount of companies per portfolio is smaller for the taxonomy-based portfolios since only companies with above 50% taxonomy eligibility are included in these portfolios.

*Table 11| Monthly BMG 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 |
|---|---|---|---|---|---|---|
| Market | 0.141 | 0.905*** | 0.488*** | 0.128** | -0.021 | -0.046 |
| | (0.174) | (0.142) | (0.122) | (0.052) | (0.065) | (0.068) |
| SMB | -1.265*** | 0.237 | 0.670*** | -0.038 | 0.044 | 0.916*** |
| | (0.344) | (0.280) | (0.241) | (0.102) | (0.128) | (0.134) |
| HML | 0.412 | 0.194 | -0.269 | 0.381*** | 0.435** | -0.395** |
| | (0.452) | (0.368) | (0.316) | (0.134) | (0.168) | (0.176) |
| RMW | 0.766 | -0.507 | -0.493 | 0.257 | 0.004 | -0.788*** |
| | (0.599) | (0.487) | (0.419) | (0.178) | (0.222) | (0.233) |
| CMA | 0.733 | -0.712 | -0.661 | 0.186 | 0.079 | -0.482* |
| | (0.628) | (0.511) | (0.440) | (0.187) | (0.233) | (0.244) |
| TRI Innovation | -3,063.660 | -3,450.250** | -1,376.292 | -38.702 | 512.332 | -371.415 |
| | (1,857.158) | (1,510.798) | (1,300.206) | (551.796) | (689.364) | (723.145) |
| Constant | -0.784 | -1.057** | -0.448 | -0.594*** | -0.341 | 0.262 |
| | (0.609) | (0.496) | (0.426) | (0.181) | (0.226) | (0.237) |
| #Companies | 35 | 42 | 56 | 156 | 156 | 156 |
| R-squared | 0.174 | 0.396 | 0.224 | 0.283 | 0.209 | 0.394 |

(Robust) Standard errors 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. However, 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 support for hypothesis 6, since E-score portfolios show no significant reaction to transition risk shocks. These results are partly at odds with previous findings in the literature by both Bua et al. (2022) for green portfolios based on E-scores and emissions as well as Ardia et al. (2022), who find that emission intensity-based portfolios react to transition risk shocks. We cannot show that either emission or E-scores 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 7, 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 portfolios, which react negatively to positive transition risk shocks. Therefore, we assert that mixed metrics are promising and should be further tested as they potentially can overcome risk metric specific shortcomings.

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 argue that 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 and taxonomy alignment of revenues appear to be well suited to detect green companies' climate transition risk. However, no tested transition risk proxy can form 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. We thus argue that the pricing debate can only be reconciled when agreeing on a valid science-based transition risk measure. This paper contributes towards this objective by showing that TRBC or taxonomy-based risk metrics are well suited to measure green firms transition risk. We are thus confident to conclude that green stocks, measured through transition risk metrics that actually react to transition risk shocks, show a robust outperformance across our time frame in line with previous findings using technology-based transition risk metrics (Fliegel, 2023; Jourde & Stalla-Bourdillon, 2023). The pricing results for brown firms transition risk are less clear due to our inability to find a robust transition risk metric for brown companies.

## 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 reported 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 for both emission-based metrics, TRBC and E-scores 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, 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 and sector/technology classifications are strong in measuring green firms' climate transition risk, but show weaknesses in measuring brown companies' climate transition risk. 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. 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. Scholars should also try new transition risk metrics such as the EU taxonomy, business technology classifications or innovative mixes of multiple transition risk measures. Future research may repeat the two-step analysis using data sources for which we did not have access to. Most notably, Trucost emissions data and MSCI E-score are widely used transition risk data foundations which should be evaluated. Finally, while the current study analyzed bundled transition risk, future studies may also want to differentiate between policy, technology, litigation or preference driven climate transition risk since, potentially, certain transition risk measure react stronger/weaker to specific kinds of transition risk.

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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 |
| Auto & Truck Wholesale | Automotive Batteries |
| Automobiles & Multi Utility Vehicles | Biodiesel |
| Coal | Biomass & Biogas Fuels |
| Coal Wholesale | Electrical (Alternative) Vehicles |
| Fossil Fuel Electric Utilities | Ethanol Fuels |
| Gasoline Stations | Geothermal Electric Utilities |
| 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 Ultilities |
| 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 | |
| Oil Exploration & Production - Onshore | |
| Oil Pipeline Transportation | |
| Oil Related - Surveying & Mapping Services | |
| 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 | |
| Unconventional Oil & Gas Production | |
| Coke Coal Mining | |
| Natural Gas Exploration & Production - Offshore | |

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 which are climate sensitive as well as all other sectors*

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

## 7.2 Summary statistics for the weekly returns

***Table A3|Summary statistics for the time series of weekly 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. Authors' own illustration with data from the Thomson Reuters Eikon database. All returns are in percentages.*

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Brown TRBC | 574 | .152 | 2.841 | -24.549 | 14.213 |
| Brown Tax. Revenue | 574 | .279 | 3.22 | -15.377 | 15.244 |
| Brown Tax. Capex | 574 | .289 | 2.998 | -20.238 | 14.173 |
| Brown Emission Intensity | 574 | .232 | 2.607 | -18.923 | 9.894 |
| Brown Scope 1-2 Intensity | 574 | .212 | 2.466 | -19.63 | 8.964 |
| Brown E Score | 574 | .441 | 2.228 | -14.391 | 13.16 |
| Brown Emission Intensity TRBC | 574 | .253 | 2.728 | -17.497 | 11.439 |
| Brown Tax. Revenue TRBC | 574 | .16 | 2.913 | -22.077 | 12.863 |
| Brown Tax. Capex TRBC | 574 | .156 | 2.89 | -24.492 | 12.698 |
| Green TRBC | 574 | .374 | 2.395 | -17.757 | 7.902 |
| Green Tax. Revenue | 574 | .327 | 2.068 | -17.87 | 6.912 |
| Green Tax. Capex | 574 | .245 | 2.367 | -20.395 | 8.828 |
| Green Emission Intensity | 574 | .21 | 2.844 | -16.218 | 11.467 |
| Green Scope 1-2 Intensity | 574 | .275 | 2.614 | -16.895 | 11.424 |
| Green E Score | 574 | .219 | 2.353 | -17.349 | 8.932 |
| Green Emission Intensity TRBC | 574 | .238 | 2.198 | -16.167 | 9.1 |
| Green Tax. Revenue TRBC | 574 | .299 | 2.246 | -18.872 | 7.342 |
| Green Tax. Capex TRBC | 574 | .237 | 2.443 | -20.78 | 8.602 |
| Market Factor | 574 | .162 | 2.381 | -18.454 | 8.704 |
| SMB Factor | 574 | .02 | 1.201 | -5.75 | 6.13 |
| HML Factor | 574 | -.097 | 1.532 | -8.51 | 9.81 |
| TRI weekly innovation | 574 | 0 | .001 | -.011 | .002 |

## 7.3 Sensitivity Analysis: Correlations

***Table A4|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. All companies with above 0% taxonomy eligibility are included. All data relates to the fiscal year 2022.*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) Tax. Revenue alignment | 1.000 | | | | | | |
| (2) Tax. Capex alignment | 0.728 | 1.000 | | | | | |
| (3) Tax. Opex alignment | 0.782 | 0.783 | 1.000 | | | | |
| (4) Total Emission Intensity | -0.257 | -0.272 | -0.295 | 1.000 | | | |
| (5) Scope 1-2 Emission Intensity | -0.274 | -0.294 | -0.319 | 0.619 | 1.000 | | |
| (6) TRBC | -0.086 | -0.125 | -0.108 | 0.220 | 0.189 | 1.000 | |
| (7) E Score | 0.242 | 0.318 | 0.263 | -0.312 | -0.251 | -0.112 | 1.000 |

***Table A5|Results for Pearson's correlation coefficient.*** *The table shows the correlation with pairwise deletion between all European transition risk metrics employed in this study as well as the opex alignment. Significance levels are in parentheses. All taxonomy specific risk measures exclude companies with below with 50% taxonomy eligibility. All data relates to the fiscal year 2022.*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) Tax. Revenue alignment | 1.000 | | | | | | |
| (2) Tax. Capex alignment | 0.638 | 1.000 | | | | | |
| | (0.000) | | | | | | |
| (3) Tax. Opex alignment | 0.766 | 0.693 | 1.000 | | | | |
| | (0.000) | (0.000) | | | | | |
| (4) Total Emission Intensity | 0.007 | -0.072 | -0.004 | 1.000 | | | |
| | (0.876) | (0.138) | (0.938) | | | | |
| (5) Scope 1-2 Emission Intensity | -0.030 | -0.102 | -0.099 | 0.191 | 1.000 | | |
| | (0.460) | (0.015) | (0.018) | (0.000) | | | |
| (6) TRBC | 0.160 | -0.050 | 0.029 | 0.065 | 0.098 | 1.000 | |
| | (0.000) | (0.071) | (0.293) | (0.047) | (0.001) | | |
| (7) E Score | 0.120 | 0.167 | 0.179 | -0.061 | 0.047 | -0.092 | 1.000 |
| | (0.001) | (0.000) | (0.000) | (0.064) | (0.103) | (0.000) | |

## 7.4 Weekly value weighted portfolios

***Table A6| Weekly 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| **VARIABLES** | **(1)<br>BMG<br>TRBC** | **(2)<br>BMG Tax.<br>Revenue** | **(3)<br>BMG Tax.<br>Capex** | **(4)<br>BMG Emission<br>Intensity** | **(5)<br>BMG Scope 1-2<br>Emission Intensity** | **(6)<br>BMG<br>E-Score** |
|---|---|---|---|---|---|---|
| Market | 0.255*** | 0.452*** | 0.220*** | -0.011 | -0.026 | -0.211*** |
| | (0.039) | (0.081) | (0.050) | (0.022) | (0.028) | (0.033) |
| SMB | 0.110 | 0.272*** | 0.368*** | 0.077* | 0.015 | 0.215*** |
| | (0.077) | (0.098) | (0.078) | (0.042) | (0.042) | (0.056) |
| HML | 0.332*** | 0.056 | 0.156** | -0.168*** | -0.065* | -0.144* |
| | (0.065) | (0.060) | (0.061) | (0.033) | (0.037) | (0.075) |
| TRI Innovation | -232.519** | -134.745 | -144.753 | -78.200 | 71.894 | -32.564 |
| | (104.215) | (119.446) | (126.150) | (78.738) | (44.712) | (53.847) |
| Constant | -0.253*** | -0.136 | 0.000 | -0.007 | -0.073* | 0.226*** |
| | (0.076) | (0.088) | (0.079) | (0.048) | (0.043) | (0.051) |
| #Companies | 144 | 80 | 114 | 374 | 484 | 628 |
| R-squared | 0.223 | 0.282 | 0.182 | 0.055 | 0.017 | 0.178 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table A7| Weekly 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| **VARIABLES** | **(1)<br>Brown<br>TRBC** | **(2)<br>Brown Tax.<br>Revenue** | **(3)<br>Brown Tax.<br>Capex** | **(4)<br>Brown Emission<br>Intensity** | **(5)<br>Brown Scope 1-2<br>Emission Intensity** | **(6)<br>Brown<br>E-Score** |
|---|---|---|---|---|---|---|
| Market | 1.040*** | 1.176*** | 1.077*** | 1.018*** | 0.978*** | 0.755*** |
| | (0.036) | (0.051) | (0.029) | (0.012) | (0.014) | (0.033) |
| SMB | 0.014 | 0.193*** | 0.178*** | 0.101*** | 0.035 | 0.200*** |
| | (0.057) | (0.063) | (0.055) | (0.024) | (0.029) | (0.056) |
| HML | 0.226*** | -0.055 | 0.095* | 0.130*** | 0.082*** | -0.095 |
| | (0.049) | (0.047) | (0.049) | (0.019) | (0.021) | (0.080) |
| TRI Innovation | 151.718* | 69.717 | 47.541 | 17.841 | 82.719* | -1.782 |
| | (79.368) | (69.042) | (62.666) | (44.799) | (44.296) | (52.911) |
| Constant | 0.011 | 0.082 | 0.122** | 0.078*** | 0.064** | 0.305*** |
| | (0.049) | (0.064) | (0.057) | (0.027) | (0.027) | (0.051) |
| #Companies | 103 | 40 | 58 | 187 | 242 | 314 |
| R-squared | 0.833 | 0.788 | 0.799 | 0.938 | 0.930 | 0.692 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table A8| Weekly 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| **VARIABLES** | **(1)<br>Green<br>TRBC** | **(2)<br>Green Tax.<br>Revenue** | **(3)<br>Green Tax.<br>Capex** | **(4)<br>Green Emission<br>Intensity** | **(5)<br>Green Scope 1-2<br>Emission Intensity** | **(6)<br>Green<br>E-Score** |
|---|---|---|---|---|---|---|
| Market | 0.785*** | 0.725*** | 0.857*** | 1.030*** | 1.005*** | 0.966*** |
| | (0.039) | (0.038) | (0.039) | (0.031) | (0.023) | (0.009) |
| SMB | -0.095 | -0.078 | -0.190*** | 0.025 | 0.021 | -0.014 |
| | (0.082) | (0.067) | (0.068) | (0.044) | (0.033) | (0.017) |
| HML | -0.105** | -0.111*** | -0.060 | 0.298*** | 0.148*** | 0.049*** |
| | (0.051) | (0.042) | (0.042) | (0.035) | (0.030) | (0.016) |
| TRI Innovation | 385.221*** | 205.446** | 193.278 | 97.025 | 11.809 | 31.766 |
| | (118.599) | (97.830) | (138.859) | (86.707) | (48.200) | (33.806) |
| Constant | 0.253*** | 0.208*** | 0.111* | 0.075 | 0.127*** | 0.069*** |
| | (0.067) | (0.054) | (0.057) | (0.047) | (0.036) | (0.018) |
| #Companies | 41 | 40 | 56 | 187 | 242 | 314 |
| R-squared | 0.567 | 0.644 | 0.683 | 0.847 | 0.893 | 0.968 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 7.5 Equally weighted portfolios

***Table A9|Monthly equally weighted BMG factor model regressions results.*** *The column headers highlight which monthly equally weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 |
|---|---|---|---|---|---|---|
| Market | 0.318*** | 0.296*** | 0.358*** | 0.157*** | 0.090** | -0.098*** |
| | (0.099) | (0.069) | (0.065) | (0.046) | (0.045) | (0.035) |
| SMB | -0.207 | 0.205 | 0.660*** | -0.014 | -0.091 | 0.730*** |
| | (0.195) | (0.136) | (0.129) | (0.091) | (0.088) | (0.068) |
| HML | 0.414 | -0.158 | -0.380** | 0.017 | 0.166 | -0.360*** |
| | (0.256) | (0.178) | (0.169) | (0.126) | (0.115) | (0.090) |
| RMW | 0.652* | 0.003 | -0.007 | 0.333* | 0.389** | -0.324*** |
| | (0.339) | (0.236) | (0.224) | (0.186) | (0.170) | (0.119) |
| CMA | 0.663* | 0.478* | 0.263 | 0.176 | 0.262 | 0.138 |
| | (0.356) | (0.248) | (0.234) | (0.193) | (0.186) | (0.125) |
| TRI Innovation | -1,042.009 | -1,013.287 | -413.327 | -74.120 | -31.999 | -553.158 |
| | (1,052.961) | (733.034) | (693.724) | (403.822) | (359.900) | (369.401) |
| Constant | -0.633* | -0.223 | -0.191 | -0.525*** | -0.538*** | 0.106 |
| | (0.345) | (0.240) | (0.228) | (0.145) | (0.134) | (0.121) |
| #Companies | 144 | 80 | 114 | 374 | 484 | 628 |
| R-squared | 0.235 | 0.169 | 0.297 | 0.154 | 0.168 | 0.589 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

***Table A10|Monthly equally weighted brown factor model regressions results.*** *The column headers highlight which monthly equally weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| **VARIABLES** | **(1)<br>Brown<br>TRBC** | **(2)<br>Brown Tax.<br>Revenue** | **(3)<br>Brown Tax.<br>Capex** | **(4)<br>Brown Emission<br>Intensity** | **(5)<br>Brown Scope 1-2<br>Emission Intensity** | **(6)<br>Brown<br>E- Score** |
|---|---|---|---|---|---|---|
| Market | 1.022*** | 1.151*** | 1.086*** | 1.094*** | 1.007*** | 0.914*** |
| | (0.073) | (0.056) | (0.051) | (0.047) | (0.044) | (0.039) |
| SMB | 0.592*** | 0.814*** | 1.000*** | 0.791*** | 0.769*** | 1.141*** |
| | (0.154) | (0.111) | (0.107) | (0.105) | (0.100) | (0.088) |
| HML | 0.858*** | 0.314** | 0.177 | 0.506*** | 0.506*** | 0.132 |
| | (0.156) | (0.146) | (0.127) | (0.112) | (0.094) | (0.086) |
| RMW | 0.456* | -0.077 | 0.012 | 0.316 | 0.365** | 0.044 |
| | (0.249) | (0.194) | (0.192) | (0.192) | (0.175) | (0.147) |
| CMA | -0.230 | -0.204 | -0.196 | -0.306 | -0.221 | -0.076 |
| | (0.313) | (0.203) | (0.223) | (0.213) | (0.200) | (0.167) |
| TRI Innovation | 680.554 | 350.749 | 878.368 | 507.125 | 486.012 | 197.999 |
| | (543.613) | (600.930) | (797.644) | (450.999) | (420.152) | (300.101) |
| Constant | -0.272 | 0.276 | 0.329** | 0.103 | 0.165 | 0.373*** |
| | (0.226) | (0.197) | (0.158) | (0.163) | (0.150) | (0.124) |
| #Companies | 103 | 40 | 58 | 187 | 242 | 314 |
| R-squared | 0.796 | 0.859 | 0.867 | 0.882 | 0.886 | 0.908 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Table A11/Monthly equally weighted green factor model regressions results. The column headers highlight which monthly equally weighted portfolio was used as dependent variable. The rows illustrate the pricing factors and the constant. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 |
|---|---|---|---|---|---|---|
| Market | 0.707*** | 0.858*** | 0.731*** | 0.939*** | 0.920*** | 1.015*** |
| | (0.088) | (0.073) | (0.058) | (0.046) | (0.040) | (0.038) |
| SMB | 0.808*** | 0.618*** | 0.349** | 0.814*** | 0.869*** | 0.421*** |
| | (0.175) | (0.144) | (0.163) | (0.110) | (0.079) | (0.095) |
| HML | 0.444* | 0.472** | 0.557*** | 0.490*** | 0.341*** | 0.492*** |
| | (0.229) | (0.189) | (0.171) | (0.134) | (0.104) | (0.101) |
| RMW | -0.187 | -0.072 | 0.028 | -0.008 | -0.015 | 0.377** |
| | (0.304) | (0.250) | (0.273) | (0.192) | (0.138) | (0.153) |
| CMA | -0.883*** | -0.673** | -0.449 | -0.472*** | -0.473*** | -0.204 |
| | (0.318) | (0.262) | (0.328) | (0.161) | (0.145) | (0.170) |
| TRI Innovation | 1,737.152* | 1,378.624* | 1,306.283 | 595.834** | 532.599 | 765.746 |
| | (942.033) | (776.271) | (829.047) | (295.424) | (427.594) | (490.346) |
| Constant | 0.314 | 0.451* | 0.473** | 0.581*** | 0.656*** | 0.220 |
| | (0.309) | (0.255) | (0.239) | (0.167) | (0.140) | (0.141) |
| #Companies | 41 | 40 | 56 | 187 | 242 | 314 |
| R-squared | 0.580 | 0.710 | 0.649 | 0.883 | 0.894 | 0.895 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 7.6 Global monthly value weighted regression results

***Table A12|Monthly global 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 Emission Intensity TRBC |
|---|---|---|---|---|---|
| Market | -0.040 | 0.020 | -0.048 | -0.057 | 0.019 |
| | (0.122) | (0.034) | (0.040) | (0.052) | (0.056) |
| SMB | -0.538* | 0.266*** | 0.345*** | 0.602*** | -0.069 |
| | (0.316) | (0.099) | (0.117) | (0.153) | (0.160) |
| HML | 0.591** | -0.166 | -0.040 | -0.098 | 0.260** |
| | (0.294) | (0.103) | (0.126) | (0.159) | (0.129) |
| RMW | 0.311 | 0.347** | 0.379** | -0.452* | -0.251 |
| | (0.457) | (0.151) | (0.157) | (0.234) | (0.220) |
| CMA | 0.755* | 0.229 | 0.149 | -0.483* | -0.454* |
| | (0.399) | (0.167) | (0.256) | (0.258) | (0.245) |
| TRI Innovation | -1,598.001 | 348.665 | 185.568 | 46.400 | 42.938 |
| | (1,304.340) | (436.727) | (376.747) | (673.542) | (494.521) |
| Constant | -1.087*** | -0.291** | -0.348** | 0.387* | -0.079 |
| | (0.394) | (0.144) | (0.152) | (0.223) | (0.207) |
| #Companies | 942 | 424 | 672 | 2100 | 162 |
| R-squared | 0.184 | 0.128 | 0.119 | 0.199 | 0.079 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table A13|Monthly global 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. 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 Emission Intensity TRBC** |
|---|---|---|---|---|---|
| Market | 0.870*** | 0.935*** | 0.819*** | 0.792*** | 0.877*** |
| | (0.043) | (0.039) | (0.039) | (0.064) | (0.047) |
| SMB | 0.086 | 0.036 | 0.099 | 0.386** | 0.141 |
| | (0.127) | (0.114) | (0.131) | (0.188) | (0.136) |
| HML | 0.584*** | 0.503*** | 0.420*** | 0.145 | 0.457*** |
| | (0.132) | (0.119) | (0.114) | (0.195) | (0.142) |
| RMW | 0.193 | 0.001 | 0.059 | -0.414 | 0.008 |
| | (0.195) | (0.175) | (0.181) | (0.288) | (0.209) |
| CMA | -0.263 | -0.477** | -0.568** | -0.860*** | -0.563** |
| | (0.215) | (0.193) | (0.230) | (0.318) | (0.230) |
| TRI Innovation | 754.962 | 796.457 | 667.880 | 655.139 | 1,054.203* |
| | (561.507) | (504.146) | (406.686) | (829.835) | (601.787) |
| Constant | -0.043 | 0.190 | 0.229 | 0.831*** | 0.309 |
| | (0.186) | (0.167) | (0.159) | (0.274) | (0.199) |
| #Companies | 731 | 212 | 336 | 1050 | 81 |
| R-squared | 0.815 | 0.862 | 0.824 | 0.655 | 0.797 |

(Robust) standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 7.7 New mixed climate transition risk metrics

***Table A14|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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| VARIABLES | (1)<br>BMG Emission Intensity TRBC | (2)<br>BMG Taxonomy Revenue TRBC | (3)<br>BMG Taxonomy Capex TRBC |
|---|---|---|---|
| Market | 0.133** | 0.267** | 0.253** |
| | (0.066) | (0.108) | (0.115) |
| SMB | -0.229* | -0.408* | 0.252 |
| | (0.130) | (0.213) | (0.228) |
| HML | 0.156 | 0.427 | 0.050 |
| | (0.171) | (0.280) | (0.299) |
| RMW | -0.295 | 0.268 | 0.143 |
| | (0.226) | (0.371) | (0.397) |
| CMA | -0.333 | 0.433 | 0.411 |
| | (0.237) | (0.389) | (0.416) |
| TRI Innovation | -330.287 | -1,937.214* | -1,359.508 |
| | (701.514) | (1,150.554) | (1,230.676) |
| Constant | 0.107 | -0.748** | -0.657 |
| | (0.230) | (0.377) | (0.404) |
| #Companies | 142 | 136 | 175 |
| R-squared | 0.168 | 0.223 | 0.077 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Table A15 | 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. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of companies per portfolio as well as the R squared. Returns are in percent per month.*

| VARIABLES | (1) Brown Emission Intensity TRBC | (2) Brown Taxonomy Revenue TRBC | (3) Brown Taxonomy Capex TRBC |
|---|---|---|---|
| Market | 1.024*** | 0.930*** | 0.898*** |
| | (0.057) | (0.087) | (0.079) |
| SMB | 0.208 | -0.062 | -0.010 |
| | (0.135) | (0.186) | (0.169) |
| HML | 0.439** | 0.729*** | 0.702*** |
| | (0.172) | (0.246) | (0.225) |
| RMW | 0.263 | 0.773* | 0.794** |
| | (0.286) | (0.392) | (0.373) |
| CMA | -0.359 | 0.281 | 0.341 |
| | (0.281) | (0.407) | (0.410) |
| TRI Innovation | 651.496 | 549.355 | 838.649 |
| | (663.356) | (898.624) | (872.038) |
| Constant | 0.342 | 0.040 | 0.069 |
| | (0.221) | (0.333) | (0.322) |
| #Companies | 71 | 83 | 107 |
| R-squared | 0.774 | 0.642 | 0.643 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 7.8 Explaining the divergence – sectoral split per portfolio

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

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Renewable Energy | 22 | 53.66 | 53.66 |
| Utilities | 19 | 46.34 | 100.00 |
| Total | 41 | 100.00 | |

***Table A17 | TRBC business sector split – TRBC brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Automobiles & Auto Parts | 11 | 10.68 | 10.68 |
| Energy - Fossil Fuels | 74 | 71.84 | 82.52 |
| Utilities | 18 | 17.48 | 100.00 |
| Total | 103 | 100.00 | |

***Table A18 | TRBC business sector split – Taxonomy revenue green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Cyclical Consumer Products | 1 | 2.50 | 2.50 |
| Cyclical Consumer Services | 1 | 2.50 | 5.00 |
| Industrial & Commercial Services | 2 | 5.00 | 10.00 |
| Industrial Goods | 4 | 10.00 | 20.00 |
| Mineral Resources | 2 | 5.00 | 25.00 |
| Real Estate | 3 | 7.50 | 32.50 |
| Renewable Energy | 3 | 7.50 | 40.00 |
| Software & IT Services | 3 | 7.50 | 47.50 |
| Technology Equipment | 1 | 2.50 | 50.00 |
| Transportation | 3 | 7.50 | 57.50 |
| Utilities | 17 | 42.50 | 100.00 |
| Total | 40 | 100.00 | |

***Table A19|TRBC business sector split – Taxonomy revenue brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Automobiles & Auto Parts | 4 | 10.00 | 10.00 |
| Chemicals | 2 | 5.00 | 15.00 |
| Cyclical Consumer Products | 3 | 7.50 | 22.50 |
| Cyclical Consumer Services | 1 | 2.50 | 25.00 |
| Energy - Fossil Fuels | 3 | 7.50 | 32.50 |
| Financial Technology (Fintech) & Infrastructure | 1 | 2.50 | 35.00 |
| Food & Beverages | 1 | 2.50 | 37.50 |
| Holding Companies | 1 | 2.50 | 40.00 |
| Industrial & Commercial Services | 3 | 7.50 | 47.50 |
| Industrial Goods | 6 | 15.00 | 62.50 |
| Mineral Resources | 1 | 2.50 | 65.00 |
| Real Estate | 1 | 2.50 | 67.50 |
| Renewable Energy | 1 | 2.50 | 70.00 |
| Software & IT Services | 6 | 15.00 | 85.00 |
| Technology Equipment | 2 | 5.00 | 90.00 |
| Telecommunications Services | 1 | 2.50 | 92.50 |
| Transportation | 2 | 5.00 | 97.50 |
| Utilities | 1 | 2.50 | 100.00 |
| Total | 40 | 100.00 | |

***Table A20|TRBC business sector split – Taxonomy capex green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Chemicals | 1 | 1.79 | 1.79 |
| Cyclical Consumer Products | 1 | 1.79 | 3.57 |
| Energy - Fossil Fuels | 2 | 3.57 | 7.14 |
| Food & Beverages | 1 | 1.79 | 8.93 |
| Industrial & Commercial Services | 5 | 8.93 | 17.86 |
| Industrial Goods | 3 | 5.36 | 23.21 |
| Mineral Resources | 1 | 1.79 | 25.00 |
| Real Estate | 1 | 1.79 | 26.79 |
| Renewable Energy | 2 | 3.57 | 30.36 |
| Software & IT Services | 4 | 7.14 | 37.50 |
| Technology Equipment | 1 | 1.79 | 39.29 |
| Transportation | 2 | 3.57 | 42.86 |
| Utilities | 32 | 57.14 | 100.00 |
| Total | 56 | 100.00 | |

***Table A21/TRBC business sector split – Taxonomy capex brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| **TRBC business sector name** | **Freq.** | **Percent** | **Cum.** |
|---|---|---|---|
| Automobiles & Auto Parts | 4 | 6.90 | 6.90 |
| Banking & Investment Services | 1 | 1.72 | 8.62 |
| Chemicals | 2 | 3.45 | 12.07 |
| Consumer Goods Conglomerates | 1 | 1.72 | 13.79 |
| Cyclical Consumer Products | 5 | 8.62 | 22.41 |
| Cyclical Consumer Services | 2 | 3.45 | 25.86 |
| Energy - Fossil Fuels | 1 | 1.72 | 27.59 |
| Food & Drug Retailing | 1 | 1.72 | 29.31 |
| Healthcare Services & Equipment | 1 | 1.72 | 31.03 |
| Holding Companies | 1 | 1.72 | 32.76 |
| Industrial & Commercial Services | 4 | 6.90 | 39.66 |
| Industrial Goods | 3 | 5.17 | 44.83 |
| Mineral Resources | 2 | 3.45 | 48.28 |
| Pharmaceuticals & Medical Research | 1 | 1.72 | 50.00 |
| Real Estate | 3 | 5.17 | 55.17 |
| Renewable Energy | 1 | 1.72 | 56.90 |
| Retailers | 5 | 8.62 | 65.52 |
| Software & IT Services | 11 | 18.97 | 84.48 |
| Technology Equipment | 2 | 3.45 | 87.93 |
| Telecommunications Services | 1 | 1.72 | 89.66 |
| Transportation | 4 | 6.90 | 96.55 |
| Utilities | 2 | 3.45 | 100.00 |
| Total | 58 | 100.00 | |

***Table A22|TRBC business sector split – Emission intensity green.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Academic & Educational Services | 1 | 0.53 | 0.53 |
| Banking & Investment Services | 63 | 33.69 | 34.22 |
| Collective Investments | 1 | 0.53 | 34.76 |
| Consumer Goods Conglomerates | 1 | 0.53 | 35.29 |
| Cyclical Consumer Products | 3 | 1.60 | 36.90 |
| Cyclical Consumer Services | 10 | 5.35 | 42.25 |
| Energy - Fossil Fuels | 1 | 0.53 | 42.78 |
| Financial Technology (Fintech) & Infrastructure | 5 | 2.67 | 45.45 |
| Food & Beverages | 2 | 1.07 | 46.52 |
| Food & Drug Retailing | 3 | 1.60 | 48.13 |
| Healthcare Services & Equipment | 2 | 1.07 | 49.20 |
| Holding Companies | 1 | 0.53 | 49.73 |
| Industrial & Commercial Services | 19 | 10.16 | 59.89 |
| Industrial Goods | 5 | 2.67 | 62.57 |
| Insurance | 19 | 10.16 | 72.73 |
| Mineral Resources | 1 | 0.53 | 73.26 |
| Pharmaceuticals & Medical Research | 3 | 1.60 | 74.87 |
| Real Estate | 5 | 2.67 | 77.54 |
| Retailers | 5 | 2.67 | 80.21 |
| Software & IT Services | 27 | 14.44 | 94.65 |
| Technology Equipment | 5 | 2.67 | 97.33 |
| Telecommunications Services | 2 | 1.07 | 98.40 |
| Transportation | 1 | 0.53 | 98.93 |
| Utilities | 2 | 1.07 | 100.00 |
| Total | 187 | 100.00 | |

***Table A23|TRBC business sector split – Emission intensity brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 10 | 5.35 | 5.35 |
| Automobiles & Auto Parts | 12 | 6.42 | 11.76 |
| Banking & Investment Services | 9 | 4.81 | 16.58 |
| Chemicals | 20 | 10.70 | 27.27 |
| Cyclical Consumer Products | 3 | 1.60 | 28.88 |
| Cyclical Consumer Services | 1 | 0.53 | 29.41 |
| Energy - Fossil Fuels | 19 | 10.16 | 39.57 |
| Food & Beverages | 8 | 4.28 | 43.85 |
| Industrial & Commercial Services | 5 | 2.67 | 46.52 |
| Industrial Goods | 28 | 14.97 | 61.50 |
| Mineral Resources | 20 | 10.70 | 72.19 |
| Personal & Household Products & Services | 2 | 1.07 | 73.26 |
| Real Estate | 6 | 3.21 | 76.47 |
| Renewable Energy | 1 | 0.53 | 77.01 |
| Retailers | 7 | 3.74 | 80.75 |
| Software & IT Services | 3 | 1.60 | 82.35 |
| Technology Equipment | 7 | 3.74 | 86.10 |
| Transportation | 11 | 5.88 | 91.98 |
| Utilities | 15 | 8.02 | 100.00 |
| Total | 187 | 100.00 | |

*Table A24 | 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 business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Academic & Educational Services | 1 | 0.41 | 0.41 |
| Banking & Investment Services | 67 | 27.69 | 28.10 |
| Collective Investments | 1 | 0.41 | 28.51 |
| Cyclical Consumer Products | 5 | 2.07 | 30.58 |
| Cyclical Consumer Services | 19 | 7.85 | 38.43 |
| Financial Technology (Fintech) & Infrastructure | 5 | 2.07 | 40.50 |
| Food & Beverages | 3 | 1.24 | 41.74 |
| Food & Drug Retailing | 2 | 0.83 | 42.56 |
| Healthcare Services & Equipment | 1 | 0.41 | 42.98 |
| Holding Companies | 1 | 0.41 | 43.39 |
| Industrial & Commercial Services | 19 | 7.85 | 51.24 |
| Industrial Goods | 7 | 2.89 | 54.13 |
| Insurance | 19 | 7.85 | 61.98 |
| Mineral Resources | 1 | 0.41 | 62.40 |
| Personal & Household Products & Services | 2 | 0.83 | 63.22 |
| Pharmaceuticals & Medical Research | 7 | 2.89 | 66.12 |
| Real Estate | 13 | 5.37 | 71.49 |
| Renewable Energy | 1 | 0.41 | 71.90 |
| Retailers | 8 | 3.31 | 75.21 |
| Software & IT Services | 46 | 19.01 | 94.21 |
| Technology Equipment | 10 | 4.13 | 98.35 |
| Telecommunications Services | 1 | 0.41 | 98.76 |
| Transportation | 1 | 0.41 | 99.17 |
| Utilities | 2 | 0.83 | 100.00 |
| Total | 242 | 100.00 | |

*Table A25|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 business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 20 | 8.26 | 8.26 |
| Automobiles & Auto Parts | 8 | 3.31 | 11.57 |
| Chemicals | 26 | 10.74 | 22.31 |
| Consumer Goods Conglomerates | 1 | 0.41 | 22.73 |
| Cyclical Consumer Products | 7 | 2.89 | 25.62 |
| Cyclical Consumer Services | 3 | 1.24 | 26.86 |
| Energy - Fossil Fuels | 25 | 10.33 | 37.19 |
| Food & Beverages | 14 | 5.79 | 42.98 |
| Food & Drug Retailing | 1 | 0.41 | 43.39 |
| Healthcare Services & Equipment | 3 | 1.24 | 44.63 |
| Industrial & Commercial Services | 9 | 3.72 | 48.35 |
| Industrial Goods | 7 | 2.89 | 51.24 |
| Insurance | 1 | 0.41 | 51.65 |
| Mineral Resources | 42 | 17.36 | 69.01 |
| Personal & Household Products & Services | 3 | 1.24 | 70.25 |
| Pharmaceuticals & Medical Research | 3 | 1.24 | 71.49 |
| Real Estate | 13 | 5.37 | 76.86 |
| Renewable Energy | 3 | 1.24 | 78.10 |
| Software & IT Services | 3 | 1.24 | 79.34 |
| Technology Equipment | 7 | 2.89 | 82.23 |
| Telecommunications Services | 5 | 2.07 | 84.30 |
| Transportation | 15 | 6.20 | 90.50 |
| Utilities | 23 | 9.50 | 100.00 |
| Total | 242 | 100.00 | |

*Table A26 | TRBC business sector split – E-Score green. The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 10 | 3.18 | 3.18 |
| Automobiles & Auto Parts | 12 | 3.82 | 7.01 |
| Banking & Investment Services | 39 | 12.42 | 19.43 |
| Chemicals | 10 | 3.18 | 22.61 |
| Cyclical Consumer Products | 21 | 6.69 | 29.30 |
| Cyclical Consumer Services | 11 | 3.50 | 32.80 |
| Energy - Fossil Fuels | 9 | 2.87 | 35.67 |
| Financial Technology (Fintech) & Infrastructure | 1 | 0.32 | 35.99 |
| Food & Beverages | 16 | 5.10 | 41.08 |
| Food & Drug Retailing | 5 | 1.59 | 42.68 |
| Healthcare Services & Equipment | 7 | 2.23 | 44.90 |
| Holding Companies | 1 | 0.32 | 45.22 |
| Industrial & Commercial Services | 18 | 5.73 | 50.96 |
| Industrial Goods | 28 | 8.92 | 59.87 |
| Insurance | 9 | 2.87 | 62.74 |
| Mineral Resources | 14 | 4.46 | 67.20 |
| Personal & Household Products & Services | 3 | 0.96 | 68.15 |
| Pharmaceuticals & Medical Research | 12 | 3.82 | 71.97 |
| Real Estate | 27 | 8.60 | 80.57 |
| Renewable Energy | 1 | 0.32 | 80.89 |
| Retailers | 15 | 4.78 | 85.67 |
| Software & IT Services | 8 | 2.55 | 88.22 |
| Technology Equipment | 6 | 1.91 | 90.13 |
| Telecommunications Services | 8 | 2.55 | 92.68 |
| Transportation | 8 | 2.55 | 95.22 |
| Utilities | 15 | 4.78 | 100.00 |
| Total | 314 | 100.00 | |

***Table A27|TRBC business sector split – E-score brown.*** *The table shows the frequency of the portfolio companies in the respective TRBC business sectors.*

| TRBC business sector name | Freq. | Percent | Cum. |
|---|---|---|---|
| Applied Resources | 3 | 0.96 | 0.96 |
| Automobiles & Auto Parts | 4 | 1.27 | 2.23 |
| Banking & Investment Services | 42 | 13.38 | 15.61 |
| Chemicals | 5 | 1.59 | 17.20 |
| Collective Investments | 4 | 1.27 | 18.47 |
| Consumer Goods Conglomerates | 2 | 0.64 | 19.11 |
| Cyclical Consumer Products | 6 | 1.91 | 21.02 |
| Cyclical Consumer Services | 9 | 2.87 | 23.89 |
| Energy - Fossil Fuels | 5 | 1.59 | 25.48 |
| Financial Technology (Fintech) & Infrastructure | 3 | 0.96 | 26.43 |
| Food & Beverages | 7 | 2.23 | 28.66 |
| Food & Drug Retailing | 1 | 0.32 | 28.98 |
| Healthcare Services & Equipment | 13 | 4.14 | 33.12 |
| Holding Companies | 2 | 0.64 | 33.76 |
| Industrial & Commercial Services | 28 | 8.92 | 42.68 |
| Industrial Goods | 40 | 12.74 | 55.41 |
| Insurance | 5 | 1.59 | 57.01 |
| Mineral Resources | 3 | 0.96 | 57.96 |
| Pharmaceuticals & Medical Research | 26 | 8.28 | 66.24 |
| Real Estate | 11 | 3.50 | 69.75 |
| Renewable Energy | 4 | 1.27 | 71.02 |
| Retailers | 5 | 1.59 | 72.61 |
| Software & IT Services | 52 | 16.56 | 89.17 |
| Technology Equipment | 22 | 7.01 | 96.18 |
| Telecommunications Services | 3 | 0.96 | 97.13 |
| Transportation | 6 | 1.91 | 99.04 |
| Utilities | 3 | 0.96 | 100.00 |
| Total | 314 | 100.00 | |