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

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Abstract

This paper aims to answer a critical yet unexplored question: How can firms' climate transition risk best be measured? While existing literature often overlooks the suitability of different metrics, I demonstrate that not all transition risk metrics are well suited to measure the transition risk of brown or green firms. I employ a new data set containing, for the first time, reported EU taxonomy alignment of both capital expenditures and revenues as proxies for companies' transition risk. I compare taxonomy alignments with carbon dioxide emissions data, E-scores from Refinitiv and MSCI, the Refinitiv Business Classification (TRBC) as a sector/technology classification, and text-based approaches. I find a strong divergence in transition risk metrics for similar companies: that is, depending on the chosen transition risk metric, a given portfolio's transition risk profile will differ substantially. Next, to assess the effectiveness of the different transition risk proxies, I measure the return sensitivity of nine brown and green portfolios – each constructed using a specific metric – to news indices that track transition risk shocks: the higher the sensitivity, the more effective the transition risk proxy. I find that green taxonomy and TRBC-based portfolios react most significantly to climate transition risk shocks. Forward-looking metrics seem to be particularly useful for green companies. Interestingly, only the brown MSCI E-score portfolio reacts significantly negatively to transition risk shocks. These findings indicate that markets currently price the transition opportunity for green firms more strongly than the transition risk for brown firms.

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1. Introduction

An unexpected acceleration in the transition to a low-carbon economy may entail changes in policy, law, technology and market expectations. Depending on the nature of the transition (orderly or disorderly), transition risks can amount to substantial financial risk for organisations (TCFD (2017)). Firms with high transition risk are called brown firms, whereas firms positioned to benefit from the low-carbon transition are referred to as green. While brown firms are expected to underperform in the event of transition risk shocks,[3] green firms should profit. A firm's exposure to climate transition risk depends mostly on two factors: the economic sector(s) the company operates in and the technology it employs. For instance, an energy company is naturally more exposed to transition risk than a healthcare company is, underscoring the importance of sectoral differences. However, whether such a company ultimately faces risks or opportunities depends on the utilised technology (Fliegel (2025b)).

Tracking, pricing and managing companies' climate transition risk requires accurately measuring transition risk over time. Interestingly, proposed approaches show substantial heterogeneity: E-scores (Pástor et al (2022), van der Beck (2021)), emission levels (Bolton and Kacperczyk (2021, 2023)), emission intensities (Ardia et al (2022), Aswani et al (2024)), estimated taxonomy alignments (Bassen et al (2022), Sautner et al (2022)), text learning approaches (Sautner et al (2023a, 2023b)) and sector classifications that incorporate technology-specific information (Fliegel (2025a), Jourde and Stalla-Bourdillon (2023)). Most empirical studies do not address in detail why a particular metric is chosen. This makes it imperative to rigorously evaluate the available measures and offer evidence-based guidance on their use. Accordingly, this paper seeks to answer the following central question: How can firms' climate transition risk best be measured? My empirical strategy follows a two-step approach.

First, I investigate whether different proposed metrics for transition risk[4] yield divergent assessments for the same firm. To this end, I compile what is, to the best of my knowledge, the most comprehensive and up-to-date data set on proposed transition risk metrics for European firms. This includes established metrics (emission intensities and two different E-scores) as well as promising new metrics (the Refinitiv Business Classification (TRBC), text-based approaches, taxonomy alignment of revenues and capital expenditures (capex)). By means of rank-correlation analysis, I demonstrate that the proposed climate transition risk metrics are uncorrelated. This implies that the assessment of a firm's transition risk can vary substantially depending on the chosen metric. Notably, firms with higher taxonomy alignments show higher emission intensities. Taxonomy alignments are largely uncorrelated with E-scores and TRBC, and strongly negatively correlated to text-based measures. Interestingly, firms with higher carbon dioxide (CO_2) emission intensities have higher Refinitiv E-scores. Overall, I find that the within-transition[5] risk metric correlation is higher than the between-metric correlation.

[3] I define transition risk shocks as unexpected positive or negative changes to financial market expectations about the speed of the transition.

[4] Proposed transition risk metrics measure the amount of transition risk of a given firm. They should not be confused with a transition risk shock, which is the materialisation of transition risk.

[5] Within-transition risk metrics refers to metrics within the same group, for example, E-scores of different providers. Between-metrics, on the other hand, refers to metrics of different groups, for example, emissions-based metrics and text-based metrics.

Second, I assess the effectiveness of the different transition risk proxies available. Rather than merely documenting divergences, I aim to provide empirical guidance on which metrics are more appropriate to capture the transition risk of green and brown firms. To this end, I rely on a nascent stream of empirical literature that develops newspaper-based indices of transition risk shocks, which capture unexpected changes in transition risk. The first climate change risk index was developed by Engle et al (2020). Subsequent research provides additional indices for specific topics or regions (Apel et al (2023); Ardia et al (2022)). My identification strategy compares the sensitivity of brown and green portfolios' stock returns – built using each proposed transition risk metric – to the transition risk shocks. The underlying assumption is that only metrics, which produce portfolios reacting significantly to transition risk shocks, accurately measure firms' transition risk.

In the baseline analysis, I create nine brown and green portfolios, with each pair based on a different transition risk metric. I expect that during months with unexpected increases in transition risk, green portfolios will outperform and brown portfolios will underperform.

My findings show that no portfolio reacts to the broad unexpected media climate change concern index (UMC) developed by Ardia et al (2022), indicating that transition risk-based portfolios do not necessarily react to general climate-related media sentiment. When I focus on a more targeted measure – the transition risk-specific business Impact innovation index (BII) – I find that only a subset of portfolios reacts systematically to transition risk shocks. Hence, scholars should be cautious when picking a transition risk proxy. Most notably, none of the portfolios based on popular metrics – scope 1–2 emission intensity, total emission intensity, text-based measures or the Refinitiv E-score – respond robustly to transition risk shocks, raising serious doubts about their validity as transition risk proxies. Among brown portfolios, only the MSCI E-score portfolio reacts significantly negatively to climate transition risk shocks. In contrast, for green portfolios, those constructed using TRBC and taxonomy alignment react significantly and positively to transition risk shocks. The most robust response is observed in the taxonomy capex portfolio, emphasising the value of forward-looking measures (such as EU capex taxonomy alignment and the climate change opportunity score) over backward-looking metrics (such as emission intensities). These findings suggest that markets are pricing climate transition opportunities in green firms more heavily than transition risks in brown firms. One plausible explanation is that market participants expect that high-transition risk firms will be bailed out or compensated by governments under stringent climate policies.

Based on this evidence, I recommend using transition risk proxies that are built on newly available data – such as EU taxonomy alignment or technology-based sector classifications – when measuring firms' climate transition risk. Moreover, I suggest that using different metrics for brown and green portfolios may enhance the accuracy of transition risk assessment.

Finally, a closer look at the sectoral composition of each portfolio offers further insight into their differing sensitivities. For instance, green portfolios based on emission intensities are strongly exposed to service and technology sectors, which are transition risk–neutral sectors and hence do not respond strongly to transition risk shocks. Portfolios based on Refinitiv E-score use a best-in-class approach, resulting in a more balanced sector composition. This leads to counterintuitive holdings – such as fossil fuel companies in green portfolios and renewable energy firms in brown ones – explaining the low sensitivity of Refinitiv's E-score to transition risk shocks. In contrast, TRBC and taxonomy-based portfolios are concentrated in transition-sensitive sectors such as energy, utilities and transportation, making them more likely to react significantly to transition risk shocks.

2. Related literature

This study addresses a significant gap in the literature: that is, the question of how to best measure firms' climate transition risk. By evaluating different proposed transition risk metrics, I contribute to multiple strands of literature. First, I extend the relatively small literature on the divergence both within and across transition risk metrics. While Berg et al (2022) coined the term "aggregate confusion" to describe inconsistencies across environmental, social and governance (ESG) ratings from different providers and Busch et al (2022) documented major discrepancies in carbon emissions data – particularly for scope 3 and estimated emissions – less attention has been given to divergence across transition risk metrics. Dumrose et al (2022) and Bassen et al (2022) explore the relationship between E-scores and estimated EU taxonomy alignment, while Binger, Colesanti et al (2022) highlight the inconsistency of forward-looking scenario-based transition risk metrics. Wilkens et al (2023) note a negative correlation between the inverted scope 1-2 CO_2 intensity and environmental score. My study extends the aforementioned papers by compiling a comprehensive, up-to-date comparison of widely used transition risk metrics. To the best of my knowledge, I am also the first to analyse reported EU taxonomy alignment data – both revenue-based and capex-based – as proxies for transition risk.

Second, I contribute to the literature on the evaluation of shock indices of transition risk. Ardia et al (2022) demonstrate that brown stocks underperform green ones on days with unexpected increases in climate risks. However, Apel et al (2023) construct a different climate transition risk shock index and find conflicting evidence. Pástor et al (2022) show that the UMC by Ardia et al (2022) is significantly related to a green-minus-brown portfolio sorted through MSCI E-scores. Bua et al (2024) construct indices for physical and transition risks but find mostly insignificant results – with the exception that green portfolios based on E-scores and emission intensity react significantly to transition risk shocks after the Paris Agreement, whereas brown portfolios do not. My empirical strategy is similar but with a different objective: rather than validating a specific shock index, I assess the validity of different transition risk proxies. I broaden the analysis by including a wider range of transition risk metrics – including EU taxonomy alignments, text-based transition risk measures and granular sector/technology classifications – and use multiple transition shock indices to ensure robustness.

Third, I contribute to the event study literature examining the impact of unexpected climate-relevant events on asset prices. Since all these studies use some form of brown/green categorisation, this literature indirectly validates transition risk metrics. For example, Kruse et al (2023) use the estimated share of sustainable business activities to investigate the effect of the Paris Agreement on the stock market. Other event studies on climate policies include Rudebusch et al (2023), who focus on the stock market reaction of the US Inflation Reduction Act, and Sen and von Schickfus (2020), who assess the market impact of an unexpected German climate policy proposal. I add to this literature by covering a longer period (2010–24), encompassing numerous climate transition risk-relevant events rather than focusing on isolated events.

Fourth, I contribute to the rapidly expanding literature on how transition risk is priced in financial markets. While some studies investigate bond market pricing with inconclusive findings (Duan et al (2025), Zerbib (2019)), a major debate has evolved around the pricing of climate transition risk on equity markets. Some authors find a brown or carbon premium mostly using carbon emissions data (Alessi et al (2021), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023), Hsu et al (2023)). Other scholars found a green premium using a variety of transition risk metrics, including emissions data, E-scores, estimated taxonomy alignment and sector/technology classifications (Bassen et al (2022), Bauer et al (2022), Fliegel (2025a), 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 differences in time frames, empirical methodologies or transition risk metrics. By demonstrating that only a few transition risk metrics respond systematically to transition shocks and therefore are suited to measure transition risk, I conclude that a large part of the divergent findings is due to the choice of the underlying climate transition risk metric. I also show that almost no brown or green portfolio outperforms when I control for climate transition risk shocks, in line with the theoretical prediction by Pástor et al (2021). In a related study, Eskildsen et al (2024) argue, consistent with my findings, that different greenium estimates are due to different measurements and empirical methodologies. However, unlike my study, theirs does not evaluate climate transition risk measures but uses all available metrics to construct a meta-metric. Therefore, rather than aggregating indiscriminately, my goal is to identify which climate-transition risk metrics are most and least appropriate for capturing actual market pricing of transition risk.

Finally, by providing recommendations on which transition risk metrics best capture transition risk exposure for green and brown firms, I also contribute to the ever-increasing empirical literature on climate finance and environmental economics, where the ability to accurately measure firms' transition risk is a first-order challenge.

3. Methodology

This section outlines the different data sources and the empirical approach.

3.1. Data

I rely on different large financial and environmental data sets.

a. **Financial data**
   Firm-level financial data, such as revenues and market capitalisations, are from Refinitiv EIKON. Stock split adjusted and dividend adjusted returns are calculated using Compustat. The final sample includes only active and listed European firms with annual sales above \$50 million, as this is the official threshold of the EU taxonomy regulation. Furthermore, I exclude financial institutions, firms lacking ISINs and companies without return information. The final sample comprises 3,032 unique European firms. To reduce the effect of frequent data-bank–specific errors and outliers, I winsorise return data at the 1% level. Additionally, I incorporate widely used asset pricing factors into the analysis. For the baseline specification, I use the European factor returns from Kenneth French's Online Data Library. The study spans from 2010 to 2024.

b. Climate transition risk metric data

Based on ISINs, I match the most recent data on climate transition risk metrics to the financial data. Three primary data sources are employed: Bloomberg for EU taxonomy data; Refinitiv EIKON for E-scores, TRBC and emissions; and Sautner et al (2023a, 2023b) for the text-based scores measuring firm-level climate change exposure (CC exposure) and climate change opportunity (CC opportunity). Most transition risk metrics vary over time, with the exception of the TRBC sector/technology classification, which is static. The EU taxonomy regulation obliges firms to disclose the alignment of revenue and capex only since the fiscal year 2022. Thus, time series coverage for this data is limited to 2022–23. To address missing data, I apply both forward and backward filling techniques. Forward fills are rare and only impute isolated missing years, reflecting the increasing availability of climate-related disclosures. Backward fills are more common, especially before 2020, and involve using the most recent available value to fill earlier years. This assumes constant transition risk profiles for many firms before 2020 for some metrics. I consider this preferable to excluding firms with incomplete transition risk data. To ensure data consistency, taxonomy eligibility and alignments, values are winsorised at the 0% and 100% levels, E-scores are trimmed to fall within the 0–100 range and emissions data are winsorised at the 1% level to reduce the impact of data-bank errors.

Availability of climate transition risk metrics in Europe — Table 1

Climate Transition Risk Metric	Data Source	Europe
Refinitiv E-scores	Refinitiv EIKON	1,783
MSCI E-scores	Pástor et al (2022)	-
Scope 1 emissions	Refinitiv EIKON	1,589
Scope 2 emissions	Refinitiv EIKON	1,593
Scope 3 emissions	Refinitiv EIKON	1,341
The Refinitiv Business Classification	Refinitiv EIKON	3,032
Climate change exposure	Sautner et al (2023a, 2023b)	1,296
Climate change opportunity	Sautner et al (2023a, 2023b)	1,296
Taxonomy revenue risk	Bloomberg	1,413
Taxonomy capex risk	Bloomberg	1,262

Notes: The table shows the number of observations per proposed climate transition risk metric for European companies with annual sales above $50 million in fiscal year 2023. Missing data have been imputed using forward-fills.

As depicted in Table 1, the overall data availability varies significantly depending on the transition risk metric. TRBC is the most comprehensive, with full coverage across all firms in the sample. Roughly half of companies have Refinitiv E-scores. The availability of emissions data depends on the scope, with scope 3 emissions data being the scarcest. Text-based metrics are available for more than a third of the companies. Newly disclosed taxonomy data are already available for almost half of companies although many firms have 0% eligibility. After listwise deletion, only 472 firms remain with complete data across all studied transition risk metrics and years.

To track unexpected shocks to climate transition risk expectations, I rely on three different indices, which track innovations in climate transition risk-related concerns: First, I derive the UMC as the prediction errors from AR(1) models fitted to the widely utilised Media Climate Change Concern (MCCC) index developed by Ardia et al (2022). The AR(1) model is estimated using a rolling window of the preceding 36 months of monthly MCCC data. The MCCC index is based on US newspapers and combines broad topics around both physical and transition risk for companies. Second, to focus more on the transition risk component of the MCCC, I derive a more targeted measure – the BII– by isolating prediction errors related specifically to "business impact" theme. Third, I employ the Transition risk innovation index (TRI) developed by Apel et al (2023), designed to differentiate between events that increase transition risk (eg Paris Agreement) and those that decrease it (eg the US withdrawal from the Paris Agreement). In contrast, most other transition risk indices implicitly assume that a greater amount of news related to transition risk corresponds to heightened transition risk and that the absence of such news indicates lower transition risk. Another advantage of the TRI is the news corpus utilised, which is based on more than 100 million documents from diverse international outlets such as the BBC and Reuters. As with the other indices used in this study, transition risk shocks are identified by extracting the prediction errors from an AR(1) model.

3.2. Empirical strategy

I adopt a two-step empirical strategy to evaluate the relevance and robustness of different climate transition risk metrics.

First, I assess the rank correlations over time of the following eight of the nine proposed transition risk metrics: the discretised TRBC sector/technology classification, scope 1-2 emission intensities, scope 1-3 emission intensities, Refinitiv environmental pillar scores, taxonomy alignment of revenues and capex, and two text-based measures from Sautner et al (2023a). Due to the limited granularity of the MSCI E-score portfolio return data, I exclude MSCI E-scores from the correlation analysis.

Second, I rely on recent advances in text learning to measure climate risk shocks using news-based indices. My empirical strategy treats these indices as exogenous shocks to the climate transition risk expectations of financial market participants. This allows me to test how different portfolios constructed on different transition risk metrics respond to such shocks. Another way to look at the identification strategy is to think of climate transition risk in terms of exposure and expectations. The exposure to transition risk is measured by the transition risk metrics (eg the emission intensity) and is usually already reflected in prices. However, once a transition risk shock shifts the expectations about the speed of the transition, heavily exposed firms are expected to be repriced more significantly. Thus, those transition risk metrics that most accurately capture exposure should show the strongest reaction to such shocks. This identification strategy follows the theoretical framework of Pástor et al (2021) and the empirical setting of Ardia et al (2022). However, the results can be interpreted causally only if the chosen transition risk shock indices adequately capture actual transition risk shocks.

To empirically test this, I construct nine brown and nine green portfolios, one for each of the aforementioned transition risk metrics. Since most transition risk metrics vary over time, I sort and rebalance the portfolios monthly according to the respective transition risk metric. To guarantee comparability and avoid bias due to differential data availability, I consider only the final sample of 472 European firms.

Each excess return *P* of a brown or green portfolio *j* at time *t* can be written as:

$$\mathrm{P_{jt}} = \mathrm{R_{jt}} - \mathrm{RF_t}\ , \qquad (1)$$

where $\mathrm{R_{jt}}$ is the return of the portfolio and $\mathrm{RF_t}$ is the risk-free rate of return. I compute both equally weighted and value-weighted portfolio returns. I create long-only green and brown portfolios to account for the possibility that some risk metrics might be better able to recognise either brown or green companies.

My empirical approach uses the three aforementioned transition shock indices (UMC, BII and TRI) as the independent variable to explain the performance of the various climate transition risk-based portfolios. To isolate the impact of transition risk shocks, I control for standard asset pricing factors.

Specifically, I estimate the following three variants of the Fama and French Five-Factor model (Fama and French (2015)), extended to include a transition risk shock term. I estimate the models using monthly data from 2010 to 2024 for both brown and green portfolios:

$$\mathrm{P_{jt}} = \alpha_j + \beta_{1j}(\mathrm{RM_t} - \mathrm{RF_t}) + \beta_{2j}\mathrm{SMB}_t + \beta_{3j}\mathrm{HML}_t + \beta_{4j}\mathrm{RMW}_t + \beta_{5j}\mathrm{CMA}_t + \beta_{6j}UMC + \epsilon_{jt} \qquad (2)$$

$$\mathrm{P_{jt}} = \alpha_j + \beta_{1j}(\mathrm{RM_t} - \mathrm{RF_t}) + \beta_{2j}\mathrm{SMB}_t + \beta_{3j}\mathrm{HML}_t + \beta_{4j}\mathrm{RMW}_t + \beta_{5j}\mathrm{CMA}_t + \beta_{6j}\mathrm{BII}_t + \epsilon_{jt} \qquad (3)$$

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

$\mathrm{RM_t}$ is the return of the market factor at time *t*. In addition to the market factor, the model also features the high-minus-low (HML) value factor and the small-minus-big (SMB) size factor. I also control for the robust-minus-weak (RMW) profitability factor as well as the conservative-minus-aggressive (CMA) investment factor. α_j i is the constant, indicating whether a portfolio outperforms the market, even when controlling for risk factors. ϵ_{jt} is the error term, that is, the portion of excess return that the systematic risk factors fail to explain. The main object of interest is the coefficient β_{6j} as it indicates whether transition risk shocks significantly explain the returns of the portfolios. In line with prior literature (Ardia et al (2022), Pástor et al (2022)), I expect that brown firms underperform when transition risk increases unexpectedly – as measured by the transition risk shock indices. Conversely, I expect that green firms overperform in months with positive climate transition risk shocks.

In what follows, I briefly present the rules for classifying firms into brown, green or transition-risk–neutral categories, according to each of the proposed transition risk metrics.

First, I use TRBC as a sector/technology classification, in line with Jourde and Stalla-Bourdillon (2023) and Fliegel (2025a). TRBC takes sectoral differences into account and can differentiate Paris-aligned and non-aligned production technologies within climate-sensitive sectors. However, given its qualitative nature, the measure is not granular (Fliegel (2025a) Jourde and Stalla-Bourdillon (2024)). Thus, I discretise the variable to differentiate green, brown and transition-risk–neutral firms. Among the multiple classification schemes proposed in the literature, I adopt the most restrictive categorisation, following Fliegel (2025a). This approach classifies only fossil-fuel–related activities as brown and only renewable or zero-emission technologies as green. All other technologies – including those for which no commercially viable green alternative production technology currently exists – are classified as neutral. This is rather restrictive, since it classifies, for example, cement and concrete manufacturing as neutral because TRBC does not indicate whether the production process is low or high emission. According to this categorisation, green companies are engaged primarily in electric vehicle manufacturing, battery technologies, renewable utilities, and renewable energy technologies. Brown firms include brown utilities, fossil-fuel–based explorers, miners and refiners, and manufacturers of internal combustion engines. As TRBC is not time-varying, I must assume constant sector/technology affiliations for this transition risk measure.

Second, I use, for the first time, the reported EU taxonomy alignment of revenues and capex to classify firms as brown, green or neutral. The EU taxonomy was developed to measure the share of a firm's revenues and capex that contribute to the climate mitigation objective, based on sector-specific technical screening criteria. As such, it functions similarly to a highly granular sector/technology classification system. Importantly, firms are required to report both taxonomy-aligned revenues (reflecting current business activities) and taxonomy-aligned capex (reflecting planned investments). These two measures thus capture both backward-looking (revenue) and forward-looking (capex) dimensions of climate transition alignment, with capex alignment reflecting future strategic orientation (Arnold et al (2023)). I therefore use revenue alignment as a backward-looking metric of transition risk exposure and capex alignment as a forward-looking proxy. However, the EU taxonomy provides only criteria defining green business activities, while not explicitly providing criteria for brown activities.[6] To overcome this limitation, I follow the approach of Dumrose et al (2022), who propose calculating relative taxonomy alignment, which accounts for the share of aligned activities conditional on eligibility:

$$\text{Relative Taxonomy Alignment} = \frac{Taxonomy\ Alignment}{Taxonomy\ Eligibilty} \times 100 \tag{5}$$

Accordingly, the higher this score, the greener the company. A low score, in contrast, indicates that a large share of a company's eligible revenue or capex fails to fulfil the technical screening criteria; I classify such a low score as indicative of brown activities. To enhance the robustness of this classification, I extend the simple relative alignment measure by introducing a minimum eligibility threshold of 50% for both revenue and capex. The rationale can be most easily illustrated by an example of two companies. Consider company A with 10% eligibility and 10% alignment and company B with 100% eligibility and 98% alignment. While company B is clearly a green pure play, a naïve relative alignment ratio would assign company A the highest possible score, despite its limited exposure to taxonomy-relevant activities. Without a minimum eligibility threshold, the taxonomy-based risk metric could yield misleading classifications. Moreover, the eligibility threshold addresses a structural limitation of the current EU taxonomy: the absence of technical screening criteria for brown activities.

In my approach, eligible but not aligned revenue or capex is treated as brown, which allows the taxonomy data to function as a possible climate transition risk metric. However, in sectors where no green alternative technology currently exists,

[6] Taxonomy-aligned economic activities must fulfil four conditions (European Commission (2020)): substantial contribution to the climate change mitigation objective, compliance with the respective technical screening criteria, no significant harm to other environmental objectives and adherence to minimum social safeguards. Large listed EU companies with more than 500 employees must report both the eligibility and alignment figures of their revenues, opex and capex

such as fossil fuel extraction, non-eligible revenue or capex cannot be reliably classified, since these sectors are not covered at all by the taxonomy. The chosen 50% threshold excludes companies in such sectors and ensures that fossil fuel companies with a small green business unit are not erroneously classified as green. Among firms passing this eligibility threshold, I then classify companies into green and brown categories based on percentile thresholds. Specifically, firms in the top 30% (≥ 70th percentile) of taxonomy alignment (for revenue or capex) are labelled green, and those in the bottom 30% (≤ 30th percentile) are labelled brown. All other firms are considered transition-risk–neutral. As taxonomy alignments are reported in annual reports, I apply a one-year publication lag, that is, data reported for the fiscal year 2023 are used in the 2024 portfolio construction.

Third, in line with a large body of the empirical literature in climate finance (eg Ardia et al (2022), Bauer et al (2022), Bolton and Kacperczyk (2021)), I employ emissions data as a proposed transition risk metric. Carbon emissions data suffer from limited availability and low reliability, particularly for scope 3 emissions (Busch et al (2022), Kalesnik et al (2022)). The common practice of excluding scope 3 emissions in empirical studies can misclassify as green those firms with substantial upstream or downstream emissions (scope 3) simply because their direct (scope 1) and indirect energy-related (scope 2) emissions are low. Moreover, it is critical to note that firms with low emissions are not necessarily green or low-risk firms; they may simply be transition-risk–neutral.

To address these challenges, I create separate portfolios based on scope 1-2 and scope 1-3 emissions, scaled by revenues.[7] This focus on emission intensities, rather than absolute emission levels, is supported by recent research (Aswani et al (2024), Zhang (2025)), which finds that absolute emissions scale linearly with revenues, thereby confounding emission levels with basic firm fundamentals. I differentiate scope 1-2 from scope 1-3 emission intensities because scope 1-2 data show higher consistency and reliability across databases (Busch et al (2022)). This distinction allows me to evaluate whether the inclusion of scope 3 emissions improves or degrades the informativeness of emissions as a transition risk proxy. For portfolio classification, I first invert the emission intensity measures to ensure consistency in directional interpretation across all transition risk metrics in the data set: higher values correspond to greener firms, while lower values indicate brown companies. Based on the distribution of inverted emission intensities, I then identify the 30th and 70th percentiles to classify firms. Companies in the lowest 30% of inverted intensities (ie the highest actual polluters) are classified as brown and those in the highest 30% as green. As with other metrics, I apply a one-year reporting lag in line with Zhang (2025), such that emissions reported for a given year inform the portfolio allocation for the subsequent year.

Fourth, I utilise widely used environmental pillar scores (eg Pástor et al (2022), van der Beck (2021)). While E-scores cover broad environmental topics– such as biodiversity, pollution and climate mitigation – they are frequently employed as climate transition risk metrics. However, ESG scores are not without criticism. Key concerns include a lack of comparability across providers (Gibson Brandon et al (2021)), measurement and scope divergence (Berg et al (2022)) and potential size-related biases (Drempetic et al (2020)). In this study, I rely on E-scores from both

[7] A potential concern with using emission intensities is that inflation over time may nominally reduce emission intensities. However, because this inflationary effect impacts all European companies roughly similarly, its distortive influence is likely limited.

Refinitiv and MSCI, as they represent two of the most widely used data sources among researchers and practitioners. Firms are categorised into green and brown portfolios based on their E-score distribution: companies in the top 30th percentile are classified as green, while those in the bottom 30th percentile are classified as brown. I apply a one-year publication lag to all E-scores. As I do not have access to raw MSCI E-scores, I rely on the aggregate E-score portfolio return data from Pástor et al (2022).

Fifth, I use a novel text-based metric developed by Sautner et al (2023a), which estimates firms' CC exposure by analysing earnings call transcripts. Their keyword discovery algorithm captures how much attention company stakeholders devote to climate-related issues, and the resulting score has been shown to predict several environmental performance indicators. I use the inverted overall CC exposure score to create green (top 30%) and brown (bottom 30%) portfolios. Additionally, I leverage the CC opportunity sub-index to construct further portfolios.

Table 2 depicts the summary statistics for monthly equally weighted European portfolio returns and the transition risk shock indices.

Summary statistics of the monthly European equally weighted portfolio returns — Table 2

Variable	Obs	Mean	Std dev	Min	Max
Brown the Refinitiv Business Classification	179	0.43	4.70	-19.61	22.53
Brown taxonomy revenue	179	0.43	5.27	-21.78	22.45
Brown taxonomy capex	179	0.49	5.28	-25.21	20.18
Brown emission intensity	179	0.55	4.77	-18.73	19.98
Brown scope 1-2 intensity	179	0.43	4.49	-17.2	19.03
Brown Refinitiv E-score	179	0.74	4.59	-18.29	16.12
Brown climate change exposure	179	0.48	4.74	-19.82	20.71
Brown climate change opportunity	179	0.38	4.64	-17.12	17.73
Brown MSCI E-score	131	0.83	4.52	-18.93	14.27
Green the Refinitiv Business Classification	179	0.74	6.84	-17.04	22.30
Green taxonomy revenue	179	0.40	4.79	-19.11	21.50
Green taxonomy capex	179	0.33	4.24	-16.45	14.91
Green emission intensity	179	0.47	4.54	-20.51	17.64
Green scope 1-2 intensity	179	0.59	4.67	-18.34	17.09
Green Refinitiv E-score	179	0.41	4.66	-20.14	21.35
Green climate change exposure	179	0.56	4.41	-17.15	14.65
Green climate change opportunity	179	0.39	4.70	-16.70	15.67
Green MSCI E-score	131	1.28	4.24	-12.32	13.45
Market factor	179	0.53	5.05	-15.44	16.62
Small-minus-big factor	179	0.04	1.67	-5.06	4.72
High-minus-low factor	179	-0.04	2.84	-11.30	12.09
Robust-minus-weak factor	179	0.25	1.65	-5.40	3.82
Conservative-minus-aggressive factor	179	-0.05	1.46	-4.39	5.21
Unexpected media climate change concern index	173	0.06	0.29	-0.79	0.96
Business impact innovation index	173	0.02	0.31	-0.94	0.96
Transition risk innovation index	131	0.00	0.00	-0.002	0.001

Notes: The table presents descriptive statistics of the monthly excess returns of equally weighted portfolios, the European market factor, the asset pricing factors from the Fama and French Five-Factor model, the UMC, the BII and TRI. All returns are in percentages. The sample period spans from 2010 to 2024.

4. Results

I first present the results of the correlations across the proposed risk metrics and then evaluate the effectiveness of different climate transition risk metrics.

4.1. Divergence of proposed transition risk metrics

Table 3 shows substantial divergence across the proposed transition risk metrics, both within and between metric groups. Within-group correlations are overall positive, ranging from 0.73 for taxonomy-based metrics to 0.60 for emission intensity and 0.58 for text-based measures. Although the within-group correlations exceed the between-group correlations, the divergence within each metric group is still considerable. This suggests that seemingly minor methodological decisions – such as the choice between scope 1–2 versus scope 1–3 emissions or whether to use revenue versus capex alignment to the EU taxonomy – can significantly alter a firm's assessed transition risk exposure.

More striking, however, is the divergence of the between-group transition risk metrics. In particular, all taxonomy-based transition risk proxies correlate negatively with inverted emission intensities. That indicates that greener firms, as measured by the EU taxonomy, emit more CO_2 emissions than brown firms. Moreover, taxonomy alignments are largely uncorrelated with both TRBC and E-scores and strongly negatively correlated with text-based measures. Similarly, Refinitiv E-scores are negatively related to inverted emission intensities, implying that firms scoring high in the environmental pillar have higher emissions compared with low-scoring firms. These findings underscore the critical importance of metric selection. Simply relying on a different transition risk metric can result in a completely different transition risk profile, heavily impacting all subsequent analysis.

Results for Spearman's rank correlation coefficient — Table 3

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(1) The Refinitiv Business Classification	1.00							
(2) Taxonomy revenue alignment	-0.08	1.00						
(3) Taxonomy capex alignment	-0.09	0.73	1.00					
(4) Total emission intensity	0.21	-0.27	-0.27	1.00				
(5) Scope 1-2 emission intensity	0.12	-0.29	-0.27	0.60	1.00			
(6) E-Score	-0.10	0.18	0.22	-0.22	-0.20	1.00		
(7) Climate change exposure	0.22	-0.55	-0.49	0.408	0.44	-0.22	1.00	
(8) Climate change opportunity	0.12	-0.25	-0.24	0.30	0.34	-0.23	0.58	1.00

Notes: The table shows the rank correlations, using listwise deletion, between the proposed transition risk metrics employed in this study. TRBC codes are discretised, with brown companies = 1, neutral = 2 and green = 3. All companies with greater than 0% taxonomy eligibility are included. Emissions and CC exposure metrics are inverted. The time frame spans from 2009 until 2023.

4.2. Evaluating proposed climate transition risk metrics: using the UMC and BII indices

The high divergence in transition risk metrics makes it unlikely that all of them can accurately classify firms' climate transition risk – particularly given that some are even negatively correlated. Therefore, I proceed to evaluate the different measurement options available to determine which transition risk metrics are better at assessing the climate transition risk of brown and green firms. I start this assessment with the relatively broad UMC. The results for both brown and green portfolios are depicted in Tables 4 and 5. Strikingly, none of the brown or green portfolios is negatively or positively related to the UMC. While this result is somewhat surprising, it may be attributed to the fact that the UMC captures overall climate change concern – encompassing topics such as business impact, environmental impact, societal debate and research. As a result, it is a general measure of climate concern rather than one focused specifically on transition risk.

Brown factor model regression results using the UMC — Table 4

Variables	(1) TRBC	(2) Tax rev	(3) Tax capex	(4) Emission int	(5) Scope 1-2 emission int	(6) E-score	(7) CC exp	(8) CC opp	(9) MSCI E-score
Market	0.66***	0.82***	0.87***	0.78***	0.72***	0.74***	0.77***	0.70***	0.75***
	(14.64)	(19.19)	(20.33)	(18.53)	(17.72)	(17.44)	(20.07)	(20.09)	(10.32)
SMB	-0.10	0.34**	0.60***	0.29***	0.24**	0.60***	0.29**	0.29**	0.18
	(-0.85)	(2.39)	(4.12)	(2.69)	(2.25)	(4.79)	(2.55)	(2.60)	(0.92)
HML	0.94***	0.46***	0.32*	0.50***	0.54***	0.14	0.57***	0.44***	0.30
	(9.19)	(2.93)	(1.77)	(4.51)	(5.39)	(1.04)	(5.36)	(4.20)	(1.63)
RMW	0.73***	0.37*	0.41*	0.50***	0.50***	0.23	0.56***	0.46***	0.94***
	(4.30)	(1.70)	(1.78)	(3.28)	(3.59)	(1.24)	(3.92)	(3.25)	(3.56)
CMA	-0.21	-0.28	-0.26	-0.20	-0.19	-0.40***	-0.24	-0.21	0.16
	(-1.26)	(-1.34)	(-1.43)	(-1.30)	(-1.18)	(-2.62)	(-1.50)	(-1.47)	(0.68)
UMC	0.44	0.37	0.06	0.31	0.13	-0.02	0.29	0.04	-0.58
	(0.91)	(0.70)	(0.11)	(0.70)	(0.32)	(-0.04)	(0.60)	(0.09)	(-1.06)
Constant	-0.08	-0.16	-0.15	-0.00	-0.08	0.25	-0.08	0.07	0.12
	(-0.47)	(-0.78)	(-0.68)	(-0.01)	(-0.51)	(1.25)	(-0.55)	(0.41)	(0.47)
Observations	173	173	173	173	173	173	173	173	131

Notes: The column headers highlight which monthly equally weighted portfolio is used as the dependent variable: (1) The Refinitiv Business Classification, (2) Taxonomy revenue alignment, (3) Taxonomy capex alignment, (4) Emission intensity, (5) Scope 1-2 emission intensity, (6) Refinitiv E-scores, (7) Climate change exposure score, (8) Climate change opportunity score, (9) MSCI E-score. The rows illustrate the pricing factors and the constant. Newey-West standard errors are employed for all models. Returns are in per cent per month. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Green factor model regression results using the UMC — Table 5

Variables	(1) TRBC	(2) Tax rev	(3) Tax capex	(4) Emission int	(5) Scope 1-2 emission int	(6) E-score	(7) CC exp	(8) CC opp	(9) MSCI E-score
Market	0.64***	0.75***	0.68***	0.76***	0.78***	0.78***	0.76***	0.78***	0.75***
	(6.48)	(16.37)	(15.71)	(17.99)	(19.75)	(19.73)	(18.24)	(17.35)	(12.27)
SMB	0.63*	0.46***	0.29**	0.38***	0.46***	0.05	0.30**	0.01	0.23
	(1.77)	(3.26)	(2.19)	(2.76)	(4.01)	(0.41)	(2.38)	(0.13)	(1.50)
HML	-0.04	0.37***	0.32***	0.21	0.15	0.56***	0.11	0.44***	-0.26
	(-0.12)	(2.63)	(2.89)	(1.50)	(1.12)	(4.55)	(0.85)	(4.11)	(-1.59)
RMW	0.06	0.39**	0.37**	0.35*	0.28	0.62***	0.33*	0.46**	0.01
	(0.17)	(2.13)	(2.35)	(1.74)	(1.60)	(3.92)	(1.84)	(2.52)	(0.03)
CMA	-0.53	-0.24	-0.08	-0.32***	-0.42***	-0.25**	-0.28**	-0.40***	0.23
	(-0.96)	(-1.00)	(-0.36)	(-2.69)	(-3.27)	(-2.04)	(-1.99)	(-2.79)	(0.93)
UMC	1.20	0.75	0.36	0.01	-0.03	-0.00	0.03	0.11	0.95
	(0.78)	(1.42)	(0.61)	(0.02)	(-0.06)	(-0.00)	(0.06)	(0.23)	(1.41)
Constant	0.33	-0.16	-0.14	-0.07	0.06	-0.18	0.02	-0.10	0.63***
	(0.63)	(-0.83)	(-0.79)	(-0.38)	(0.31)	(-1.11)	(0.10)	(-0.54)	(2.82)
Observations	173	173	173	173	173	173	173	173	131

Notes: The column headers highlight which monthly equally weighted portfolio is used as the dependent variable: (1) The Refinitiv Business Classification, (2) Taxonomy revenue alignment, (3) Taxonomy capex alignment, (4) Emission intensity, (5) Scope 1-2 emission intensity, (6) Refinitiv E-scores, (7) Climate change exposure score, (8) Climate change opportunity score, (9) MSCI E-score. The rows illustrate the pricing factors and the constant. Newey-West standard errors are employed for all models. Returns are in per cent per month. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

I therefore focus on the transition-risk–specific component of business impact to gauge which portfolios react significantly to shocks in the corresponding index (BII). Results for the brown portfolios in Table 6 indicate that only one portfolio is significantly and negatively associated with the BII: the brown MSCI E-score portfolio. This finding is consistent with both Ardia et al (2022) and Pástor et al (2022), who show that a brown MSCI E-score portfolio underperforms following positive transition risk shocks.

Brown factor model regression results using the Business Impact Innovation index									Table 6
Variables	**(1) TRBC**	**(2) Tax rev.**	**(3) Tax capex**	**(4) Emission int**	**(5) Scope 1-2 emission int**	**(6) E-score**	**(7) CC exp**	**(8) CC opp**	**(9) MSCI E-score**
Market	0.66***	0.82***	0.87***	0.78***	0.72***	0.74***	0.77***	0.70***	0.75***
	(14.61)	(19.18)	(20.16)	(18.57)	(17.59)	(17.25)	(19.96)	(19.89)	(10.54)
SMB	-0.11	0.34**	0.59***	0.29***	0.24**	0.60***	0.29**	0.29**	0.18
	(-0.91)	(2.37)	(4.15)	(2.64)	(2.20)	(4.78)	(2.50)	(2.59)	(0.96)
HML	0.93***	0.46***	0.31*	0.50***	0.54***	0.14	0.56***	0.43***	0.31*
	(9.14)	(2.92)	(1.74)	(4.49)	(5.34)	(1.00)	(5.29)	(4.07)	(1.72)
RMW	0.72***	0.37*	0.41*	0.49***	0.50***	0.23	0.55***	0.46***	0.96***
	(4.29)	(1.68)	(1.78)	(3.29)	(3.63)	(1.23)	(3.92)	(3.24)	(3.55)
CMA	-0.20	-0.28	-0.26	-0.19	-0.18	-0.39**	-0.22	-0.20	0.16
	(-1.17)	(-1.32)	(-1.38)	(-1.23)	(-1.09)	(-2.51)	(-1.38)	(-1.35)	(0.70)
BII	0.74	0.25	0.20	0.44	0.46	0.20	0.62	0.41	-1.29***
	(1.46)	(0.44)	(0.38)	(0.83)	(0.90)	(0.34)	(1.14)	(0.81)	(-2.73)
Constant	-0.07	-0.14	-0.15	0.01	-0.08	0.24	-0.08	0.06	0.13
	(-0.42)	(-0.72)	(-0.71)	(0.04)	(-0.54)	(1.26)	(-0.55)	(0.39)	(0.56)
Observations	173	173	173	173	173	173	173	173	131

Notes: The column headers highlight which monthly equally weighted portfolio is used as the dependent variable: (1) The Refinitiv Business Classification, (2) Taxonomy revenue alignment, (3) Taxonomy capex alignment, (4) Emission intensity, (5) Scope 1-2 emission intensity, (6) Refinitiv E-scores, (7) Climate change exposure score, (8) Climate change opportunity score, (9) MSCI E-score. The rows illustrate the pricing factors and the constant. Newey-West standard errors are employed for all models. Returns are in per cent per month. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, I examine the response of the nine green portfolios to the BII. As shown in Table 7, the MSCI E-score portfolio does not exhibit a positive reaction to transition risk shocks. By contrast, the portfolios based on TRBC, taxonomy revenue alignment and taxonomy capex alignment do respond positively to such shocks. In other words, these portfolios outperform when transition risk increases unexpectedly. The largest coefficient is observed for the TRBC-based portfolio, followed by the taxonomy-capex portfolio. The EU taxonomy is specifically designed to measure the green share of revenues and capex; hence, it is to be expected that only green portfolios react to transition risk shocks. Notably, none of the widely used portfolios based on emission intensity, text analysis or E-scores react to transition risk shocks.

Green factor model regression results using the Business Impact Innovation index — Table 7

Variables	(1) TRBC	(2) Tax rev	(3) Tax capex	(4) Emission int	(5) Scope 1-2 emission int	(6) E-score	(7) CC exp	(8) CC opp	(9) MSCI E-score
Market	0.65***	0.75***	0.68***	0.76***	0.78***	0.78***	0.76***	0.78***	0.75***
	(6.42)	(16.23)	(15.38)	(17.81)	(19.54)	(19.52)	(18.18)	(17.09)	(12.51)
SMB	0.60*	0.45***	0.28**	0.38***	0.46***	0.04	0.29**	0.01	0.23
	(1.67)	(3.20)	(2.12)	(2.78)	(4.03)	(0.40)	(2.39)	(0.10)	(1.50)
HML	-0.08	0.36**	0.31***	0.21	0.14	0.55***	0.11	0.43***	-0.24
	(-0.24)	(2.56)	(2.77)	(1.47)	(1.09)	(4.48)	(0.83)	(4.01)	(-1.51)
RMW	0.02	0.38**	0.35**	0.35*	0.28	0.62***	0.32*	0.45**	0.03
	(0.05)	(2.10)	(2.30)	(1.73)	(1.60)	(3.94)	(1.83)	(2.52)	(0.14)
CMA	-0.46	-0.22	-0.06	-0.31**	-0.42***	-0.25*	-0.28*	-0.39***	0.23
	(-0.82)	(-0.91)	(-0.25)	(-2.60)	(-3.15)	(-1.92)	(-1.93)	(-2.61)	(0.91)
BII	3.11**	0.96*	1.01*	0.15	0.12	0.28	0.12	0.43	0.03
	(2.21)	(1.66)	(1.79)	(0.29)	(0.24)	(0.66)	(0.25)	(0.77)	(0.04)
Constant	0.33	-0.14	-0.14	-0.07	0.06	-0.18	0.02	-0.11	0.67***
	(0.70)	(-0.75)	(-0.84)	(-0.41)	(0.30)	(-1.23)	(0.10)	(-0.57)	(2.98)
Observations	173	173	173	173	173	173	173	173	131

Notes: The column headers highlight which monthly equally weighted portfolio is used as the dependent variable: (1) The Refinitiv Business Classification, (2) Taxonomy revenue alignment, (3) Taxonomy capex alignment, (4) Emission intensity, (5) Scope 1-2 emission intensity, (6) Refinitiv E-scores, (7) Climate change exposure score, (8) Climate change opportunity score, (9) MSCI E-score. The rows illustrate the pricing factors and the constant. Newey-West standard errors are employed for all models. Returns are in per cent per month. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3. Evaluating proposed climate transition risk metrics: using the TRI

I now replicate the previous analyses, this time using the TRI for both equally weighted and value-weighted returns. As depicted in the Appendix, only the brown MSCI E-score portfolio shows the expected (negative) coefficient in response to the TRI; however, it is not statistically significant. Most other brown portfolios are either unrelated or even positively associated with the TRI, which indicates that they are unable to measure the brown firms' transition risk.

For green portfolios, a greater number of coefficient estimates show the expected positive and statistically significant sign. Both taxonomy-based portfolios react robustly and positively to transition risk shocks captured by the TRI– a finding that is comparable to the BII results in Table 7. Additional high and consistently positive coefficients stem from the portfolio based on the CC opportunity metric. The Refinitiv E-score portfolio is positive and statistically significant as well, albeit with a smaller coefficient. Regarding the text-based CC metrics, the CC opportunity metric focuses on topics related to positive business prospects and new market opportunities, whereas the broader CC exposure metric includes both risks and opportunities. The results suggest that markets are more inclined to price-anticipated opportunities rather than risks.

4.4. Robustness

The decision to apply listwise deletion significantly reduces the number of firms included in the sample. To address this limitation, I rerun the baseline regressions without listwise deletion, thereby increasing the sample size – particularly for the portfolios based on E-score, TRBC, emissions, and text analysis, as the availability of taxonomy data is the main constraint under listwise deletion. The findings remain largely consistent with the baseline results. Most notably, when applying the BII index to the green portfolios, only the TRBC and capex-alignment portfolios have a positive and statistically significant coefficient. This suggests that forward-looking measures are better suited to measure green transition risk compared with backward-looking measures, such as revenue alignment. Employing the TRI index, I find a positive and statistically significant value for portfolios based on TRBC, taxonomy alignment, CC opportunities and scope 1-2 emission intensity -based portfolio. In contrast, the total (scope 1-3) emission intensity green portfolio is not positively associated with the TRI.

To test the robustness of these findings further, I also assess the results using value-weighted returns. The outcomes are broadly confirmed. When using the BII index, the green portfolios based on TRBC and taxonomy capex are the only specifications that produce a significant and positive coefficient.

Thus, for each transition risk shock index, I employ three specifications: value-weighted returns, equally weighted returns and equally weighted returns without listwise deletion. To provide a comprehensive overview of robustness across all specifications, Table 8 and Table 9 summarise the regression outcomes for all green and brown transition risk portfolios. The summary shows that only MSCI E-scores show negative and significant results for brown portfolios. For green portfolios, the portfolio based on taxonomy capex is the only one that is consistently significant across all specifications. The taxonomy revenue portfolio and the TRBC-based portfolios yield positive and significant coefficients in four out of six cases, while the portfolio based on CC opportunity is significant in three out of six setups.

Regression results for all brown portfolios — Table 8

Brown portfolios	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Equally weighted BII									X
Value-weighted BII									X
Equally weighted BII without listwise deletion									X
Equally weighted TRI									
Value-weighted TRI									
Equally weighted TRI without listwise deletion									

Notes: This table highlights the significantly positive results at the 10% level across all six empirical specifications for each of the nine transition risk metric-based portfolios.

Regression results for all green portfolios — Table 9

Green portfolios	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Equally weighted BII	X	X	X						
Value-weighted BII	X		X						
Equally weighted BII without listwise deletion	X		X						
Equally weighted TRI		X	X	X	X	X		X	
Value-weighted TRI		X	X			X		X	
Equally weighted TRI without listwise deletion	X	X	X		X			X	

Notes: This table highlights the significantly positive results at the 10% level across all six empirical specifications for each of the nine transition risk metric-based portfolios.

4.5. Explaining the divergence: examining portfolio constituents

To explain why some metrics react more strongly or weakly to transition risk shocks, I examine the composition of the brown and green portfolios for all proposed transition risk measures. Specifically, I tabulate the portfolio constituents by TRBC business sector, without applying listwise deletion. Most notably, both the green and brown TRBC-based portfolios are (by construction) highly concentrated in climate-sensitive industries such as automotive, energy and utilities. Compared with other risk metrics, TRBC excludes sectors that are not particularly exposed to transition risk shocks. Consequently, it is to be expected that TRBC-based green portfolios – composed of pure-play companies highly sensitive to climate transition dynamics – exhibit one of the strongest responses to transition risk shocks.

Both taxonomy-based green portfolios show a high concentration in the utility sector. Other green companies within these portfolios are found in energy-intensive sectors, such as industrial goods and industrial and commercial services. The high representation of utilities highlights that renewables are already relatively established in European electricity markets. In contrast, green firms in heavy industry – such as those producing low-CO_2 steel, aluminium or cement – remain comparatively rare. Meanwhile, taxonomy-based brown portfolios display more dispersion across business sectors.

A closer look into the green portfolios based on emission intensity reveal the previously discussed issue: these portfolios struggle to distinguish green companies from those that are merely transition-risk–neutral. Most companies in these portfolios operate in service and information technology sectors. While these firms tend to report low emissions relative to revenue, they are not actively enabling the green transition. Green portfolios based on emission intensity thus conflate high-revenue, low-emission firms in neutral sectors with genuinely green firms. As a result, it is unsurprising that neither scope 1-2 nor scope 1-3 green portfolios based on emission intensity react significantly to transition risk shocks. By contrast, the emission-intensity–based brown portfolios include more expected sectors such as chemicals, fossil fuels, mining, industrial goods, automotive, utilities and transportation.

Portfolios based on E-scores show the widest dispersion across sectors. This reflects the methodology of E-scores, which assesses companies relative to their industry peers (Kotsantonis and Serafeim (2019)). As a result, both high and low E-score portfolios are broadly diversified and do not concentrate on firms sensitive to climate transition risk. It is therefore expectable that these portfolios exhibit muted reactions to transition risk shocks compared with more targeted pure-play transition portfolios.

Finally, the CC exposure and CC opportunity portfolios are relatively dispersed across many sectors. Interestingly, both green and brown portfolios share many common industries, highlighting the ability of text-based measures to differentiate transition risk profiles at a more granular level, even within the same sector.

5. Conclusion

The correlation results for the proposed transition risk metrics demonstrate that the choice of metric significantly influences the assessment of firms' climate transition risk. In the second part of the analysis, I show that only some transition risk metrics react significantly to transition risk shocks. Interestingly, only one transition risk proxy

– MSCI E-score – can form brown portfolios that are negatively exposed to such shocks. Widely used metrics based on emission intensity and text analysis fail to do so across all three transition risk shock indices. There are different explanations for this finding. One possibility is that transition risk metrics are more effective at identifying green firms than brown ones. Alternatively, financial markets might currently not price the downside risks faced by brown companies but emphasise the opportunities for green firms associated with the climate transition. Investors may also expect that brown firms will be shielded from adverse outcomes through political lobbying or government intervention, such as bailouts or compensation in cases where transition shocks result in stranded assets (von Dulong et al (2023)).

In contrast, the results for green portfolios indicate that financial markets price the transition risk opportunities, as many portfolios react positively in the event of transition risk shocks as measured by the BII and TRI indices. The strongest reactions stem from portfolios based on sector/technology classifications and EU taxonomy metrics. I also find some evidence that the text-based CC opportunity metric is helpful in measuring transition risk for green companies. Interestingly, both taxonomy capex and the CC opportunity metric are forward-looking in nature. This suggests that financial markets price future business opportunities more strongly than they do current involvement in green sectors. It therefore becomes crucial to assess firms' preparedness for transition risk shocks rather than merely their current exposure.

Another implication of my findings is that the prevailing practice of using a single metric to construct both brown and green portfolios is flawed. As demonstrated, some metrics – such as the EU taxonomy or the MSCI E-scores – are better suited to measure green or brown firms' transition risk, respectively, but not both. Scholars should therefore consider employing different metrics for different purposes and adopt a more nuanced, composite approach to measuring transition risk (Fliegel (2025b)).

Finally, with respect to transition risk shock indices, the results reveal that broader indices such as the UMC can fail to capture the portfolios' exposure to transition risk shocks. This underscores the importance of using indices that target specific aspects of climate risk – such as physical risk or transition risk – when analysing the pricing of climate-related risks in financial markets.

Addressing the question of how to best measure companies' climate transition risk is critical for the success of the green transition, because only what is correctly measured can be adequately priced and managed. This is not merely a technical concern – it has far-reaching real-world implications. At present, investors are often uncertain about how to measure companies' transition risk (Berg et al (2022)). If investors misclassify brown, high-risk companies as green, the growing funds devoted to sustainable or ESG-oriented investments will be misallocated (Chatterji et al (2016)). This can lead to systematic mispricing of transition risk in financial markets, potentially reducing the cost of capital for brown firms or inflating it for genuinely green ones. When climate policies tighten unexpectedly, such distortions may cause widespread asset stranding and threaten financial stability (van der Ploeg and Rezai (2020)). Furthermore, ambiguity surrounding transition risk metrics enables firms to engage in "cheap talk" during earnings communications (Bingler, Kraus et al (2022)), facilitating greenwashing and allowing companies to appear more sustainable than they truly are. This may help them deflect scrutiny by consumers and policymakers (Drempetic et al (2020)). Reducing the confusion surrounding transition risk measurement could therefore improve the accuracy of climate risk pricing in financial markets and drive more effective capital allocation – enhancing the real-world impact of the green transition. At the same time, it will enable policymakers to better monitor and manage the transition risk of companies.

Looking ahead, researchers should place greater emphasis on how they measure firms' climate transition risk. I advocate for a stronger emphasis on stability and robustness of findings with respect to the choice of transition risk metrics. This includes, for example, testing results using emissions data or environmental scores from different vendors, comparing metrics based on scope 1–2 versus scope 1–3 emissions, and incorporating alternative transition risk metrics such as TRBC classifications, EU taxonomy alignment or text-based indicators. Such robustness checks can help strengthen the validity of empirical findings and provide a more comprehensive understanding of transition risk exposure.

References

Alessi, L, E Ossola and R Panzica (2021): "What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures", *Journal of Financial Stability*, vol 54, 100869, doi.org/10.1016/j.jfs.2021.100869.

Apel, M, A Betzer and B Scherer (2023): "Real-time transition risk", *Finance Research Letters*, vol 53, 103600, doi.org/10.1016/j.frl.2022.103600.

Ardia, D, K Bluteau, K Boudt and K Inghelbrecht (2022): "Climate change concerns and the performance of green vs brown stocks", *Management Science* vol 69, no 12, pp 7607–32, doi.org/10.1287/mnsc.2022.4636.

Arnold, J L, T Cauthorn, J Eckert, C Klein and S Rink (2023): *Let's talk numbers: EU taxonomy reporting by German companies. What can we learn from the first EU taxonomy reporting season?* Berlin, Frankfurt, Kassel: econsense, Frankfurt School, Universität Kassel.

Aswani, J, A Raghunandan and S Rajgopal (2024): "Are carbon emissions associated with stock returns?" *Review of Finance*, vol 28, no 1, pp 75–106, doi.org/10.1093/rof/rfad013.

Bassen, A, O Kordsachia, K Lopatta and W Tan (2025): "Revenue alignment with the EU taxonomy regulation in developed markets", *Journal of Banking & Finance,* vol 170, doi.org/10.1016/j.jbankfin.2024.107339.

Bauer, M D, D Huber, G D Rudebusch and O Wilms (2022): "Where is the carbon premium? Global performance of green and brown stocks", *Journal of Climate Finance,* vol 1, 100006, doi.org/10.1016/j.jclimf.2023.100006.

Berg, F, J F Kölbel and R Rigobon (2022): "Aggregate confusion: the divergence of ESG ratings", *Review of Finance*, vol 26, no 6, pp 1315–44, doi.org/10.1093/rof/rfac033.

Bingler, J A, C Colesanti Senni and P Monnin (2022): "Understand what you measure: where climate transition risk metrics converge and why they diverge", *Finance Research Letters*, vol 50, 103265, doi.org/10.1016/j.frl.2022.103265.

Bingler, J A, M Kraus, M Leippold and N Webersinke (2022): "Cheap talk and cherry-picking: what ClimateBert has to say on corporate climate risk disclosures", *Finance Research Letters*, vol 47, part B, 102776, doi.org/10.1016/j.frl.2022.102776.

Bolton, P and M Kacperczyk (2021): "Do investors care about carbon risk?" *Journal of Financial Economics*, vol 142, no 2, pp. 517–49, doi.org/10.1016/j.jfineco.2021.05.008.

——— (2023): "Global pricing of carbon-transition risk", *Journal of Finance*, vol 78, no 6, pp 3677–754, doi.org/10.1111/jofi.13272.

Bua, G, D Kapp, F Ramella and L Rognone (2024): "Transition versus physical climate risk pricing in European financial markets: a text-based approach", *European Journal of Finance*, vol 30, no 17, pp 2076–110, doi.org/10.1080/1351847X.2024.2355103.

Busch, T, M Johnson and T Pioch (2022): "Corporate carbon performance data: Quo vadis?", *Journal of Industrial Ecology*, vol 26, no 1, pp 350–63, doi.org/10.1111/jiec.13008.

Chatterji, A K, R Durand, D I Levine and S Touboul (2016): "Do ratings of firms converge? Implications for managers, investors and strategy researchers", *Strategic Management Journal*, vol 37, no 8, pp 1597–614, doi.org/10.1002/smj.2407.

Drempetic, S, C Klein and B Zwergel (2020): "The influence of firm size on the ESG score: corporate sustainability ratings under review", *Journal of Business Ethics*, vol 167, no 2, pp 333–60, doi.org/10.1007/s10551-019-04164-1.

Duan, T, F W Li and Q Wen (2025): "Is carbon risk priced in the cross section of corporate bond returns?", *Journal of Financial and Quantitative Analysis*, vol 60, no 1, pp 1–35, doi.org/10.1017/S0022109023000832.

Dumrose, M, S Rink and J Eckert (2022). "Disaggregating confusion? The EU Taxonomy and its relation to ESG rating", *Finance Research Letters*, vol 48, 102928, doi.org/10.1016/j.frl.2022.102928.

Engle, R F, S Giglio, B Kelly, H Lee and J Stroebel (2020): "Hedging climate change news", *Review of Financial Studies,* vol 33, no 3, pp 1184–216, doi.org/10.1093/rfs/hhz072.

Eskildsen, M, M Ibert, T I Jensen and L H Pedersen (2024): "In search of the true greenium", *SSRN*, doi.org/10.2139/ssrn.4744608.

European Commission (2020): *Taxonomy: final report of the Technical Expert Group on Sustainable Finance*. Brussels: European Commission.

Fama, E F and K R French (2015): "A five-factor asset pricing model", *Journal of Financial Economics*, vol 116, no 1, pp 1–22, doi.org/10.1016/j.jfineco.2014.10.010.

Fliegel, P. (2025a): "'Brown' risk or 'green' opportunity? The dynamic pricing of climate transition risk on global financial markets", *Energy Economics*, vol 145, 108456, doi.org/10.1016/j.eneco.2025.108456.

——— (2025b): "How (not) to measure companies' climate transition risk: a framework and categorized literature review", *Corporate Social Responsibility and Environmental Management*, vol 32, no 3, pp 3049–77, doi.org/10.1002/csr.3094.

Gibson Brandon, R, P Krueger and P S Schmidt (2021): "ESG rating disagreement and stock returns", *Financial Analysts Journal*, vol 77, no 4, pp 104–27, doi.org/10.1080/0015198X.2021.1963186.

Görgen, M, A Jacob, M Nerlinger, R Riordan, M Rohleder and M Wilkens (2020): "Carbon Risk", *SSRN*, dx.doi.org/10.2139/ssrn.2930897.

Hsu, P-H, K A Li, and C-Y Tsou (2023): "The pollution premium," *Journal of Finance,* vol 7, no 3, pp 1343–92, doi.org/10.1111/jofi.13217.

Jourde, T and A Stalla-Bourdillon (2024): "Environmental preferences and sector valuation", *Review of World Economics*, doi.org/10.2139/ssrn.4481313.

Kalesnik, V, M Wilkens and J Zink (2022): "Do corporate carbon emissions data enable investors to mitigate climate change?" *Journal of Portfolio Management*, vol 48, no 10, pp 119–47, doi.org/10.3905/jpm.2022.1.410.

Kotsantonis, S and G Serafeim (2019): "Four things no one will tell you about ESG data", *Journal of Applied Corporate Finance*, vol 31, no 2, pp 50–58, doi.org/10.1111/jacf.12346.

Kruse, T, M Mohnen and M Sato (2023): "Do financial markets respond to green opportunities?" *Journal of the Association of Environmental and Resource Economists*, vol 11, no 3, pp 549–76, doi.org/10.1086/727370.

Pástor, Ľ, R F Stambaugh and L A Taylor (2021): "Sustainable investing in equilibrium", *Journal of Financial Economics*, vol 142, no. 2, pp 550–71, doi.org/10.1016/j.jfineco.2020.12.011.

——— (2022): "Dissecting green returns", *Journal of Financial Economics*, vol 146, no 2, pp 403–24, doi.org/10.1016/j.jfineco.2022.07.007.

Rudebusch, G, E Offner and M D Bauer (2023): "The effect of US climate policy on financial markets: an event study of the Inflation Reduction Act," *Brookings Institution*, September 19.

Sautner, Z, L van Lent, G Vilkov and R Zhang (2023a): "Firm-level climate change exposure", *Journal of Finance*, vol 78, no 3, pp 1449–98, doi.org/10.1111/jofi.13219.

——— (2023b): "Pricing climate change exposure", *Management Science*, vol 69, no 12, pp 7540–61, doi.org/10.1287/mnsc.2023.4686.

Sautner, Z, J Yu, R Zhong and X Zhou (2022): "The EU taxonomy and the syndicated loan market", *SSRN*, doi.org/10.2139/ssrn.4058961.

Sen, S and M-T von Schickfus (2020): "Climate policy, stranded assets, and investors' expectations", *Journal of Environmental Economics and Management*, vol 100, 102277, doi.org/10.1016/j.jeem.2019.102277.

Task Force on Climate-related Financial Disclosures (TCFD) (2017): *Recommendations of the Task Force on Climate-related Financial Disclosures*, TCFD.

van der Beck, P (2021): "Flow-driven ESG returns," Swiss Financial Institute Research Paper No 21-27, doi.org/10.2139/ssrn.3929359.

van der Ploeg, F and A Rezai (2020): "The risk of policy tipping and stranded carbon assets", *Journal of Environmental Economics and Management*, vol 100, 102258, doi.org/10.1016/j.jeem.2019.102258.

von Dulong, A, A Gard-Murray, A Hagen, N Jaakkola and S Sen (2023): "Stranded assets: research gaps and implications for climate policy", *Review of Environmental Economics and Policy*, vol 17, no 1, pp 161–69, doi.org/10.1086/723768.

Wilkens, M, M Görgen and M Rohleder (2023): "Equity greenium, futures pricing, and lending fees, *SSRN*, doi.org/10.2139/ssrn.4399738.

Zerbib, O D (2019): "The effect of pro-environmental preferences on bond prices: evidence from green bonds", *Journal of Banking & Finance*, vol 98, pp 39–60, doi.org/10.1016/j.jbankfin.2018.10.012.

Zhang, S (2025): "Carbon Returns across the globe", *Journal of Finance*, vol 80, no 1, pp 615–45, doi.org/10.1111/jofi.13402.

Appendix

Equally weighted brown factor model regression results using the TRI — Table A.1

Variables	(1) TRBC	(2) Tax rev	(3) Tax capex	(4) Emission int	(5) Scope 1-2 emission int	(6) E-score	(7) CC exp	(8) CC opp	(9) MSCI E-score
Market	0.72***	0.80***	0.84***	0.78***	0.73***	0.74***	0.79***	0.70***	0.75***
	(12.18)	(14.45)	(16.03)	(14.02)	(13.40)	(12.84)	(15.75)	(14.80)	(10.24)
SMB	-0.11	0.33*	0.53***	0.24*	0.16	0.53***	0.26*	0.28*	0.17
	(-0.80)	(1.85)	(2.90)	(1.71)	(1.19)	(3.29)	(1.82)	(1.92)	(0.92)
HML	0.88***	0.53**	0.32	0.47***	0.52***	0.12	0.54***	0.38**	0.30
	(6.46)	(2.43)	(1.25)	(2.77)	(3.51)	(0.62)	(3.60)	(2.30)	(1.57)
RMW	0.73***	0.31	0.39	0.43**	0.45**	0.21	0.52***	0.34*	0.93***
	(3.78)	(1.12)	(1.21)	(2.06)	(2.48)	(0.78)	(2.94)	(1.80)	(3.60)
CMA	-0.31*	-0.46*	-0.25	-0.32**	-0.33**	-0.47***	-0.36**	-0.28*	0.15
	(-1.83)	(-1.85)	(-1.04)	(-2.09)	(-2.20)	(-2.78)	(-2.36)	(-1.72)	(0.61)
TRI	800.37**	307.44	906.37*	578.73	498.79	662.93	1050.48***	674.23 **	-765.87
	(2.13)	(0.59)	(1.88)	(1.33)	(1.28)	(1.52)	(2.75)	(1.99)	(-1.05)
Constant	-0.07	-0.10	-0.03	0.11	0.01	0.42*	-0.00	0.11	0.07
	(-0.33)	(-0.40)	(-0.11)	(0.46)	(0.03)	(1.68)	(-0.00)	(0.51)	(0.29)
Observations	131	131	131	131	131	131	131	131	131

Notes: The column headers highlight which monthly equally weighted portfolio is used as the dependent variable: (1) The Refinitiv Business Classification, (2) Taxonomy revenue alignment, (3) Taxonomy capex alignment, (4) Emission intensity, (5) Scope 1-2 emission intensity, (6) Refinitiv E-scores, (7) Climate change exposure score, (8) Climate change opportunity score, (9) MSCI E-score. The rows illustrate the pricing factors and the constant. Newey-West standard errors are employed for all models. Returns are in per cent per month. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Equally weighted green factor model regression results using the TRI

Table A.2

Variables	(1) TRBC	(2) Tax rev	(3) Tax capex	(4) Emission int	(5) Scope 1-2 emission int	(6) E-score	(7) CC exp	(8) CC opp	(9) MSCI E-score
Market	0.51***	0.71***	0.64***	0.76***	0.78***	0.77***	0.73***	0.79***	0.74***
	(4.21)	(13.90)	(11.67)	(13.56)	(14.63)	(15.27)	(13.00)	(12.77)	(12.32)
SMB	0.29	0.39**	0.16	0.33*	0.42***	-0.02	0.18	-0.07	0.23
	(0.79)	(2.32)	(1.07)	(1.86)	(2.82)	(-0.17)	(1.15)	(-0.50)	(1.51)
HML	0.68*	0.48**	0.44***	0.21	0.13	0.61***	0.18	0.44***	-0.22
	(1.70)	(2.53)	(3.37)	(1.00)	(0.67)	(3.49)	(1.01)	(2.99)	(-1.35)
RMW	0.36	0.37	0.31*	0.30	0.24	0.66***	0.38	0.46*	0.04
	(0.80)	(1.63)	(1.67)	(1.07)	(0.97)	(3.16)	(1.54)	(1.87)	(0.19)
CMA	-1.15**	-0.37	-0.24	-0.35**	-0.44***	-0.34**	-0.32*	-0.47***	0.20
	(-2.11)	(-1.44)	(-1.03)	(-2.43)	(-2.74)	(-2.32)	(-1.78)	(-2.96)	(0.81)
TRI	1303.21	1342.05**	1016.17**	945.98**	1039.76**	869.87**	698.98	1399.41***	-1161.85*
	(0.71)	(2.32)	(2.37)	(2.35)	(2.46)	(2.27)	(1.61)	(3.59)	(-1.71)
Constant	1.04*	0.00	0.15	0.08	0.22	-0.02	0.26	0.02	0.64***
	(1.94)	(0.01)	(0.82)	(0.35)	(0.95)	(-0.12)	(1.16)	(0.08)	(2.91)
Observations	131	131	131	131	131	131	131	131	131

Notes: The column headers highlight which monthly equally weighted portfolio is used as the dependent variable: (1) The Refinitiv Business Classification, (2) Taxonomy revenue alignment, (3) Taxonomy capex alignment, (4) Emission intensity, (5) Scope 1-2 emission intensity, (6) Refinitiv E-scores, (7) Climate change exposure score, (8) Climate change opportunity score, (9) MSCI E-score. The rows illustrate the pricing factors and the constant. Newey-West standard errors are employed for all models. Returns are in per cent per month. Robust *t*-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1