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Addressing companies' low-carbon transition challenges requires diversified investments in environmental initiatives

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Abstract
The energy, utilities, industrial, and material sectors are crucial suppliers of essential goods and services, but their business operations are among the largest sources of anthropogenic greenhouse gas emissions. Consequently, companies in these sectors play a pivotal role in the low-carbon transition and face substantial stakeholder pressure to manage their transition risks and reduce their environmental impact. Here, we argue that effective responses to transition challenges require diversifying investments in adaptation and mitigation initiatives across a broad range of activities and goals. Analysing financial and nonfinancial data from a global sample of publicly traded companies, we find that those who extensively diversify their investments are better able to reduce their emissions over time. Diversification also reduces carbon pricing risk, thereby lowering exposure to transition risks, under several climate policy scenarios. Our findings provide empirical evidence that business leaders in critical sectors for the low-carbon transition should incorporate well-diversified investments in adaptation and mitigation initiatives into their sustainability strategies to manage interconnected transition challenges.

Keywords Response diversity · Sustainability behaviour · Transition risk

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1 Introduction

Publicly traded companies in utilities, energy and energy-intensive sectors[1] provide essential services to modern societies, from industrial production to transportation and energy distribution; they offer critical competitive advantages to countries and are a crucial source of employment (Kartha et al. 2018; De Bruyn et al. 2020). However, their production processes are responsible for the largest share of anthropogenic greenhouse gas (GHG) emissions, and their operations are one of the leading causes of climate change (Damert et al. 2017; Dietz et al. 2021).

Due to their climate impact but central role in global economies, these companies play a crucial role in the low-carbon transition. Hence, they face increasing pressure from investors and policymakers to reduce emissions while maintaining the provision of affordable goods and services (Ahman 2020). Striking a balance between conflicting stakeholders' pressures is challenging due to technological barriers to achieving net-zero targets (Hanna and Victor 2021; Yang et al. 2022) and the significant exposure of earnings stability to transition risks, such as policy, legal and market risks (Dietz et al. 2021).

Here, we show that extensive diversification of investments in environmental initiatives - including both mitigation and adaptation initiatives - across a broad range of activities and goals, can support companies in addressing transition challenges, such as concurrently lowering emissions and exposure to transition risks. Specifically, we collect extensive financial and nonfinancial data from a global sample of publicly traded companies in the crucial sectors for the low-carbon transition. We document historical, geographical, and sectoral trends in the diversification of investments in environmental initiatives and characterise the determinants of diversified investment choices. Furthermore, we examine the implications of diversification for companies' climate impact and exposure to transition risks, particularly those related to carbon pricing costs. Our work contributes to understanding what companies in critical sectors of the economy should do to support the low-carbon transition, and it identifies factors that can drive effective behavioural changes.

The paper is organised as follows: in Section 1.1, we develop our hypothesis and provide a qualitative overview of our study. In Section 2, we provide a detailed description of our dataset and empirical approach. Finally, in Section 3 and 4, we present our results and discuss their economic, business and policy implications.

1.1 Overview of the study

Complex adaptive systems evolving in continuously changing environments, from ecosystems to socio-economic systems, are characterised by the development of multiple ways to deal with disruption and to maintain stability in the face of unexpected changes. That is, they employ a diversity of responses to perturbations (Page 2011; Walker et al. 2023), and this diversification is at the core of their adaptive capacities. For example, diversification of financial portfolios lowers investors' exposure to variability in idiosyncratic factors and reduces risk (Markowitz 1952; Haldane and May 2011); diversification of governance strategies increases resilience in socio-economic systems (Leslie and McCabe 2013; Helbing 2013); and response diversity in complex ecosystems increases stability against environ-

[1] Industries that require large amount of energy for their production processes, such as Chemical, Steel and Iron Production, and Cement Manufacturing.

mental fluctuations (Elmqvist et al. 2003; Nyström et al. 2019). Indeed, recently, (Walker et al. 2023) have argued that societies as a whole should actively design and manage policies that consider response diversities - a system's variety of responses to disruptions of all kinds - across ecological and social domains.

Against this backdrop, and in line with the conceptualisation of organisations as complex adaptive systems (Schneider and Somers 2006), here we put forward and test the hypothesis that response diversity is a crucial mechanism for companies to address their transition challenges and balance emission reduction capabilities with earning stability. Conceptually, we measure response diversity as diversification of investments in adaptation and mitigation initiatives that span a broad range of activities and goals. Decision-makers in large publicly traded corporations have several tools at their disposal to reduce their emissions and their earnings' exposure to environmental risks. They can, for example, invest in risk mitigation activities, such as modification of existing assets and procedures; they can invest in long-term transformations, such as the development of new organisational structures and new products; or they can engage with stakeholders to change corporate cultures and incentivise sustainable behaviours (Damert et al. 2017; Vishwanathan et al. 2020). Similarly, they can focus exclusively on environmental goals directly related to GHG emissions or, if they understand the importance of the interconnections between different segments of their processes, they can improve their operations across all sustainability dimensions (van Zanten and van Tulder 2021b, a). A diversified response to sustainability challenges is one that employs multiple tools to address interconnected goals.

Practically, to measure companies' response diversity, we use a structured behavioural dataset developed in (Cenci et al. 2023) from a large-scale analysis of textual data from sustainability reports - annual reports where companies disclose activities undertaken to address societal challenges. The dataset collects information on corporate environmental initiatives, which are activities (e.g. investments in research and development, modifications of existing assets) implemented to address environmental sustainability goals (e.g., increase renewable sources in the energy mix, improve the efficiency of production processes). Greater details on the dataset can be found in Section 2.1.1.

Using the behavioural dataset, we measure companies' response diversity as the entropy resulting from investments' diversification across initiatives' types, i.e., investments across a diverse range of activities and goals (see Section 2.1.2). Entropy is often used to measure diversity in fields as diverse as ecology (Chao et al. 2013), physics (Ghavasieh and De Domenico 2024), strategy and management science (Palepu 1985; Raghunathan 1995). Intuitively, the entropy of a system measures uncertainty in the identity of an individual randomly sampled from a population - higher uncertainties (entropy) imply higher diversity in individuals' identity (Chao et al. 2013). Here, our unit of analysis (individual identity) is a sustainability initiative - the higher the entropy, the higher the diversity of the initiatives across activities and goals.

To illustrate our measure, Fig. 1 shows an example of two firms sampled from the bottom and top quartile of the response diversity distribution in our dataset. Importantly, the two firms belong to the same sector (Industrial) and have a comparable average number of initiatives throughout the sample period. They mainly differ in how these initiatives are distributed or spread across the sustainability dimensions (activities and goals, although, for ease of visualisation, here we only show the distribution across activities). Each segment in the pie chart represents the proportion of initiatives allocated in the activity types, which

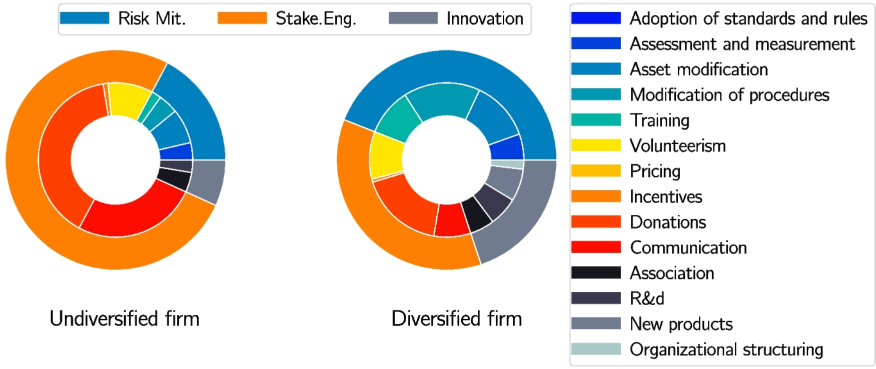

Fig. 1 Diversification of environmental investments. The figure shows an example of the distribution of sustainability initiatives across activity types (defined in Section A in the Supplementary Information) in a firm with low (left) and high (right) response diversity. The inner circles show the distribution of initiatives across all activity types (right legend). The outer circles show the distribution after grouping the activities into three macro categories (top legend). For ease of visualisation, we do not show the distribution across SDGs, which can be found in Fig. S4 in the Supplementary Information

here we show at a granular (inner circle) and coarse (outer circle) level (see Section A in the Supplementary Information, SI, for a detailed description of the activities). The less diversified firm on the left focuses mainly on stakeholder engagement activities, particularly in donation & funding, and communication activities. The more diversified firm on the right, on the other hand, distributes sustainability investments more evenly across all the behavioural dimensions.

In this study, we investigate response diversity as a mechanism to address companies' transition challenges. To this end, we assembled a dataset comprising behaviour, financial and climate data for a large sample of publicly traded companies (Section 2). Then, we estimate the impact of firms' investment diversification on companies' GHG emissions (Section 2.2.2). To investigate response diversity's capacity to reduce exposure to transition risks and therefore support the sustainable continuation of production of goods and services, we estimate the impact of firms' investments diversification on carbon earnings-at-risk, i.e., the proportion of earnings that will be lost under a diverse range of policy scenarios for carbon pricing (Section 2.2.3). Finally, we discuss our study's limitations and economic, business, and policy implications (Section 4).

2 Data and methods

2.1 Data sources

In this study, we analyse the behaviour of companies in the Energy, Utilities, Material, and Industrial sectors as defined by the Global Industry Classification Standard (GICS). Our final dataset comprises information on companies' fundamentals, GHG emissions, carbon earnings at risk, sustainability behaviour as well as country-level policy data.

Companies' fundamentals are from COMPUSTAT and Refinitiv, two leading providers of financial data. Specifically we collect data of firms' Size;[2] Investment Intensity;[3] Tangibility;[4] Profitability;[5] Market leverage;[6] Market-to-book;[7] Stock return volatility;[8] Competitive pressure.[9]

Companies' emissions data are from Trucost. We measure total GHG emissions as direct plus first-tier indirect emissions, which are defined as Scope 1 and 2 emissions, plus the company's first-tier upstream supply chain. Emissions data in the Trucost database are not always those reported by the companies. When companies do not disclose their emissions in a particular year, Trucost uses their internal models to estimate them. In our analysis, we will control for the source of emissions data to correct for the noise introduced by the discretionary nature of the disclosure.

To characterise companies' exposure to transition risks, we use data on exposure of earnings to future carbon prices (henceforth, earnings at risk) from TruCost. Earnings at risk are calculated by estimating the difference between today's carbon costs (the amount a company pays for carbon emissions) and expected carbon costs at a specified time horizon as a function of given policy scenarios for carbon prices. Trucost analysts evaluate three possible scenarios, called "Low", "Medium" and "High" carbon price scenarios. In the "Low" scenario Trucost analysts assume that countries fully implement their Nationally Determined Contributions to the Paris Agreement. In the "Medium" scenario, they assumed delayed short-term climate actions, but long-term commitments to limit global warming below 2°C. In the "High" scenario, they assume that countries will implement short-term climate actions to limit global warming within the goal of the Paris Agreement by the end of the century. For each policy scenario, earnings are considered to be at risk if carbon costs are greater than 10% of earnings before interests, tax (EBIT), depreciation and amortisation (EBITDA).

Finally, we source country-level policy data from the OECD's Policy Instruments for the Environment database. Specifically, we collect yearly data on the number of active environmental policies by country, the number of environmental domains targeted by each policy (e.g., water quality, air quality) and the policy instrument type (e.g., tax, tradable permits). Then, we construct two variables that track the diversity of policy effort in any given year and country as the ratio between the number of environmental domains and the number of policies, as well as the number of unique instrument types and the number of policies (see Section B in the SI for a more detailed description of the variables).

[2] Log of sales (SALE, in USD) adjusted for inflation

[3] Capital Expenditure (CAPX, in USD) divided by sales

[4] Property plant and equipment (PPENT, in USD) divided by book assets (AT, in USD)

[5] Earnings Before Interests, Tax, Depreciation and Amortization (EBITDA in USD) over previous-year book asset

[6] Long-term plus short-term debt (F.DebtTot) divided by market value of assets: total assets (F.TotAssets) - book equity (F.ShHoldEqCom) + market equity (F.MktCap)

[7] Market value of assets divided by Total Book Asset

[8] Measured as the standard deviation of the distribution of weekly stock returns over a calendar year

[9] $1 - \frac{\mathrm{SALE}}{\mathrm{Sector}_{\mathrm{SALE}}}$, where the second term is the ratio between a company's revenue and the total revenue of the companies in the sectors. To calculate total revenue in the sector we use the GICS Industry classification and all the companies in the North America and Global Compustat dataset

To match companies in the different datasets, we use ISIN numbers. Companies that cannot be matched by ISIN numbers are first matched by company name and then by standardised company name, i.e., names obtained after removing punctuation and common suffix such as for example “corp”, “llc”, “inc”. Table ST1 in the SI shows the summary statistics of companies in our dataset.

2.1.1 Overview of the behavioural dataset

To track corporate actions to address environmental challenges, we use the dataset developed in (Cenci et al. 2023), which is constructed from an extensive analysis of information on corporate efforts to lower the environmental impact of their business operations from nonfinancial disclosures in sustainability and integrated reports. For clarity, here we provide a brief overview of the data-generating process. Greater details can be found in (Cenci et al. 2023). The main unit of analysis of the dataset is a sustainability initiative, which is defined as an activity (e.g., an asset modification) implemented by a company to meet a specific sustainability goal (e.g., increase the energy efficiency of production processes). Notably, initiatives can have mitigation or adaptation objectives. The activity types are classified based on 14 corporate activities defined in Section A and commonly used in the corporate sustainability literature (see, for example, the systematic review in (Vishwanathan et al. 2020)). For the classification of the sustainability goals, the dataset uses the United Nations Sustainable Development Goals (SDGs), and here we focus on SDGs 6,7,9,11,12,13,14,15.

Initiatives identification from sustainability reports and their classification in activities and goals is performed using an ensemble of BERT and RoBERTa base models trained on a large sample of annotated sustainability reports. The final output consists of a company-year matrix, that here we call behavioural matrix. Each entry in the matrix counts the total number of identified initiatives in the particular activity-type (row)/SDG (columns) combination. Figure S3 in the SI shows the Sankey diagram of the behavioural matrix to highlight the logical flow of an initiative as an implemented activity (left) to achieve a specific sustainability goal (right). In what follows, we will only include observations with more than one initiative, and we will group the activity types into three categories: risk mitigation (activities capture companies’ incremental investments in the modification of existing assets and procedures); stakeholder engagement (activities are related to corporates’ efforts to increase external visibility and relationship with various stakeholders); and innovation (activities relate to companies’ investments in the creation of new product, structure and growth opportunities), see Section A in the SI.

2.1.2 Measuring response diversity

Our main variable of interest, response diversity, captures the diversification of environmental activities across sustainability goals. To measure response diversity we transform the behavioural matrix ($\mathcal{B}$) of companies in our sample into a frequency distribution of initiatives across the behavioural dimensions by normalising the matrix to one. That is, for every company n and time t, we calculate: $\tilde{\mathcal{B}}_{n,t,ij} = \frac{\mathcal{B}_{n,t,ij}}{\sum_{i \in A, j \in S} \mathcal{B}_{n,t,ij}}$ where A is the set of activity types and S is the set of SDGs. Then we calculate the Shannon entropy of the normalised matrix as:

$$\text{response diversity}_{n,t} = \sum_{i \in A, j \in S} \tilde{\mathcal{B}}_{n,t,ij} \log(\frac{1}{\tilde{\mathcal{B}}_{n,t,ij}}) \tag{1}$$

Importantly, in order to capture the whole approach of a company to environmental sustainability issues, when measuring response diversity we include activities that are both directly and indirectly linked to GHG emissions. The main advantage of using Shannon entropy as a measure of response diversity, as opposed to other diversity statistics, such as the Simpson index, is that the Shannon entropy is additive and, therefore, we can study the contribution of its components in isolation. Specifically, we make use of the following decomposition of Eq. 1:

$$\begin{aligned}\text{response diversity}_{n,t} = \underbrace{\sum_{i \in \mathrm{RM}, j \in S} \tilde{\mathcal{B}}_{n,t,ij} \log(\frac{1}{\tilde{\mathcal{B}}_{n,t,ij}})}_{\text{Risk mitigation}} + \underbrace{\sum_{i \in \mathrm{SE}, j \in S} \tilde{\mathcal{B}}_{n,t,ij} \log(\frac{1}{\tilde{\mathcal{B}}_{n,t,ij}})}_{\text{Stakeholder engagement}} + \\ + \underbrace{\sum_{i \in \mathrm{IN}, j \in S} \tilde{\mathcal{B}}_{n,t,ij} \log(\frac{1}{\tilde{\mathcal{B}}_{n,t,ij}})}_{\text{Innovation}}\end{aligned} \tag{2}$$

The activity types that characterise the three behavioural components of response diversity are defined in Section A in the SI.

2.2 Empirical approach

In this Section we describe our empirical approach to estimate the relationship between response diversity (Eqs. 1 and 2), asset characteristics, corporate emissions and transitions risks.

2.2.1 Determinants of response diversity

Our first objective is to identify factors associated with characteristic levels of response diversity to establish if investments' diversification is a function of companies' idiosyncratic characteristics and country-level policy choices. Specifically, we estimate a series of regression specifications to measure the association of response diversity with firms' Size, Investment Intensity, Market-to-Book, Tangibility, Leverage, Profitability, Volatility, Competition levels, GHG emissions as well as diversification of policies across environmental domains and economic instruments (see Section 2). To isolate the total effects of each independent variable $\mathcal{I}$, we run multiple regression specifications controlling for factors ($\mathrm{X}_{\mathcal{I}}$) that can potentially be related to both response diversity and $\mathcal{I}$ (Keele et al. 2020; Cenci 2024). The control sets for each independent variable are discussed in Section C in the SI.

Each regression specification also includes: (1) country fixed-effect to control for potential impact of differences in regulatory framework among companies in our sample, including regulation on corporate disclosure of non-financial information; (2) sector fixed-effects to account for idiosyncratic differences of sectors' technological basis; (3) year-fixed effects to account for the growing importance of pressure from shareholders, other stakeholders and policymakers on corporate behaviour;[10] (4) the total number of initiatives.

The publication of the sustainability reports we use to measure companies' response diversity is a largely voluntary process in the observation period. Hence, there is a potential self-selection bias in the sample. To address this bias we use the Heckman two-stage model (Heckman 1979). The first model estimates the probability that a company disclose nonfinancial information in a sustainability report. Specifically, we run a Probit where the independent variable is a binary indicator that takes the value of one if company n publishes a report in year t and zero otherwise. We collect data on voluntary disclosure from Refinitiv Asset4.[11] The independent variables include Profitability, Size, Tangibility, and year-fixed effects. We also control for the proportion of companies in any given country and sector that issue sustainability reports. We call the control set of the Probit model $\tilde{\mathbf{X}}$ to distinguish it from the control set of the main regressions. Results of the Probit regression are shown in Table ST3. From the fitted Probit model, we estimate the inverse Mills ratio, $\mathcal{M}$, which is defined as: $\mathcal{M} = \frac{f(x)}{F(x)}$ where $f(x)$, $F(x)$ are the (normal) probability density function and the cumulative distribution, respectively. Then we use the inverse Mills ratio from the Probit as an additional covariate in each of the regression specification.

Overall, for each independent variable $\mathcal{I}$, we run the following models:

$$\begin{aligned}&\mathbb{P}[\mathrm{Disclosure}_t|\tilde{\mathbf{X}}_t] = \Phi(\tilde{\mathbf{X}}_t^T\tilde{\boldsymbol{\beta}})\\&\text{response diversity}_t = c + \alpha\mathcal{I}_{\langle 3\rangle} + \boldsymbol{\beta}\mathbf{X}_{\mathcal{I},\langle 3\rangle} + \boldsymbol{\gamma}\mathbf{F} + \delta\mathcal{T}_t + \eta\mathcal{M}_t + \epsilon\end{aligned} \tag{3}$$

Where $\mathbf{F}$ and $\mathcal{T}_t$ denote fixed effects and total number of initiatives, respectively. Our coefficient of interest is α. The control set $\mathbf{X}_{\mathcal{I},\langle 3\rangle}$ for each independent variable $\mathcal{I}$ is discussed in Section C in the SI. All the dependent variables in $\mathbf{X}_{\mathcal{I},\langle 3\rangle}$ are estimated as historical averages over the previous three years in order to limit the probability of simultaneity bias. Because the determinants of response diversity are all expressed in different units, in Eq. 3, and in all the other regressions in this study, we standardise the coefficients by multiplying them by the ratio of the standard deviations of independent and dependent variables. Standardised coefficients can be interpreted as measuring the relative change in the standard deviation of the dependent variable upon a one-standard deviation-change of the independent variable.

2.2.2 Measuring the impact of response diversity on emission reduction capabilities

To estimate the association between response diversity and corporate emissions, we run four regression specifications, each using a different measure of GHG emissions as dependent variable. The first and second specifications use contemporaneous GHG emissions measured in absolute and intensity terms. To estimate emission intensity, we divide emissions by total revenue. The third and fourth specifications instead use cumulative emissions measured up to two years after the measurement of response diversity. The control sets are the same for the four specifications and include competition, total number of initiatives,

[10] We do not control for firm-fixed effects because we do not have continuous observations for most of the companies in our sample.

[11] Item TR.CSRReporting

Tangibility, Size, Leverage, Market-to-book, and average emissions over the previous two years. The model also includes country, sector, and year-fixed effects. In theory, there is a potential self-selection bias for companies that disclose emissions versus those that do not. However, because non-disclosed emissions are estimated by Trucost when production data are available, we also control for the source of emissions data (see Section 2) by adding a fixed effect factor for whether a particular emission datum is fully estimated, partially estimated, or collected from companies disclosures. Specifically:

$$\mathrm{GHG}_k = c + \alpha \mathrm{response\ diversity}_t + \boldsymbol{\beta}\mathbf{X}_{\langle 3 \rangle} + \boldsymbol{\gamma}\mathbf{F} + \delta\mathcal{T}_t + \boldsymbol{\eta}\mathbf{D}_t + \epsilon \tag{4}$$

Where the subscript k in the dependent variable denotes the type of emission data used (contemporaneous, lagged, intensity, absolute). $\mathbf{F}$ and $\mathcal{T}_t$ denote the fixed effects and total number of initiatives, respectively. $\mathbf{D}_t$ denotes the control for the source of emission data (see Section 2). Our coefficient of interest is α.

2.2.3 Measuring the capacity of response diversity to moderate transition risks

To estimate the association between response diversity and earnings at risk, we estimate a Probit model where the dependent variable is one if, for a given policy scenario (“Low”, “Medium”, “High”) and time-horizon (2030, 2040, and 2050), carbon costs are greater than 10% of earnings before interests, tax, depreciation and amortisation (EBITDA), and zero otherwise. The independent variables are the same as those used in Eq. 4. However, we also include equity returns and their volatility to account for possible alternative sources of risk. Before estimating the model, we standardised the independent variables to zero mean and unitary variance so that the marginal effects estimated from the Probit are measured in units of standard deviations of the explanators.

3 Results

Our sample includes 1464 global companies that account for approximately 67% of global market share measured over 13461 companies in the sectors, and 68% of the sectors’ emissions, measured over 5504 companies. Table ST1 and Fig. S5 in the SI show detailed statistics of the sample after merging all the datasets as explained in Section 2.

3.1 Temporal evolution of response diversity

Figure 2 panel **A**, left y-axis, shows the temporal evolution of response diversity (red solid line). We observe a significant and positive correlation between response diversity and the total number of initiatives (see Fig. S6 in the Supplementary Information). Notably, the positive and statistically significant correlation between the number of initiatives and response diversity persists after accounting for several companies’ idiosyncratic characteristics and fixed effects that could potentially bias the association (see Section ST2 in the Supplementary Information). The positive correlation would not be expected under random distributions of initiatives that match the empirical distribution at the population level (see Fig. S6 in the SI). That is, companies that take on more initiatives do not distribute them randomly

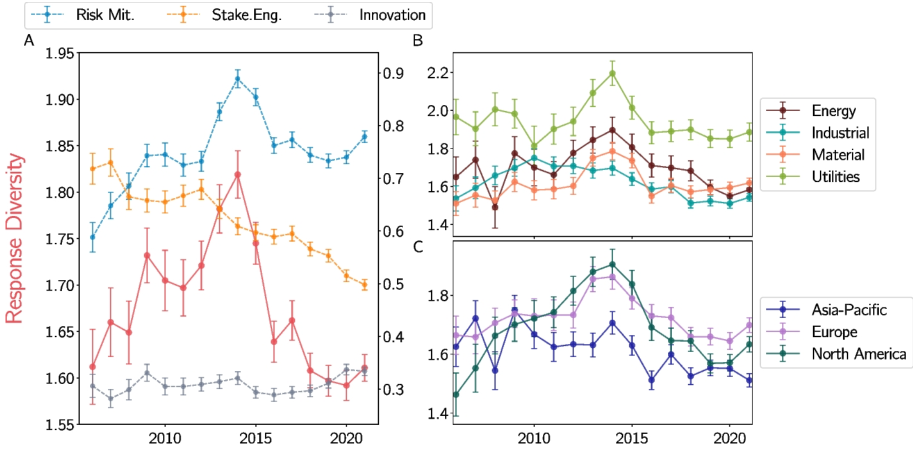

Fig. 2 Temporal evolution of response diversity. Panel **A**, left y-axis, shows the temporal evolution of response diversity averaged over all firms in the sample before matching datasets (red solid line). The right y-axis in the panel shows the decomposition of response diversity into the three macro behavioural categories (top legend). Panel **B** and **C** show the temporal evolution of response diversity across sectors and geographies, respectively. Error bars are standard errors of the means

across the sustainability dimensions, but rather, they tend to distribute them so to increase their response diversity.

The right y-axis in Fig. 2 panel **A** shows the decomposition of the entropy into the three main behavioural components: risk mitigation, stakeholder engagements, and innovation activities. We observe a clear diversion of response diversity from being mostly concentrated around stakeholder engagement activities at the beginning of the observation period, to being dominated by risk mitigation activities in most recent years. Response diversity in innovation investments is stable and has only marginally increased during the last four years of the observation period.

Panel **B** and **C** show the temporal evolution of response diversity across sectors and geographies, respectively. We have found a substantially larger diversification in the Utilities sector compared to other sectors and a lower diversification in companies with headquarters in the Asia-Pacific regions compared to companies located in other macro regions. These differences in response diversity across sectors and geographical regions are expected due to the different technological bases, material issues, and policy constraints faced by companies that operate in markedly different environments. Therefore, due to the strong dependency on both, the reason for and the effect of response diversity across time, geography and sectors in the following, we will study the characteristics and impact of response diversity relative to the year, sector and geography average.

3.2 Determinants of response diversity

To identify the determinants of companies' response diversity, we estimate its association with historical values of a series of asset characteristics (e.g., Size, invested capital, stock return volatility) and country-level policy choices, after controlling for a broad set of sources of endogeneity as explained in Section 2.2.1 and Section C in the SI. Large companies can be seen as well-diversified portfolios of investment projects (Vuolteenaho 2002) and, not surprisingly, have a greater response diversity (Fig. 3 top bar). Among large companies, response diversity is also associated with a greater value of growth opportunities (market-to-book), a lower proportion of tangible assets in companies' books (Tangibility) and higher volatility of stock returns. These three factors are often associated with the presence of information asymmetry between insiders and outsiders.

Response diversity is also associated with greater competition for revenue and lower historical emissions. Notably, we have found that response diversity is unrelated to the historical level of diversification of environmental policies across environmental domains but positively correlated with the diversity of economic instruments through which policies are implemented. Overall, Fig. 3 suggests that companies that integrate response diversity measures in their sustainability strategies are systematically different from those that do not.

3.3 Impact of response diversity on companies' GHG emissions

In this section we investigate the relationship between response diversity and characteristic levels of corporate emissions under direct management control (see Section 2.2.2). We focus on the impact of response diversity on contemporaneous and future emissions in absolute and intensity terms. Future emissions are measured cumulative up to two years ahead, and emissions intensity are measured per unit of revenue (in USD).

The first set of coefficients on the left of the vertical line in Fig. 4 panel **A**, show that response diversity is negatively and statistically significantly associated with emissions. The effects are stronger when estimated over future emissions in intensity scales. The results are robust to alternative measures of response diversity (Fig. S8 in the SI). The coefficients are standardised by multiplying them by the ratio of the standard deviation of the independent and dependent variables. Therefore, for example, a standard deviation increase in response diversity is associated with an average negative change of 10% standard deviations of future emissions intensity (orange bar). The coefficients on the right of the vertical line show the association between the emissions measures and the three behavioural components of

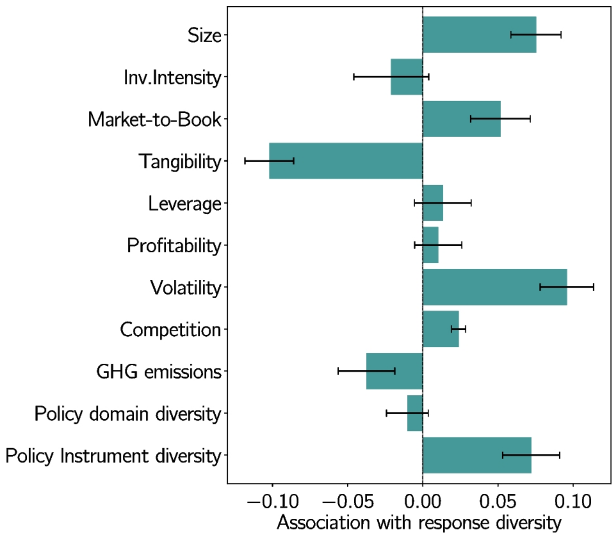

Fig. 3 Determinants of response diversity. The figure shows the associations of response diversity (x-axis) with a series of firm and policy level determinants (y-axis). The bars are the standardised regression coefficients, and their 95% confidence intervals, as estimated from the models described in Section 2.2 and Section C in the Supplementary Information

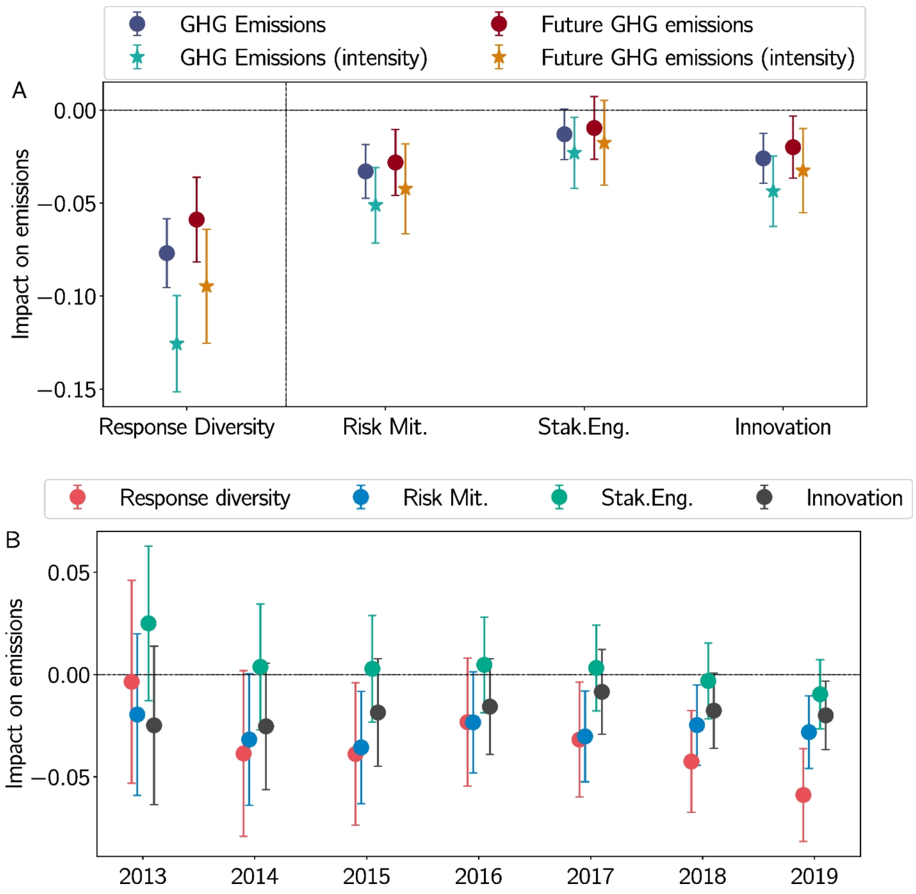

Fig. 4 Response diversity and GHG emissions. Panel **A** shows the associations of response diversity with absolute and intensity GHG emissions measured contemporaneously (blue and green) and cumulative up to two years ahead (red and orange). The model to estimate the associations is described in Section 2.2. Panel **B** shows the coefficients of the models (and their 95% confidence intervals) estimated across time on an expanding window. The dependent variable in panel **B** is absolute GHG emissions measured cumulatively up to two years ahead. Negative values indicate that higher levels of response diversity are associated with lower emissions

response diversity (see Section 2.1.2, Eq. 2). The strongest contribution to the negative associations comes from risk mitigation and innovation activities. Notably, the magnitude of the associations of total response diversity with emissions is substantially stronger than that of individual behavioural components.

Figure 4 panel **B** shows the temporal evolution of the associations of response diversity (total and across the individual components) with absolute levels of future emissions. A clear pattern emerges from the figure: the association of response diversity with future emissions was dominated by the contribution of risk mitigation activities at the beginning of the 2010s. Throughout the observation period, however, we observe a decline in the relative importance of these activities with respect to the importance of response diversity across all the sustainability dimensions, which has become substantially stronger (in absolute terms) in recent years.

The comparison of the standardised coefficients across time can be misleading because associations are estimated over rolling windows and, therefore, over different samples. Hence, inter-year differences could be due to changes in the variance of the sample as opposed to changes in the strength of the associations. To support our findings, in the SI, we have re-estimated the time series of the coefficients without standardisation. Results are qualitatively unchanged (Fig. S9).

3.4 Response diversity as a mechanism to moderate transition risks

In the previous analysis, we have shown that response diversity is associated with lower levels of cumulative future GHG emissions. However, companies do not invest in sustainability solely to reduce their environmental impact but also because they now understand that climate change is a financially material, and even legal, issue (Wetzer et al. 2024). Indeed, companies' bottom lines and earnings stability are exposed to a broad range of transition risks, which are becoming increasingly important as new regulatory frameworks that impose changes in business models emerge throughout the globe[12] (Buhr 2023).

Can response diversity be an effective strategy to reduce exposure to transition risks? To answer this question, we estimate the association between response diversity and the probability that corporate earnings are impacted by changes in carbon prices under a variety of policy scenarios and time horizons, as explained in Section 2.

Figure 5 illustrates a negative relationship between response diversity and earnings at risk before interest, tax, depreciation, and amortisation (EBITDA). That is, greater diversification of investments in adaptation and mitigation initiatives across corporate activities and goals is associated with reduced exposure to transition risks. This effect is more pronounced over longer time horizons and in medium to high carbon price policy scenarios (orange and red marks in the figure). The results remain consistent even when we exclude depreciation and amortisation from the earnings measure (Fig. S10 in the SI) and when we use alternative measures of response diversity (see Fig. S11). Notably, as the coefficients in Fig. 5 are marginal effects expressed in units of standard deviations, comparing the magnitude of the effects across the panels illustrate that response diversity across all sustainability dimensions is substantially more important than diversification within the macro dimensions.

4 Discussion

Companies in utilities, energy and energy-intensive sectors are responsible for a large share of global GHG emissions but also provide essential goods and services to modern societies. Due to their central role in the transition to a just and low-carbon economy, companies in these sectors face substantial transition risks and increasing pressure from stakeholders and policymakers to lower their emissions while still maintaining the affordable provision of goods and services. In this paper, we argued that to balance these often contrasting

[12] Companies are also exposed to physical risks caused by long-term changes in climate patterns and increased frequency and severity of natural disasters. However, physical risks are complicated to measure empirically, and we do not explore them in this study.

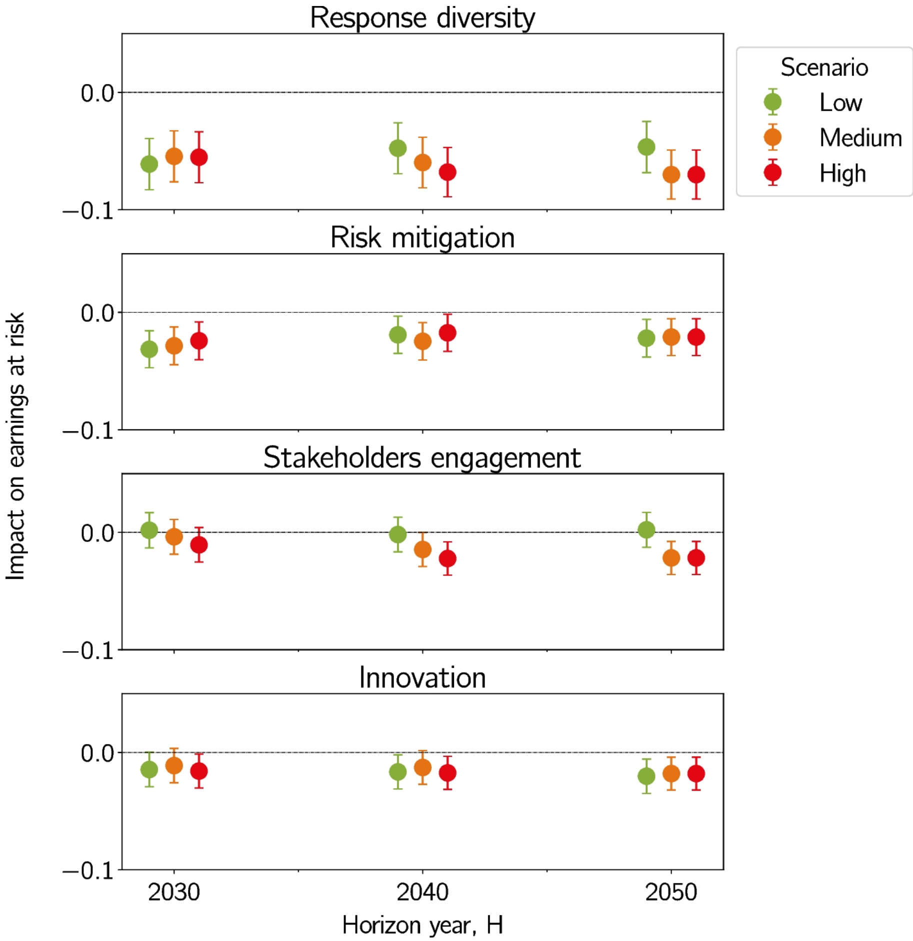

Fig. 5 Response diversity and earnings at risk. The figure shows the associations of response diversity with the probability of earnings at risk under a series of policy scenarios (low, medium and high carbon prices) and time horizon (x-axis). Negative values indicate that a greater response diversity is associated with lower probabilities of earning at risk. The model to estimate the association is described in Section 2.2. The coefficients are marginal effects and error bars denote their 95% confidence intervals

needs, companies should diversify their investments in adaptation and mitigation initiatives across a broad range of activities and goals. That is, they should adopt response diversity mechanisms in their sustainability strategies. We derived an empirical measure of response diversity from a large-scale behavioural dataset, and investigated the relationship between response diversity and corporates' emissions and exposure to transition risks.

Our analysis shows that response diversity is positively associated with emission reduction capabilities, and the strength of the association - the importance of response diversity as a mechanism to lower emissions from business operations - has grown stronger over time. Our results also illustrate that companies adopting response diversity mechanisms tend to exhibit a lower exposure to transition risks associated with future carbon prices, particularly under high-risk climate policy scenarios over long time horizons. In this section, we discuss the most relevant limitations and implications of our study.

This study has two main limitations. First, as with any empirical research, there could be unaccounted endogeneity issues. To address endogeneity concerns, we have carefully constructed independent models for each association we set to estimate; we controlled for idiosyncratic companies' characteristics, fixed effects, self-selectivity, the origin of the emission data, and we also tested the validity of our main result against an alternative measure of response diversity. However, given the empirical nature of our analysis we cannot conclusively claim to have identified a causal relationship between response diversity, GHG emissions and earnings at risk.

The second limitation concerns the accuracy of the measurements of the relevant variables. When measuring response diversity, we rely on self-disclosed information. Even though we account for the bias generated by the voluntary nature of sustainability reporting, we do not account for the discretion on what to disclose in those reports. GHG emissions also are measured with error. To mitigate this issue, in the empirical specification, we add fixed effects to control for the source of emission data. However, there is a fundamental (unobservable) observational error in the measurement process of the emissions that we cannot address in our specification.

Notwithstanding its limitations, our work has important theoretical and practical implications. Building on studies that illustrate the importance of response diversity in socio-economic systems from a theoretical standpoint (Leslie and McCabe 2013; van Zanten and van Tulder 2021b; Walker et al. 2023), here we have provided an empirical measure and tests for the validity of these theoretical expectations in the context of sustainable business practices. Importantly, we conjecture that our empirical measure of response diversity is a manifestation of fundamental cognitive processes that take place at the organisation level and drive the overall behaviour of a company. Specifically, we expect that response diversity is driven by the capability of organisations to understand the interactions between seemingly unconnected phenomena and how those interactions drive their overall dynamics. These capabilities are often associated with system thinking capacities (Burato et al. 2023), which we speculate can explain the tendency of companies to diversify their investment across multiple sustainability issues beyond those strictly associated with their business challenges (i.e., response diversity). Explaining the behavioural mechanisms that drive companies' response diversity can have important implications for developing intervention strategies to create organisational changes that can support companies in the low-carbon transition.

In this context, our study is relevant for business leaders in their development of sustainability strategies. Whilst there is often a tendency to focus strategies around issues that are financially material to a business (Heras-Saizarbitoria et al. 2022), our analysis suggests that specialisation in limited activities and goals is seldom an effective strategy to lower emissions and preserve earning stability. Therefore, we recommend that business leaders integrate response diversity in their environmental sustainability strategies, even across those sustainability dimensions seemingly unrelated to idiosyncratic business challenges.

Notably, our results also have relevant policy implications. Our findings suggest that response diversity is more prevalent in companies subject to environmental regulatory frameworks characterised by diverse mixes of policy instruments, from environmental taxes to tradable permits and subsidies (Fig. 3). Hence, our preliminary results suggest that companies subject to a broader set of economic incentives, an effective policy strategy to achieve emission reduction objectives (Stechemesser et al. 2024), are more likely to implement response diversity measures within their environmental sustainability investments. Future research should investigate the relationship between response diversity and policy choices in further depth, as a better understanding of effective incentive systems for nudging corporate behavioural changes is crucial to inform the development of impactful climate policies.

Overall, we have provided an empirical framework to study response diversity mechanisms in crucial sectors for the low-carbon transition. Importantly, our study provides empirical evidence that underscores the crucial role that response diversity can play as a sustainability strategy in socio-economic systems (Walker et al. 2023), and the importance of integrating adaptation and mitigation initiatives to address companies' interconnected low-carbon transition challenges (Howarth and Robinson 2024).

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Author Contributions SC designed the study. SC and ST develop the theoretical framework. SC performed the analysis and wrote the first draft of the paper. SC and ST wrote the final version of the paper.

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Data Availability The response diversity measure is available at https://doi.org/10.7910/DVN/9UREL9. Data from COMPUSTAT, Trucost, and Refinitiv can be accessed directly from the data providers for a fee, see Refs. (Compustat 2023; Refinitiv 2023b; Trucost 2023; Refinitiv 2023a). The policy dataset is publicly available, see Refs (OECD 2024).

Code Availability The code to reproduce our results is available at https://doi.org/10.7910/DVN/9UREL9.

Declarations

Competing interests The authors declare no competing interests.

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