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"Carbon" boards and transition risk: Explicit and implicit exposure implications for total stock returns and dividends payouts

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ABSTRACT

Transition risk disclosure facilitates investors' understanding of the potential company-level risks associated with a low-carbon transition. Among the others, stricter regulations could undermine companies' financial performances, affecting operations costs and revenues and their impact being proportional to the business carbon intensity. Transition risk disclosure takes two forms. One is a textual description of transition risk in compulsory and voluntary non-financial disclosure. The other is the disclosure of carbon emissions and intensity, which is implicitly associated with transition risk exposure. We empirically assess the impact of the two transition risk measures on shareholder returns to test the "carbon premium" hypothesis. We consider shareholder return as the sum of capital gain and dividend paid and analyse the impact of transition risk on both. Evidence supports the "carbon premium" hypothesis but suggests such a premium is transferred to shareholders primarily via dividend payouts. One possible explanation consistent with this evidence is that boards in highly polluting companies use dividends to compensate investors for the relatively lower capital gain, dissuading them from divesting due to low returns, stigmatisation effects and regulatory risks.

1. Introduction

Climate change and its financial uncertainties could affect 93% of the capital markets, or $27.5 trillion, indicating a relevant concern for investors (Sustainability Accounting Standards Board, 2017). On the one hand, financial markets are put under stress by stringent climate mitigation policies intended to curb CO2 emissions (Task Force on Climate-related Financial Disclosures (TCFD), 2017) while, on the other hand, have the potential to upscale the effects of mitigation policies through disinvestment/investment dynamics. As a consequence, carbon-intensive sectors are experiencing a period of financial stigmatisation, with institutional investors designing portfolios that are less and less dependent on carbon-intensive activities (Bolton and Kacperczyk, 2021b) and, more in general, with a trend of negative stock performances since before the 2008 crisis (Bressan Bocardo, 2016).

Companies' disclosure activity is the primary source of climate information for financial markets. Transition risk exposure can be disclosed in two manners: explicitly and implicitly. The first relates to the risk exposure statements in voluntary disclosure and, most importantly, legally binding reports. Under a regulatory mechanism for compulsory disclosure, omissions in mandatory reports can implicate litigations and allow shareholders, associations, and trustees to open lawsuits for undisclosed climate transition risks. The US case is representative here, as the SEC[1] since 2010 has indicated that corporations must disclose climate-related impending regulations, taxes, physical and other financial risks when exposed (Wang, 2017). Kolbel et al. (2020) have shown

Abbreviations: DPR, Dividend Payouts Ratio; SR, Stock Returns; TSR, Total Stock Returns; ROE, Return on Equity; ROTA, Returns on Total Assets; IPCC, Intergovernmental Panel for Climate Change; GHG, Green-house Gasses; SEC, Securities and Exchange Commission.

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[1] Securities and Exchange Commission (SEC) is the US regulatory system agency that oversees the applications of mandatory disclosures, indicating which risks ought to be revealed to potential investors.

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that the information included in such mandatory filings can be effectively used to measure transition risk exposure. The second relates to the emissions disclosure, which results from voluntary communication to markets. Emissions indirectly measure transition risk exposure under the assumption that emission-intensive activities will be more penalised by stricter regulations (Bertolotti and Kent, 2019; Bolton and Kacperczyk, 2020; Ilhan et al., 2020; Jona and Lim, 2016). Emissions considered for risk assessment are primarily Scope 1 emissions (directly generated by the company), but, depending on the industry, these can be complemented by Scope 2 (indirectly generated through energy use) and Scope 3 (emissions produced along the value chain). Scope 2 emissions alone represent 73% of global GHG emissions, of which 91% are CO2 (Climate Watch, 2017). Carbon Disclosure Project (CDP), ESGcook, TruCost and many others are attempting to systematically track firm-specific emissions to provide markets and investors with reliable and comparable information.

The extent to which transition risk, implicit or explicit, is priced in financial instruments has been the object of multiple studies. Many of these have, so far, considered implicit measures of transition risk, finding that a high risk reduces the distance to default (Capasso et al., 2020), increases the probability for call options to be out of money (Ilhan et al., 2020), increases debt cost (Lee and Choi, 2019), and affects asset prices (Liesen et al., 2017). More specifically, a few studies have looked at stock price performances (Matsumura et al., 2014; Nguyen et al., 2020) to address the “carbon premium” hypothesis, according to which brown companies should guarantee a return premium to compensate investors for the higher risk. Bolton and Kacperczyk (2020) compare the impact of transition risk on stock prices across countries and find evidence of a carbon premium that depends on the country’s climate policy. The use of explicit measures has led to somehow similar conclusions. Albarrak et al. (2019) find that disseminating carbon emissions on social media platforms negatively influences the cost of equity. Kolbel et al. (2020) and Jaggi et al. (2017) used text-based indicators to assess the impact of disclosed risk on 10-K reports, and their results suggest a positive association of risk exposure with credit default swaps spreads and market-to-book ratio.

In none of the studies that consider the carbon premium hypothesis, implicit and explicit measures of transition risk have been considered together and compared. In addition, stock returns have been computed primarily as simple price variations over a period (Bolton and Kacperczyk, 2021b; Matsumura et al., 2014; Nguyen et al., 2020), thus neglecting the contribution of dividend payout. While dividend policies have long been studied (Lintner, 1956; Michaely and Roberts, 2006; Miller and Modigliani, 1961; Perez-Gonzalez, 2002), their relationship with transition risk has not been addressed, to the authors’ knowledge. Exploring such relations between different components of stock market returns and other measures of transition risk is of utmost importance for two reasons. Firstly, it sheds new light on how financial operators price transition risk, balancing the uncertainty of future capital gains under transition scenarios with the immediate and certain income gains represented by dividends; secondly, it allows an understanding of how boards cope with market behaviours managing the dividend payouts ratios concerning the disclosed transition risk.

Understanding the relationship between transition risk and dividends is crucial for environmental policies. Boards in carbon-intensive companies can decide to use operative profits to pay the premium that compensates shareholders for the higher risk or to invest these resources to accelerate the carbon neutrality transition. Empirical evidence on the relationship between risk factors and dividend policies is mixed (Cheung et al., 2018; Hail et al., 2014; Michaely and Roberts, 2006; Miller and Rock, 1985). A positive relationship is coherent with the carbon premium hypothesis, as investors expect a higher reward to compensate for the higher risk, and dividends represent the only option when capital gains are limited. A negative relationship, in contrast, may result from the decision to use profits to invest in decarbonisation, increasing investors’ expectations about future earnings at the price of limited shareholders’ short-term rewards. Depending on whether the relationship is positive, negative or null, the effect of transition risk on total stock returns (TSR) may differ from that on simple stock returns (SR), the former incorporating the dividend payouts ratio (DP).

This work fills this literature gap by examining how explicit and implicit transition risk impacts TSR, SR, and DP. The contribution to the existing literature is twofold. Firstly, we consider the impact of transition risk on multiple sources of shareholder returns to determine whether the carbon premium effect, if any, results from the market efficiency in risk pricing or is the consequence of deliberate board strategies. Secondly, considering that transition risk indicators used in literature are heterogeneous and often yield contrasting indications about the relationship with financial performance, we examine two measures of transition risk, one explicit and one implicit, that are alternatively used in literature but never compared. Explicit measures originate from documents stating a company’s transition risk exposure explicitly. Our approach leverages text analysis and Natural Language Processing (NLP) algorithms to match mandatory report texts with specific transition risk glossaries. The implicit transition risk measure is carbon intensities (tons of GHG equivalents per thousand dollars of revenues). The panel includes a sample of US firms that disclosed emission intensities and transition risk in 10-K reports between 2011 and 2022. The work focuses on the US market because the consolidated discipline of implicit and explicit transition risk disclosure makes the computed indicators comparable across the firms and sectors.

The work is structured as follows. Section 2 presents a brief literature review of the financial consequences of a low-carbon transition. Section 3 explains the analytical approach and the data. Section 4 presents the estimation results, while Section 5 discusses the summary evidence in relation to previous studies results. Section 6 concludes the work.

2. Literature

The paper links themes of corporate environmental performance and corporate finance by connecting two streams of literature, one that investigates the reasons and factors that push companies to release dividends from net revenues (Divecha and Morse, 2019; Hail et al., 2014; Michaely and Roberts, 2006) and the other that studies the determinants of total stock returns for shareholders (Abowd, 1990; Bressan Bocardo, 2016; Burgman and Van Clieaf, 2012; Stewart, 2014).

As for dividend policies, Lintner (1956) was the first to study dividend strategies and hypothesised that dividends tend to be “sticky” and directed to a long-term target, a phenomenon later defined as “dividend smoothing” (Divecha and Morse, 2019; Michaely and Roberts, 2006; Miller and Rock, 1985; Rozeff, 1982). Miller and Modigliani (1961) postulated that a company might use dividends instead of equity or debt to finance its activities in a frictionless world. In reality, there are various sources of friction stemming from information asymmetry (Cheung et al., 2018; Miller and Rock, 1985) to agency costs (Hail et al., 2014; Rozeff, 1982), tax reforms (Perez-Gonzalez, 2002) and information shocks (Hail et al., 2014) that can affect firms’ decision not to use internal resources to finance projects and even to pay dividends to shareholders.

Uncertainties determined by the climate transition might determine specific frictions for carbon-intensive companies, guiding them to use dividends for purposes other than internal financing. Nguyen et al. (2020) noted that financially constrained corporations in Australia reduced their dividend payout ratio after their government signed the Kyoto Protocol. The relationship between dividend payout and transition risk did not receive additional attention, perhaps to the authors’ knowledge. However, from a theoretical perspective, transition risk creates expectations of lower investment returns and higher financing costs, negatively affecting stock market performance (Günther and Ferns, 2017; Huberman, 1984; Trumpp and Guenther, 2017). In response to poor risk-adjusted returns expected by investors, boards can use dividends to guarantee them certain and immediate returns.

Consistent with this hypothesis, Bressan Bocardo (2016) reports that the US oil sector stock returns experienced a downward trend between 2004 and 2014, but paid dividends have grown in the same period. In addition, many studies have found that dividend policies respond to climate regulation risk (Hail et al., 2014; Harakeh et al., 2019; Michaely and Roberts, 2006).

As for the literature on the determinants of shareholders' returns, theoretical and empirical studies suggest that shareholders and investors price risk by incorporating its information in the investment (and disinvestment) decisions (Fama and French, 1992, 2002). Without information asymmetry, the instrument value prices all the available information, including risks (Grossman and Stiglitz, 1976). To guarantee the necessary information symmetry on climate-related issues, starting in 2010, the SEC required US-listed companies to report their climate risk exposure in a manner compliant with TCFD (2017) guidance, thus considering plausible changes in climate policies, consumer preferences, and technologies in addition to reputation damages. Measures of transition risk based on mandatory disclosure have been used, among the others, by Kolbel et al. (2020), who find that disclosed climate risk in mandatory documents increases default probability, and Cohen et al. (2020), who find that disclosure and data presented in mandatory filings contain information capable of predicting firms' financial performances.

Mandatory disclosure represents an explicit form of risk information. Companies must report all factors that may affect their business, as well as how and to what extent (Campbell et al., 2014). In addition, companies follow strict language rules and use predetermined formats, which makes the documents compatible with automated text-mining. This specific language format allows using such information to identify a genuine set of risks, create exposure indicators, and compare companies. There are also some drawbacks to using mandatory disclosure to measure transition risk. Formats are standardised to allow comparability among companies but are also limited in dimension and definitions. As a result, a company must specify the more significant risks for the sector and its economic activity to the best of its knowledge within the limited space of a few lines. Furthermore, firms are encouraged to disclose perceived risks to their activity autonomously and, hence, have an incentive to design their disclosure activity to avoid lawsuits due to undisclosed risks (Liesen et al., 2017; Litterman et al., 2020). Such behaviour may affect the genuineness of declarations and bias the risk exposure measures accordingly.

For this reason, some authors have preferred using exposure metrics based on indicators signalling risk implicitly. In the context of transition risk, for instance, GHG emissions have become a standard transition risk metric to estimate the carbon premium (Bolton and Kacperczyk, 2020, 2021a, 2021b) and, more in general, to understand the stock market effects of transition risk (Trumpp and Guenther, 2017). Unfortunately, GHG disclosure is voluntary, and the metric is not always observable. Alternatively, some authors have employed ESG scores, and in particular environmental scores (Fatemi et al., 2018; Friede et al., 2015; Whitelock, 2015), which, however, suffer from the same availability problem and, in addition, do not necessarily capture risk-related aspects.

Explicit and implicit measures of transition risk have always been considered alternatives in literature. Mandatory disclosure is undoubtedly the preferred documentation to elaborate text-based indicators because the mandatory nature of disclosing activity makes the documents comparable. At the same time, non-mandatory disclosure is known to increase stock market efficiency (Krueger et al., 2020; Liesen et al., 2017), and, in the case of GHG, equity transactions implicitly contain the acceptance of climate-related risk (Giese et al., 2021; Ilhan et al., 2020; Zhang et al., 2016). Non-binding disclosure is free from mandatory limits, and no litigation costs might arise. Nevertheless, greenwashing accusations could tarnish disclosing companies' reputations (Cooper et al., 2018; Lyon and Maxwell, 2011).

3. Empirical framework and data

3.1. Empirical framework

The dependent variable used in the empirical model is the investment return for the shareholder, distinguishing its two components, namely stock returns (SR) and dividend payout (DP), and considering the total shareholder returns (TSR), which includes both SR and DP. While both TSR and SR are observable, DP is only partially; in particular, it is observable only if the company decides to pay dividends in a given year. This partial observability is considered a potential source of endogeneity bias in our model, specifically selectivity bias, and is treated with a standard sample selection estimation (Heckman, 1979) adapted for panel data models (Wooldridge, 1995).

Regression models follow the framework of stock returns analysis in Fama and French (2002) and Bolton and Kacperczyk (2020), with explanatory variables lagged by one time period to avoid simultaneity bias and including two-way fixed effects to account for firm-specific unobserved time-invariant characteristics and time events that affected all companies like the Paris Agreement and the pull-out of the US from it (Berkman et al., 2019; Diaz-Rainey et al., 2021; Fan et al., 2020). For each company $i = 1, 2, \ldots, N$ in the sample, the dependent variables at a given period $t = 2010, 2012, \ldots, 2022$ are related to explicit (*Risk*) and implicit (*Int*) transition risk indicators. The implicit risk indicators are Scope 1, Scope 2, and Scope 3 emission intensities, measured as the ratio between emissions and net revenues. Each model is estimated with emission intensities included separately and jointly.

The regression model is presented in Eq. 1. The β_1 and β_2 coefficients quantify the impact of transition risk, measured explicitly and implicitly, respectively, on the different measures of stock returns ($Y \in [TSR, SR, DP]$). All risk metrics are lagged by one year to avoid possible simultaneity bias. The matrix Z condensated all the control variables that have proven to influence the risk-return relationship in the existing literature, and these are also measured using a one-year lag. ε indicates the composite error structure, including fixed effects and the idiosyncratic component.

$$Y_{i,t} = \beta_1 \cdot Risk_{i,t-1} + \beta_2 \cdot Int_{i,t-1} + \beta_3 Z_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

In the only case of $Y = DP$ the estimation is augmented via a first-stage regression, a probit model of a binary indicator equal to one if the company paid dividends at a given time (*DP_BIN*) on transition risk metrics and controls (eq. 2). The estimates are retrieved and used to compute the inverse Mill's ratio (IMR), which is then pulled into eq. 1 to test and correct the selectivity bias.[2] The estimation approach follows the indications about estimating a panel data model with selectivity in the presence of fixed effects in both the main and auxiliary regressions (Wooldridge, 1995; Semykina and Wooldridge, 2010). More specifically, we apply the Mundlack-Chamberlain device in both equations to wipe out fixed effects and use a bootstrap procedure to compute the correct standard error in the main equations.

$$P(DP > 0) = \gamma_1 Risk_{i,t-1} + \gamma_2 Int_{i,t-1} + \gamma_3 Z_{i,t-1} + u_{it} \tag{2}$$

3.2. Financial performance data

Eqs. 3, 4, and 5 describe in detail the three dependent variables and the computation approach. *SR* represents the capital gain/loss realised by investors and is commonly employed in the climate finance literature as a general measure of return (Bolton and Kacperczyk, 2020; Liesen et al., 2017). *DP* represents the paid dividends over the net profits ratio without considering dividends paid to special shareholders. The measure is intended to represent the income gains for investors; hence, only ordinary dividends are considered, while share repurchases or other

[2] Standard Errors in the second stage regression are computed via bootstrap.

buyback forms are excluded. *TSR* adds to SR the dividend per share paid during the period in the return.

$$SR_{i,t} = 100\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{3}$$

$$DP_{i,t} = 100\frac{Common\ Dividends}{Net\ Profits - Preferred\ Dividend\ Requirement} \tag{4}$$

$$TSR_{i,t} = 100\frac{P_{i,t} + D_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{5}$$

Fig. 1 displays the differences in DP across GHG quantiles (first and fourth quartiles) in our sample, with non-disclosing companies on the right. Although overlapping in observed values exist between top and bottom polluters, the median values are substantially different. DP is estimated to be 10.28% to 36.295% higher in major polluters compared to low polluters, and this suggests a preliminary correlation between dividend policies and risk factors that aligns with existing literature (Michaely and Roberts, 2006; Perez-Gonzalez, 2002; Wong and Hasan, 2021).

Table 1 presents a synthesis of the carbon intensities (tons of GHG emissions per thousand dollars) of the various SIC sectors in the US. Scope 1 registers fugitive emissions and fuel combustion of company vehicles. Scope 2 represents part of the indirect emissions, especially those "bought" to continue the activity: purchased electricity, heat and steam. Finally, Scope 3 emissions account for all the emissions produced by the supply chain of corporate activity: purchased goods and services, business travels, employee commuting, waste disposal, use of sold products, transportation and distribution (upstream and downstream), investments, leased assets and franchises. Estimates of Scope 3 are rare to find as their computation requires significant investment. Probably for this reason, previous studies considered mainly Scope 1 and Scope 2 emission intensities (Bolton and Kacperczyk, 2020, 2021b; Ilhan et al., 2020; King and Lenox, 2001; Wang et al., 2014). Various studies used predicted or inferred carbon intensity datasets, either direct, indirect or downstream ones, drastically increasing the sample of observations (Bolton and Kacperczyk, 2020, 2021b; Ilhan et al., 2020). However, the drawback of this approach is that results may differ from those based on voluntarily disclosed information (Aswani et al., 2024). The sectors with the highest Scope1 emissions are the Utilities, Energy and Materials sectors. Indeed, these are also the sectors with the highest DP. Not surprisingly, Scope 2 intensities are the highest in the Materials sector, characterised by energy-intensive production. Finally, Scope 3 intensities are the largest again in the Utilities sector. IT and Financials are the sectors with the lowest emissions.

The explicit transition risk measure is a text-based indicator derived from the "Risk disclosure" section of the 10-K report, the annual document disclosing the legally binding risks listed companies must produce. Corporations are expected to disclose risks to the best of their knowledge to avoid liability exposure (Lee and Choi, 2019; Loughran and McDonald, 2011; Matsumura et al., 2014). Consequently, the information reported in 10-K reports can be considered complete. The rationale for this indicator grounds on the assumption that the frequency of appearance of some risk-related words in documents indicates the relative importance assigned by the document writers to that risk. The more frequently a specific vocabulary is used, the more relevant the disclosing company considers the risk. The structure of 10-K filings is fixed for all firms. All relevant risk factors are contained in section 1A. The total length of this section provides a gross dimension of a firm's riskiness: the more risk factors are reported, the thicker section 1A will be. Furthermore, definitions of risks are often similar across firms, which, combined with the fixed structure, makes the documents more easily comparable.

After cleaning text from redundant words, NLP algorithms are applied to the remaining text to retrieve risk measures. The technical procedure involves several steps of data cleaning. At first, a machine-learning process transforms each line of text into a data entry. Proper packages with neural networks are trained to capture English vocabulary and drop out irrelevant words such as articles or other reiterated expressions.[3] Indexes are generated by matching words or groups of words with a reference library, which in this paper is an unordered set of definitions of the transition risk. Previous works have employed the IPCC glossary and definition for climate negativism and effective scientific presentations on media (Rogova and Aprelkova, 2020; van der Geest and Warner, 2020). In this study, the library of relevant definitions is borrowed by Sautner et al. (2023). This list has been elaborated using textual analyses from interviews and official documents published by listed US companies, defining various risks managers and boards perceive.

The text-analysis algorithm first identifies the matches between the words in the clean document and the library. The definitions of risk and the set of words must follow a specific coding sequence. Specifically, definitions of risk could take one word (monogram) or two words (bigram) or even more. Previous works suggested setting the algorithms to find only bigrams, the most recurring ones in English (Cohen et al., 2020; Loughran and McDonald, 2011). The transition risk indicator (*Risk*) is then computed using eq. 7. For every identified bigram, the term frequency (*tf*), the number of matches with the library, is computed and weighted by the inverse document frequency (*idf*), the inverse of the number of documents in which the bigram appears. The bigram-specific *tf-idf* indicators are summed up for a given document and rescaled by the total number of bigrams *B* in the document to produce a measure contained in the 0–1 interval (Luhn, 1957).

$$Risk_{i,t} = tf_{i,t}idf_{i,t} = \frac{1}{B_{i,t}}\sum_{\forall b}\left(tf_{b,i,t} * idf_{b,t}\right) \tag{7}$$

Fig. 2 shows the yearly average number of bigrams, representing raw data on the width of risk definitions reported within the 10 K reports, on the left panel (A), and the risk indicator computed according to Eq. 7 on the right one (B) with the respective 95% intervals in shaded grey. Panel A shows that the width of climate risk reporting has increased over time. There are two possible explanations for an increased number of bigrams. One relates to the increased use of the risk section to reduce the likelihood of litigation, as companies may prefer to be more specific to prevent litigation, even with low risk. The other is the actual intention to highlight the emergence of risk factors. The *Risk* indicator in panel B, in contrast, declines over time. Thus, while the mandatory disclosure risk section size has increased between 2010 and 2022, the role of transition risk compared to other risks declined over time in 10-K reports. This is potentially due to the increase in the number of new sources of risk that entered the disclosure section.

The explicit measure of risk exposure computed also varies significantly across industries. Table 2 provides summary statistics by industry, and there is indeed high heterogeneity among sectors. The sectors that mostly disclose transition risk are energy, utilities, industrial, and materials. The Jarque-Bera Test has been used to assess the normality of the distribution within these sectors. In most cases, the distribution of the number of bigrams presents a fat right tail that suggests the presence of a few companies disclosing significant parts of their risk about climate transition. Four sectors, namely healthcare, IT, communications, and financials, present an average of substantially higher numbers of bigrams. In contrast, there is more homogeneity across industries in the *Risk* indicator, suggesting that standardising the raw number of bigrams in eq. 7 is appropriate for comparing text-based risk measures across companies operating in different industries.

Table 3 summarises the variables used in this work. Observations match firms that disclosed climate-related risks and emissions between 2010, the first year of climate risk mandatory disclosure, and 2022, the latest year for which information is available. Control variables are

[3] In this work we used the text-mining "tm" package from R (Feinerer, 2024).

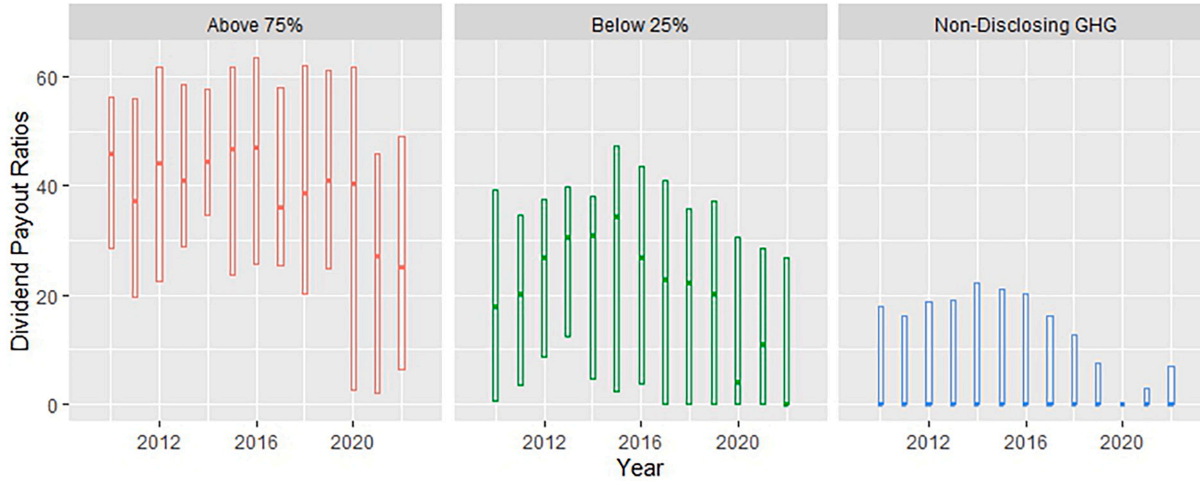

Fig. 1. Dividend's payouts ratios (distribution and median) by carbon footprint (Scope 1 + 2 + 3) quartiles, selected US companies, 2010–2022.

Table 1
Average emission intensity according to sector and scope category.

SECTOR	SCOPE_1_INT	SCOPE_2_INT	SCOPE_3_INT
Utilities	1.422	0.049	0.139
Energy	0.332	0.031	0.036
Materials	0.114	0.103	0.039
Consumer Staples	0.02	0.029	0.008
Consumer Discretionary	0.014	0.029	0.013
Industrial	0.009	0.012	0.004
Health Care	0.006	0.01	0.002
Communication	0.004	0.022	0.001
Real Estate	0.003	0.017	0.009
IT	0.002	0.017	0.002
Financials	0.001	0.008	0

Capital expenditure over assets (CAPEX), corporate leverage (CORP_LEV) earnings before taxes over total assets (ROTA), the natural logarithm of net assets (DIMENSION), market to book value ratio (MTBV), net margins (MARGINS), and the standard deviation of the stock returns (VOLATILITY). We used a natural logarithm transformation for the carbon intensity indicators to make the distribution more similar to a normal distribution and have comparable estimates with the *Risk* indicator.

4. Results

Table 4 reports the DP model's panel sample selection estimates, including the panel probit first stage and the linear panel second stage. In both, we consider two-way fixed effects that account for unobservable company-specific characteristics and time trends common to all companies. We estimated the model using implicit and explicit risk measures. Implicit measures (Scope 1,2,3) have been considered separately and then jointly.

The text-based *Risk* indicator is positively associated with the probability of distributing dividends, but the coefficient is not significant when either Scope1 (column 1) or 2 (column 3) or both (column 7) intensities are included in the model. Likewise, emission intensity shows the same positive association in the case of Scope 1 and 3 intensities, but only in the sooner case the association is statistically significant.

In the second stage (columns 2, 4, 6, and 8), the IMR coefficient is always statistically significant, supporting the selectivity bias hypothesis and the need for a correction. In this case, the evidence shows that the text-based *Risk* indicator is not associated with the amount of dividend paid, as the related coefficient is never statistically significant. In contrast, intensity-based measures exert the expected positive and significant effect across all models. However, when intensities are combined in the same model (column 8), the only significant effect becomes

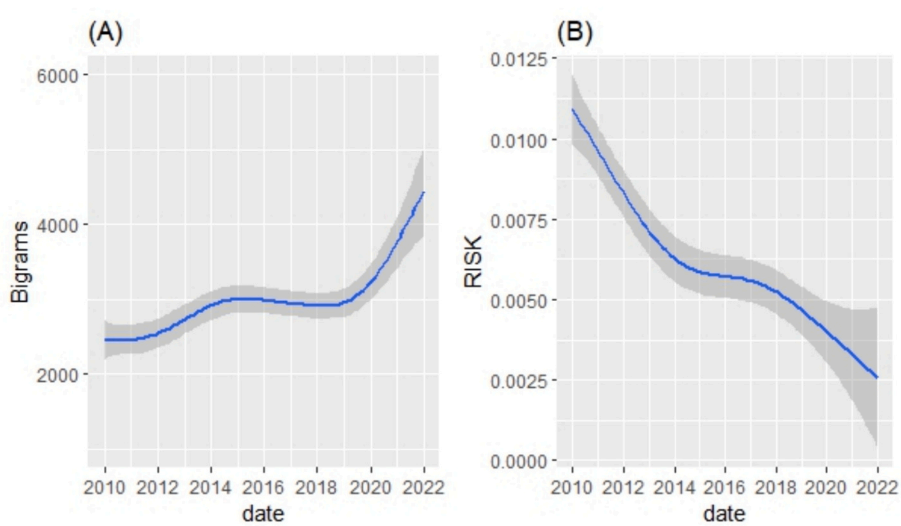

Fig. 2. Text-Based Indicators. (A) is the plot of the total number of bigrams per 10-K Filings; (B) tf-idf adjusted to bigrams, using a confidence interval of 95%.

Table 2
Sectorial distributions of 10-K bigrams of 1A item and tf-idf RISK indicator. The values have been approximated to the third decimal.

SECTOR	mean	median	sd	Perc 25	Perc 75	skew	kurt	JB test	mean	median	sd	Perc 25	Perc 75	skew	kurt	JB test
Communication	4736.795	3876	4671.787	1934	5676	3.863	22.53	38.245***	0.002	0.002	0.004	0.001	0.004	2.543	10.045	28.542***
Consumer Discretionary	2091.421	1378	1648.484	1073	2120	1.648	4.435	40.939***	0.008	0.003	0.011	0.001	0.015	1.748	5.454	57.783***
Consumer Staples	1185.931	1096	578.481	814	1347	1.328	4.949	26.222***	0.007	0.005	0.003	0.005	0.009	1.115	2.924	12.03***
Energy	3494.211	2765	2395.887	1817.75	4245.75	1.598	5.164	117.904***	0.011	0.007	0.011	0.004	0.016	2.31	10.053	562.855***
Financials	98,537.34	4254	823,992	1854	5201	8.689	76.499	37,314.354***	0.003	0.002	0.004	0.001	0.003	5.257	34.972	7410.23***
Health Care	4145.133	4210	819.314	3579	4724	−0.024	2.834	0.056	0.008	0.007	0.003	0.006	0.011	0.641	1.735	6.079**
IT	4052.443	4692	2252.376	1441	5610	−0.177	2.012	3.628	0.004	0.002	0.005	0.001	0.005	2.597	9.284	218.764***
Industrial	2124.719	1588	1243.031	1312	2556	1.129	3.475	25.291***	0.008	0.005	0.008	0.004	0.01	2.922	12.999	637.164***
Materials	3771.738	1798	5854.73	1456	3634.25	3.857	18.119	2520.716***	0.007	0.005	0.006	0.003	0.009	1.609	5.485	144.645***
Utilities	2233.023	2024	957.392	1684.5	2766.5	0.359	2.302	3.676	0.009	0.007	0.007	0.004	0.01	1.794	5.926	78.587***

Table 3
Summary statistics of dependent and independent variables.

Statistic	N	Mean	Median	St. Dev.	Pctl (25)	Pctl (75)
DP	2870	40.377	37.480	21.233	24.930	54.500
DP_BIN(=1 if DP > 0)	2870	0.608	1	0.488	0	1
SR	2870	16.649	12.791	39.478	−5.178	31.642
TSR	2870	18.595	14.647	39.360	−3.146	33.519
SCOPE_1_INT	2870	0.260	0.009	0.834	0.001	0.071
SCOPE_2_INT	2870	0.053	0.017	0.167	0.007	0.038
SCOPE_3_INT	2870	0.050	0.0004	0.116	0.0004	0.037
RISK	2870	0.001	0.000	0.002	0.000	0.002
DIMENSION	2870	15.275	15.163	1.356	14.426	16.092
CAPEX	2870	8.338	4.165	11.685	2.390	8.797
CORP_LEV	2870	47.905	44.960	34.324	29.320	60.565
MARGINS	2870	14.045	13.825	17.288	7.370	20.952
ROTA	2870	7.185	6.665	8.253	3.580	11.168
MTBV	2870	2.799	2.845	62.782	1.710	5.380
VOLATILITY	2870	24.024	22.380	8.616	17.665	28.520

that of Scope 1 intensity.

We conclude that the likelihood of paying dividends, and the amount paid to a lower extent, is higher for companies more exposed to transition risk, as measured by disclosed emission intensity, all else being equal. In contrast, no evidence suggests that carbon risk disclosure is somehow related to the company's dividend policy.

Table 5 reports the estimation results using *SR* as a dependent variable. In this case, the *Risk* coefficient is negative across all models but never statistically significant. Consistently, the sign of the intensity indicators is also negative and significant only for Scope 1 and 2 intensities, either when considered alone (columns 1 and 2) or combined (column 4). The result suggests that more exposed companies are characterised, on average and other things being equal, by lower capital gains. Like in the DP case, there is no evidence associating returns to the text-based measure of transition risk.

Estimation results for TSR are summarised in Table 6. The results are very similar to those presented in Table 5: both text-based and emission-based indicators of transition risk are negatively associated with total stock returns, but the coefficient is significant only in the case of direct emissions (columns 1 and 4). TSR combines capital gains and paid dividends, and the overall effect of transition risk exposure results from the combination of the positive effect on DP and the negative effect on SR, where the letter clearly prevails in the aggregation.

The presented results are overall consistent with the carbon premium hypothesis (Bolton and Kacperczyk, 2021a; Jaggi et al., 2017) inasmuch they reveal that higher returns are associated with transition risk exposure, in particular when exposure is measured implicitly by observing disclosed emissions, corroborating the hypothesis that financial operators are aware of transition risk and consider it into investment/divestment strategies. At the same time, results suggest that the premium is transferred to shareholders not via capital gains but rather via paid dividends. In contrast, the simple capital gain of brown companies is lower than non-brown companies, as confirmed by other studies in this literature (Aswani et al., 2024; Chava, 2014; Matsumura et al., 2014). The overall effect on total stock returns, however, is negative, indicating that higher dividends paid to compensate shareholders for the relatively lower capital gain are not, in fact, fully capable of compensating. This evidence supports the argument that boards in carbon-exposed companies use dividends to guarantee shareholders a risk-adjusted premium that would not be otherwise realisable without a generous dividend, corroborating the findings of Jaggi et al. (2017).

While the number of companies releasing dividends is disappearing (Fama and French, 2001), the volume of dividends in the US economy is increasing. A great component of such growth is represented by dividends paid by major polluters, who have been responsible for carbon concentrations in the atmosphere since the Industrial Revolution of the

Table 4
Explicit and implicit transition risk impact on Dividend Payouts – estimation results.

	Dependent Variable:							
	DP_BIN	DP	DP_BIN	DP	DP_BIN	DP	DP_BIN	DP
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RISK	29.938	−10.507	22.478	−86.335	42.229**	−24.465	27.648	−23.532
	(19.626)	(240.012)	(18.169)	(209.237)	(19.320)	(220.546)	(18.523)	(226.220)
SCOPE_1_INT	0.099***	1.328***					0.089***	0.509
	(0.015)	(0.318)					(0.016)	(0.316)
SCOPE_2_INT			−0.043	0.900*			−0.061**	0.513
			(0.028)	(0.524)			(0.028)	(0.515)
SCOPE_3_INT					0.006	0.702***	−0.010	0.379**
					(0.010)	(0.149)	(0.010)	(0.155)
CAPEX	−0.005	−0.014	0.002	0.082	0.002	0.092	−0.005	−0.024
	(0.003)	(0.064)	(0.004)	(0.066)	(0.003)	(0.063)	(0.004)	(0.059)
CORP_LEV	0.001	0.109***	0.001	0.111***	0.001	0.100***	0.001	0.104***
	(0.001)	(0.021)	(0.002)	(0.022)	(0.002)	(0.024)	(0.001)	(0.022)
DIMENSION	−0.157**	−4.113***	−0.220***	−3.825**	−0.202***	−4.569***	−0.187**	−3.794***
	(0.070)	(1.487)	(0.075)	(1.459)	(0.072)	(1.517)	(0.072)	(1.439)
MARGINS	0.014***	0.035	0.013***	−0.009	0.014***	0.023	0.013***	0.040
	(0.004)	(0.088)	(0.004)	(0.093)	(0.004)	(0.091)	(0.004)	(0.089)
ROTA	0.073***	−1.092***	0.072***	−1.253***	0.072***	−1.175***	0.075***	−1.172***
	(0.008)	(0.205)	(0.007)	(0.214)	(0.008)	(0.207)	(0.008)	(0.208)
VOLATILITY	−0.052***	−1.260***	−0.052***	−1.061***	−0.051***	−1.129***	−0.054***	−1.125***
	(0.008)	(0.192)	(0.008)	(0.186)	(0.008)	(0.199)	(0.008)	(0.193)
IMR		19.721***		13.569***		17.624***		16.672***
		(4.745)		(4.911)		(4.847)		(4.622)
Observations	2870	1745	2870	1745	2870	1745	2870	1745
Pseudo R2/R2	0.352		0.345		0.336		0.357	
Adjusted R2		0.865		0.864		0.864		0.866

Notes to table: *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.
Standard error in parenthesis.
All models include two-way fixed effects.

Table 5
Explicit and implicit transition risk impact on Stock Returns – estimation results.

	Dependent variable: SR			
	(1)	(2)	(3)	(4)
RISK	−890.393	−947.133	−968.459	−909.739
	(591.217)	(590.994)	(591.878)	(591.076)
SCOPE_1_INT	−0.835***			−0.722**
	(0.274)			(0.303)
SCOPE_2_INT		−1.119***		−0.816*
		(0.422)		(0.465)
SCOPE_3_INT			0.073	0.360
			(0.253)	(0.265)
DIMENSION	0.025	0.109	0.214	0.285
	(0.516)	(0.515)	(0.551)	(0.551)
CAPEX	0.135**	0.077	0.042	0.125*
	(0.065)	(0.060)	(0.060)	(0.066)
CORP_LEV	−0.043**	−0.049**	−0.052***	−0.044**
	(0.020)	(0.020)	(0.020)	(0.020)
MARGINS	0.009	0.016	0.010	0.013
	(0.045)	(0.045)	(0.045)	(0.045)
ROTA	1.082***	1.094***	1.105***	1.080***
	(0.097)	(0.097)	(0.097)	(0.097)
VOLATILITY	1.016***	1.050***	1.058***	1.012***
	(0.086)	(0.085)	(0.085)	(0.087)
Observations	2870	2870	2870	2870
R2	0.093	0.093	0.090	0.095
Adjusted R2	0.087	0.086	0.084	0.088
F Statistic	36.700***	36.388***	35.431***	29.813***

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

nineteenth century (Heede, 2014). In the considered period, the value of dividends paid by companies exposed to transition risk amounts to 5115.07 billion dollars, almost one-third of all the dividends paid by all US corporations and equivalent to a yearly average of 2% of the US GDP. This is undoubtedly a considerable amount of financial resources that could have been instead invested in a low-carbon transition.

Table 6
Explicit and implicit transition risk impacts on Total Stock – estimation results.

	Dependent variable: (TSR)			
	(1)	(2)	(3)	(4)
RISK	−740.935	−574.796	−852.610	−591.652
	(515.583)	(515.653)	(520.365)	(514.048)
SCOPE_1_INT	−0.883*			−0.956*
	(0.464)			(0.498)
SCOPE_2_INT		−0.609		−0.504
		(0.668)		(0.680)
SCOPE_3_INT			0.018	0.186
			(0.302)	(0.304)
DIMENSION	5.517**	5.545***	5.886***	5.317**
	(2.148)	(2.147)	(2.165)	(2.151)
CAPEX	0.246**	0.210**	0.163*	0.244**
	(0.097)	(0.093)	(0.095)	(0.097)
CORP_LEV	−0.037	−0.041*	−0.034	−0.038
	(0.024)	(0.024)	(0.024)	(0.024)
MARGINS	0.139**	0.148**	0.128**	0.145**
	(0.064)	(0.064)	(0.064)	(0.064)
ROTA	1.301***	1.311***	1.300***	1.320***
	(0.127)	(0.127)	(0.129)	(0.127)
VOLATILITY	1.484***	1.470***	1.505***	1.444***
	(0.218)	(0.217)	(0.220)	(0.217)
Constant	−3523.831***	−2146.333***	804.226	−2896.347***
	(744.257)	(582.087)	(508.071)	(815.714)
Observations	2870	2870	2870	2870
R^2	0.202	0.204	0.187	0.215
Adjusted R^2	0.195	0.197	0.180	0.206
Residual Std. Error	35.320	35.272	35.651	35.071
F Statistic	27.691***	28.061***	25.158***	24.273***

*Note:**p < 0.1; **p < 0.05; ***p < 0.01.

5. Conclusion

The paper analysed the effects of explicit and implicit transition risk disclosure on multiple measures of financial market returns, disentangling capital gains/losses from dividends, in a sample of US-listed companies. Explicit measures of transition risk are built by applying text analysis to mandatory disclosure documents, matching the risk section of 10-K reports with a specific transition risk vocabulary. Implicit measures of transition risk are the publicly disclosed emissions scaled by revenues to account for known firm-size effects. The results underlined an overall positive and statistically significant effect of implicit risk on the probability that a company pays dividends and, to a minor extent, on the amount paid and a negative effect on stock returns. At the same time, we find no relationship between explicitly disclosed risk and stock market returns.

Evidence in this paper has substantial implications concerning the long-term investment and strategic decisions of carbon-intensive firms. In light of the ambitious target of the Paris Agreement and the amount of resources necessary to reduce GHG emissions, it is inevitable for the private sector to contribute substantially with credible targets, transition plans, and adequate investments. While everyone has to do their part on that, private companies' timely and active role, especially in high-emission sectors, is crucial for the transition to be orderly, with the lowest negative impact on the real economies and financial stability. Despite this shared awareness, we find evidence that companies more exposed to transition risk are more likely to pay dividends - and higher dividends - subtracting resources to decarbonisation investment in a phase of paradigmatic shift. Combined with the evidence that the same companies have relatively lower stock returns, we infer that the boards use dividends to compensate shareholders for the low capital gains and avoid divestments.

Another important implication of the paper has to do with how financial markets price transition risk information. Transition risk measures used in climate finance literature broadly belong to two groups: explicit measures, based on the text-analysis of non-financial disclosure, public speaking, and web resources, and implicit measures, based on disclosed emissions. The first measure considers the public discourse and the perception of transition risk that the company wants to project to shareholders and stakeholders, commonly called "Climate Talk". The second is a measure of actually achieved performance, hence of "Climate Walk". The evidence we gather from the analysis demonstrates that Climate Walk outpaces Climate Talk in providing signals for financial markets and investors. This result should be taken into appropriate consideration in future research on the economic and financial effects of climate talking and walking.

CRediT authorship contribution statement

Matteo Mazzarano: Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing, Methodology, Software. **Gianni Guastella:** Conceptualization, Investigation, Methodology, Writing – review & editing, Formal analysis, Validation. **Stefano Pareglio:** Conceptualization, Funding acquisition, Supervision, Project administration. **Anastasios Xepapadeas:** Conceptualization, Project administration, Supervision. **Simone Borghesi:** Project administration, Supervision, Writing – review & editing.

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Appendix A. Text analysis

A.1. List of bigrams used in the text analysis

Table A1
List of bigrams from Sautner et al. (2023).

bigram	word1	word2	bigram	word1	word2	bigram	word1	word2
greenhouse gas	greenhouse	gas	emission trade	emission	trade	environmental legislation	environmental	legislation
save technology	save	technology	produce renewable	produce	renewable	achieve carbon	achieve	carbon
control upgrade	control	upgrade	require utility	require	utility	carbon market	carbon	market
carbon emission	carbon	emission	dioxide emission	dioxide	emission	control regulation	control	regulation
issue air	issue	air	transition clean	transition	clean	economy emission	economy	emission
gas emission	gas	emission	market carbon	market	carbon	emission reduce	emission	reduce
carbon economy	carbon	economy	nox emission	nox	emission	energy clean	energy	clean
gas regulation	gas	regulation	produce clean	produce	clean	capture sequestration	capture	sequestration
carbon dioxide	carbon	dioxide	effective energy	effective	energy	trade scheme	trade	scheme
talk clean	talk	clean	energy renewable	energy	renewable	global climate	global	climate
emission profile	emission	profile	reduce nox	reduce	nox	technology clean	technology	clean
profile air	profile	air	impact clean	impact	clean	clean job	clean	job
air pollution	air	pollution	energy independence	energy	independence	emission intensity	emission	intensity
energy alternative	energy	alternative	carbon disclosure	carbon	disclosure	gas initiative	gas	initiative
nitrous oxide	nitrous	oxide	product carbon	product	carbon	emission improve	emission	improve
carbon price	carbon	price	epa regulation	epa	regulation	energy carbon	energy	carbon
meet renewable	meet	renewable	emission rate	emission	rate	talk carbon	talk	carbon
receive air	receive	air	development renewable	development	renewable	impact climate	impact	climate
energy regulatory	energy	regulatory	target energy	target	energy	efficient natural	efficient	natural

(continued on next page)

Table A1 (*continued*)

bigram	word1	word2	bigram	word1	word2	bigram	word1	word2
address environmental	address	environmental	recovery pollution	recovery	pollution	emission energy	emission	energy
air clean	air	clean	support renewable	support	renewable	reduce air	reduce	air
carbon tax	carbon	tax	investment clean	investment	clean	promote energy	promote	energy
change climate	change	climate	emission compare	emission	compare	generate renewable	generate	renewable
produce carbon	produce	carbon	deliver clean	deliver	clean	ciency renewable	ciency	renewable
combine heat	combine	heat	emission increase	emission	increase	source electricity	source	electricity
power initiative	power	initiative	market clean	market	clean	nation energy	nation	energy
reduce sulfur	reduce	sulfur	air resource	air	resource	carbon offset	carbon	offset
sulfur	sulfur	156	emission low	emission	low	energy smart	energy	smart
environmental standard	environmental	standard	reduction carbon	reduction	carbon	disclosure project	disclosure	project
climate action	climate	action	address climate	address	climate	efficiency environmental	efficiency	environmental
national renewable	national	renewable	gas reduction	gas	reduction	ghg emission emission free	ghg emission	emission free

A.2. SEC 10-K structure

The 10-K filing is a mandatory non-financial disclosure document any listed company files to the SEC sixty days before the end of the fiscal year. It comprises four parts, of which the first is divided into four items. The first item introduces the business characteristics, subsidiaries and in which markets the firms operates. Among other factors, it might be possible to find insurance information, operating cost characteristics and seasonal factors. The sub-item 1 A condensates the risk factors to which the firm is exposed. These factors are often described with few phrases to avoid confusion for potential investors. The following sub-item 1B contains any reference to previously unresolved matters in the dealings with the SEC staff. A recent addition is sub-item 1C, which collects relevant cyber-security threats and past events that could influence the investment decision. This section should also describe the board and management oversight of the risk response.

Part 1
Item 1 – Business.
Item 1A – Risk Factors.
Item 1B – Unresolved Staff Comments.
Item 1C - Cybersecurity.
Item 2 – Properties.
Item 3 – Legal Proceedings.
Item 4 – Mine Safety Disclosures.
Part 2
Item 5 – Market.
Item 6 – Consolidated Financial Data.
Item 7 – Management's Discussion and Analysis of Financial Condition and Results of Operations.
Item 7A – Quantitative and Qualitative Disclosures about Market Risks, Forward Looking Statements.
Item 8 – Financial Statements.
Item 9. Changes in and Disagreements with Accountants on Accounting and Financial Disclosure.
Item 9A. Controls and Procedures.
Item 9B. Other Information.
Part 3
Part 4

A.3. Validation

The paper develops a risk indicator for US-listed companies from 10-K filings using consolidated bigrams from Sautner et al. (2023) using the tf-idf algorithm. We validated the approach by looking at the correlation between the RISK and all the indicators used to determine the variables in Sautner et al. work. All indicators presented a positive and statistically significant correlation with ours, except for cc_sent_ew, calculated according to the bigrams connected to the sentiment captured in the earnings call. We summarised in Table A2 the correlation table for the companies that were present both in our and in Sautner et al. samples.

Table A2
Correlation table with the risk indicators.

	RISK	cc_expo_ew.y	cc_risk_ew	cc_pos_ew	cc_sent_ew	op_expo_ew	rg_expo_ew
cc_expo_ew	0.26***						
cc_risk_ew	0.16***	0.67***					
cc_pos_ew	0.11***	0.77***	0.52***				
cc_sent_ew	0.01	0.34***	0.24***	0.79***			
op_expo_ew	0.22***	0.91***	0.64***	0.76***	0.46***		
rg_expo_ew	0.16***	0.43***	0.42***	0.49***	0.46***	0.48***	
ph_expo_ew	0.08***	0.33***	0.15***	0.26***	0.03**	0.12***	0.14***

The definitions of the variables contained in Table A2 are collected in Table A3. They have been taken directly from the cited paper.

Table A3
Validation variable meaning, source: Sautner et al. (2023).

Name	Definition
cc_expo_ew	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts.
op_expo_ew	Relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts.
rg_expo_ew	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts.
ph_expo_ew	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide them by the total number of bigrams in the transcripts.
cc_risk_ew	Relative frequency with which bigrams related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of earnings conference calls. We count the number of such bigrams and divide them by the total number of bigrams in the transcripts.
cc_pos_ew	Relative frequency with which bigrams related to climate change are mentioned together with positive tone words that are summarised by Loughran and McDonald (2011) in one sentence in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts.
cc_sent_ew	Relative frequency with which bigrams related to climate change are mentioned together with the negative tone words that are summarised by Loughran and McDonald (2011) in one sentence in the transcripts of earnings conference calls.

Appendix B. Data

B.1. Correlation table

The correlations between the variables used in this paper are reported in Table B1. Firms's characteristics are controlled by Corporate Leverage (CORP_LEV), capital expenditure over assets (CAPEX), logarithm of assets (DIMENSION), earnings before interests and taxes (called also EBIT) over assets (ROTA), net margins as in the complementary to one of the bottom-line over net revenues (MARGINS), market to book value (MTBV) and stock price volatility (VOLATILITY). The correlation between the RISK indicator and emission indicators is positive. It is positive as well between the three indicators of carbon intensity. All climate risk indicators are positively correlated with a company's probability of releasing dividends.

Table B1
Correlation table.

	DPR	DP	SR	TSR	RISK	SCOPE_1_INT	SCOPE_2_INT	SCOPE_3_INT	DIMENSION	CAPEX	CORP_LEV	MARGINS	ROTA	MTBV
DP	0.77****													
SR	−0.14****	−0.03****												
TSR	−0.11****	−0.02****	1.00****											
RISK	−0.02*	0.05****	0.00	0.00										
SCOPE_1_INT	0.23****	0.04**	−0.09****	−0.08****	0.13****									
SCOPE_2_INT	0.18****	−0.01	−0.08****	−0.07****	0.09****	0.58****								
SCOPE_3_INT	0.22****	0.05**	−0.02	−0.02	0.04**	0.44****	0.31****							
DIMENSION	−0.12****	0.41****	−0.05****	−0.04****	0.07****	−0.14****	−0.06****	−0.01						
CAPEX	0.12****	−0.02****	0.00	0.00	0.00	0.03*	0.04***	0.13****	−0.02**					
CORP_LEV	0.03***	0.00	0.02****	0.02****	0.00	0.09****	0.05***	0.09****	−0.01*	0.00				
MARGINS	−0.01	0.02****	0.00	0.00	0.00	−0.03*	−0.04***	−0.07****	0.07****	−0.12****	0.00			
ROTA	0.06****	0.00	0.00	0.00	0.00	−0.08****	−0.04**	−0.02	0.01	0.00	0.00	0.85****		
MTBV	0.06****	0.00	0.00	0.00	0.00	−0.02	0.00	−0.04*	0.00	0.00	0.00	0.00	0.00	
VOLATILITY	−0.24****	−0.52****	0.10****	0.10****	−0.03****	0.03*	0.01	−0.02	−0.68****	0.03****	−0.02****	−0.09****	0.00	0.00

We collected the definitions, sources and simple names of the variables used in this paper in Table B2.

Table B2
Variables, definitions and sources.

Variable Name	Name in the article	Definition	Source
Risk	RISK	Tf-idf of risk definition from IPCC as benchmark against SEC 10 K Documents	EDGAR.gov and IPCC Glossary, 10-K filings, self-calculated
Bigrams		Sum of non-articles, non- discursive bigrams in 10-K filings	EDGAR.gov, 10-K filings, self-calculated
Scope 1 Intensity	SCOPE_1_INT	Direct Emissions divided by Earnings after taxes and interests, GHG emissions per thousand dollars	LSEG
Scope 2 Intensity	SCOPE_2_INT	Indirect Emissions divided by Earnings after taxes and interests, GHG emissions per thousand dollars	LSEG
Scope 3 Intensity	SCOPE_3_INT	Downstream Emissions divided by Earnings after taxes and interests, GHG emissions per thousand dollars	LSEG
Dimension	DIMENSION	Natural Logarithm of the End of the Year net assets	LSEG
Capital Expenditure	CAPEX	Percentage of Capital Expenditure over end of the year total assets	LSEG
Corporate Leverage	CORP_LEV	Ratio of the sum of short-term and long-term debt over Assets	LSEG
Returns on Assets	ROTA	Ratio of company's earnings before interest and taxes (EBIT) relative to its Assets	LSEG
Market to Book Ratio	MTBV	Ratio between the market value of equity over the book value of equity	LSEG
Net Margins	MARGINS	Difference between net revenues and bottom line over net revenues	LSEG

(*continued on next page*)

Table B2 (*continued*)

Variable Name	Name in the article	Definition	Source
Total Stock Returns	TSR	Yearly percentage variation of Equity price while considering dividend payed	LSEG
Dividend Payouts Ratio	DPR	Percentage of net revenues given to common shareholders	LSEG
Dividend Policy	DP	Dummy variable indicating positive dividend payout ratios presence of Dividends	Self-calculated from LSEG
Stock Returns	SR	Percentage annual variation of stock prices	LSEG

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107779.

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