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Climate regulation costs and firms' distress risk

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Abstract

In 2013, the European Union's Emission Trading Scheme (EU-ETS) entered Phase III. The majority of emission permits in Phase III are auctioned instead of being allocated for free as in Phases I and II. Using a difference-in-differences method, we show that this change has led to an increase in the financial distress risk of the EU-ETS-regulated firms when compared to unregulated firms, suggesting that the EU-ETS imposes a significant financial burden on regulated firms. This result is robust to an array of validation tests, alleviating concerns that it is driven by unobserved factors. In additional analyses we show that the increase in distress risk of regulated firms during Phase III can be explained by, (i) an additional climate regulation cost to purchase pollution permits and (ii) a low average environmental score that possibly (via high sustainability risk) lowers investors expectations regarding firms' performance. Our findings also show that the distress risk increase is higher for regulated firms operating within countries with lower control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and voice accountability before the EU-ETS implementation.

KEYWORDS
emission permits, EU-ETS, distress risk, emission cost, environmental score, difference-in-differences

JEL CLASSIFICATION
G32, G34

1 | INTRODUCTION

Climate change and its economic consequences are currently a top priority on the agenda of global economic institutions (IMF Annual Report, 2020). Global warming and large-scale shifts in weather patterns are the biggest challenges resulting from climate change; according to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2014) there is more than 95% probability that human activity has been a cause of our planet warming over the last 50 years. The largest driver of this warming is the emission of greenhouse gases (GHG), of which almost 80% are carbon dioxide (CO_2).[1] Early efforts focusing on the economic consequences of climate change include the seminal work of Nordhaus (1977), who established a line of research suggesting that one efficient way to reduce CO_2 emissions is to set a market price on them. Carbon prices may be set by adopting a regulatory limit on the number of allowable emissions and establishing trading through a "cap-and-trade" emissions system.

To provide incentives for sustainable economic growth, the European Union (EU) launched its Emission Trading System (ETS) in 2005, which became the largest cap-and-trade system globally.[2] Despite the importance of the topic, only a relatively small number of recent studies have been devoted to assessing the financial implications of carbon emissions at the firm level in the U.S. (Capasso et al., 2020; Kabir et al., 2021; Nguyen et al., 2023) and cap-and-trade programs around the world (Bartram et al., 2021; Dang et al., 2022; Nguyen and Phan, 2020).[3]

In this paper, we exploit the introduction of the EU-ETS in 2005 as a quasi-natural experimental setting to investigate whether the new regulation affected financial distress risk at the firm level. In 2013, the EU-ETS entered Phase III, in which the majority of pollution permits were auctioned, instead of being allocated for free to regulated firms as in Phase I (2005–2007) and Phase II (2008–2012). In other words, Phase III internalizes the social cost of emissions at the firm level, forcing EU-ETS-regulated firms to acquire emission allowances at the prevailing traded price. As a consequence, other things being constant, introducing Phase III of the EU-ETS is expected to increase a firm's climate regulation cost and eventually increase its financial distress risk (DR). At the same time, distress risk may also increase due to investors' concerns regarding the environmental sustainability of regulated firms which may limit their access to capital and their future growth opportunities. These effects may also lead to lower long-term value for all stakeholders, i.e. an environmental risk factor, and higher cost of equity capital, especially for firms with low environmental scores (Clarkson et al., 2004; Eccles et al., 2014).[4]

In order to address identification challenges related to our research question, we use a difference-in-differences research design. The treated sample includes firms regulated by the EU-ETS (*regulated*), while the *control* sample includes firms that are part of the widely used STOXX Europe 600 equity index. Figure 1 plots the yearly cross-sectional average DR for the regulated (solid line) and control (dashed line) samples. As observed, and in line with our conjecture, the DR of regulated firms increases substantially after 2013 (i.e., at the launch of Phase III). In contrast, control firms do not exhibit the same increase in DR.

Our main regression analysis shows that the implementation of EU-ETS Phase III triggers a 0.30% increase in DR of regulated firms, which is not observed in the control sample. This effect is economically important, considering that the average distress risk of all firms in the sample is 0.20%. We verify the robustness of these findings by using two additional control samples (*matched samples*) based on the propensity score matching method; which our findings survive. In addition, a setup with year-by-year dummies shows that the timing of the increase of distress risk starts in Phase III and not earlier, i.e. we document parallel trends in the pre-Phase III period. This finding precludes further the possibility that our results are driven by unobserved factors. Furthermore, our results are robust and overall stronger using the Altman (1968) Z-score as an alternative measure of distress risk as well as including sector and year fixed effects, country and financial crises indicators and computing firm clustered standard errors. In robustness analysis,

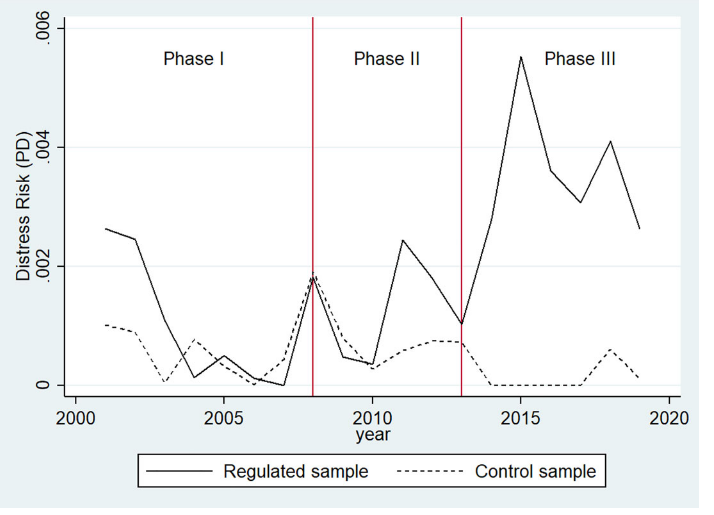

FIGURE 1 Average distress risk (DR) for regulated and control samples
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: This figure plots the yearly cross-sectional average of the distress risk (DR) as measured using the Merton probability of default model, for regulated and control samples.

we show that our main findings are unchanged using propensity score matching and entropy balancing methods which are designed to preclude the possibility of sample bias related to our regulated sample.

To test further the robustness of our findings and explore possible channels through which the distress risk increases for regulated firms in Phase III, we test the following assertions. First, using a new variable designed to capture the magnitude of the monetary payment for obtaining emission allowances, we show that the increase in distress risk of regulated firms during Phase III is explained by additional climate regulation costs caused by purchasing pollution permits. The second test relates to our conjecture that the distress risk of regulated firms is upward affected by an environmental risk factor. For example, Ecless et al. (2014) show that firms with high ESG scores are associated with superior market and financial performance. Therefore, we expect that firms with low environmental scores to experience inferior investors' expectations regarding firms' future performance, compared to firms with high environmental scores, resulting in an increase in distress risk of regulated firms during Phase III. To this end, we show that the distress risk increase is higher for regulated firms with low average environmental scores (as measured in earlier years), which is consistent with our hypothesis that lower environmental scores decrease investors' expectations regarding firms' performance.[5] It is also consistent with our additional findings concurring that the distress risk increase is higher for regulated firms operating within countries with lower control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and voice accountability before the EU-ETS implementation.

Earlier efforts in quantifying the effect of climate regulation cost on distress risk include Capasso et al. (2020) and Kabir et al. (2021) who use global samples of firms to show that higher carbon emissions lead to higher distress risk as measured by Merton's distance to default. Furthermore, Nguyen et al. (2023) use the non-financial companies of the S&P 500 index and show that climate risk disclosures reduce Merton's distance to default. Capasso et al. (2020) and Nguyen et al. (2023) use the 2015 Paris Climate Agreement to also show that the tightening of environmental regulations increases distress risk.

Our study extends this literature in several ways. First, we examine for the first time the effect of the EU-ETS mandatory climate regulation on European firms' distress risk by adopting a difference-in-difference method, i.e. examining a regulated vs. control sample and a period before and after the event (Phase III of the EU-ETS in 2013). Specifically, we exploit an environmental regulation that is mandatory within the EU jurisdiction and which translates into a direct emission cost at the firm level through a continuously traded carbon emission price. This estimation setting overcomes the standard limitations of the (dynamic) panel data models in terms of endogeneity and sample selection bias, i.e. it provides superior identification of the research question. This is important since prior studies examine the impact of other climate regulation protocols from the perspective of (pollution) risk faced by regulated firms. The use of a risk measure or term related to climate regulation in prior studies was consistent with the voluntary nature of other climate regulation milestones tested in those studies (Kyoto Protocol ramification, Trump election in the U.S., Paris Agreement), resulting in a slow and indirect implementation. Consequently, these alternative climate regulations may not provide the ideal environmental setting to investigate the transition impact on firms' financial wealth. By contrast, in this study, we quantify the mandatory climate regulation *cost* imposed by the EU-ETS regulation and assess its effect on financial distress risk at the firm level. In this way, we extend and supplement the evidence presented by Capasso et al. (2020), Kabir et al. (2021), and Nguyen et al. (2023).

Second, the long-term implementation process of EU-ETS provides an ideal quasi-experimental setting that allows comparing the behaviour of the regulated firms during Phases I and II (2005-2012) when emissions were allocated for free, with their behaviour during Phase III (2013-2019) when firms must purchase their emissions in auctions. This design helps to precisely set the timing of an additional direct regulation cost which is the residual from the allocated and verified emissions.[6] These features are not supported by other quasi-natural settings, such as the 2015 Paris Agreement, the ratification of the Kyoto Protocol, or the election of Trump in the United States.[7] Therefore, we extend prior studies as we quantify this climate regulation cost and examine whether it explains the documented increase in firms' distress risk.

Furthermore, we extend prior studies which have examined Australian or global samples and typically lack data on measuring emissions at the firm level. For example, Nguyen and Phan (2020) use a sample of firms from Australia and distinguish them as heavy or light emitters according to their industry classification. The authors exploit the ratification of the Kyoto Protocol by Australia to show that it has led to a decrease in the financial leverage of heavy carbon-emitting firms, which is more pronounced for financially constrained firms.

Another strand of the literature focuses on the California cap-and-trade system or other cap-and-trade programs such as the Nitrogen Oxides Budget Trading Program of 2004 in 11 states in the U.S. Bartram et al. (2021) apply a difference-in-difference framework using plant-level data to show that financially constrained firms shift emissions and output from California to other states to avoid climate regulation costs. The important effects of climate policy risk on firm financial decisions are further documented by Dang et al. (2022) who show that manufacturing firms adopt more conservative capital structures as a response to the cap-and-trade programme Nitrogen Oxides Budget Trading Program of 2004 in 11 states in the U.S. We extend this literature by showing the positive association of firms' distress risk and climate regulatory cost imposed by the mandatory EU-ETS regulation.

Another strand of the literature uses carbon costs associated with green-type borrowing, i.e. examine credit risk at the security or bank loan level rather than the firm level.[8] For instance, Antoniou et al. (2020) exploit EU-ETS Phase III, to show that the distress risk increases and the cost of firm financing falls with higher permit storage and lower permit prices. Javadi and Masum (2021) show that firms in locations with higher exposure to climate risk pay significantly higher spreads on their bank loans, using historical data from the National Climate Data Center (NCDC) to construct a measure of climate risk. Krueger et al. (2020) run a survey about climate risk perceptions and show that institutional investors believe climate risks have financial implications for their portfolio firms and that these risks, particularly regulatory risks, already have begun to materialize. Jung et al. (2018) measure the carbon risk awareness of Australian firms as the firm's willingness to respond to the Carbon Disclosure Project (CDP) survey to show a positive association between firms' cost of debt (bond spreads) and carbon risk.

One main limitation of using bank loan spreads or default rates is that it requires firms to borrow at the bank level and consequently, these spreads and rates depend on the syndicate loan indentures. It has been shown that bank loan rates are subject to the default risk assessment of a bank, which does not always capture the borrower's distress risk if substantial collateral and/or other legal clauses are added to the loan agreement (Eom et al., 2004). The issue of modeling the relationship between the bank and the borrower in a bank loan agreement is central in the relevant literature (Roberts and Sufi, 2009). In a similar manner, the use of bond ratings or spreads to examine the impact of climate regulation on capital markets also faces specific restrictions. For instance, examining credit (bond) spreads requires firms having issued bonds and consequently, the spreads are heavily affected by the trading microstructure of bond markets, which is substantially different from that of the equity market. Particularly, it has been shown that credit risk accounts for only a small fraction of bond spreads (Huang and Huang, 2012).[9]

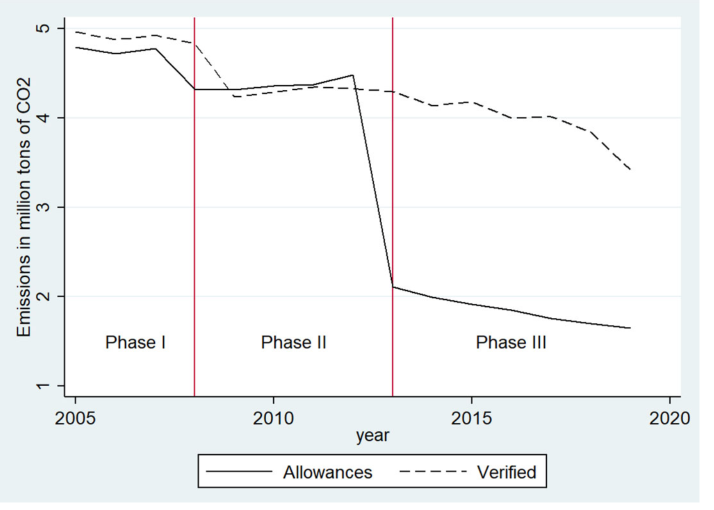

FIGURE 2 Yearly cross-sectional averages of the allocated allowances and the verified emissions of EU-ETS regulated firms
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: This figure plots the yearly cross-sectional averages of the allocated (emission) allowances and the verified emissions for EU-ETS regulated firms.

In contrast to the literature focusing on climate regulation-induced credit risk at the security level, we examine financial distress risk (DR) at the firm level using Merton's option-based default model, which is a forward-looking measure, capturing investors' expectations for firms' future performance. Furthermore, Merton's distress risk measure is derived directly from market expectations and consequently, it is timely, precise, and time-varying.[10] In this way, we refrain from using debt contract characteristics, for instance, loan or bond spreads, which often carry heterogeneous debt covenants (seniority), credit rating induced effects, embedded options and involve moral hazard effects and an explicit modeling of bank–borrower relationships.

The rest of this paper is organized as follows: Section 2 presents the institutional background of EU-ETS. Section 3 describes our dataset and Section 4 outlines our econometric methodology. Section 5 presents the main results, along with those from additional analyses, while Section 6 provides a brief discussion of the results and concludes the paper.

2 | THE EU-ETS INSTITUTIONAL BACKGROUND

As a response to climate change, the 1992 Kyoto Protocol proposed for the first time the trading of emission allowances in organized financial markets. In 2005, the EU introduced the ETS in order to cap, trade, and price carbon emissions. According to the EU, the ETS in 2021 remains the largest carbon market globally, as it accounts for around 40% of the EU's GHG emissions resulting from more than 11,000 heavy energy-using installations i.e., power stations and industrial plants, along with airlines operating within and between these countries.[11,12]

According to the ETS, the EU allocates to member states a limit on the total amount of emissions every year; these emissions are divided into units of permitted pollution, the so-called emission unit allowances (EUAs), where one EUA provides the right to emit one tonne of CO_2 per year. In turn, each member state allocates EUAs to firms within its jurisdiction, which must hold a number of EUAs equivalent to their emissions in tonnes of CO_2 per year to avoid paying a significant fine. This provides financial incentives for firms to reduce their environmental footprint since the regulation imposes a charge on emissions exceeding a cap (ceiling). Alternatively, firms exceeding their allowance and thus facing an emission allowance deficit can purchase extra allowance in the EU-ETS open market from firms with a surplus. Thus, EUAs are traded on an exchange, and in this way, they establish a market price associated with one unit of pollution. During Phase I (2005–2007) and Phase II (2008–2012), emission allowances were granted free of charge, but in Phase III (2013–2019) the majority of allowances were auctioned. Figure 2 shows a significant reduction in the allocated emission allowances of EU-ETS-participating firms (solid line) during Phase III, which started in 2013. Verified

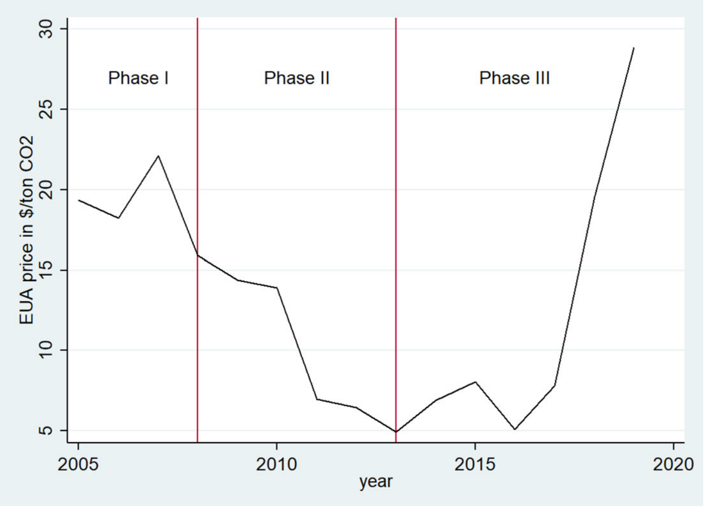

FIGURE 3 Emission Unit Allowance (EUA) price over time [Color figure can be viewed at wileyonlinelibrary.com]
Notes: This figure plots the price of one Emission Unit Allowance (EUA) quoted in $ / tonne CO_2 over time. One EUA provides the right to emit one tonne of CO_2 per year. The series depicted is constructed by rolling over the corresponding futures contract written on EUA price with maturity on December of each year.

emissions (dashed line) also drop over time, but at a lower rate, since these are linked with firms' production capacity that is typically slower to adjust.

Figure 3 plots the price of one EUA quoted in $/tonne CO_2 over time.[13] As observed, the EUA price has been severely depressed since the 2009 global financial crisis, and the ensuing global economic recession led to an over-supply of carbon allowances. However, the EU took a series of actions to remove the EUA surplus inventory, increasing the price as of mid-2017. For instance, the introduction of the Market Stability Reserve mechanism in January 2019 allowed the EU to adjust the (previously fixed) supply of EUAs to the level of varying demand.[14]

Figures 1–3 also point to the fact that, during the period 2017 to 2019, emission prices increased but the DR of treated firms decreased. This can be attributed to the fact that, during the same period, the verified emissions experienced an important drop resulting in reduced acquisitions of allowances.

3 | DATA, VARIABLES AND SUMMARY STATISTICS

We match data from different sources. The starting point of constructing our dataset is the universe of 1,012 parent firms included in the EU-ETS company database, which consolidates the information reported at the firm level by the European Union Transaction Log i.e., the European Commission's dedicated source of GHG emission information.[15,16] The database provides information regarding firms' allocated (emission) allowances and verified emissions, covering 17 industries and 31 EU member states over the period 2005–2019. From the outset, we manually search and cross-match the name and ISIN identifier of each firm through the Refinitiv Eikon database. This leads to 302 unique listed firms over the period 1998–2019 that constitute our regulated sample.

To apply a difference-in-differences research design, a control sample of firms (non-regulated) is required. These firms must not participate in the EU-ETS, so Phase III would not influence their DR. Accordingly, for the same sample period, we collect data from firms on the STOXX Europe 600 equity index to serve as our control sample.[17] We exclude 101 firms from the control sample, as they are also included in the regulated sample. We also exclude other 155 firms from the control sample which belong to sectors non-regulated by EU-ETS.[18] The final sample comprises 646 listed firms, i.e. 302 regulated firms and 344 control firms, and 14,212 firm-year observations over the period 1998–2019.[19]

3.1 | Measuring financial distress risk

The main variable we use to capture financial distress risk (DR) at the firm level is the option-based probability of default at debt maturity proposed by Merton (1973, 1974). Specifically, we use the probability of default of the "naïve" Merton model as in Bharath and Shumway (2008).

$$DR_{i,t} = N\left(-DD_{i,t}\right) \tag{1}$$

where $DD_{i,t}$ is the distance-to-default for firm *i* in year *t* computed as follows:

$$DD_{i,t} = \frac{ln\left(\frac{V}{D}\right) + \left(AR_{t-1} - 0.5\sigma_{BS}^2\right)T}{\sigma_{BS}\sqrt{T}} \tag{2}$$

where V is the total value of the firm's assets in year *t*, calculated as the firm's market value of equity (ME) plus the face value of debt (D) in year *t*. $AR_{i,\,t-1}$ is the expected return on the firm's total asset value in year *t-1*, computed using the previous year's monthly returns. σ_{BS} is the volatility of the firm's total asset value returns, calculated as the weighted average of the volatility of a firm's equity and debt. *T* stands for the debt maturity, always set equal to one year. The inputs used are either computed based on monthly market prices or observed through annual financial statements. This approach arguably exhibits higher accuracy in predicting DR and avoids the computational issue of solving systems of equations (see also, Charitou et al., 2013; Andreou et al., 2021).

The Merton default prediction model is one of the most influential models in corporate finance. It has been widely used to investigate, inter alia, default probabilities and recovery rates (e.g., Bharath and Shumway, 2008; Hillegeist et al., 2004), default risk and returns (Chava and Purnanandam, 2010; Garlappi et al., 2008), default risk and executive compensation (e.g., Kadan and Swinkels, 2008), as well as default correlations and default determinants (e.g., Campbell et al., 2008).

The basic premise behind the Merton option-based bankruptcy prediction model is that the equity of a levered firm can be viewed as a call option to acquire the value of the firm's assets (V) by paying off (i.e., having as an exercise price) the face value of the debt (D) at the debt's maturity (T).[20] From this perspective, a firm will be insolvent if the value of its assets falls below what it owes its creditors at debt maturity (i.e., when $V_T < D$).

The main advantage of using option-pricing models in estimating DR is that they provide the necessary structure to infer default-related information from market prices. Option-pricing models enable the construction of a distress risk measurement that contains forward-looking information, as market prices reflect investors' expectations about a firm's future performance. This is more appropriate than historical estimates for estimating the market's assessment of the firm's likelihood of exercising its default or reorganization option in the future.

3.2 | EU-ETS-related variables

In order to ensure that our findings are not driven by possible effects of the EU-ETS characteristics on individual firms' DR, we control for several variables. *Verified* is the actual verified emissions obtained from the EU-ETS database. *EUA price* is the monthly settlement price of EUA futures contracts for the price of EUAs obtained through the Refinitiv Eikon, in line with Oestreich and Tsiakas (2015).[21] Next, the variable $VAS = \frac{(Verified - Allocated)}{Sales}$ is the emission allowance surplus/deficit over sales, where *Allocated* is allocated emission allowances and *Sales* is firm's sales obtained from the Worldscope database (WC01001).[22] We also compute the variable $VAPS = \frac{((Verified - Allocated) * EUA\ Price)}{Sales}$, which measures the monetary outflow (inflow) for acquiring (selling) emission allowances over sales. All EU-ETS-related variables take the value zero for the *control* sample of firms.

3.3 | Control Variables

A set of additional control variables are included in the estimations in order to account for other potential determinants of financial distress risk as previously identified in the literature (see, among others, Capasso et al., 2020). Specifically, the following firm-level control variables are included in the model specification (3): (1) *Log(Age)* is the natural logarithm of the age of the firm measured in years, based on the first year of available data in the Worldscope database. This variable accounts for the fact that older firms might exhibit better performance as a result of more experienced management. (2) *Capx* is capital expenditure, defined as capital expenditures (WC04601) over total assets (WC02999). (3) *Cash* is cash and equivalents, defined as Cash & Equivalents (WC02001) over total assets (WC02999). (4) *Lev* is the Leverage ratio, defined as total debt (WC03255) over total assets (WC02999). (5) *MVBV* is the market-to-book ratio, defined as the Price/Book Value Ratio (WC09302). A high *MVBV* (over 1) implies that a firm's stock has a higher value than the replacement cost of its assets, indicating good growth prospects. (6) *MVvol* is the annualized volatility (standard deviation) of the firm's stock returns over a 60-month rolling window. Stock volatility is positively related to a firm's DR. (7) *RE* is the retained earnings, defined as retained earnings (WC03495) over total assets (WC02999) (8) *ROA* is the return on assets, defined as net income (WC01751) over total assets (WC02999). (9) *Stock Return* is the annual return of stock prices from Refinitiv Eikon (datatype: RI). (10) *Log(TA)* is the natural logarithm of the total assets (WC02999). (11) *ENV Score* is the Environmental pillar score from the ASSET4 database. (12) *EPU EU* is the Economic Policy Uncertainty index as introduced by Baker et al. (2016). This news-based index is calculated as the proportion of press articles referring to this specific type of uncertainty over a given period. Table A1 in the Appendix provides the definitions and sources of data for all variables considered in this study.

Table 1 presents summary statistics of the main variables for the full sample (regulated and control firms), which have been winsorized at the 1st and 99th percentiles to avoid the effects of possible outliers and data errors. Statistics show that the average DR is 0.20% across all firms, with a standard deviation of 1.40%. The average verified emissions are almost 2.0 million tonnes of CO_2 per year with a large standard deviation equal to 8.67 million tonnes. The EPU index exhibits an average value of 125.31, with a standard deviation of 46.05 over the period examined in this study. These statistics are consistent with those in prior studies (Charitou et al., 2013, Antoniou et al. 2020).

Table 2 shows the main summary statistics separately for regulated and control firms as well for the pre-Phase III and Phase III periods of the EU-ETS. It shows the statistics for Verified emissions, DR and Environmental score (*ENV Score*); along with (two-sample) t-tests for differences between the regulated and control samples and between the pre-Phase III and Phase III periods. The results show that the average firm's verified emissions in Phase III are equal to 4.06 million tonnes of CO_2 per year, which is a notable reduction from the equivalent of 4.72 million tonnes before Phase III. Furthermore, over the whole period examined, regulated firms exhibit a significantly higher DR (0.25%) than the control sample (0.06%). The difference in DR is (0.19%) and statistically significant (t-stat. = 6.25). The same pattern is observed in the Phase III period, where the DR of regulated and control samples is 0.36% and 0.01%, respectively. This difference (0.35%) is statistically significant (t-stat. = 5.99). By contrast, the difference between the DR of regulated and control firms is notably smaller (0.10%) and less significant in the period before Phase III (t-stat. = 3.05), providing preliminary evidence that regulated firms experienced an increase in DR after 2013 that is not observed for other (control) firms. Finally, the average environmental score before Phase III is 32.20 and 29.00 for regulated and control samples, respectively. However, the environmental score during Phase III is 42.79 and 49.74 for regulated and control samples, respectively.

4 | METHODOLOGY

The main empirical findings are obtained by estimating the following panel data regression model:

$$DR_{it} = a_0 + a_1 Regulated_{i,t} + a_2 Phase3_t + a_3 Regulated_{i,t} \times Phase3_t + E_{i,t} + F_{i,t} + EPU_t + u_{i,t} \quad (3)$$

TABLE 1 Summary statistics, sample period 1998–2019

Variable	Obs.	Mean	St. Dev.	Min	Max
Regulated	14212	0.467	0.499	0.000	1.000
Phase3	14212	0.273	0.445	0.000	1.000
DR(%)	8788	0.200	1.400	0.000	18.50
Altman	9655	4.120	3.097	−2.267	24.155
Verified (million $)	9690	1.998	8.676	0.000	149
Allocated (million $)	9690	1.529	6.835	0.000	143
EUA price	9690	13.236	7.071	4.950	28.840
Age	11894	10.603	6.218	1.000	22.000
Capx	11737	0.052	0.041	0.000	0.226
Cash	11468	0.104	0.100	0.001	0.537
Lev	11878	0.255	0.161	0.000	0.698
MVBV	12166	4.187	4.886	0.220	32.535
MVvol	11522	0.141	0.155	0.000	0.910
RE	11464	0.217	0.244	−0.731	0.821
Roa	11891	0.048	0.066	−0.216	0.256
Sales (million $)	11838	30.601	129.000	0.058	1490.000
Stock Return	11166	0.026	0.021	0.000	0.105
TA (million $)	11894	47.500	197.000	0.015	2,380
ENV Score	10362	36.478	34.388	0.000	98.930
EPU EU	14212	125.305	46.048	62.107	216.835

Note: This table shows the summary statistics for the variables entering Eq. (3). See Table A1 in the Appendix for variable definitions. All financial variables have been winsorized at the 1% level.

TABLE 2 Summary statistics of key variables for regulated and control samples

	Regulated Sample		Control Sample		Difference	
	Mean	St. Dev.	Mean	St. Dev.	Mean	t-stat.
Verified Emissions Whole period (million tonnes of CO_2)	4.46***	12.53	–	–	–	–
Verified Emissions Pre-Phase III (million tonnes of CO_2)	4.72***	13.35	–	–	–	–
Verified Emissions Phase III (million tonnes of CO_2)	4.05***	11.12	–	–	–	–
DR(%) Whole period	0.25***	1.77	0.06***	0.89	0.19	6.25***
DR(%) Pre-Phase III	0.20***	1.38	0.10***	1.07	0.10	3.05
DR(%) Phase III	0.36***	2.39	0.01*	0.44	0.35	5.98***
ENV Score Whole period	36.18***	35.87	36.72***	33.04	−0.54	−0.80
ENV Score Pre-Phase III	32.20***	34.27	29.00***	31.65	−3.19	−3.89
ENV Score Phase III	42.79***	37.46	49.74***	31.20	−6.95	−6.30***

Note: This table presents the mean, standard deviation, and t-stats of the mean difference in key variables between the regulated and control samples. Column ‘Difference’ shows the mean and t-stat of the differences between the two samples. *, **, *** test the hypothesis that the means are equal to zero. See Table A1 in the Appendix for variables definitions.

where DR_{it} is Merton's probability to default; $i = 1, 2, \ldots$, n identifies the firm; t = 1, 2,…,T denotes the period (year). Following the terminology of a difference-in-differences methodology, the *Regulated* dummy variable distinguishes the treatment from the *control* sample (group). Thus, *Regulated* is a dummy that equals 1 if the firm participates in the EU-ETS (regulated sample) and 0 if it does not (control sample).

In all model specifications we define a dummy variable (*Phase*3) for Phase III, which equals 1 for years between 2014 and 2019 and 0 otherwise. It starts in 2014 instead of 2013 since each year the computation of Merton's DR requires data from the balance sheet of the previous year. Accordingly, we lag by one year in the explanatory variables in all specifications. Model (3) also includes EU-ETS-related variables in vector E, while firm-year-specific variables are included in vector F. The EPU index is also used to capture the average economic policy uncertainty across the EU member states. We also include sector, country and year-fixed effects to capture unobserved heterogeneity.[23] In this setting, a positive and significant coefficient for a_3 means that the DR of firms in the EU-ETS (regulated sample) is higher in Phase III, compared to the control firms.

One commonly violated assumption of OLS estimation is that the error terms are correlated across observations and thus the OLS standard errors are biased downwards. Therefore, we follow the advice of Petersen (2009) and estimate cluster-adjusted standard errors at the firm level, instead of two-way cluster-adjusted standard errors at the firm and year levels.[24] Finally, the pair-wise correlations between the variables entering Eq. (3) are far less than 0.6, mitigating concerns regarding the existence of multicollinearity.[25]

5 | EMPIRICAL RESULTS

5.1 | Baseline results

Table 3 reports the baseline results across five different model specifications presented in columns 1 to 5. Columns 1 and 2 include only the key variables of our models with and without fixed effects i.e., firm, sector, country and year, respectively. In columns 3 to 5 we control for three sets of group variables, specifically, (i) accounting variables and firm age, (ii) EU-ETS-related variables, i.e. EUA price and Verified emissions and (iii) the variables used to calculate Merton's DR, i.e. Leverage, MVvol and Stock Return; along the Capx over total assets ratio.

The results show that the coefficient of the interaction term, *Regulated* × *Phase*3, is positive and statistically significant across all model specifications. This result suggests that the implementation of EU-ETS Phase III caused an increase in the DR of regulated firms by 0.30% compared to control firms, on average and across all models. This DR increase is economically important considering that the average DR of all firms in the sample is 0.20% as reported in Table 1. Furthermore, this result is consistent with our expectation that, in Phase III, regulated firms would face an additional direct polluting cost in the form of emission allowances as well as an indirect environmental cost, which would result in higher DR. We confirm this main result further through a set of validation tests discussed below. Regarding the control variables, the EU-ETS-related variables are insignificant. On the other hand, the leverage (*Lev*) is always positive and statistically significant and the stock volatility (*MVvol*) is positive, but insignificant after introducing the EU-ETS-related variables in the model specification in column 3.

As a robustness test we replace sector, country and year fixed effects with sector-by-year fixed effects. In this way, we address possible concerns that our results might be driven by time-varying sector specific shocks, i.e. that each year and for each sector there might be omitted variables affecting regulated and control firms in a different way. We do not report these results as they are qualitatively similar in terms of statistical significance and almost identical in terms of magnitudes of coefficients to our main findings in Table 3.[26]

5.2 | Parallel trends (year-by-year dummies) and propensity score matching

In this section, we provide additional tests to reveal the robustness of our findings. The first test we perform is an estimation setup with parallel trends (year-by-year dummies) which reveals the timing of the increase of distress risk.

TABLE 3 Baseline results, dependent variable: DR Merton

	(1)	(2)	(3)	(4)	(5)
Regulated	0.001*				
	(1.74)				
Phase3	−0.001**				
	(−2.24)				
Regulated X Phase3	0.003*	0.003**	0.003**	0.003**	0.003**
	(1.93)	(2.51)	(2.49)	(2.46)	(2.34)
Age			0.001	0.001	0.001**
			(1.06)	(1.25)	(2.16)
Capx			−0.016**	−0.014**	
			(−2.16)	(−1.99)	
Cash			−0.003	−0.001	−0.004*
			(−1.12)	(−0.41)	(−1.71)
Lev			0.010***	0.011***	
			(3.44)	(4.13)	
MVvol			0.021	0.018***	
			(1.61)	(3.72)	
Retained Earnings			−0.001	−0.001	−0.004**
			(−0.77)	(−0.53)	(−2.11)
Roa			−0.008	−0.013**	−0.020***
			(−1.32)	(−2.57)	(−3.30)
Stock Return			−0.058**	−0.047**	
			(−2.52)	(−2.34)	
TA			−0.000	−0.000	−0.000
			(−0.04)	(−0.57)	(−1.29)
EPU EU			0.001	0.001	0.001
			(0.00)	(0.00)	(0.00)
EUA price			0.001		
			(0.00)		
Verified			0.000		
			(0.79)		
Constant	0.001***	0.001***	−0.002	−0.001	0.004
	(2.69)	(5.a41)	(−0.48)	(−0.33)	(1.44)
Observations	8788	8788	6186	7955	8104
Adjusted R^2	0.0060	0.0881	0.1661	0.1455	0.1045
Sector and Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes

Note: This table presents the results of the estimated panel regressions following the econometric model in Eq. (3) over the period 1998–2019. We define Phase3 equal to 1 for years between 2014 and 2019, and 0 otherwise, i.e. it starts in 2014, instead of 2013, since the computation of Merton's DR requires previous year's financial data. Thus, Phase3 distinguishes Phase III (2013-2019) from Phases I and II (2005-2012). Accordingly, we lag by one year the explanatory variables in all specifications. The coefficients of sector, country and year fixed effects (FE) are suppressed. t-statistics are reported in the parentheses below coefficients; while robust standard errors are clustered at the firm level, following the advice from Petersen (2009). Statistical significance of the estimated coefficients is denoted with *, ** and *** for 10%, 5% and 1% significance levels, respectively. See Table A1 in the Appendix for variables definitions.

Results reported in Columns (1) and (2) of Table 4 show that the coefficient of the interaction term is statistically *significant* in Phase III and *insignificant* for the false treatment years before 2014. For instance, *Post2014* is a dummy variable equal to 1 for all years after 2014 (included) and zero otherwise. As observed in Table 4, the statistical significance of the coefficient of the interaction term increased across the false treatment years from 2011 to 2014. This result establishes that the increase of DR for the regulated firms vs. the control firms starts in Phase III and not earlier, i.e. we document parallel trends in the pre-Phase III period. Therefore, our findings are not falsely driven or biased by an upwards trajectory of DR starting from the years before EU-ETS Phase III.

Another potential criticism of the research design of this paper is that the results reported may be driven by specific characteristics of the firms in the two samples i.e., the regulated and control samples. For instance, firm characteristics in each of the two samples may differ considerably. In order to mitigate such endogeneity concerns, we use the propensity score matching (PSM) technique (for details, see Rosenbaum and Rubin, 1983) to create two separate and independent propensity score matching samples. Specifically, we pair each regulated firm with a firm from the control sample that is most similar based on the following two key sets of characteristics, (i) firm's age, total assets and market-to-book value ratio ("PSM control sample 1")[27], and (ii) MVvol, leverage, country and year ("PSM control sample 2"). In this way, the matched control samples consist of control firms that exhibit the closest financial characteristics to the regulated (treated) firms.[28] Furthermore, as an alternative matching approach, we apply the entropy balancing method (EB) as in Hainmueller (2012). The EB avoids certain shortcomings of the matching techniques commonly used in observational studies with binary treatments under the selection on observables assumption (i.e. the PSM). The main shortcomings of matching techniques are that they are typically tedious to apply and result in low levels of covariate balance in practice. In essence, such techniques involve an indirect search process that often fails to jointly balance out all the covariates. By contrast, the entropy balancing method addresses such shortcomings by using a pre-processing scheme where covariate balance is directly built into the weight function that is used to adjust the control units (for details see, Hainmueller, 2012).[29]

Columns 1 to 3 and 4 to 6 of Table 5 replicate the main model specifications of Table 3 by utilizing the two PSM samples. Columns 7 to 9 of Table 5 replicate the main model specifications of Table 3 by employing the entropy balancing method. As observed, the results are qualitatively similar to those reported in Table 3, confirming that differences in firm-specific characteristics (and/or the number of firms) between the treated and control samples do not drive our baseline findings.

Next, we test the robustness of our results using the Altman (1968) Z-score which is widely used as an alternative distress risk proxy in prior relevant studies.[30] Consistent with our baseline results, Table 6 shows that the interaction term (*Regulated* $\times$ *Phase3)* is negative and significant across all model specifications.[31] Although accounting-based default models such as the Z-score are not ideal alternatives to the market-based Merton distress model, our main findings become in several specifications even more significant at the 1% level.[32,]

5.3 | Climate regulation cost, environmental score and changes in distress risk

This sub-section aims to explore potential channels through which the distress risk of regulated firms increases in Phase III of the EU-ETS. The first potential channel is through firms' additional climate regulation cost caused by purchasing emissions allowances. To test this conjecture, we construct the variables *VAS* and *VAPS* that capture the deficit/surplus of emission allowances and the magnitude of the monetary payment for obtaining emission allowances, deflated by sales in both cases to incorporate possible simultaneous changes in firms' production output. Then, we re-estimate the baseline model specifications of Table 3 to examine the impact of *VAS* and *VAPS* in Phase III through the interaction terms (*VAS* $\times$ *Phase 3)* and (*VAPS* $\times$ *Phase 3)*. Results in Table 7 show that the interaction term is positive and statistically significant suggesting that during Phase III of the EU-ETS firms with higher emission allowance deficit (i.e. verified emissions are more than the emission allowances) and higher payments to acquire additional

TABLE 4 Distress risk and Phase III of the EU-ETS – dynamic model (parallel trends)

	(1)	(2)
Regulated*Post2014	0.003**	0.003**
	(2.24)	(2.31)
Regulated*Post2013	−0.001	−0.000
	(−1.16)	(−0.91)
Regulated*Post2012	−0.001	−0.001
	(−0.83)	(−0.81)
Regulated*Post2011	−0.000	0.000
	(−0.07)	(0.25)
Post2014	−0.000	
	(−0.36)	
Post2013	−0.000	
	(−1.49)	
Post2012	0.001**	
	(2.42)	
Post2011	0.001**	
	(2.43)	
Regulated	0.001	
	(1.27)	
Age	0.001	0.001
	(1.36)	(1.25)
Capx	−0.016***	−0.014**
	(−2.62)	(−1.99)
Cash	−0.003	−0.001
	(−1.60)	(−0.40)
Lev	0.013***	0.011***
	(3.75)	(4.13)
MVvol	0.018***	0.018***
	(4.23)	(3.72)
Retained Earnings	−0.000	−0.001
	(−0.30)	(−0.54)
Roa	−0.012**	−0.013**
	(−2.37)	(−2.56)
Stock Return	−0.045***	−0.047**
	(−2.74)	(−2.33)
TA	−0.000	−0.000
	(−1.26)	(−0.55)
EPU EU	−0.000*	0.001
	(−1.95)	(0.01)
Constant	0.000	−0.001
	(0.15)	(−0.34)

(Continues)

TABLE 4 (Continued)

	(1)	(2)
Observations	7955	7955
Adjusted R^2	0.0797	0.1452
Sector and Country FE	No	Yes
Year FE	No	Yes

Note: This table shows a year-by-year (parallel trends) setup using placebo treatment years as cut-off points (2011, 2012, 2013). Post*Year* is a dummy that equals 1 for years between *Year* and 2019, and 0 otherwise. For instance, *Post2014* is a dummy variable equal to 1 for all years after 2014 (included) and zero otherwise. See Table A1 in the Appendix for variables definitions.

emission permits experience higher DR.[33] These results confirm our hypothesis that Phase III of the EU-ETS imposed an additional and important climate regulation cost upon regulated firms which leads to a significant distress risk increase.

Another channel through which Phase III of the EU-ETS may have resulted in an increase in DR for regulated firms is the existence of an environmental risk factor. Environmental sustainability has been shown to form an important factor for investors in the last two decades. Prior studies have shown that firms with high sustainability (high ESG scores) are less vulnerable to reputation, political and regulatory risk; leading to higher stock market and accounting performance (among others, see Ecless et al., 2014). Since regulated firms are typically highly exposed to these risks, we conjecture that the increase in distress risk of regulated firms during Phase III should be more pronounced for firms with lower environmental scores in previous years, i.e. during Phases I and II. To test this prediction, we use the environmental score of regulated and control firms during Phases I and II of the EU-ETS to capture firms' efforts to reduce their environmental profile before Phase III.[34] Specifically, we classify firms into high and low environmentally compliant if their average environmental score during Phases I and II of the EU-ETS was above or below (respectively) the annual average environmental score of all firms in our sample. Based on this metric, we estimate the baseline model specifications separately for firms into the top (high) and bottom (low) of the sample observations, respectively. The results are reported in columns (2) and (3) of Table 7. As observed, the coefficient of the interaction term (*Regulated* × *Phase*3) is positive and significant only for firms being classified in the low environmental (score) group. These findings confirm our hypothesis that firms failing to reduce their environmental footprint during Phases I and II, as captured by their environmental pillar score, faced a significant DR increase in Phase III. This corroborates our conjecture that firms' environmental performance/profile is another important factor through which the distress risk increases for the regulated firms during Phase III of the EU-ETS.

Next, we complement the empirical evidence by exploring whether countries' institutional environment exacerbates or mitigates the effects of the climate regulatory costs on firms' distress risk. To this end, we re-estimate the main analysis separately for high and low scores of the worldwide governance indicators (using the median value as a threshold) measured at the country-year level and published by the World Bank.[35] These indicators are designed to proxy for six different dimensions of governance: control of corruption (cc), government effectiveness (ge), political stability (ps), regulatory quality (rq), rule of law (rl) and voice accountability (va).[36] Table 8 shows the results of this empirical exercise. As observed, the estimated coefficient of our main interaction term (Regulated × Phase 3) remains positive and statistically significant for the countries with low environmental scores across the governance indicators examined. This suggests that firms operating within countries with lower "control of corruption", "government effectiveness", "political stability", "regulatory quality", "rule of law" and "voice accountability", experience a higher increase in distress risk because of the implementation of Phase III of the EU-ETS climate regulation.

TABLE 5 Analysis using matched samples using (i) propensity score matched (PSM) and (ii) entropy balancing (EB) methods

	PSM control sample 1			PSM control sample 2			Entropy balancing control sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	As in Table 3 column 2	As in Table 3 column 3	As in Table 3 column 4	As in Table 3 column 2	As in Table 3 column 3	As in Table 3 column 4	As in Table 3 column 2	As in Table 3 column 3	As in Table 3 column 4
Regulated × Phase3	0.003***	0.003**	0.003***	0.003**	0.003**	0.003***	0.003***	0.003***	0.003***
	(2.73)	(2.39)	(2.64)	(2.50)	(2.47)	(2.61)	(4.21)	(4.20)	(4.52)
Age		0.001*	0.001		0.001	0.001		0.000	0.000
		(1.69)	(1.55)		(1.09)	(1.33)		(0.55)	(0.69)
Capx		−0.016*	−0.013*		−0.017**	−0.014*		−0.017***	−0.016***
		(−1.89)	(−1.67)		(−2.09)	(−1.95)		(−3.76)	(−3.49)
Cash		−0.007	−0.005		−0.005	−0.002		−0.007***	−0.004**
		(−1.62)	(−1.47)		(−1.37)	(−0.65)		(−3.26)	(−2.46)
Lev		0.010***	0.011***		0.011***	0.011***		0.013***	0.013***
		(2.82)	(3.60)		(3.32)	(4.08)		(4.92)	(6.07)
MVvol		0.024	0.021***		0.024*	0.019***		0.018***	0.018***
		(1.58)	(3.55)		(1.70)	(3.74)		(3.19)	(6.38)
Retained Earnings		−0.002	−0.001		−0.002	−0.001		−0.002	−0.002
		(−0.91)	(−0.61)		(−0.98)	(−0.81)		(−1.46)	(−1.37)
Roa		−0.016*	−0.018**		−0.012*	−0.017***		−0.009	−0.013**
		(−1.88)	(−2.57)		(−1.79)	(−3.04)		(−1.37)	(−2.38)
Stock Return		−0.060**	−0.051**		−0.061**	−0.049**		−0.061***	−0.045***
		(−2.27)	(−2.21)		(−2.47)	(−2.32)		(−4.76)	(−4.16)
TA		0.000	−0.000		0.000	−0.000		−0.000	−0.000
		(0.17)	(−0.45)		(0.15)	(−0.41)		(−0.03)	(−0.87)
EPU		0.001	0.001		0.001	0.001		0.000	−0.000
		(0.00)	(0.00)		(0.00)	(0.00)		(0.60)	(−0.53)

(Continues)

TABLE 5 (Continued)

	PSM control sample 1			PSM control sample 2			Entropy balancing control sample		
	(1) As in Table 3 column 2	(2) As in Table 3 column 3	(3) As in Table 3 column 4	(4) As in Table 3 column 2	(5) As in Table 3 column 3	(6) As in Table 3 column 4	(7) As in Table 3 column 2	(8) As in Table 3 column 3	(9) As in Table 3 column 4
EUA price		0.001			0.001			−0.002	
		(0.00)			(0.00)			(−1.13)	
Verified		0.000			0.000			0.000***	
		(0.16)			(0.63)			(3.05)	
Constant	0.001***	−0.004	−0.001	0.001***	−0.003	−0.002	0.006***	0.001	0.001
	(5.02)	(−0.57)	(−0.31)	(5.61)	(−0.63)	(−0.48)	(3.01)	(0.19)	(0.33)
Observations	7275	5116	6567	8088	5624	7368	7955	6186	7955
Adjusted R^2	0.1013	0.1883	0.1649	0.0901	0.1777	0.1526	0.1018	0.1809	0.1594
Sector and Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows robustness tests by replicating columns 2, 3 and 4 of Table 3 using two independent control samples matched using the propensity score matching technique (PSM) and using the entropy balancing technique as in Hainmueller (2012). The PSM control sample 1 is matched based on the variables (average values for the regulated vs. matched samples are reported in the parentheses): total assets (€72.6 mln. vs. €34.6mln.), age (10.49 years vs. 10.89 years) and market-to-book value ratio (2.25 vs. 2.81); while PSM control sample 2 is matched based on the variables MVvol (0.143 vs. 0.145), leverage (0.27 vs. 0.26), country and year. The entropy balancing method achieves superior matching based on the average values of all covariates used in the regressions (available by authors upon request). See Table A1 in the Appendix for variables definitions.

TABLE 6 Alternative distress risk measure, dependent variable: Altman's Z-score

	(1)	(2)	(3)	(4)	(5)
Regulated	−2.214***				
	(−9.46)				
Phase3	0.171				
	(1.28)				
Regulated × Phase3	−0.377**	−0.836***	−0.336***	−0.330**	−0.752***
	(−2.26)	(−4.37)	(−2.76)	(−2.31)	(−4.26)
Age			−0.329	−0.220	−0.285
			(−0.85)	(−0.54)	(−0.72)
Capx			−1.559	2.416	2.615
			(−0.63)	(0.89)	(1.15)
Cash			2.655**		
			(2.48)		
Lev			0.874		
			(1.13)		
MVvol			−2.634*	−2.799*	0.055
			(−1.87)	(−1.72)	(0.10)
Retained Earnings			1.687***		
			(4.50)		
Roa			11.047***		
			(6.18)		
Stock Return			5.651*	10.148***	10.564***
			(1.72)	(2.78)	(3.01)
TA			−0.454***		
			(−6.89)		
EPU EU			0.001	0.001	0.001
			(0.00)	(0.00)	(0.00)
EUA price			0.001	0.001	
			(0.00)	(0.00)	
Verified			−0.011	−0.066***	
			(−0.73)	(−3.81)	
Constant	5.065***	4.218***	10.872***	4.939***	4.381***
	(24.01)	(39.80)	(7.92)	(4.82)	(5.00)
Observations	9655	9654	6250	6273	8627
Adjusted R^2	0.1243	0.3441	0.4633	0.3627	0.3746
Sector and Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table replicates the baseline results reported in Table 3 using Altman's Z-score as the dependent variable instead of Merton's DR. See also notes in Table 3.

TABLE 7 Emission allowance surplus/deficit (VAS), direct costs (VAPS) and environmental performance

	VAS	VAPS	Mean Environmental score during Phases I and II	
	(1)	(2)	(2) High	(3) Low
VAS × Phase3	0.000**			
	(2.19)			
VAPS × Phase3		0.000**		
		(2.02)		
Regulated × Phase3			0.002	0.004**
			(1.24)	(2.50)
Age	0.001	0.001	0.003*	0.001
	(1.58)	(1.58)	(1.80)	(0.77)
Capx	−0.016**	−0.016**	−0.005	−0.027**
	(−2.05)	(−2.06)	(−0.84)	(−2.14)
Cash	−0.003	−0.003	−0.005	0.000
	(−1.10)	(−1.10)	(−0.65)	(0.21)
Lev	0.010***	0.010***	0.004*	0.013***
	(3.40)	(3.40)	(1.83)	(3.34)
MVvol	0.020	0.020	0.005*	0.023**
	(1.57)	(1.57)	(1.90)	(2.23)
Retained Earnings	−0.001	−0.001	−0.006	0.002
	(−0.86)	(−0.86)	(−1.51)	(1.21)
Roa	−0.010*	−0.010*	−0.009	−0.011
	(−1.67)	(−1.67)	(−1.36)	(−1.64)
Stock Return	−0.056**	−0.056**	−0.017	−0.086***
	(−2.47)	(−2.47)	(−0.97)	(−2.66)
TA	0.000	0.000	−0.000	−0.000
	(0.10)	(0.10)	(−0.63)	(−0.20)
EPU EU	0.001	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	−0.003	−0.003	−0.004	−0.002
	(−0.64)	(−0.64)	(−1.05)	(−0.21)
Observations	6172	6172	3426	3905
Adjusted R^2	0.1613	0.1613	0.1426	0.2049
Sector and Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: This table replicates column 4 of Table 3 for the following additional analyses: (i) including the variables VAS and VAPS and (ii) splitting the sample into High vs. Low Mean Environmental Score over Phases I and II of the EU-ETS. In order to split firms into high and low environmental score we first calculate the mean environmental score across all firms per year, and then classify a firm as a high (low) environmental score if its mean environmental score over Phases I and II of the EU-ETS (2005-2012) is above (below) the mean environmental score across all firms per year. See Table A1 in the Appendix for variables definitions.

TABLE 8 Governance quality indicators

	High *cc*	Low *cc*	High *ge*	Low *ge*	High *ps*	Low *ps*	High *rq*	Low *rq*	High *rl*	Low *rl*	High *va*	Low *va*
Regulated × Phase3	−0.000	0.005**	−0.001	0.005**	−0.001	0.003**	−0.000	0.005**	−0.001	0.005**	−0.000	0.005**
	(−1.26)	(2.39)	(−1.52)	(2.38)	(−1.28)	(2.27)	(−1.46)	(2.29)	(−1.43)	(2.39)	(−1.25)	(2.38)
EPU EU	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Age	−0.001	0.003	−0.001	0.002	−0.002	0.001	−0.001	0.003	−0.001	0.002	−0.001	0.002
	(−0.77)	(1.45)	(−0.75)	(1.08)	(−0.79)	(1.02)	(−1.29)	(1.54)	(−0.87)	(1.28)	(−1.11)	(1.37)
Capx	−0.009	−0.024*	−0.011	−0.023	−0.022	−0.021*	−0.001	−0.023*	−0.009	−0.023	−0.010	−0.023
	(−1.07)	(−1.66)	(−1.30)	(−1.60)	(−1.19)	(−1.89)	(−0.54)	(−1.75)	(−1.04)	(−1.62)	(−1.11)	(−1.57)
Cash	0.001	−0.009	0.001	−0.008	0.002	−0.006	0.001	−0.011	0.001	−0.009	0.001	−0.008
	(1.06)	(−1.27)	(0.56)	(−1.24)	(0.63)	(−1.50)	(1.34)	(−1.48)	(1.01)	(−1.37)	(0.70)	(−1.21)
Lev	0.005**	0.016**	0.005**	0.017**	0.005	0.013***	0.003*	0.017***	0.005**	0.017**	0.005**	0.015**
	(2.02)	(2.47)	(2.17)	(2.49)	(1.15)	(2.66)	(1.67)	(2.60)	(1.99)	(2.51)	(2.16)	(2.41)
MVvol	0.016**	0.021	0.015**	0.023	0.017*	0.018	0.005	0.029**	0.015**	0.023	0.014**	0.025
	(2.19)	(1.45)	(2.14)	(1.54)	(1.84)	(1.56)	(1.55)	(2.06)	(2.19)	(1.51)	(2.12)	(1.56)
Retained Earnings	0.001	−0.008	0.001	−0.006	0.001	−0.002	0.000	−0.007	0.001	−0.007	0.001	−0.007
	(1.51)	(−1.45)	(1.27)	(−1.18)	(0.74)	(−0.71)	(1.33)	(−1.27)	(1.40)	(−1.25)	(1.47)	(−1.37)
Roa	−0.005**	−0.012	−0.006**	−0.012	−0.014**	−0.006	−0.002	−0.012	−0.006**	−0.014	−0.006**	−0.014
	(−2.24)	(−0.60)	(−2.52)	(−0.67)	(−2.06)	(−0.60)	(−1.63)	(−0.63)	(−2.37)	(−0.76)	(−2.35)	(−0.75)
Stock Return	−0.009	−0.098**	−0.009	−0.091**	0.000	−0.069**	−0.012	−0.096**	−0.009	−0.096**	−0.010	−0.089**
	(−0.73)	(−2.30)	(−0.80)	(−2.28)	(0.04)	(−2.31)	(−0.93)	(−2.31)	(−0.75)	(−2.22)	(−0.88)	(−2.27)

(Continues)

TABLE 8 (Continued)

	High *cc*	Low *cc*	High *ge*	Low *ge*	High *ps*	Low *ps*	High *rq*	Low *rq*	High *rl*	Low *rl*	High *va*	Low *va*
TA	0.000	−0.001	−0.000	−0.001	−0.000	−0.000	0.000	−0.001	0.000	−0.001	0.000	−0.001
	(0.03)	(−1.05)	(−0.37)	(−1.06)	(−0.40)	(−0.76)	(0.59)	(−0.98)	(0.02)	(−1.10)	(0.01)	(−1.15)
Constant	−0.000	0.003	0.001	0.004	0.003	0.001	0.002	0.001	0.000	0.004	0.001	0.004
	(−0.15)	(0.44)	(0.43)	(0.63)	(0.93)	(0.23)	(0.89)	(0.14)	(0.18)	(0.62)	(0.56)	(0.64)
Observations	3478	3573	3513	3538	3472	3570	3474	3577	3484	3567	3425	3626
Adjusted R^2	0.0666	0.1412	0.0650	0.1383	0.0876	0.1058	0.0243	0.1453	0.0671	0.1386	0.0627	0.1403
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table replicates column 4 of Table 3 for high-low scores of governance indicators (using the median value as threshold) measured at the country-year level and published by the World Bank. These indicators are designed to proxy for six different dimensions of governance: control of corruption (cc), government effectiveness (ge), political stability (ps), regulatory quality (rq), rule of law (rl), voice accountability (va).

6 | DISCUSSION AND CONCLUSION

In this study, we have exploited EU-ETS Phase III as a quasi-natural experimental setting to identify whether the imputed environmental cost has resulted in an increase in financial distress risk for regulated firms. Using a difference-in-differences methodology, we show that the introduction of Phase III resulted in a DR increase of 0.30% on average for regulated firms compared to various control samples. This can be attributed to two main reasons: (i) the fact that in Phase III the emission permits were mostly auctioned, instead of being allocated for free to emitting firms as during Phases I and II, and (ii) the poor environmental profile of regulated firms in the period prior to Phase III. We test these mechanisms and show that regulated firms exhibit higher distress risk during Phase III when they pay more to obtain additional pollution permits and when they exhibit a low environmental score during Phases I and II.

Our findings are robust to a battery of robustness tests including alternative model specifications controlling for a wide range of other firm characteristics, along with sector and year fixed-effects, as well as country and financial crises indicators and firm clustered standard errors. Also, propensity matching and entropy balancing methods are used to ensure the unbiasedness of our regulated sample. We have also employed Altman's model as an alternative distress risk measure and controlled for confounding effects due to financial crises during the period examined. Furthermore, we confirm that two possible channels of the distress risk increase of regulated firms are the extra climate regulation cost in purchasing pollution permits and the high sustainability risk before the EU-ETS implementation. The latest channel is also consistent with our additional evidence that the distress risk increase is higher for regulated firms operating within countries with lower control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and voice accountability before the EU-ETS implementation.

Our study provides new insights into the ways environmental policy affects financial distress risk and contributes to the ongoing academic and policy debate on sustainable economic growth. We provide comprehensive evidence that introducing the EU-ETS Phase III cap-and-trade system, in which allowances must be purchased by the regulated firms, causes an increase in distress risk. This is particularly important considering no such evidence was found in Phases I and II when emission allowances were provided for free. The results of this study, therefore, complement and extend previous evidence on the impact of the EU-ETS on regulated firms by revealing that regulated firms experience higher financial distress risk in Phase III when compared to European control samples. Thus, regulated firms should aim to reduce their emissions by pursuing low-carbon innovations to avoid the added cost of emission allowances and the resulting increase in their distress risk. The empirical evidence presented in this paper could motivate (i) emission-regulated firms to prioritize the reduction of their carbon footprint and (ii) policy institutions to counteract the increase of financial distress risk through, for example, enhancing green financing schemes.

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ENDNOTES

[1] US EPA (2020). "Overview of Greenhouse Gases". Retrieved on 17th of April 2021: https://www.epa.gov/ghgemissions/overview-greenhouse-gases.

[2] The origins of the EU-ETS go back to 1992 when 180 countries signed the United Nations Framework Convention on Climate Change (UNFCCC). Later, the Kyoto Protocol, agreed in 1997, specified actions that led to the establishment of the

EU-ETS. Other large emission trading systems are those of California's cap-and-trade program launched in 2013, South Korea's Emissions Trading Scheme (KETS) launched in 2015, and China's ETS launched in 2021. Schmalensee and Stavins (2017) discuss and compare the design and effectiveness of seven of the most prominent emission trading systems over a period of three decades.

[3] Bolton and Kacperczyk (2021) find that investors are already demanding compensation for their exposure to carbon emission risk; while Aswani et al. (2023) show that these effects are sensitive to (i) using vendor-estimated emissions as they systematically differ from firm-disclosed emissions and (ii) using unscaled emissions since they are correlated with stock returns instead of using emissions intensity (i.e., emissions scaled by firm size) which is not.

[4] Eccles et al. (2014) show that high sustainability companies tend to facilitate higher stakeholder engagement, be more long-term oriented, and exhibit wider disclosure of non-financial information. Such companies are shown to significantly outperform their peers in terms of the long-term stock market and accounting performance.

[5] Our empirical exercise does not rule out the case that paying more for acquiring pollution permits may co-exist with a low environmental score for a given firm. We show that both effects are at play.

[6] For instance, using industry classifications as a proxy for firms' carbon intensity in the absence of actual verified emissions is subject to aggregation error; an issue discussed in Martin et al. (2016).

[7] The 2015 Paris Climate Agreement's goal is to limit global warming by lowering the global average temperature by 1.5 degrees Celsius compared to pre-industrial levels. Countries need to submit their plans for climate action known as nationally determined contributions (NDCs) on a 5-year cycle of increasingly ambitious climate actions.

[8] Earlier efforts in this strand of the literature also include Oikonomou et al. (2014), who show that the different dimensions of sustainability performance reduce corporate bond spreads

[9] Using bond downgrades and upgrades as a measure of default relies implicitly on the assumption that all assets within a rating category share the same DR and that this DR is equal to the historical average DR. It also assumes that a firm can't experience a change in its default probability without also experiencing a rating change.

[10] Overall, the main advantage of using option-pricing models in calculating the default likelihood is that they provide guidance about the theoretical determinants of bankruptcy and supply the necessary structure to extract bankruptcy-related information from market prices. The main advantage of the Merton measure lies in its nature to capture investors' futures expectations. This is particularly important in our study as this reflects how investors evaluate firms' ability and willingness to facilitate and/or incorporate green and sustainable policies.

[11] The EU-ETS raises the possibility of carbon leakage i.e., firms' relocation of production outside the EU in order to avoid this particular regulation (Meunier et al., 2014). However, Branger et al. (2016) documented no evidence during Phases I and II of the EU-ETS of carbon leakage in the short run, at least with regards to the cement and steel industries.

[12] A number of studies have examined whether the introduction of the EU-ETS placed European firms in a competitive disadvantage against their global peers and report no such evidence during Phases I and II of the EU-ETS, where allowances were allocated for free (Martin et al., 2016, 2014).

[13] The series depicted is constructed by rolling over the corresponding futures contract written on the EUA price with maturity in December of each year, as in Krokida et al. (2020).

[14] Each year, by May 15th, the Commission publishes the total number of allowances in circulation.

[15] The relevant documentation regarding the EU ETS Company database is available here (last accessed 24 July 2022): https://www.carbonmarketdata.com/files/publications/EUETS_company_database.pdf

[16] "Participation in the EU ETS is mandatory for companies in the following sectors: electricity and heat generation, energy-intensive industry sectors including oil refineries, steel works, and production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals, commercial aviation within the European Economic Area. However, the following exceptions may apply for some sectors: (i) only installations above a certain size are included, (ii) certain small installations can be excluded if governments put in place fiscal or other measures that will cut their emissions by an equivalent amount, (iii) in the aviation sector the EU ETS will apply only to flights between airports located in the European Economic Area (until 31 December 2023)", https://ec.europa.eu/clima/policies/ets_en (last accessed 18 July 2021).

[17] The STOXX Europe 600 equity index was introduced in 1998 by STOXX Ltd. This index has a fixed number of constituents (i.e., 600) representing large, mid-sized and small capitalization companies from 17 European countries, covering approximately 90% of the free-float market capitalization of the European stock market.

[18] These sectors are banks, consumer services, health care providers, investment banking and brokerage services, life insurance, media, precious metals and mining, real estate investment and services, software and computer services, telecommunications service providers, tobacco, waste and disposal services.

[19] The final number of firm-year observations entering each model specification may be lower than 14,212 due to missing values and the inclusion of lag variables.

[20] From an economic perspective, creditors are considered to be the owners of the firm (rather than the equity holders, who are the legal owners), with equity holders having the right to acquire the firm after paying off what they owe.

[21] Such futures contracts are traded on the European Climate Exchange, which is owned by the Intercontinental Exchange. In line with Oestreich and Tsiakas (2015), we construct a continuous price series combining a series of futures contracts as follows: In Phase I (2005–2007), our series is equal to the price of the December 2008 contract. In Phase II (2008–2012) the series is equal to the price of the December 2009 contract until its last trading day, then switches to December 2010 until its last trading day, and so on, until December 2012. In Phase III (2013–2018), we follow the same procedure and set the series equal to the futures contract with maturity on December of each year.

[22] Using VAS, which is essentially a carbon-intensity measure, is important in light of the recent and important evidence presented by Aswani et al. (2023). Specifically, Aswani et al. (2023) show that investors are demanding compensation for their exposure to carbon emission as shown by Bolton and Kacperczyk (2021) but these effects are sensitive to (i) using vendor-estimated emissions as they systematically differ from firm-disclosed emissions and (ii) using unscaled emissions since they are correlated with stock returns instead of using emissions intensity (i.e., emissions scaled by firm size) which is not.

[23] Inserting firm fixed effects instead of sector and country fixed effects yields identical or stronger results for the empirical evidence reported below. The results are available by the authors.

[24] Our main findings survive and in most cases are stronger when computing two-way (firm and year) rather than one-way (firm) clustered adjusted standard errors (Petersen, 2009). The results are also robust to country and year clustered standard errors, on this see also Abadie et al. (2023). The results are available by the authors.

[25] The same ad-hoc threshold of 0.6 is adopted in the general finance literature (see, for example, Dick-Nielsen et al., 2012). As a robustness diagnostic test for the absence of multicollinearity we also use the Variance Inflation Factors (VIF) (for details, see James et al., 2013 p. 101).

[26] As another robustness test (untabulated), we re-estimate our main results by omitting year fixed effects and including a dummy variable that takes the value one for the years 2009 up to 2012 and zero otherwise, i.e. capturing the periods of the global financial crisis and European debt crisis. These results are qualitatively similar in terms of statistical significance and almost identical in terms of the magnitudes of coefficients to our main findings in Table 3. They are available from the authors upon request.

[27] Including return on assets (ROA) in the matching variables yields qualitatively identical results. The results are available from the authors upon request.

[28] The statistics of the main variables of both PSM samples are similar to those of the treated sample, and look to match better with the treated sample than the broader control sample does. These statistics confirm the efficiency of our implementation of the propensity score matching and are available by the authors upon request.

[29] We use Stata's package *ebalance* and specify that the 1st, 2nd, and 3rd moments for all covariates will be adjusted (see, Hainmueller and Xu, 2013).

[30] The Altman (1968) Z-score is an accounting-based proxy of the probability to default computed as follows:

Z-score = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5, where (Worldscope's database items are provided in the parentheses in first appearance): X1 = working capital (WC03151) / total assets (WC02999), X2 = retained earnings (WC03495) / total assets, X3 = earnings before interest and tax (WC18191) / total assets, X4 = market value of equity (WC08001) / total liabilities (WC03351), X5 = sales (WC01001) / total assets.

[31] The negative coefficient of the interaction variable when using the Altman Z-score as the dependent variable is in line with our previously reported positive coefficient of the interaction variable when using the DR of Merton's model, because lower values of Z-score indicate higher distress risk by definition. Note that column 5 of Table 6 omits the accounting variables related to the calculation of Z-score.

[32] In fact, the effectiveness of bankruptcy probability measures based on accounting data has been debated over time for several reasons (Begley et al., 1996; Hillegeist et al., 2004). For instance, financial statements are designed to measure past performance and may therefore not be very informative about the future status of a firm. Furthermore, financial statements are formulated under the going-concern principle, which consequently limits, by design, the accuracy and reliability of the bankruptcy probability assessment. Additionally, accounting-based bankruptcy models fail to incorporate asset volatility measures, which can lead to a substantial reduction in their performance, since firms exhibit considerable cross-sectional variation in volatility; at the same time, they rely on the assumption that the market can impound all publicly available information into prices.

[33] The results for the rest of the model specifications reported in Table 3 are qualitatively the same.

[34] We use the environmental pillar score out of the overall ESG score for each firm through the ASSET4 database.

[35] Worldwide Governance Indicators are freely available through the World Bank's website (last access 27th May 2023): https://databank.worldbank.org/source/worldwide-governance-indicators).

[36] The six governance indicators exhibit pair-wise correlations over 0.8.

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APPENDIX

TABLE A1 Variables, definitions and sources of data

Variable	Definition and source
	Panel A. Dummy variable
Regulated	Dummy that equals 1 if the firm participates in the EU-ETS scheme (*regulated* sample) and 0 if the firm does not participate (*control* sample).
Phase3	Dummy that equals 1 for years between 2014 and 2019, and 0 otherwise. It starts at 2014, instead of 2013, since the computation of Merton's DR requires previous year's financial data. It distinguishes Phase III (2013-2019) from Phases I and II (2005-2012).
PostYear	Dummy that equals 1 for years between *Year* and 2019, and 0 otherwise, i.e. each *Year* from 2010 to 2013 is used as a false (placebo) treatment year in the falsification test.
	Panel B. Financial distress risk measures
DR	The distress risk is the probability of default based on Merton's model.
Z-score	Altman Z-score is computed as: Z-Score $= 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$, where: $X_1 =$ working capital (WC03151) / total assets (WC02999), $X_2 =$ retained earnings (WC03495) / total assets, $X_3 =$ earnings before interest and tax (WC18191) / total assets, $X_4 =$ market value of equity (WC08001) / total liabilities (WC03351), $X_5 =$ sales (WC01001) / total assets.
	Panel C. Variables to calculate Merton probability of default (DR)
D	The face value of debt is defined as the debt in current liabilities plus half of the long-term debt (WC03251).
ME	The market value of equity is the stock price multiplied by the number of shares outstanding.
V	The total asset value is the firm's market value of equity (ME) plus the face value of debt (D).
σ_{BS}	The volatility of total asset returns is estimated as: $\sigma_{BS} = (\frac{ME}{ME+D})\sigma_E + (\frac{D}{ME+D})\sigma_D$, where σ_E is the annualized equity volatility over a 60-month window adjusted for cash dividends and σ_D is the debt volatility estimated using the following formula as an approximation: $\sigma_D = 0.05 + 0.25\sigma_E$.
DD	The distance-to-default is the "naïve" model approach of Bharath and Shumway (2008).
	Panel D. EU-ETS variables
Verified	The amount of verified emissions per firm-year, obtained through the EU-ETS Company Database. It takes the value zero for the non EU-ETS firms.
EUA price	The natural logarithm of the (traded) price of the Emission Unit Allowance (EUA). Each EUA permit provides to the buyer (firm) the right to emit one tonne of CO_2 per year to the atmosphere. It takes the value zero for the non EU-ETS firms.
VAPS	$VAPS = \frac{((Verified-Allocated)*EUA\ Price)}{Sales}$, where *Verified* are the realized emissions and *Allocated* are the allocated emission allowances, both obtained through the EU-ETS company database; *Sales* are obtained from the Worldscope database (WC01001). It variable takes the value zero for the non EU-ETS firms.
VAS	NEED DEFINITION
	Panel E. Firm-year variables
Age	The natural logarithm of the years a firm appears in the Worldscope database.
Capx	The ratio of capital expenses (WC04601) over total assets.
Cash	The ratio of cash and cash equivalents (WC02001) over total assets.
Lev	The leverage ratio of the firm, defined as total liabilities (WC03351) over total assets.
MVBV	The ratio of market value (WC08001) over book value (WC09302).
MVvol	The annualized volatility (standard deviation) of the firm's stock returns over a 60 month rolling window.

(Continues)

TABLE A1 (Continued)

Variable	Definition and source
Retaind Earnings	The ratio of retained earnings (WC03495) over total assets.
ROA	The ratio of net income (WC01751) over total assets.
Stock Return	The annual return of stock prices from Refinitiv Eikon (RI).
TA	The natural logarithm of the total assets (WC02999) of the firm.
ENV Score	The aggregate Environmental pillar score from the ASSET4 database.
Panel F. Macro variables	
EPU EU	The average Economic Policy Uncertainty index across the following EU members (as per data available through the website: https://www.policyuncertainty.com/): France, Germany, Spain, Italy, Netherlands, Sweden, Greece, UK.
Panel G. World Governance Indicators	
CC	*Control of Corruption* captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the World Governance Indicators (WGI).
GE	*Government Effectiveness* captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI.
PS	*Political Stability and Absence of Violence/Terrorism* measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI.
RQ	*Regulatory Quality* captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI.
RL	*Rule of Law* captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI.
VA	*Voice and Accountability* captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI.

Note: This table provides definitions and sources of data for all the variables considered in this study.

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