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Carbon assurance: Does it have an impact on credit ratings?

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Abstract

This paper examines the impact of firm-level carbon assurance on credit ratings among U.S. publicly traded firms. The findings reveal a positive relationship, indicating that carbon assurance enhances credit ratings by reducing information asymmetry and attracting analyst following. These results are robust to alternative measures of variables, model specifications, and endogeneity tests. U.S. firms with higher carbon assurance benefit from improved creditworthiness, particularly in competitive markets and Democratic-leaning states. These findings support signalling theory and show the strategic importance of carbon assurance in credit assessments and corporate sustainability.

KEYWORDS

assurance level, assurance percentage, carbon assurance, credit ratings, climate change, climate action (SDG13)

JEL CLASSIFICATION

G14, G34, Q50

1 | INTRODUCTION

Addressing climate change and its impacts is a key priority among the 17 Sustainable Development Goals (SDGs) established by the United Nations, specifically SDG13: Climate Action. In response, countries worldwide are taking urgent steps to combat climate change. Simultaneously, the demand for climate-related and other environmental, social, and governance (ESG) information has drawn significant attention. (Cuadrado-Ballesteros et al., 2017; He et al., 2022b; Seltzer et al., 2022). For example, the U.S. Securities and Exchange Commission (SEC) has responded by forming the climate and ESG task force to develop initiatives to detect

ESG-related misconduct[1] and proposed enhancing and standardising climate-related reporting for investors.[2]

The importance of credible carbon reporting has been further emphasised by the recent formation of the International Sustainability Standard Board (ISSB) and the adoption of the integrated reporting framework in ISSB standards to provide comprehensive environmental information to intended users (International Accounting Standards Board (IASB, 2023). In this study we support these developments by examining the relationship between carbon assurance, which refers to the process of independent verification or validation of a company's carbon emissions data and related environmental performance metrics, and firm-level credit ratings in the U.S. market.

Existing research investigating climate-related risks documents the significant impacts of carbon emissions on firms and capital markets. Climate change risk is found to be priced in corporate stocks and bonds (Bolton & Kacperczyk, 2021; Huynh & Xia, 2021) and mortgage costs (Nguyen et al., 2022). Carbon/greenhouse gas (GHG) emissions are also found to influence firm value (Choi & Luo, 2021; Matsumura et al., 2014). Such actions and findings reinforce the importance of environmental sustainability reporting by firms. Prior studies offer important insights into carbon/GHG emissions and their impacts on various aspects of firms and/or capital markets.

However, there is limited research that examines the reliability and credibility of the carbon emissions disclosures and how the debt market participants perceive such assured carbon disclosures. As most environmental disclosures are self-reported (Matsumura et al., 2014), their credibility can be questionable (Cuadrado-Ballesteros et al., 2017). On the one hand, Matsumura et al. (2014) argue that despite not being assured, carbon disclosures can be considered "reasonably credible" as investors can compare the information across firms in the same industry, and the cost of untruthful reporting is relatively high. On the other hand, other scholars share concerns over the credibility of such disclosures.[3] Disclosing environmental issues is considered a strategic decision of managers. Coram et al. (2009) show that only assurance reports about positive (non-financial) performance disclosures affect stock prices. Also, management compensation is closely tied to sustainability targets (Christensen et al., 2021; Mio et al., 2015). As a result, climate disclosures can be subject to credibility problems (Cuadrado-Ballesteros et al., 2017; Fan et al., 2021; Freedman & Jaggi, 2005).

Indeed, relevant regulatory bodies, such as the SEC, have also proposed accounting standards/policies requiring firms to have their climate reporting assured.[4] Similarly, as specified in Australia's National Greenhouse and Energy Reporting Act (2007), although carbon assurance is not compulsory, regulators may require firms to audit their relevant GHG emissions.[5] Given the debates on the credibility of climate reporting and relevant policy changes, we, however observe a lack of research on carbon assurance. The literature review shows that a few recent studies investigate the relevant environmental assurance and

[1] https://www.sec.gov/news/press-release/2021-42.

[2] https://www.sec.gov/news/press-release/2022-46.

[3] Volkswagen's emissions fraud in 2015 is an example of false carbon emissions reporting. Particularly, the carmaker claimed that their engines were environmentally friendly, however, in fact they installed a deceptive software to "cheat" the testing system and reported false information. (https://www.nytimes.com/2015/10/29/business/international/volkswagen-earnings-q3.html).

[4] According to the SEC proposal, climate reporting (e.g., Scope 1 and Scope 2 GHG emissions) by large accelerated and accelerated filers is subject to limited assurance by 2024 and 2025, respectively (https://frv.kpmg.us/reference-library/2022/sec-proposes-climate-reporting-requirements.html) (possible assurance compliance dates if the proposal is approved and becomes effective). Two years later, those firms are required to upgrade their climate reporting assurance to a reasonable level.

[5] https://assets.bbhub.io/company/sites/60/2021/10/FINAL-2017-TCFD-Report.pdf.

its impact on firms. For example, Bui et al. (2021) find that carbon reporting assurance negatively influences earnings management. Luo et al. (2023) show that compared to firms that do not have their carbon reporting assured, firms that adopt the assurance tend to have better carbon disclosure quality.

Examining the credibility of carbon reporting through carbon assurance and its relationship with credit ratings is important for at least three main reasons. First, assurance enhances the credibility of sustainability reports, thus improving users' confidence in using such statements (Simnett et al., 2009). Second, credit ratings are fundamental as they affect not only the firm's cost of capital but also stock and bond valuations (Jung et al., 2013). Prior literature has documented many factors affecting firm credit ratings, including corporate governance (Ashbaugh-Skaife et al., 2006) and chief executive officer (CEO) characteristics (Ma et al., 2021). Nevertheless, to the best of our knowledge, there is little evidence of the impact of carbon assurance on firm-level credit ratings. Third, the US corporate bond market has shown significant growth over the last 10 years and has received great attention due to a recent increase in inflation and changes in monetary policies[6] (Smolyansky & Suarez, 2021). Moreover, the bond market (rather than the stock market) is considered "the marginal source of finance" for many firms; thus, the impact of climate-related risk can be captured easily in this market (Seltzer et al., 2022, p. 1; see also Gourio, 2013). Therefore, this market is an important context for examining firm climate-related actions and their impacts.

In this paper we use signalling and legitimacy theory to explain the relationship between carbon assurance and credit ratings. According to signalling theory (Spence, 1978), high-quality signallers tend to send costly and observable information to reflect their quality (Connelly et al., 2011). Following that, high-quality firms (in terms of carbon performance and commitments) are likely to adopt carbon assurance to reflect their environmental commitment and credibility of carbon reporting, which in turn can improve their credit ratings. Indeed, Datt et al. (2018), investigating determinants of a firm's voluntary carbon assurance with a global sample of 44 countries, find that firms that employ an environmental committee, adopt carbon reduction initiatives, or have better carbon reporting scores tend to seek carbon assurance. Rohani et al. (2023) also document that firms with high carbon assurance levels are likely to have (marginally) better carbon performance in terms of carbon emissions. Similarly, Luo et al. (2023) show that firms that adopt carbon assurance tend to have better carbon reporting quality. According to legitimacy theory, firms need to behave in a socially responsible way to operate successfully within society (Dowling & Pfeffer, 1975). Thus, low-quality or carbon-intensive firms can be motivated to send misleading signals to change receivers' perceptions (Baier et al., 2022; Connelly et al., 2011) and show their legitimacy. As the carbon reporting framework and assurance are still in their infancy and face relevant criticisms (Kaplan & Ramanna, 2021),[7] firms can take advantage of such drawbacks and adopt external assurance to greenwash their actual carbon activities and prove their legitimacy (Clarkson et al., 2019; Kaplan & Ramanna, 2021). Following this line of reasoning, carbon assurance can reflect firms' low carbon commitment and decrease their credit ratings. Given these two competing perspectives on carbon assurance, the relationship between carbon assurance and firm-level credit ratings is theoretically ambiguous. This ambiguity motivates us to undertake this study.

We examine the relationship between carbon assurance and firm-level credit ratings, using a sample of US publicly traded firms over 11 years (2007–2017)[8] and find support for the posi-

[6]https://www.federalreserve.gov/monetarypolicy/2023-03-mpr-summary.htm.

[7]Please also see more here https://hbr.org/2022/04/we-need-better-carbon-accounting-heres-how-to-get-there.

[8]Credit rating data is available from COMPUSTAT up to 2017, and we do not find recent credit rating data in any other database.

tive relationship (contemporaneous and 1-year lagged effect) of carbon assurance and credit ratings. Our findings support a positive relationship—both contemporaneous and lagged—between carbon assurance and credit ratings, consistent with signalling theory. These results are robust to alternative measures of carbon assurance and credit ratings, different model specifications, and endogeneity tests. We also explore the impact of carbon assurance under varying levels of product market competition and political environments and find that firms with high carbon assurance tend to receive higher credit ratings when operating in highly competitive markets or when headquartered in Democratic-leaning states. To address potential endogeneity concerns, including reverse causality, sample selection bias, unobservable heterogeneity, and omitted variables, we employ lagged independent variables, propensity score matching (PSM), and two-stage least squares (2SLS) instrumental variable analysis. The results consistently demonstrate robust evidence of a positive relationship between carbon assurance and credit ratings.

We also investigate the mechanism through which carbon assurance influences credit ratings. Sustainability assurance is found to mitigate the asymmetric information problem between informed and uninformed stakeholders (Cuadrado-Ballesteros et al., 2017). At the same time, more information transparency can attract more analyst coverage (Jiraporn et al., 2012). Financial analysts act as information intermediaries in the market (Healy & Palepu, 2001), thus, having more analysts following reduces cash flow uncertainty and information risk, which can lower firm default risk and improve credit ratings (Cheng & Subramanyam, 2008). Following that, we test if analyst following is a channel through which carbon assurance influences firm-level credit ratings. Our result reveals a significantly positive link between both carbon assurance proxies and analyst coverage, supporting the analyst following channel.

We contribute to the literature in the following ways. First, given the two competing views (i.e., signalling theory versus legitimacy theory) on carbon assurance and its impact on firm credit ratings, we offer evidence of the positive relationship between carbon assurance and credit ratings. Our finding thus supports signalling theory. Second, our study extends the well-established literature on credit ratings and their determinants. Particularly, in addition to existing factors that are found to affect firm-level credit ratings, such as corporate governance (Ashbaugh-Skaife et al., 2006) and CEO characteristics (Ma et al., 2021), we add a new determinant of carbon assurance to this line of research. We also advance the current sustainability literature to examine carbon assurance instead of general sustainability assurance. As carbon reporting and assurance is governed by particular accounting standards (e.g., International Standard on Assurance Engagements-ISAE 3410, SEC Guidance Regarding Disclosure Related to Climate Change), which require specific knowledge and expertise, it is important to investigate carbon assurance specifically (Luo et al., 2023). Our finding thus highlights the critical role of carbon reporting and assurance in credit assessment and capital markets. Third, consider how the relationship between carbon assurance and credit rating varies across high and low product market competition environments and external political contexts. Our study emphasises the role of market and institutional characteristics in shaping a firm's behaviour and performance, supporting institutional theory (Campbell, 2007). Last, we show how carbon assurance influences firm credit ratings through analyst coverage, highlighting the informational role of financial analysts. Our results reveal that firms with a high level or percentage of carbon assurance tend to attract more analyst coverage, reducing default risk and improving credit ratings (Cheng & Subramanyam, 2008).

The remainder of the paper is organised as follows. We review relevant literature and present our hypothesis in Section 2. Section 3 discusses our study's data, variable measurement, and method. We offer the main findings, relevant robustness tests, and channel analysis in Section 4. Section 5 summarises and concludes our study.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 | Sustainability assurance versus carbon assurance

The increasing demand from various stakeholders on sustainability-related issues has pressured firms around the world to publish their sustainability reports. Simnett et al. (2009) refer to such reports as relevant non-financial information with the following six categories in the Global Reporting Initiative (GRI) 2007: economic, environment, human rights, product responsibility, labour, and society. However, given the public concerns over the credibility of such reports, the authors find that firms also voluntarily adopt sustainability assurance to enhance their credibility. There are multiple types of sustainability assurance that correspond to these categories of sustainability information (Hazaea et al., 2022), such as social assurance (Gao & Zhang, 2006), environmental assurance (Zhang et al., 2022), and carbon assurance (Bui et al., 2021; Luo et al., 2023).

While environmental assurance includes various components such as energy, water usage, and carbon emissions (Zhang et al., 2022), carbon assurance only focuses on carbon emissions assurance. As carbon reporting and assurance is governed by particular accounting standards (e.g., International Standard on Assurance Engagements-ISAE 3410, SEC Guidance Regarding Disclosure Related to Climate Change), which require specific knowledge and expertise, there is a shift to examine carbon disclosure and assurance specifically (Luo et al., 2023). However, like other types of sustainability disclosure, it is challenging to assess the reliability and credibility of carbon reporting (Freedman & Jaggi, 2005). Furthermore, such information asymmetry in carbon reporting cannot be resolved with financial auditing, thus firms are motivated to adopt carbon assurance (Fan et al., 2021).

The literature on carbon assurance is still limited and mainly focuses on carbon assurance practice and its determinants (He et al., 2022a). Particularly, as carbon assurance is voluntary, firms can choose to adopt different carbon assurance levels (e.g., Scope 1, Scope 2) and use various assurance providers (e.g., audit firms, consulting firms) (Datt et al., 2018; He et al., 2022a). Such assurance practices are also influenced by various factors. For example, Datt et al. (2018) analyse a global sample of firms across 44 countries and find that firms that implement carbon reduction initiatives or have higher carbon disclosure scores tend to adopt carbon assurance. Similarly, Simic et al. (2023) show that sustainability-related compensation or higher director compensation is associated with voluntary carbon assurance in UK firms. Tang (2019) examines Chinese firms and documents that governmental green funding and the forming of carbon institutions are associated with carbon assurance. In summary, while prior studies have offered important insights into carbon assurance and its determinants, little is known about how carbon assurance impacts various firm outcomes, especially credit ratings.

2.2 | Carbon assurance and credit ratings

According to signalling theory (Connelly et al., 2011; Spence, 1978), when information asymmetry is present, high-quality individuals or organisations tend to send "costly" and "observable" information to reduce the asymmetric information problem among parties and signal their high quality. In the context of environmental reporting, firms and executives know best about their carbon activities. Despite the carbon disclosures, such disclosures can be difficult for external stakeholders to verify (Fan et al., 2021), leading to information asymmetry between firms and intended users. Fan et al. (2021) document that firms with high carbon information asymmetry voluntarily adopt external assurance for their GHG statements to alleviate the asymmetry problem. This adoption of assurance a signals the firms' strong commitment to sustainability (Clarkson et al., 2019).

A quality signal must possess two characteristics: First, it must be costly (i.e., the signal must be costly for signallers to produce to avoid copying or cheating) and second, it must be observable (i.e., the signal must be observable by receivers) (Connelly et al., 2011; Spence, 1978). The assurance process is costly due to the fees paid to the auditor or specialist and the efforts devoted by the management team during the process (Baier et al., 2022; Kausar et al., 2016). It is also observable, as the assurance statement is available as part of the company reports. As a result, carbon assurance can act as a strategic signal for high-quality firms (in terms of carbon performance). These high-quality firms tend to have lower regulatory and climate-change risks related to their carbon emissions, which can improve their credit ratings.

The current carbon reporting framework and relevant assurance requirements are challenging for intended users to verify and are also subject to criticism (Fan et al., 2021; Kaplan & Ramanna, 2021); firms can take advantage of this to send false signals to users. For example, Kaplan and Ramanna (2021) claim that the current carbon emission reporting of some firms ignores emissions from their supply/distribution chains. Moreover, although the assurance statement is available it should be noted that the outcomes may vary depending on how recipients perceive and interpret the assurance signal and its credibility. (Baier et al., 2022). "Not surprisingly, auditors of these reports often resort to double negatives 'We found no evidence of misreporting in the company's ESG report' and the reports themselves have had little impact on either corporate actions or external stakeholders" (Kaplan & Ramanna, 2021, p. 122). Consequently, low-quality firms can take advantage of these inconsistencies and choose to disclose selective information and adopt external assurance to "greenwash" their actual carbon activities and show their legitimacy (legitimacy theory) (Clarkson et al., 2019; Kaplan & Ramanna, 2021). In such cases, carbon assurance can be associated with more risks due to potential greenwash problems, reducing firm credit ratings. Given the two competing views on the relationship between carbon assurance and credit ratings, we posit the following hypothesis:

H1. Carbon assurance is associated with firm-level credit ratings.

3 | SAMPLE AND RESEARCH DESIGN

3.1 | Data and sample

The sample for the study covers US publicly traded firms over the period 2007–2017 due to COMPUSTAT credit rating data only being available until 2017. The data is collected from a number of different sources. Data on carbon emissions is collected from the CDP database, a comprehensive database that has been used extensively in carbon studies (Bui et al., 2021). Data on firm credit rating is collected from the COMPUSTAT database.

The UK-based non-profit organisation, CDP, partners with institutional investors and supply chain members to prompt large corporations to disclose carbon emissions information. In 2002, CDP sent letters co-signed by institutional investors to CEOs of all Financial Times Global 500 companies, urging completion of a questionnaire covering: (i) climate change risks and opportunities; (ii) the firm's climate change strategy; and (iii) greenhouse gas emissions. The survey became an annual practice after follow-up questionnaires in 2003 and 2005.

In 2017, disclosures were received by CDP, collectively representing more than 55% of firms based on global market capitalisation. Our initial sample consists of 7579 firm-year observations. First, we drop 4214 firm-year observations that do not have any identifier (e.g., ISIN). Subsequently, 482 firm-year observations are dropped due to missing independent variables.

Finally, 346 firm-year observations are dropped due to missing dependent and control variables. Our ultimate sample comprises 441 firms, encompassing 2537 firm-year observations. Then, for each variable (except carbon assurance), we Winsorise both the top and bottom 1% of observations to reduce the effect of outliers on the results. The sample selection process is described in Table 1 (Panel A). We exhaust the two sources to prepare the dataset necessary to test the study hypothesis.

Table 1 Panels B and C reports the sample distribution by year and industry. 2014, 2015, 2016, and 2017 have above 400 firm-year observations each year. 2012 and 2013 have more than 300 firm-year observations each year. The rest of the sample has less than 300 observations per year. Regarding the sample distribution by industry, the industrial sector reports the highest number of observations (15.32%), followed by information technology (14.71), financials (13.69%), consumer discretionary (12.55%), and consumer staples (11.45%). Conversely, communication services (2.20%), energy (3.39%), and real estate (3.79%) have the fewest observations.

3.2 | Measurement of variables

We use Standard & Poor's (S&P) rating as a proxy for firm credit rating (*RATING*). The rating reflects the overall quality of the firm's outstanding debt, both private and public. We convert the S&P ratings into numerical scores, where 22 indicates an AAA rating (highest rating) and 1 represents a D rating (lowest rating i.e., defaulting on a debt payment). Consistent

TABLE 1 Sample selection and distribution.

Panel A: Sample selection	**No. of observations**
Firms included in the CDP Database 2007–2017	7579
Less: Observations do not have any identifies (ISIN)	(4214)
Less: Observations where independent variable is missing	(482)
Less: Observations where dependent and control variable are missing	(346)
Final sample	2537

Panel B: Sample distribution by year			**Panel C: Sample distribution by industry (GICS)**		
Year	**Freq.**	**Percent**	**GICS sector**	**Freq.**	**Percent**
2007	2	0.08	Energy	105	3.39
2008	3	0.12	Materials	238	7.49
2009	12	0.47	Industrials	470	15.32
2010	48	1.89	Consumer discretionary	285	12.55
2011	161	6.35	Consumer staples	260	11.45
2012	305	12.02	Healthcare	224	9.86
2013	326	12.85	Financials	311	13.69
2014	434	17.11	Information technology	334	14.71
2015	413	16.28	Communication services	71	2.20
2016	428	16.87	Utilities	126	5.55
2017	405	15.96	Real estate	113	3.79
Total	2537	100.00		2537	100.00

with previous studies on credit ratings (Ma et al., 2021), we use S&P's long-term issuer credit rating for a firm. Following Bui et al. (2021), we use two proxies to capture carbon assurance: assurance level and assurance percentage. The first proxy of carbon assurance is measured as the assurance level (*ASSUR_LEV*) for both Scope 1 and Scope 2 emissions, ranging from 0 to 4 for five different levels of carbon assurance (low to high): 0 for no verification, 1 for limited assurance, 2 for moderate assurance, 3 for reasonable assurance, and 4 for high assurance. The ranking scores are then added across the two emission scopes to derive our measure of carbon assurance.

Similarly, the second proxy for carbon assurance is measured as the carbon assurance percentage (*ASSUR_PER*) for both Scope 1 and Scope 2 emissions (ranging from 0 to 100), reflecting the percentage of Scope 1 and Scope 2 emissions verified in a given year. Particularly, the assurance percentage is computed for each Scope 1 and Scope 2 emissions and then averaged, the total of which represents our carbon assurance percentage measure (Bui et al., 2021).

The choice of control variables is guided by relevant previous studies on credit ratings (for example, Bonsall & Miller, 2017; Ham & Koharki, 2016; Jiraporn et al., 2014; Ma et al., 2021). Firm size (*SIZE*), computed as the natural logarithm of total assets, is controlled because a firm's credit rating is found to be positively associated with firm size (Ashbaugh-Skaife et al., 2006; Bhojraj & Sengupta, 2003). Profitability (*ROA*), measured as earnings before interest and tax divided by total assets, is included because highly profitable firms often have higher credit ratings (due to a firm's ability to pay their interest and debt) (Ashbaugh-Skaife et al., 2006). Considering that the coverage of interest and debt is related to firm credit rating owing to the agency cost of debt (Jensen & Meckling, 1976; Myers, 1977), we control for the interest coverage (*INTEREST_COVE*) and leverage (*LEV*). We also control for Tobin's *q* (*TOBINSQ*) as we expect it to be positively associated with credit rating (Lim & Mali, 2024). Following Elyasiani et al. (2010), we control return volatility (*ROA_SD*) because high-volatility firms are likely to have a higher default risk (Ma et al., 2021). Since capital expenditure (*CAPX*) and research and development intensity (*R&D_INTENS*) have future value implications (Jiraporn et al., 2014; Klapper & Love, 2004), we include *CAPX*, which is computed as capital expenditure divided by total assets, and R*&D_INTENS*, measured as research and development expenditure divided by total assets. Finally, firms with a low default risk (high *Z-SCORE*) and low forecast error (*FORECAST_BIAS*) tend to have a better credit rating (Jiraporn et al., 2014; Lamy & Thompson, 1988).

Research also shows that credit ratings of firms are associated with carbon emissions (Safiullah et al., 2021) and relevant governance characteristics such as board size (Lin et al., 2020), gender diversity (Kinateder et al., 2021), board independence, and CEO duality/CEO power (Ashbaugh-Skaife et al., 2006; Papadimitri et al., 2020). Particularly, firms with high carbon emissions are found to face more cash flow uncertainty, lowering their credit ratings (Safiullah et al., 2021). On the other hand, firms with strong corporate governance tend to have better credit ratings (Ashbaugh-Skaife et al., 2006). Following that, we further control for carbon emission (*CARBON EMISS*) (i.e., firm-level total carbon emissions including Scope 1 and Scope 2 carbon emissions) and the relevant corporate governance variables including board size (*BSIZE*), gender diversity (*BGENDERDIV*), board independence (*BINDEPENDENCE*), CEO duality, and whether the current chairman is the previous CEO (*CHAIREXCEO*).

Following Datt et al. (2020), we include industry dummies (2-digit SIC industry) in our analysis to control for any differences in firms' inherent business risk and the unobserved heterogeneity across firms in various industries. We also include year dummies to control for changes across time in the firms' operational activities. All variable definitions are summarised in the Appendix.

3.3 | Research design

We use the following model to examine the relationship between carbon assurance and credit ratings:

$$RATING_{it} = \alpha + \beta CA_{it} + \Sigma\theta_i Controls_{it} + \Sigma\ Year + \Sigma\ Industry + \varepsilon, \tag{1}$$

$$RATING_{it} = \alpha + \beta CA_{it-1} + \Sigma\theta_i Controls_{it-1} + \Sigma\ Year + \Sigma\ Industry + \varepsilon, \tag{2}$$

where, $RATING_{it}$ is the S&P issuer-level credit ratings (dependent variable) for a firm i in year t. CA_{it} is the measure of carbon assurance (carbon assurance level and carbon assurance percentage) scores for a firm i in year t. $Controls_{it}$ refers to firm-level control variables. Particularly, in our study, we test four alternative model specifications in which model (1) examines the contemporaneous effect of carbon assurance level on credit ratings, model (2) examines the contemporaneous effect of carbon assurance percentage on credit ratings, model (3) examines the 1-year lagged effect of carbon assurance level on credit ratings, and model (4) examines the 1-year lagged effect of carbon assurance percentage on credit ratings where all independent and control variables have been lagged by 1 year. We use year-fixed effects to control for macroeconomic trends, and industry-fixed effects to control for time-invariant industry characteristics that may affect credit ratings. As credit ratings data is by nature ordinal, we employ ordered probit regression as our model specification, which is commonly used in the prior literature on credit ratings.

3.4 | Descriptive statistics and correlation

We present the descriptive statistics and correlation matrix in Tables 2 and 3, respectively. The mean value of credit ratings in our sample is 7.498, with a standard deviation of 7.664. Our carbon assurance level, which has an average (standard deviation) value of 1.585 (1.769) (Table 2), is relatively comparable to the carbon assurance variable in Bui et al. (2021) (i.e., mean of 1.77 and standard deviation of 2.02). The mean value of our carbon assurance percentage is 59.394, with a standard deviation of 47.032. The correlation matrix shows that credit ratings are positively correlated with the two independent variables: carbon assurance level and assurance percentage, and such control variables as firm size, return on assets, leverage, Tobin's q, capital expenditure, Z-score, carbon emissions, board size, and CEO duality, but negatively correlated with return volatility, forecast bias, and board gender diversity (Table 3). The carbon assurance level is positively correlated with carbon assurance percentage, firm size, carbon emissions, board size, board independence, but negatively correlated with interest coverage ratio, return volatility, capital expenditure, research and development expenditure, and Z-score. Similarly, the carbon assurance percentage is positively correlated with firm size, capital expenditure, carbon emissions, board size, board gender diversity, CEO duality, chairman as ex CEO but negatively correlated with Tobin's q, return volatility, research and development expenditure, and forecast bias.

4 | EMPIRICAL RESULTS AND DISCUSSION

4.1 | Baseline regressions

Table 4 reports the results of the regressions of the firm-level credit rating on carbon assurance, controlling for firm-specific characteristics, industry, and year-fixed effects. Panel A presents the contemporaneous results and Panel B shows the 1-year lagged effects (where all independent and control variables are lagged by 1 year). Results from the two

TABLE 2 Descriptive statistics.

Variable(s)	Mean	SD	P25	P50	P75
C_RATINGS	7.498	7.664	0.000	7.000	15.000
ASSUR_LEV	1.585	1.769	0.000	2.000	2.000
ASSUR_PER	59.394	47.032	0.000	95.000	100.000
SIZE	8.269	3.473	8.404	9.579	10.523
ROA	0.108	0.104	0.032	0.109	0.159
INTEREST_COVE	13.147	39.433	1.321	5.688	12.532
LEV	0.224	0.178	0.078	0.212	0.332
ROA_SD	0.020	0.025	0.005	0.013	0.027
TOBINSQ	1.772	1.373	1.059	1.493	2.264
RETURN_VOL	0.320	0.268	0.170	0.255	0.371
CAPX	0.033	0.037	0.004	0.023	0.048
R&D_INTENS	0.032	0.067	0.000	0.000	0.028
Z_SCORE	0.671	0.692	0.000	0.543	0.935
FORECAST_BIAS	−1.372	2.719	2.643	3.633	4.918
CARBON EMISS	3.844	1.959	2.303	2.398	2.485
BSIZE	2.400	0.203	16.667	22.222	28.571
BGENDER DIV	23.011	9.286	80.000	86.667	91.667
BINDEPENDENCE	84.616	8.804	0.000	1.000	1.000
CEO Duality	0.691	0.462	0.000	1.000	1.000
CHAIR EX CEO	0.631	0.483	0.000	1.000	1.000

Note: All variable definitions are in the Appendix.

panels reveal a significantly positive relationship between carbon assurance and credit ratings. The significant relationship is also robust to two carbon assurance proxies (carbon assurance level in models (1) and (3) and carbon assurance percentage in models (2) and (4)). Particularly, regarding the contemporaneous effects (Panel A, Table 4), the coefficients of carbon assurance level and percentage are positive (0.029, z-statistic = 1.86, and 0.002, z-statistic = 3.77, respectively) and statistically significant, suggesting that firms that have their carbon report and emissions assured tend to receive a higher credit rating in the same year. The relationship is also economically significant, with a one-standard-deviation increase in the carbon assurance level associated with a 5.13% (1.769*0.029) increase in the firm credit rating (model (1), Table 4). Similarly, a one-standard-deviation increase in the carbon assurance percentage is associated with a 0.094% (47.032*0.002) increase in the rating (model (2), Table 4). As shown in Panel B (Table 4), the coefficients of carbon assurance level and percentage in the previous year are also positive (0.031, z-statistic = 1.84 and 0.002, z-statistic = 2.54, respectively) and economically significant. A one-standard-deviation increase in the carbon assurance level is associated with a 5.48% (1.769*0.031) increase in the firm credit rating (model (3), Table 4) and a one-standard-deviation increase in the assurance percentage is associated with a 0.094% (47.032* 0.002) increase in the credit rating (model (4), Table 4). This implies that the carbon assurance practice in the previous year also improves the firm credit rating in the current year. Overall, these findings support signalling theory (Connelly et al., 2011; Spence, 1978), that is, high-quality firms (in terms of environmental performance) tend to have their carbon report/emissions assured (signals) to reduce the information asymmetry problem (Fan et al., 2021) and signal their good quality (Clarkson et al., 2019). The positive relationships also suggest that carbon assurance

TABLE 3 Carbon assurance and credit rating—correlation matrix.

Variable(s)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
C_RATINGS (1)	1.00																			
ASSUR_LEV (2)	0.06*	1.00																		
ASSUR_PER (3)	0.10*	0.07*	1.00																	
SIZE (4)	0.42*	0.05*	0.07*	1.00																
ROA (5)	0.18*	0.01	−0.01	0.45*	1.00															
INTEREST_COVE (6)	0.03	−0.04*	−0.03	0.15*	0.24*	1.00														
LEV (7)	0.10*	0.02	−0.01	0.46*	0.25*	−0.15*	1.00													
ROA_SD (8)	0.07*	−0.01	−0.02	0.28*	0.24*	0.09*	0.18*	1.00												
TOBINSQ (9)	0.14*	0.00	−0.06*	0.56*	0.62*	0.25*	0.35*	0.29*	1.00											
RETURN_VOL (10)	−0.07*	−0.04*	−0.10*	−0.29*	−0.05*	0.04*	−0.13*	0.25*	−0.09*	1.00										
CAPX (11)	0.19*	−0.04*	0.07*	0.32*	0.26*	0.02	0.29*	0.35*	0.18*	0.06*	1.00									
R&D_INTENS (12)	0.02	−0.05*	−0.07*	0.21*	0.16*	0.24*	−0.02	0.27*	0.35*	0.09*	−0.05*	1.00								
Z_SCORE (13)	0.17*	−0.12*	0.00	0.33*	0.43*	0.13*	0.18*	0.21*	0.37*	0.09*	0.28*	−0.02	1.00							
FORECAST_BIAS (14)	−0.05*	−0.02	−0.07*	−0.29*	−0.22*	−0.07*	−0.05*	0.02	−0.19*	0.11*	0.01	−0.04*	−0.08*	1.00						
CARBON EMISS (15)	0.07*	0.07*	0.13*	−0.09*	−0.03	−0.12*	0.29*	0.11*	−0.17*	−0.06*	0.50*	−0.18*	−0.09*	0.22*	1.00					
BSIZE (16)	0.06*	0.11*	0.12*	0.07*	−0.03	−0.10*	−0.04*	−0.10*	−0.04*	−0.10*	−0.06*	−0.14*	−0.03	−0.11*	0.06*	1.00				
BGENDER DIV (17)	−0.15*	0.00	0.06*	−0.10*	−0.06*	−0.08*	−0.04*	−0.09*	−0.03	−0.18*	−0.03	−0.08*	−0.01	0.01	0.04	0.11*	1.00			
BINDEPENDENCE (18)	0.03	0.06*	0.148	0.01	−0.02	−0.04*	−0.01	−0.08*	−0.05*	−0.13*	−0.02	−0.03	−0.07*	−0.07*	0.02	0.02	0.13*	1.00		
CEO Duality (19)	0.08*	0.01	0.07*	0.04*	−0.02	−0.06*	−0.01	−0.05*	−0.02	−0.06*	0.01	−0.06*	−0.02	−0.12*	−0.07	0.09*	0.08*	−0.02	1.00	
CHAIR EX CEO (20)	−0.03	−0.02	0.04*	0.01	−0.03	−0.07*	0.01	−0.06*	−0.01	−0.10*	−0.02	−0.03	−0.02	−0.11*	−0.01	0.08*	0.12*	0.05*	0.87*	1.0

Note: Table reports the correlation matrix of variables. All variable definitions are in the Appendix. * represents statistical significance at the 5% level.

TABLE 4 Carbon assurance and credit ratings—main results.

	Panel A: Contemporaneous effect DV = C_RATINGS		Panel B: 1-year lagged effect DV = C_RATINGS	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
Variable(s)	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**
ASSUR_LEV	0.029*		0.031*	
	(1.86)		(1.84)	
ASSUR_PER		0.002***		0.002**
		(3.77)		(2.54)
SIZE	0.812***	0.811***	0.849***	0.846***
	(20.06)	(20.18)	(16.99)	(16.95)
ROA	0.061	0.153	2.437***	2.605***
	(0.21)	(0.52)	(2.98)	(3.18)
INTEREST_COVE	−0.001*	−0.001	0.001	0.001
	(−1.23)	(−1.25)	(0.91)	(0.87)
LEV	−0.287	−0.270	−0.214	−0.221
	(−1.18)	(−1.11)	(−0.70)	(−0.72)
ROA_SD	−5.469***	−5.979***	−5.228***	−5.754***
	(−3.30)	(−3.61)	(2.63)	(−2.89)
TOBINSQ	−0.000	0.012	−0.157***	−0.148**,*
	(−0.01)	(0.34)	(−2.82)	(−2.64)
RETURN_VOL	−1.143***	−1.112***	−1.033***	−1.007***
	(−8.86)	(−8.62)	(−7.27)	(−7.09)
CAPX	−1.803	−1.629	−2997*	−2.743***
	(−1.38)	(−1.25)	(−1.68)	(1.54)
R&D_INTENS	−0.498	−0.276	1.354*	1.536**
	(−0.86)	(−0.47)	(1.95)	(2.20)
Z_SCORE	0.318***	0.308***	0.352***	0.328***
	(4.19)	(4.08)	(3.95)	(3.71)
FORECAST_BIAS	−0.015***	−0.015	−0.014	−0.015
	(−1.21)	(−1.22)	(−0.92)	(−0.95)
CARBON EMISS	−0.049*	−0.053*	−0.022	−0.027
	(−1.67)	(−1.80)	(−0.62)	(−0.74)
BSIZE	0.105	0.096	0.122	0.115
	(0.71)	(0.65)	(0.71)	(0.67)
BGENDER DIV	0.007**	0.006**	0.003	0.003
	(2.14)	(1.96)	(0.88)	(0.74)
BINDEPENDENCE	0.003	0.003	0.001	0.000
	(1.05)	(0.98)	(0.13)	(0.10)
CEO Duality	0.240**	0.233**	0.344***	0.332***
	(2.19)	(2.13)	(2.94)	(2.81)

TABLE 4 (Continued)

	Panel A: Contemporaneous effect DV = C_RATINGS		Panel B: 1-year lagged effect DV = C_RATINGS	
	Model (1)	Model (2)	Model (3)	Model (4)
Variable(s)	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)
CHAIR EX CEO	−0.127	−0.119	−0.199*	−0.193*
	(1.25)	(−1.17)	(−1.82)	(−1.77)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.3271	0.3282	0.3801	0.3805
Observations	2537	2537	2184	2184

Note: Table reports the ordered probit regressions results of testing the relationship between carbon assurance and credit ratings. The dependent variable is credit ratings. Panel A shows the contemporaneous effect of carbon assurance level on credit ratings (model (1)) and carbon assurance percentage on credit ratings (model (2)). Panel B shows the 1-year lagged effect of carbon assurance level on credit ratings (model (3)) and carbon assurance percentage on credit ratings (model (4)) where all independent and control variables have been lagged by 1 year. All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

can be a strategic signal for a firm credit rating, justifying the benefits of adopting carbon assurance and the proposed carbon assurance requirements.[9]

We also observe significant relationships between the various control variables and firm-level credit ratings. Particularly, firm size, z-score, board gender diversity, and CEO duality are positively associated with credit ratings, while interest coverage, ROA standard deviation, return volatility, forecast bias, and carbon emissions are negatively associated with the ratings. These results are consistent with a number of relevant studies (e.g., Ashbaugh-Skaife et al., 2006; Bhojraj & Sengupta, 2003; Jiraporn et al., 2014). For example, large firms are found to have better credit ratings as they are likely to face lower risks (Ashbaugh-Skaife et al., 2006; Bhojraj & Sengupta, 2003). Firms with a low default risk (high Z-score) tend to have a better credit rating (Jiraporn et al., 2014; Lamy & Thompson, 1988). On the other hand, high-volatility firms are likely to have a higher default risk (Elyasiani et al., 2010). Consistently, we show that volatility is also negatively associated with firm credit ratings.

4.2 | Robustness tests

4.2.1 | Alternative measure for credit ratings

We employ an alternative measure for credit ratings: investment-grade ratings (dummy variable) (Bhandari & Golden, 2021).[10] Investment-grade bonds are often issued by high-quality firms (Datta et al., 1997) that tend to have more (scarce) resources (as opposed to non-investment-grade bonds) to invest in CSR-related activities (Stellner et al., 2015). Consequently,

[9]All results remain consistent when we use an ordered logit model. Detailed results are available from the corresponding author upon request.

[10]We also run regressions based on two alternative measures of carbon assurance that is, assurance provider and assurance adoption. We use a dummy carbon assurance provider of 1 if the assurance provider is a Big 4 auditor and 0 otherwise. For assurance adoption, a dummy variable equal to 1 if the firm adopts carbon assurance and 0 otherwise. The results (not reported for brevity) are statistically insignificant, indicating that bondholders care more about the level and percentage of carbon assurance than the mere adoption or assurance provider.

we test if there are any significant associations between carbon assurance and investment-grade bonds. Following Bhandari and Golden (2021), we code 1 for firms with a credit rating of BBB and above (i.e., investment-grade rating firms) and 0 otherwise. We then reperform all four regressions in Table 4 with the new credit rating measure. Our results still hold (Table 5). The positive contemporaneous relationships suggest that firms that adopt a high level of carbon assurance tend to be rated in the top group of bond issuers (investment grade bonds) (0.109, z-statistic = 3.43) (model (1), Table 5). We also find a similar result for the 1-year lagged relationship with carbon assurance level (model (3), Table 5) (0.102, z-statistic = 2.95) and carbon assurance percentage (model (4), Table 5) (0.02, z-statistic = 1.66).

4.2.2 | Carbon intensive versus carbon non-intensive firms

We also examine if there are differences between carbon intensive firms and non-intensive firms. This is because carbon-intensive firms (i.e., firms in industries that involve high energy consumption or carbon emissions, including energy, utilities, and materials (Ding et al., 2023)) tend to have higher climate change risks (Al-Fakir Al Rabab'a et al., 2023; Ben-Amar et al., 2017). Thus, credit rating agencies may treat these firms differently from their counterparts (carbon non-intensive firms). Moreover, carbon-intensive firms are pressured to demonstrate their responsibility and accountability in carbon activities. These firms may report more relevant information to prove their legitimacy (Ding et al., 2023). To test this relationship, we classify firms into carbon-intensive and carbon non-intensive firms. We then conduct the analysis with these two sub-samples (Table 6). Panel A presents the results for carbon-intensive firms while Panel B shows the results for carbon non-intensive firms. The coefficients of carbon assurance level and assurance percentage for carbon intensive firms (models (1) and (2), Panel A) are positive and statistically significant (0.060, z-statistic = 1.68, 0.074, z-statistic = 4.58, respectively).

Similarly, the result also holds for carbon assurance percentage in the carbon non-intensive firm subsample (0.012, z-statistic = 1.70), suggesting our results are robust to different subsamples. Moreover, we also observe that the magnitude of the effects is larger in the carbon-intensive firm subsample than the carbon non-intensive firm subsample. One potential explanation is carbon-intensive firms are under pressure to demonstrate ethical behaviour and tend to face more climate-related risks and reputational losses than their counterparts (Al-Fakir Al Rabab'a et al., 2023; Ben-Amar et al., 2017; Ding et al., 2023). Thus, carbon assurance acts as a strong signal to prove their legitimacy and low-risk level, strengthening the relationship between carbon assurance and credit ratings. Our findings are also relatively consistent with prior research that the impact of carbon-related performance/events on firm/stock market appears to be more pronounced for carbon-intensive firms (Shen et al., 2023; Wang et al., 2021).

We perform a Chow test (Chow, 1960) of the joint null hypothesis that the coefficients of carbon assurance percentage are the same for both carbon-intensive and carbon-non-intensive firms. The null hypothesis is rejected. The results imply that the carbon assurance percentage exerts differential effects on the credit ratings of carbon-intensive and carbon-non-intensive firms.

4.2.3 | Product market competition

Prior research shows that high market competition encourages increased market scrutiny of managers by the firm's competitors, discouraging firms from adopting assurance services in such an environment (because stakeholders can rely more on the product market scrutiny)

TABLE 5 Carbon assurance and credit ratings—alternative measure of credit ratings.

Variable(s)	Panel A: Contemporaneous effect DV = INVESTMENT_GRADE Model (1) Coefficient (z-value)	Model (2) Coefficient (z-value)	Panel B: 1-year lagged effect DV = INVESTMENT_GRADE Model (3) Coefficient (z-value)	Model (4) Coefficient (z-value)
ASSUR_LEV	0.109***		0.102***	
	(3.43)		(2.95)	
ASSUR_PER		0.002		0.020*
		(1.48)		(1.66)
SIZE	0.913***	0.949***	0.902***	0.914***
	(11.86)	(12.42)	(9.69)	(9.72)
ROA	−0.395	−0.286	−0.481	−0.285
	(−0.90)	(−0.65)	(−0.36)	(−0.21)
INTEREST_COVE	−0.005***	−0.005***	−0.002	−0.002
	(−3.94)	(−3.87)	(−1.61)	(−1.63)
LEV	−1.159***	−1.088**	−0.844	−0.840
	(−2.68)	(−2.53)	(−1.56)	(−1.56)
ROA_SD	−9.745***	−10.657***	−9.700***	−9.971***
	(−3.61)	(−3.97)	(−3.04)	(−3.14)
TOBINSQ	−0.051	−0.050	−0.186**	−0.191**
	(−0.96)	(−0.94)	(−2.03)	(−2.10)
RETURN_VOL	−1.596***	−1.446***	−1.368***	−1.302***
	(−6.75)	(−6.36)	(−5.25)	(−5.12)
CAPX	−0.456	−0.635	−0.137	−0.634
	(−0.20)	(−0.28)	(−0.04)	(−0.20)
R&D_INTENS	−0.607	−0.448	1.309	1.161
	(−0.62)	(−0.45)	(1.12)	(0.99)
Z_SCORE	0.467***	0.462***	0.421***	0.410***
	(3.38)	(3.30)	(2.67)	(2.61)
FORECAST_BIAS	−0.023	−0.016	−0.041	−0.037
	(−0.97)	(−0.69)	(−1.26)	(−1.16)
CARBON EMISS	−0.142***	−0.131***	−0.117**	−0.117**
	(−2.88)	(−2.69)	(−1.96)	(−1.96)
BSIZE	0.516**	0.525**	0.442	0.462
	(2.01)	(2.03)	(1.49)	(1.56)
BGENDER DIV	−0.002	−0.002	−0.008	−0.009
	(−0.29)	(−0.42)	(−1.26)	(−1.36)
BINDEPENDENCE	−0.003	−0.004	−0.007	−0.007
	(−0.55)	(−0.68)	(−1.02)	(−1.03)
CEO Duality	0.806***	0.790***	0.945***	0.923***
	(3.10)	(3.08)	(3.47)	(3.41)

(Continues)

TABLE 5 (Continued)

Variable(s)	Panel A: Contemporaneous effect DV = INVESTMENT_GRADE Model (1) Coefficient (z-value)	Model (2) Coefficient (z-value)	Panel B: 1-year lagged effect DV = INVESTMENT_GRADE Model (3) Coefficient (z-value)	Model (4) Coefficient (z-value)
CHAIR EX CEO	−0.723***	−0.741***	−0.753***	−0.773***
	(−2.85)	(−2.97)	(−2.86)	(−2.95)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.7153	0.7120	0.7593	0.7569
Observations	2537	2537	2184	2184

Note: Table reports the ordered probit regressions results of testing the relationship between carbon assurance and credit ratings. The dependent variable is investment grade. Panel A shows the contemporaneous effect of carbon assurance level on investment grade (model (1)) and carbon assurance percentage on investment grade (model (2)). Panel B shows the 1-year lagged effect of carbon assurance level on investment grade (model (3)) and carbon assurance percentage on investment grade (model (4)) where all independent and control variables have been lagged by 1 year All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

(Leventis et al., 2011). A number of studies also document a significant relationship between product market competition and firms' voluntary disclosures with external assurance (Allee et al., 2021; Babar & Habib, 2021; Ryou et al., 2022). On the one hand, managers can consider reporting such information as a threat to their firm's competitive position as its competitors may use such information to compete against the firm (the proprietary cost hypothesis; Verrecchia, 1983, 2001). Consequently, when market competition is high, firms are reluctant to assure CSR information (Ryou et al., 2022). On the other hand, according to signalling theory (Spence, 1978), firms in a more competitive industry tend to disclose more (voluntary) assured information to discourage potential competitors and/or signal their high quality (Allee et al., 2021; Babar & Habib, 2021; Board, 2009; Burks et al., 2018; Clarkson et al., 2019). According to Clarkson et al. (2019), assurance of CSR reports signals firms' high sustainability commitment.

Motivated by these two competing views, we determine if the relationship between carbon assurance and credit ratings is conditioned on the level of product market competition. Following prior studies (Babar & Habib, 2022; Lerner, 1934), we measure product market competition using the Lerner index (LI) (or the price cost margin index—PCM index), which reflects a firm's pricing power (i.e., the ability to set the price higher than the product's marginal cost). As the degree of product market competition may be influenced by industry-specific factors, following prior studies (Babar & Habib, 2022; Gaspar & Massa, 2006), we further adjust the PCM index as follows:

$$IPCM = LI_i - \sum_{i=1}^{N} W_i * LI_i, \tag{3}$$

where $ICPM$ is the industry-adjusted price cost margin index, LI_i is the Lerner index for firm i, computed as follows: profits = sales—costs of goods sold—selling, general, and administrative expenses, N is the number of firms in an industry, and W_i is the percentage of firm i's revenues from the industry's total revenues. We then split the sample into two sub-samples: firms with high product market competition and those with low product market competition. We re-estimate Equation (2) again with the two sub-samples (Table 7). Panel A (Table 7) shows a significant positive link between carbon assurance and credit ratings in the high product market competition

TABLE 6 Carbon assurance and credit ratings—carbon intensive vs. carbon non-intensive firms.

	Panel A: Carbon intensive firms DV = C_RATINGS		Panel B: Carbon non-intensive firms DV = C_RATINGS	
	Model (1)	Model (2)	Model (3)	Model (4)
Variable(s)	Coefficient (*z*-value)	Coefficient (*z*-value)	Coefficient (*z*-value)	Coefficient (*z*-value)
ASSUR_LEV	0.060*		0.024	
	(1.68)		(1.24)	
ASSUR_PER		0.074***		0.012*
		(4.58)		(1.70)
SIZE	0.615***	0.576***	0.788***	0.779***
	(5.57)	(5.18)	(15.69)	(15.38)
ROA	0.339	1.255	2.240***	2.295***
	(0.15)	(0.54)	(2.71)	(2.78)
INTEREST_COVE	−0.001	−0.001	−0.001	−0.001
	(−0.75)	(−0.61)	(−0.86)	(−0.79)
LEV	−0.525	−0.410	0.054	0.019
	(−0.68)	(−0.53)	(0.19)	(0.06)
ROA_SD	5.355	8.071**	−3.554*	−3.543*
	(1.34)	(2.00)	(−1.74)	(−1.73)
TOBINSQ	0.162	0.075	−0.222***	−0.219***
	(0.96)	(0.44)	(−3.96)	(−3.91)
RETURN_VOL	−1.115**	−1.373**	−1.340***	−1.335***
	(−2.05)	(−2.51)	(−8.05)	(−8.05)
CAPX	2.634	3.652	−0.425	−0.522
	(0.70)	(0.96)	(−0.33)	(−0.41)
R&D_INTENS	−5.892***	−5.655***	0.465	0.401
	(−3.39)	(−3.30)	(0.77)	(0.66)
Z_SCORE	−0.199	−0.265	0.241***	0.236***
	(−0.93)	(−1.25)	(3.62)	(3.58)
FORECAST_BIAS	−0.111**	−0.125***	−0.040***	−0.040***
	(−2.31)	(−2.58)	(−2.59)	(−2.62)
CARBON EMISS	−0.096	−0.100	0.018	0.021
	(−1.42)	(−1.47)	(0.66)	(0.78)
BSIZE	0.191	−0.153	0.385*	0.380*
	(0.58)	(−0.45)	(1.83)	(1.80)
BGENDER DIV	−0.017*	−0.021**	0.019***	0.019***
	(−1.69)	(−2.06)	(4.50)	(4.45)
BINDEPENDENCE	0.013	0.013	0.002	0.002
	(0.97)	(0.97)	(0.41)	(0.38)
CEO Duality	0.639**	0.572**	0.255*	0.257*
	(2.36)	(2.10)	(1.89)	(1.91)

(Continues)

TABLE 6 (Continued)

Variable(s)	Panel A: Carbon intensive firms DV = C_RATINGS Model (1) Coefficient (z-value)	Model (2) Coefficient (z-value)	Panel B: Carbon non-intensive firms DV = C_RATINGS Model (3) Coefficient (z-value)	Model (4) Coefficient (z-value)
CHAIR EX CEO	−0.326	−0.221	−0.119	−0.123
	(−1.31)	(−0.88)	(−0.94)	(−0.98)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.3372	0.3361	0.3503	0.3535
Observations	426	426	1758	1758
Chow test: F-statistics	3.438**			

Note: Table reports the ordered probit regressions results of testing the relationship between carbon assurance and credit ratings. The dependent variable is credit ratings. Panel A shows the effect of carbon assurance level on credit ratings (model (1)) and carbon assurance percentage on credit ratings (model (2)) in carbon intensive firms. Panel B shows the effect of carbon assurance level on credit ratings (model (3)) and carbon assurance percentage on credit ratings (model (4)) for carbon non-intensive firms. All independent variables are lagged by 1 year. All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

sub-sample (0.048, z-statistic = 2.53, 0.002, z-statistic = 2.23 for carbon assurance level and carbon assurance percentage, respectively). However, we find no supporting evidence for the low product market competition sub-sample (Panel B, Table 7). These findings suggest that when faced with the threat of increased competition, firms that have high carbon assurance, which is a strong signal for their high quality, tend to receive higher credit ratings. These results confirm signalling theory and are consistent with a number of studies (Allee et al., 2021; Board, 2009).

4.2.4 | External political environment

A number of studies also highlight the important role of the external political environment in corporate social responsibility (Cornett et al., 2016; Di Giuli & Kostovetsky, 2014; Hong & Kostovetsky, 2012). For example, a Democratic external political environment is found to foster more socially responsible behaviour than a Republican one (Di Giuli & Kostovetsky, 2014). According to these authors, there are two potential explanations: these firms are under more pressure from (i) their stakeholders, who tend to live in their home Democratic state, to conduct sustainable business; and/or (ii) relevant CSR policies in the state. Given the sustainability pressure and favourable policies in Democratic-learning states, we argue firms in these states have better carbon performance and such "high-quality" firms are more likely to adopt carbon assurance to signal their quality. Thus, the carbon assurance-credit rating relationship is stronger for firms headquartered in Democratic-leaning states. To test this moderating effect, we divide our sample into two sub-samples: firms headquartered in Democratic-leaning states (Table 8, Panel A) versus Republican-leaning states (Table 8, Panel B). Consistent with prior studies (Cornett et al., 2016; Di Giuli & Kostovetsky, 2014; Hong & Kostovetsky, 2012), we find a significant positive link between carbon assurance and credit ratings for firms headquartered in Democratic-leaning states (0.063, z-statistic = 3.40 and 0.002, z-statistic = 2.38 for carbon assurance level and percentage, respectively). Our result suggests that firms with higher carbon assurance tend to have high credit ratings when they are headquartered in Democratic-leaning states (rather than Republic-leaning ones).

TABLE 7 Carbon assurance and credit ratings—product market competition.

	Panel A: High product market competition DV = C_RATINGS		Panel B: Low product market competition DV = C_RATINGS	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
Variable(s)	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**
ASSUR_LEV	0.048**		0.006	
	(2.53)		(0.20)	
ASSUR_PER		0.002**		0.001
		(2.23)		(0.57)
SIZE	0.634***	0.639***	0.970***	0.963***
	(11.12)	(11.22)	(9.95)	(9.79)
ROA	−0.641	−0.614	3.636***	3.692***
	(−0.64)	(−0.61)	(3.15)	(3.21)
INTEREST_COVE	−0.000	−0.001	0.002	0.002
	(−0.59)	(−0.76)	(1.24)	(1.25)
LEV	−0.549*	−0.488*	0.291	0.311
	(−1.93)	(−1.72)	(0.61)	(0.65)
ROA_SD	−4.704**	−5.133**	7.861**	7.632**
	(−2.18)	(−2.38)	(2.55)	(2.45)
TOBINSQ	0.004	0.025	−0.167*	−0.166*
	(0.06)	(0.40)	(−1.91)	(−1.90)
RETURN_VOL	−1.074***	−1.033***	−1.238***	−1.241***
	(−6.53)	(−6.29)	(−5.29)	(−5.36)
CAPX	−0.620	−0.578	−1.688	−1.643
	(−0.44)	(−0.41)	(−0.90)	(−0.88)
R&D_INTENS	−0.179	−0.186	1.674*	1.692*
	(−0.30)	(−0.31)	(1.68)	(1.70)
Z_SCORE	0.096	0.079	0.233***	0.227***
	(0.92)	(0.76)	(2.87)	(2.85)
FORECAST_BIAS	−0.042**	−0.041**	−0.051**	−0.051**
	(−2.12)	(−2.06)	(−2.57)	(−2.54)
CARBON EMISS	0.043	0.036	−0.013	−0.017
	(1.52)	(1.26)	(−0.34)	(−0.45)
BSIZE	0.518***	0.555***	0.264	0.258
	(2.66)	(2.86)	(0.91)	(0.89)
BGENDER DIV	0.010**	0.009**	0.015**	0.014**
	(2.34)	(2.13)	(2.33)	(2.32)
BINDEPENDENCE	0.016***	0.016***	−0.017***	−0.018***
	(3.48)	(3.52)	(−2.74)	(−2.80)
CEO Duality	0.471***	0.440***	0.033	0.041
	(3.40)	(3.18)	(0.17)	(0.21)

(Continues)

TABLE 7 (Continued)

	Panel A: High product market competition DV = C_RATINGS		Panel B: Low product market competition DV = C_RATINGS	
	Model (1)	Model (2)	Model (3)	Model (4)
Variable(s)	Coefficient (*z*-value)	Coefficient (*z*-value)	Coefficient (*z*-value)	Coefficient (*z*-value)
CHAIR EX CEO	−0.182	−0.187	−0.024	−0.023
	(−1.36)	(−1.39)	(−0.14)	(−0.13)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.3372	0.3369	0.3503	0.3504
Observations	1406	1406	778	778

Note: Table reports the ordered probit regressions results of testing the relationship between carbon assurance and credit ratings. The dependent variable is credit ratings. Panel A shows the effect of carbon assurance level on credit ratings (model (1)) and carbon assurance percentage on credit ratings (model (2)) in high product market competition. Panel B shows the effect of carbon assurance level on credit ratings (model (3)) and carbon assurance percentage on credit ratings (model (4)) for low product market competition. All independent variables are lagged by 1 year. All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

4.2.5 | Excluding financial firms

Consistent with prior studies we exclude financial firms due to their unique characteristics and re-estimate the analysis (Papadimitri et al., 2020). These results still find a positive (contemporaneous and 1-year lagged) relationship between carbon assurance and credit ratings, suggesting that our results are robust to different industry sectors (Table 9). Regarding the contemporaneous effects (Panel A, Table 9), the coefficients of carbon assurance level and percentage are significantly positive (0.098, z-statistic = 2.19, and 0.003, z-statistic = 4.07, respectively). Similarly, we observe consistent findings for the 1-year lagged effects for both carbon assurance level and percentage (0.036, z-statistic = 1.87, and 0.002, z-statistic = 2.93, respectively).

4.3 | Channel analysis

We also examine the channel through which carbon assurance influences firm-level credit ratings. One potential channel is that carbon assurance reduces information asymmetry, attracting more analyst following (Cuadrado-Ballesteros et al., 2017; Jiraporn et al., 2012), which in turn can lower default risk and improve credit ratings (Cheng & Subramanyam, 2008). Cuadrado-Ballesteros et al. (2017) find that assured sustainability reports are associated with lower information asymmetry between informed and uninformed stakeholders, as assurance helps improve the credibility and accuracy of such reports. At the same time, a low level of information asymmetry or a high level of transparency can create a good information environment, attracting more analyst coverage (Jiraporn et al., 2012). Financial analysts act as information intermediaries in the market (Healy & Palepu, 2001), thus having more analysts following reduces cash flow uncertainty and information risk, lowering firm default risk and improving credit ratings (Cheng & Subramanyam, 2008). Indeed, prior studies document a positive (negative) relationship between analyst following and credit ratings (default risk) (Cheng & Subramanyam, 2008) or a significant moderating role of analyst coverage in default risks (Baghdadi et al., 2020).

TABLE 8 Carbon assurance and credit ratings—external political environment.

	Panel A: Firms headquartered in democratic-leaning states DV = C_RATINGS		Panel B: Firms headquartered in republican-leaning states DV = C_RATINGS	
	Model (1)	Model (2)	Model (3)	Model (4)
Variable(s)	Coefficient (*z*-value)	Coefficient (*z*-value)	Coefficient (*z*-value)	Coefficient (*z*-value)
ASSUR_LEV	0.063***		−0.025	
	(3.40)		(−0.78)	
ASSUR_PER		0.002**		0.000
		(2.38)		(0.34)
SIZE	0.735***	0.736***	0.682***	0.665***
	(14.61)	(14.60)	(8.50)	(8.29)
ROA	1.386	1.525*	2.176	2.055
	(1.63)	(1.80)	(1.54)	(1.46)
INTEREST_COVE	0.001	0.001	−0.002	−0.002
	(1.07)	(1.03)	(−1.29)	(−1.31)
LEV	0.012	0.044	−1.221**	−1.160**
	(0.04)	(0.16)	(−2.49)	(−2.32)
ROA_SD	−3.058	−3.510*	1.169	1.173
	(−1.49)	(−1.72)	(0.35)	(0.35)
TOBINSQ	−0.150***	−0.130**	−0.107	−0.099
	(−2.68)	(−2.32)	(−0.96)	(−0.89)
RETURN_VOL	−1.054***	−0.971***	−1.358***	−1.348***
	(−7.03)	(−6.57)	(−4.48)	(−4.45)
CAPX	−1.550	−1.387	−2.152	−2.110
	(−1.01)	(−0.90)	(−1.17)	(−1.15)
R&D_INTENS	0.973*	0.972*	−1.835	−1.612
	(1.75)	(1.75)	(−1.36)	(−1.20)
Z_SCORE	0.179**	0.138**	0.209**	0.231**
	(2.54)	(1.97)	(2.16)	(2.47)
FORECAST_BIAS	−0.039**	−0.040**	−0.045	−0.048*
	(−2.44)	(−2.51)	(−1.59)	(−1.70)
CARBON EMISS	−0.006	−0.009	0.073*	0.074*
	(−0.21)	(−0.32)	(1.81)	(1.83)
BSIZE	0.403**	0.406**	0.465	0.462
	(2.14)	(2.15)	(1.48)	(1.46)
BGENDER DIV	0.013***	0.013***	0.011*	0.011
	(3.07)	(3.16)	(1.76)	(1.64)
BINDEPENDENCE	0.008*	0.007	0.002	0.001
	(1.80)	(1.61)	(0.21)	(0.18)
CEO Duality	0.410***	0.385***	0.097	0.092
	(3.24)	(3.04)	(0.39)	(0.37)

(Continues)

TABLE 8 (Continued)

	Panel A: Firms headquartered in democratic-leaning states DV = C_RATINGS		Panel B: Firms headquartered in republican-leaning states DV = C_RATINGS	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
Variable(s)	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**
CHAIR EX CEO	−0.165	−0.166	0.038	0.049
	(−1.42)	(−1.42)	(0.16)	(0.20)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.3316	0.3305	0.3687	0.3685
Observations	1513	1513	671	671

Note: Table reports the ordered probit regressions results of testing the relationship between carbon assurance and credit ratings. The dependent variable is credit ratings. Panel A shows the effect of carbon assurance level on credit ratings (model (1)) and carbon assurance percentage on credit ratings (model (2)) in firms headquartered in Democratic-leaning states. Panel B shows the effect of carbon assurance level on credit ratings (model (3)) and carbon assurance percentage on credit ratings (model (4)) in firms headquartered in Republican-leaning states. All independent variables are lagged by 1 year. All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

Following Cheng and Subramanyam (2008) and Baghdadi et al. (2020), we measure analyst following by the number of financial analysts issuing an annual forecast for a firm in a fiscal year. This information is available from the Institutional Brokers' Estimate System (IBES) database. We then regress analyst following on carbon assurance and other control variables as in Equations (1) and (2), following prior studies (Baghdadi et al., 2020, 2023). Table 10 (1st stage) shows our channel analysis results, which confirm a significantly positive relationship between analyst following and the two carbon assurance proxies (0.150, z-statistic = 2.14 for carbon assurance level, and 0.029, z-statistics = 2.13 for carbon assurance percentage). Such findings suggest that firms with a high level or percentage of carbon assurance tend to have better analyst coverage. In the second stage, we show that analyst following is positively associated with firms' credit ratings (0.001, z-statistics = 2.52 for carbon assurance percentage), supporting our channel analysis.

4.4 | Endogeneity tests

We document a significantly positive relationship between carbon assurance and firm-level credit ratings. Although this finding is robust to various alternative measures and tests, including using lagged variables, the relationship can be subject to endogeneity problems. Particularly, credit ratings and carbon assurance can be jointly correlated with unobserved variables (omitted variables), or firms with high credit ratings tend to have more resources to adopt a higher level of carbon assurance (reverse or simultaneous causality) (Bascle, 2008; Hamilton & Nickerson, 2003; Hill et al., 2020). We employ three methods to address potential endogeneity issues: propensity score matching, instrumental variables, and Heckman selection bias. Table 11 presents the results of our propensity score matching. Following prior studies (Li, 2013; Smith, 2016), we first define (control group) the treated group as firms that (do not) adopt carbon assurance in a given year (firm-year observations). We then estimate the probability that a firm has adopted carbon assurance (propensity scores) using a logit regression (carbon assurance dummy with a value of 1 if a firm adopts carbon assurance in a particular year and 0 otherwise) with all the covariates in our baseline regression model. Next,

TABLE 9 Carbon assurance and credit ratings—excluding financial firms.

	Panel A: Contemporaneous effect DV = C_RATINGS		Panel B: 1-year lagged effect DV = C_RATINGS	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
Variable(s)	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**
ASSUR_LEV	0.098**		0.036*	
	(2.19)		(1.87)	
ASSUR_PER		0.003***		0.002***
		(4.07)		(2.93)
SIZE	0.701***	0.828***	0.850***	0.853***
	(8.47)	(19.41)	(15.93)	(16.10)
ROA	−2.541*	0.337	3.607***	3.923***
	(−1.83)	(1.12)	(4.09)	(4.41)
INTEREST_COVE	−0.004***	−0.001**	0.000	0.000
	(−3.37)	(−2.01)	(0.02)	(0.00)
LEV	3.408***	−0.230	−0.338	−0.331
	(6.05)	(−0.90)	(−1.05)	(−1.03)
ROA_SD	−1.054	−4.714***	−4.178**	−4.576**
	(−0.33)	(−2.80)	(−2.07)	(−2.26)
TOBINSQ	−0.039	0.020	−0.174***	−0.172***
	(−0.58)	(0.53)	(−2.93)	(−2.89)
RETURN_VOL	−0.893***	−1.192***	−1.054***	−1.040***
	(−4.40)	(−8.64)	(−6.99)	(−6.88)
CAPX	−3.729	−2.064	−4.397**	−4.157**
	(−1.23)	(−1.57)	(−2.45)	(−2.31)
R&D_INTENS	−0.700	−0.701	1.064	1.306*
	(−0.62)	(−1.16)	(1.50)	(1.83)
Z_SCORE	1.023***	0.336***	0.354***	0.335***
	(4.91)	(4.05)	(3.59)	(3.42)
FORECAST_BIAS	0.031	−0.026**	−0.022	−0.022
	(1.03)	(−1.96)	(−1.22)	(−1.26)
CARBON EMISS	0.177***	−0.030	0.010	0.005
	(2.90)	(−1.00)	(0.26)	(0.14)
BSIZE	0.192	0.272*	0.350*	0.350*
	(0.58)	(1.71)	(1.87)	(1.87)
BGENDER DIV	0.014*	0.008**	0.005	0.004
	(1.92)	(2.37)	(1.18)	(1.04)
BINDEPENDENCE	0.005	0.000	−0.002	−0.003
	(0.68)	(0.10)	(−0.57)	(−0.67)
CEO Duality	0.934**	0.210*	0.332**	0.310**
	(2.45)	(1.70)	(2.49)	(2.33)

(Continues)

TABLE 9 (Continued)

Variable(s)	Panel A: Contemporaneous effect DV = C_RATINGS		Panel B: 1-year lagged effect DV = C_RATINGS	
	Model (1)	Model (2)	Model (3)	Model (4)
	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)
CHAIR EX CEO	−1.154***	−0.089	−0.175	−0.156
	(−3.03)	(−0.77)	(−1.43)	(−1.27)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.3225	0.3238	0.3748	0.3756
Observations	2537	2537	2184	2184

Note: Table reports the ordered probit regressions results of testing the relationship between carbon assurance and credit ratings. The dependent variable is credit ratings. Panel A shows the contemporaneous effect of carbon assurance level on credit ratings (model (1)) and carbon assurance percentage on credit ratings (model (2)). Panel B shows the 1-year lagged effect of carbon assurance level on credit ratings (model (3)) and carbon assurance percentage on credit ratings (model (4)) where all independent and control variables have been lagged by 1 year. All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

based on the nearest propensity scores (the nearest neighbour approach), we stratify data to match firms that adopt carbon assurance (treated group) with those that do not adopt carbon assurance (control group). We conduct a t-test to compare whether the means of the covariates significantly differ across the treated and control groups (Table 11, Panel B). The results show that any differences in all the covariates between the two groups are insignificant, suggesting that the covariates are balanced between the treated and control groups. We re-estimate the baseline regression models based on the propensity score matching estimates (Table 11, Panel A). Consistent with our main findings, we report a significant positive relationship between carbon assurance (both level and percentage) and firm-level credit ratings.

An instrumental variable method is also recommended to mitigate potential endogeneity problems (Hill et al., 2020). Following prior studies (Fu et al., 2020; Liu et al., 2015; Saeed et al., 2022), we employ the industry level of carbon assurance as the instrumental variable. The instrumental variable must be relevant (i.e., highly correlates with a firm's carbon assurance level) and exclusive (i.e., only influences the firm's credit rating through its carbon assurance level) (Ebbes et al., 2016; Jiraporn et al., 2014). We argue that the carbon assurance level of a firm is highly correlated with that of its industry peers due to their similar business nature (Liu et al., 2015). However, the industry carbon assurance level should not influence a firm's credit rating, except through the firm's carbon assurance level.

We estimate a 2SLS analysis. In the first stage, we estimate the carbon assurance level using the industry average level, controlling for all the relevant variables as in our baseline model. Results show a significantly positive coefficient for the average carbon assurance level (0.148, z-statistic = 2.10) (Table 12, model (1)). In the second stage, we regress firm credit ratings on the predicted carbon assurance level from the first stage and other control variables and also document a significantly positive relationship between the predicted carbon assurance level and firm-level credit ratings (1.388, z-statistic = 5.47) (Table 12, model (2)). The result supports our main finding, confirming a positive influence of carbon assurance on credit ratings.

Lastly, since we only include firms in our sample that report information to the CDP, which may introduce potential self-selection bias, we also employ Heckman's two-stage selection test to address this bias (Bui et al., 2021; Fan et al., 2021). Following Fan et al. (2021) and Bui et al. (2021),

TABLE 10 Carbon assurance and credit ratings—channel analysis.

Variable(s)	1st stage DV = ANALYST_FOLLOW Model (1) Coefficient (z-value)	Model (2) Coefficient (z-value)	2nd stage DV = C_RATINGS Model (3) Coefficient (z-value)	Model (4) Coefficient (z-value)
ASSUR_LEV	0.150**		0.052*	
	(2.14)		(1.82)	
ASSUR_PER		0.029**		0.003***
		(2.13)		(3.28)
ANALYST FOLLOWING			0.002	0.001**
			(0.36)	(2.52)
SIZE	0.016	−0.002	1.564***	0.861***
	(0.20)	(−0.03)	(16.76)	(16.82)
ROA	−2.474*	−2.345*	5.752***	1.597*
	(−1.87)	(−1.77)	(3.62)	(1.85)
INTEREST_COVE	0.002	0.002	−0.001	0.000
	(1.27)	(1.37)	(−0.63)	(0.63)
LEV	−0.179	−0.217	−0.967*	−0.150
	(−0.37)	(−0.46)	(−1.67)	(−0.48)
ROA_SD	2.873	2.954	−9.356***	−6.256***
	(0.86)	(0.88)	(−2.71)	(−3.06)
TOBINSQ	0.039	0.041	−0.187*	−0.083
	(0.55)	(0.58)	(−1.79)	(−1.34)
RETURN_VOL	−0.082	−0.050	−1.955***	−0.924***
	(−0.32)	(−0.19)	(−7.48)	(−5.85)
CAPX	1.846	1.616	−6.330**	−1.954
	(0.62)	(0.54)	(−1.98)	(−1.08)
R&D_INTENS	0.512	0.372	2.015	1.205*
	(0.47)	(0.34)	(1.59)	(1.70)
Z_SCORE	0.215	0.222	0.563***	0.317***
	(1.46)	(1.51)	(3.72)	(3.51)
FORECAST_BIAS	−0.042*	−0.038*	−0.026	−0.015
	(−1.83)	(−1.66)	(−0.91)	(−0.92)
CARBON EMISS	−0.048	−0.054	−0.019	−0.043
	(−0.89)	(−0.99)	(−0.30)	(−1.15)
BSIZE	0.106	0.093	0.453	0.119
	(0.32)	(0.28)	(1.47)	(0.68)
BGENDER DIV	0.003	0.002	0.003	0.001
	(0.38)	(0.31)	(0.43)	(0.19)
BINDEPENDENCE	−0.004	−0.003	0.004	−0.000
	(−0.51)	(−0.43)	(0.55)	(−0.11)

(Continues)

TABLE 10 (Continued)

Variable(s)	1st stage DV = ANALYST_FOLLOW Model (1) Coefficient (z-value)	 Model (2) Coefficient (z-value)	2nd stage DV = C_RATINGS Model (3) Coefficient (z-value)	 Model (4) Coefficient (z-value)
CEO Duality	0.432	0.423	0.924***	0.337***
	(1.38)	(1.35)	(3.68)	(2.79)
CHAIR EX CEO	−0.389	−0.381	−0.565**	−0.187*
	(−1.30)	(−1.27)	(−2.42)	(−1.68)
YEAR_FE	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.3910	0.3860	0.3883	0.3798
Observations	1929	1929	1929	1929

Note: Table reports the regressions results of the channel analysis. The dependent variable is analyst following. We employ carbon assurance level in models (1) and (3) and carbon assurance percentage in models (2) and (4). All independent variables are lagged by 1 year. All variable definitions are in the Appendix. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

in the first stage, we estimate the probability that firms will participate in the CDP. In addition to the control variables in our baseline model, following the study conducted by Fan et al. (2021), we further control for: (i) the previous year's decision to report carbon information (a dummy variable that equals 1 if a firm reports carbon information to the CDP last year, and 0 otherwise—$CDISC_{t-1}$); and (ii) the industry-average carbon disclosure index (INDCDISC) in this stage. Research also shows that firms that provide carbon information to the CDP in the previous year tend to join the CDP in the current year (Fan et al., 2021). According to Fan et al. (2021), managers' disclosure decisions can be driven by industry practices, thus, we also control for the industry *INDCDISC* variable. Our first stage results show support for those relationships (Table 13, model (1)). In the second stage, we include the inverse Mills ratios (*INVERSE_MILLS_R*) obtained from the first stage in our models. The inverse Mills ratios are insignificant for both models (carbon assurance level and percentage). Importantly, the positive relationship between carbon assurance and firm credit rating still holds (Table 13, models (2) and (3)).

5 | DISCUSSION AND CONCLUSION

Motivated by the questionable reliability and credibility of carbon reporting, we examine the role of carbon assurance in firm-level credit ratings. Using a sample of US publicly traded firms from 2007 to 2017 (2537 firm-year observations), we find that carbon assurance positively relates to credit ratings, which is robust to alternative measures, subsamples, and endogeneity tests. Given the conflicting views of whether carbon assurance improves credit ratings (signalling theory) or is just a tool for firms to "greenwash" to show their legitimacy (legitimacy theory), our finding of a positive relationship supports signalling theory (Spence, 1978). This implies that carbon assurance can act as a strategic signal for firms to reflect the high quality and credibility of their carbon performance/reporting, lowering information asymmetry, and improving their credit ratings. Our channel analysis also shows that firms adopting high carbon assurance tend to have lower information asymmetry, attracting more analyst following, which in turn can lower default risk and improve credit ratings.

TABLE 11 Carbon assurance and credit rating—propensity score matching (PSM).

Panel A: Quality of propensity score matching (PSM)

Variable(s)	Mean Treated	Control	Difference	*t*-Statistic
SIZE	9.392	9.417	−0.27	0.788
ROA	0.130	0.132	−0.30	0.761
INTEREST_COVE	18.618	20.017	−0.30	0.766
LEV	0.243	0.239	0.30	0.767
ROA_SD	0.024	0.024	−0.30	0.768
TOBINSQ	1.9721	2.097	−1.14	0.257
RETURN_VOL	0.339	0.343	−0.14	0.891
CAPX	0.040	0.038	0.63	0.529
R&D_INTENS	0.037	0.046	−1.29	0.198
Z_SCORE	0.826	0.882	−0.94	0.345
FORECAST_BIAS	−1.235	−1.592	1.45	0.147
CARBON EMISS	3.902	3.974	−0.43	0.664
BSIZE	2.350	2.380	−1.77	0.077
BGENDER DIV	22.917	22.097	0.97	0.331
BINDEPENDENCE	84.316	83.976	0.41	0.684
CEO Duality	0.645	0.688	−1.03	0.304
CHAIR EX CEO	0.571	0.630	−1.35	0.177

Panel B: Carbon assurance and credit rating—PSM regression

Variable(s)	Pre-match DV = ASSUR_DUMMY Coefficient (*z*-value)	Post-match DV = ASSUR_DUMMY Coefficient (*z*-value)
ASSUR_LEV	0.027**	
	(2.72)	
ASSUR_PER		0.003*
		(1.93)
SIZE	0.915***	0.936***
	(9.55)	(9.91)
ROA	1.923	2.329*
	(1.39)	(1.66)
INTEREST_COVE	−0.002	−0.002
	(−1.36)	(−1.38)
LEV	−0.249	−0.220
	(−0.44)	(−0.39)
ROA_SD	−6.006**	−6.507**
	(−2.13)	(−2.30)
TOBINSQ	−0.060	−0.079
	(−0.72)	(−0.95)

(Continues)

TABLE 11 (Continued)

Panel B: Carbon assurance and credit rating—PSM regression

	Pre-match DV = ASSUR_DUMMY	**Post-match DV = ASSUR_DUMMY**
Variable(s)	**Coefficient (*z*-value)**	**Coefficient (*z*-value)**
RETURN_VOL	−1.265***	−1.202***
	(−4.32)	(−4.12)
CAPX	−4.352	−3.985
	(−1.34)	(−1.24)
R&D_INTENS	−0.681	−0.370
	(−0.55)	(−0.30)
Z_SCORE	0.398**	0.386**
	(2.45)	(2.40)
FORECAST_BIAS	−0.011	−0.008
	(−0.40)	(−0.30)
CARBON EMISS	−0.077	−0.082
	(−1.16)	(−1.24)
BSIZE	0.498	0.513
	(1.55)	(1.60)
BGENDER DIV	0.006	0.005
	(0.86)	(0.78)
BINDEPENDENCE	−0.002	−0.002
	(−0.26)	(−0.36)
CEO Duality	0.217	0.233
	(0.88)	(0.95)
CHAIR EX CEO	−0.063	−0.068
	(−0.27)	(−0.30)
YEAR_FE	Yes	Yes
INDUSTRY_FE	Yes	Yes
Pseudo R^2	0.3243	0.3257
Observations	568	568

Note: Panel A shows the quality of matching between the treatment and control firms after the PSM procedure. Panel B presents the results of the impact of carbon assurance on credit ratings using the propensity score matching method. The dependent variable is credit ratings. All independent variables are lagged by 1 year. All variable definitions are in the Appendix. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

We extend the current literature which mainly focuses on general sustainability assurance by providing empirical evidence for the significant impact of carbon assurance, an important type of sustainability assurance that has become increasingly popular among scholars and practitioners. Indeed, recent studies have attempted to examine carbon assurance and its influence on various corporate activities/performance (Bui et al., 2021; Luo et al., 2023; Rohani et al., 2023). From a practical perspective, regulatory bodies, such as the SEC in the US, have also proposed accounting standards/policies requiring firms to have their climate reporting assured.[11] In Australia, although carbon assurance is still a voluntary decision, regulators may

[11]See Footnote 4.

TABLE 12 Carbon assurance and credit rating: instrumental variable (IV) analysis.

Variable(s)	DV = ASSUR_LEV Model (1) Coefficient (z-value)	DV = C_RATINGS Model (2) Coefficient (z-value)
ASSUR_LEV_INDUSTRY	0.148**	
	(2.10)	
ASSUR_LEV_PREDICTED		1.388***
		(5.47)
SIZE	0.284***	1.284***
	(8.80)	(10.19)
ROA	0.626	2.398
	(1.16)	(1.15)
INTEREST_COVE	−0.001	−0.007***
	(−1.02)	(−2.90)
LEV	0.146	1.312*
	(0.80)	(1.91)
ROA_SD	−1.150	−8.554
	(−0.84)	(−1.62)
TOBINSQ	0.010	0.016
	(0.33)	(0.14)
RETURN_VOL	0.173	−3.964***
	(1.57)	(−9.84)
CAPX	0.618	0.108
	(0.65)	(0.03)
R&D_INTENS	−0.557	3.407**
	(−1.17)	(2.16)
Z_SCORE	−0.211***	1.251***
	(−4.53)	(6.61)
FORECAST_BIAS	0.018*	−0.074*
	(1.82)	(−1.95)
CARBON EMISS	0.009	0.073
	(0.50)	(1.07)
BSIZE	0.468***	−0.597
	(3.40)	(−1.09)
BGENDER DIV	0.001	0.021*
	(0.22)	(1.85)
BINDEPENDENCE	0.001	0.010
	(0.31)	(0.89)
CEO Duality	0.023	1.273***
	(0.20)	(2.95)
CHAIR EX CEO	−0.159	−0.930**
	(−1.48)	(−2.23)
YEAR_FE	Yes	Yes
INDUSTRY_FE	Yes	Yes
Pseudo R^2	0.069	0.665
Observations	2184	2184

Note: Model (1) reports the results on the first stage of instrumental variable using assurance level as a dependent variable. In the second stage results (model (2)) on the effect of carbon assurance on credit rating, controlling for predicted debt assurance level score obtained in model (1). All independent variables are lagged by 1 year. All variable definitions appear in the Appendix. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

TABLE 13 Heckman selection bias test results.

	Panel A: 1st stage DV = CDISC	Panel B: 2nd stage DV = C_RATINGS	
	Model (1)	**Model (2)**	**Model (3)**
Variable(s)	**Coefficient (z-value)**	**Coefficient (z-value)**	**Coefficient (z-value)**
$CDISC_{t-1}$	0.008***		
	(10.48)		
INDCDISC	0.020*		
	(1.74)		
ASSUR_LEV		0.028*	
		(1.83)	
ASSUR_PER			0.004***
			(5.35)
INVERSE MILLS R		−0.009	0.041
		(−0.02)	(0.07)
SIZE	0.070	0.802***	0.836***
	(1.41)	(5.73)	(5.85)
ROA	0.065	0.071	−0.024
	(0.20)	(0.24)	(−0.08)
INTEREST_COVE	−0.001	−0.001	−0.001
	(−0.62)	(−1.09)	(−1.34)
LEV	0.205	−0.269	−0.247
	(0.66)	(−0.97)	(−0.87)
ROA_SD	−0.410	−5.607*	−6.957**
	(−0.18)	(−1.81)	(−2.19)
TOBINSQ	−0.131***	−0.001	0.033
	(−2.91)	(−0.01)	(0.81)
RETURN_VOL	−0.051	−1.175***	−1.064***
	(−0.30)	(−8.59)	(−7.07)
CAPX	−0.215	−1.876	−1.328
	(−0.13)	(−0.88)	(−0.61)
R&D_INTENS	0.099	−0.452	−0.336
	(0.12)	(−0.68)	(−0.49)
Z_SCORE	0.034	0.324**	0.284**
	(0.31)	(2.40)	(2.06)
FORECAST_BIAS	−0.016	−0.014	−0.013
	(−1.15)	(−1.17)	(−1.03)
CARBON EMISS	0.042	−0.048	−0.066**
	(1.11)	(−1.64)	(−2.16)
BSIZE	0.355*	0.121	0.097
	(1.75)	(0.81)	(0.64)

TABLE 13 (Continued)

Variable(s)	Panel A: 1st stage DV = CDISC Model (1) Coefficient (*z*-value)	Panel B: 2nd stage DV = C_RATINGS Model (2) Coefficient (*z*-value)	Model (3) Coefficient (*z*-value)
BGENDER DIV	0.005	0.006*	0.004
	(1.27)	(1.88)	(1.25)
BINDEPENDENCE	0.009**	0.003	0.001
	(2.06)	(0.78)	(0.36)
CEO Duality	0.064	0.230**	0.251**
	(0.36)	(2.09)	(2.23)
CHAIR EX CEO	−0.106	−0.121	−0.125
	(−0.62)	(−1.19)	(−1.20)
YEAR_FE	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes
Pseudo R^2	0.0652	0.3254	0.3284
Observations	1640	1640	1640

Note: Table reports the Heckman selection bias test results. The dependent variable is credit ratings. All variable definitions are in the Appendix.

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

require firms to audit their relevant GHG emissions (as specified in the National Greenhouse and Energy Reporting Act (2007)). Our findings provide empirical evidence supporting the benefits of carbon assurance (i.e., enhancing credit ratings), and have important implications for policy-makers (e.g., promoting the adoption of carbon assurance). Given its positive impact, firms can consider having their carbon reporting assured. Carbon assurance can also be relevant to investors/creditors in assessing a firm's creditworthiness and subsequently their investment decisions.

Moreover, we show how the carbon assurance-credit rating relationship varies across different levels of product market competition and external political environment. Specifically, firms with high carbon assurance operating in highly competitive product markets, tend to receive higher credit ratings. Similarly, firms with higher carbon assurance are also likely to receive high credit ratings when headquartered in Democratic-leaning states. Our findings suggest the important role of market and institutional characteristics in shaping a firm's behaviour and performance, consistent with institutional theory (Campbell, 2007). As firms may conduct business across different product markets and/or political environments, our results have important implications. In particular, firms operating in product markets with high competition and/or in Democratic-leaning states may benefit from adopting high carbon assurance to enhance their credit rating scores.

It is also important to acknowledge some limitations in our research, which can be further investigated in future studies. First, our sample only includes US listed firms in a limited period (2007–2017), so our findings may not be generalised in other countries and/or time periods. We thus call for further research on carbon assurance and credit ratings using a global sample with more updated data to capture the latest developments in this area. Finally, we also encourage research that extends the scope of our study by examining other characteristics of carbon assurance to provide a more comprehensive understanding of the carbon assurance-credit rating relationship.

DATA AVAILABILITY STATEMENT

Data is available on request from the corresponding author but can't make public as some data requires subscription.

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APPENDIX

VARIABLE DEFINITIONS

Variable	Label	Description	Source
Credit ratings	*C_RATINGS*	Standard & Poor's (S&P) long-term issue of credit rating. We transformed the S&P ratings into conventional numerical scores, where 22 represents an AAA rating and 0 reflects no rating	Compustat North America
Carbon assurance level	*ASSUR_LEV*	Proxy for the carbon assurance strength for both Scope 1 and Scope 2 emissions. Ranking score indexed the level of verification undertaken for either Scope 1 or Scope 2 (i.e., assurance level) ranging from 0 to 4. Particularly, 0 is coded for "no verified", 1 is coded for "limited assurance", 2 is coded for "moderate assurance", 3 is for "reasonable assurance", and 4 is for "high assurance". After computing the ranking index for Scope 1 and Scope 2 emissions, we sum them up to obtain our final assurance level measure. [Source: CPD Climate Change. Referred to questions 8.6a and 8.7a for Scope 1 and Scope 2 emissions, respectively. The index ranges from 0 to 8. Max score: 8.]	CDP 2007–2017
Carbon assurance percentage	*ASSUR_PER*	Carbon assurance percentage is the percentage of emissions verified, which ranges from 0 to 100. The percentage is computed for each Scope 1 and Scope 2 emissions, and then averaged, the total of which represent our carbon assurance percentage measure. [Source: CDP Climate Change. Referred to questions 8.6a and 8.7a for Scope 1 and Scope 2 emissions, respectively]	CDP 2007–2017
Firm Size	*SIZE*	The natural logarithm of firms' total assets	Compustat North America
Return on assets	*ROA*	Earnings before interest and tax divided by total assets	Compustat North America

Variable	Label	Description	Source
Interest coverage	*INTEREST_COVE*	Interest expense divided by operating income before depreciation	Compustat North America
Leverage	*LEV*	Total long-term debt divided by total assets	Compustat North America
Convergence of ROA	*ROA_SD*	Standard deviation of return on assets	Compustat North America
TOBINSQ	*TOBINSQ*	The sum of the market value of equity plus the book value of total debt scaled by total assets	Compustat North America
Return volatility	*RETURN_VOL*	The standard deviation of annual stock return over a five-year period ($t - 4$, t)	Compustat North America
Capital expenditure	*CAPX*	Capital expenditure divided by total assets	Compustat North America
Research and development	*R&D_INTENS*	Research and development expenditure divided by total assets	Compustat North America
Z-SCORE	*Z_SCORE*	*Z*-Score is the unleveraged *Z*-Score. It is calculated as 0.012*(wcap/at) + 0.014*(re/at) + 0.033*(ebit/at) + 0.006*(csho*prcc_f/lt) + 0.999 * (sales)	Compustat North America
Forecast bias	*FORECAST_BIAS*	The absolute value of the difference between the median analyst quarterly earnings-per-share forecast and the actual earnings per share, divided by the fiscal year-end share price	Compustat North America
Investment grade	*INVESTMENT_GRADE*	Dummy variable equals 1 for firms with a credit rating of BBB- and above and 0 otherwise	Compustat North America
Assurance dummy	*ASSUR_DUMMY*	Dummy variable equals 1 for firms that adopt carbon assurance in a particular year and 0 otherwise	CDP 2007–2017
Analyst following	*ANALYST_FOLLOW*	The natural log of the number of analysts issuing an annual forecast for a firm in a fiscal year	I/B/E/S
Carbon emissions	*CARBON EMISS*	The natural log of the total carbon emissions (Scope 1 and Scope 2) reported by a firm in a fiscal year	Refinitiv ASSET 4/ESG
Board size	*BSIZE*	Number of directors on a board of a firm *i* in year *t*	Refinitiv ASSET 4/ESG

Variable	Label	Description	Source
Board gender diversity	*BGENDER DIV*	Number of female directors divided by total number of directors on a board of a firm *i* in year *t*	Refinitiv ASSET 4/ESG
Board independence	*BINDEPENDENCE*	Percentage of independent directors on a board of firm *i* in year *t*	Refinitiv ASSET 4/ESG
CEO duality	*CEO Duality*	Dummy variable equals 1 if the CEO and Chairman is the same individual and 0 otherwise	Refinitiv ASSET 4/ESG
Chairman previous CEO	*CHAIR EX CEO*	Dummy variable equals 1 if the current Chairman is the previous CEO of the company and 0 otherwise	Refinitiv ASSET 4/ESG
Carbon disclosure	*CDISC*	Firms reporting carbon disclosure information equal to one and zero otherwise	CDP 2007–2017
One year lag carbon disclosure	$CDISC_{t-1}$	Previous year's decision to disclose carbon information equal to one and zero otherwise	CDP 2007–2017
Industry adjusted carbon disclosure	*INDCDISC*	Industry-specific proportion of firms reporting carbon information of firm *i* in year *t*	CDP 2007–2017
Inverse Mill ratio	*INVERSE MILLS R*	Inverse Mills ratio	
Year fixed effects	*YEAR_FE*	A vector of dummy variables indicating year	Compustat North America
Industry fixed effects	*INDUSTRY_FE*	A vector of dummy variables indicating industry	Compustat North America