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Do Financial Analysts See through the Cloud of Carbon Emissions?

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SYNOPSIS: Carbon risk management plays a crucial role in global environmental development, increasing the demand from environmentally conscious investors and stakeholders for carbon disclosure and control. In parallel with the U.S. Securities and Exchange Commission's (SEC) release of climate rules in 2024 for enhanced carbon disclosure, this study investigates the effect of voluntary carbon disclosure on analyst forecast accuracy. Using a sample of S&P 500 firms from 2009 to 2020, we find that high-quality carbon disclosure and performance is positively associated with earnings forecast accuracy. Superior disclosures reduce firm-level uncertainties and result in more accurate forecasts. The positive effect is strong in firms that voluntarily disclose climate risks because analysts better comprehend the financial implications of firms' integrated climate-control strategies. This study contributes to environmental, social, and governance (ESG) disclosure practices and offers implications through specific carbon disclosures. Our evidence supports the SEC in validating its move toward enhanced reporting guidelines.

Data Availability: The data for this study are collected from subscription-based databases like Compustat-Capital IQ, I/B/E/S, and Bloomberg and manually from various publicly available sources identified.

JEL Classifications: C36; G32; M14; M41; M48; Q51.

Keywords: analyst forecast accuracy; carbon disclosure and performance; climate risk exposure; SEC climate-related disclosure rule; XBRL.

I. INTRODUCTION

Carbon risk management is now a global priority due to escalating climate advocacy. Shareholder resolutions on climate issues have surged in corporate America (Berridge 2020),[1] with carbon-neutral investors securing board seats as seen with ExxonMobil in 2021 (Matthews 2021). Consequently, financial markets closely monitor

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Any errors remain our own.

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[1] During the 2020 proxy season, shareholders' meetings received over 140 climate-related shareholder proposals (Berridge 2020).

greenhouse gas (GHG) emission disclosures (Griffin, Neururer, and Sun 2020). In October 2023, California ratified climate accountability and disclosure legislation, followed by similar proposals in other states. An important and related question arises: what is the impact of voluntary carbon disclosure on analyst forecast accuracy?

To enhance climate-related risk identification, assessment, and management, the U.S. Securities and Exchange Commission (SEC) passed Rules 33-11275 and 34-99678 in March 2024,[2] highlighting the material financial impacts from severe weather events and conditions in the financial statement, and a section of climate-related disclosure requiring registrants to phase in and follow a consistent structure (U.S. Securities and Exchange Commission (SEC) 2024). The new rules contain aspects of governance, strategy, risk management, and targets and goals. The objectives of recent legislation are to enhance data transparency and standardize climate- and carbon-related disclosure, resembling the goals of the Carbon Disclosure Project (CDP).

Before the SEC's new guideline, the CDP has been a leading voluntary initiative in climate-control efforts. With growing backing from institutional signatories, the CDP conducts comprehensive surveys to monitor progress and meet targets, serving as a crucial reference for setting carbon disclosure standards (CDP Report 2023).[3] However, managers face difficult decisions when handling questionnaires, weighing the costs and benefits of climate- and carbon-related disclosure (Matsumura, Prakash, and Vera-Muñoz 2024; Ott, Schiemann, and Günther 2017; Demertzidis, Tsalis, Loupa, and Nikolaou 2015). There is apprehension that equity markets might penalize carbon disclosure (e.g., Matsumura, Prakash, and Vera-Muñoz 2014; Griffin, Lont, and Sun 2017). As expected, some business communities have dissented from imposing mandatory disclosure.[4]

Coinciding with the SEC (2024) rules on carbon disclosure and its task force on environmental, social, and governance (ESG) issues,[5] we examine the impact of voluntary carbon disclosure on analyst forecast accuracy. This study analyzes Standard & Poor's (S&P) 500 firms from 2009 to 2020 using Bloomberg Intelligence ESG (BI ESG) data. Utilizing the CDP score in BI ESG to measure carbon disclosure quality and performance, we find that a high CDP score is positively associated with analysts' forecast accuracy. This effect is particularly pronounced in firms disclosing climate risk exposure, as such disclosure improves analysts' understanding of its financial implications, leading to more accurate forecasts. Furthermore, forecast accuracy increases after firms participate in the CDP, especially in subsequent years.

Prior literature finds that climate-related information has been valuable for practitioners.[6] Financial analysts play an intermediary role in helping investors understand the various aspects of such information (Chan 2022). Although Luo, Wang, Raithel, and Zheng (2015) and Fieseler (2011) find that analysts integrate corporate social performance (CSP) and corporate social responsibility (CSR) data into their forecasts, previous studies suggest differences between carbon-related and general CSR disclosure (Hoffmann and Busch 2008; Labatt and White 2007). Although voluntary and mandatory disclosure regimes have different dynamics, our findings remain valuable for evaluating the potential outcomes of mandates and are informative of climate- and carbon-related disclosure.

This study enriches ESG disclosure literature by focusing on climate- and carbon-related disclosure, whereas broader CSR studies cover all ESG pillars. In response to the call for economic analyses, our research provides valuable implications to support the SEC's (2024) guideline of offering investors consistent, comparable, and reliable climate-related disclosures. Despite ongoing challenges in carbon disclosure and performance, our findings that improved carbon disclosure and performance associated with forecast accuracy suggest that such disclosure contains financially material information that investors desire. These implications underline the financial relevance of the SEC's climate-related rule and provide valuable insights for executives and stakeholders.

II. LITERATURE REVIEW AND RESEARCH QUESTIONS

Carbon Disclosure and Performance on Forecast Accuracy

According to legitimacy theory (Cho and Patten 2007; Milne and Patten 2002; Patten 2002), disclosing carbon emissions is motivated by compelling reasons. Luo, Lan, and Tang (2012) identify economic and social pressures as primary

[2] "The Enhancement and Standardization of Climate-Related Disclosures for Investors": https://www.sec.gov/files/rules/final/2024/33-11275.pdf
[3] Please refer to the CDP website (https://www.cdp.net/en/) for information on its mission and engagement in climate strategies toward environmental leadership. The website also defines the CDP score (https://www.cdp.net/en/scores/cdp-scores-explained) (CDP Report 2023).
[4] https://www.sec.gov/news/statement/uyeda-statement-mandatory-climate-risk-disclosures-030624
[5] The SEC created a climate and ESG task force in 2021. One example of their actions is the case against Fiat/Chrysler Automobiles for misleading statements regarding emissions.
[6] Anecdotal evidence indicates that certain technical aspects of carbon emission disclosure demand thorough evaluation by specialists or expert opinions in investment banks, complicating the production of analyst forecasts. We gain insights through conversations with an equity analyst at Goldman Sachs and a partner in an accounting firm on how CDP has been used in their work. Both practitioners indicate that clients focus on the compliance of carbon disclosure and reporting with the Task Force on Climate-related Financial Disclosure (TCFD) framework, within which the CDP questionnaire has aligned with TCFD recommendations for years (CDP Report 2023).

drivers for corporate carbon disclosure. Indeed, high carbon emitters may face penalties in capital markets (Matsumura et al. 2014).

Previous research indicates a connection between general CSR information and analyst forecast accuracy. Vanstraelen, Zarzeski, and Robb (2003) find that forward-looking nonfinancial information in annual reports (10-Ks) enhances forecast accuracy in three European countries. Muslu, Mutlu, Radhakrishnan, and Tsang (2019) and Dhaliwal, Radhakrishnan, Tsang, and Yang (2012) show that analysts incorporate CSR reports and narratives into forecasting. The impact of CDP (carbon disclosure and performance) on forecast accuracy is of interest to governments and other stakeholders (SEC 2024, 2022).

Environmental liabilities impact financial reporting (Deloitte 2022). Some researchers suggest that environmental and climate-related information within CSR activities is the most concrete and verifiable (Busch and Shrivastava 2017; Wahyuni and Ratnatunga 2015). Additionally, Liesen, Figge, Hoepner, and Patten (2017) argue that firm-specific complexity in carbon disclosure aids in estimating future cash flows. Carbon disclosure also influences various financial outcomes, such as insurance contracts and business operations (Hoffmann and Busch 2008; Labatt and White 2007), suggesting its value relevance and potential to enhance forecast accuracy. However, technical challenges and uncertainty in assessing related business risks may hamper forecast accuracy (Liesen et al. 2017; Hope, Hu, and Lu 2016; Aerts, Cormier, and Magnan 2008), which is echoed by business professionals as stated earlier. The discussion prompts our first research question.

RQ1: Does carbon disclosure and performance influence analyst forecast accuracy?

Disclosed Climate Risk Exposure

Given the severe impact of extreme weather events and the substantial global economic losses they cause, 53 percent of firms surveyed in the 2018 CDP report disclosed climate risks (CDP Report 2019). These management-identified risks include physical and regulatory risks, which expose firms to litigation, reputation damage, intensified competition, and negatively influence customer decisions and business operations (Subramaniam, Wahyuni, Cooper, Leung, and Wines 2015; Chen and Gao 2012; Hoffmann and Busch 2008; Labatt and White 2007; UNEP FI 2006). Some firms address climate-related risk concerns by reporting estimated environmental liabilities in their annual reports.

Therefore, we anticipate that firms voluntarily acknowledging their exposure to climate-related risks would likely improve carbon disclosure and performance, reducing the uncertain adverse business consequences for analysts to consider. Hence, we investigate the second research question.

RQ2: Does disclosed climate risk exposure influence the effect of carbon disclosure and performance on forecast accuracy?

III. RESEARCH DESIGN

Analyst Forecast Accuracy

We define analyst forecast accuracy as the inverse of forecast error, expressed as follows (Muslu et al. 2019; Dhaliwal et al. 2012):

$$FERROR(Y)_{it} = 100 \times \frac{\frac{1}{N}\sum_{j=1}^{N} |FC_{itj}^{Y} - EPS_{it}^{Y}|}{P_{it}} \qquad (1)$$

where:

$FERROR(Y)$ = Y-year-ahead forecast errors ($Y = 0, 1, 2$);
FC_{itj}^{Y} = Y-year-ahead analyst earnings forecast j for firm i in year t; and
EPS_{it}^{Y} = the actual Y-year(s) earnings per share for firm i in year t.

Carbon Disclosure and Performance

We use the *CDP_SCORE* developed by the CDP. BI ESG features the *CDP_SCORE* (on a scale of 0–5) by integrating the carbon disclosure score and performance score. The former evaluates the completeness and quality of a respondent's disclosure, indicating extensive information on the firm's carbon footprint, climate change procedures, plans, actions, achievements, and inclusion in The Climate Disclosure Leadership Index. The latter assesses efforts to mitigate climate change concerns and risks, as well as to meet carbon reduction goals. A higher *CDP_SCORE* signifies better overall carbon disclosure and performance.

Empirical Models

As some S&P 500 firms, for which analysts issue earnings forecasts, may not participate in the CDP survey, there are no CDP scores for these firms.[7] We utilize the Heckman two-stage approach (Heckman 1979) to mitigate potential selection bias.[8]

We first estimate Equation (2) to predict the likelihood of a firm participating in the CDP survey (*CDP_PART*) by incorporating four instrumental variables from Muslu et al. (2019) and Deng, Kang, and Low (2013). These include the blue state (*BLUE_STATE*) and a state's religious ranking (*RELIGIOUS*), which likely influence a firm's beliefs on CSR activities. Additionally, we use inclusion in the Dow Jones Sustainability Index (*DJINDEX*) and the Newsweek Green Score (*GREEN*) as additional instruments. Firms performing well in environmental and social aspects, as indicated by their inclusion in the index or with high scores, are likely to engage in CSR activities. Therefore, we expect these instruments to positively affect a firm's decision to participate in the CDP survey, fulfilling the relevance condition. Conversely, a firm's headquarters location or social performance is unlikely to directly impact analyst forecasts, meeting the exclusion requirement for instruments (Muslu et al. 2019).

We include control variables suggested by the literature (Ott et al. 2017; Matsumura et al. 2014), along with a time trend variable (*TREND*) to account for the rising CDP participation frequency over time (Ott et al. 2017; Griffin et al. 2017; Liesen et al. 2017).

$$\begin{aligned} CDP\_PART_{it} = {} & \alpha_0 + \alpha_1 BLUE\_STATE_{it} + \alpha_2 DJINDEX_{it-1} + \alpha_3 GREEN_{it} \\ & + \alpha_4 RELIGIOUS_{it} + \alpha_5 MARKET\_SHARE_{it} + \alpha_6 MGMT\_FCST_{it} \\ & + \alpha_7 LAT_{it} + \alpha_8 BTM_{it} + \alpha_9 LEV_{it} + \alpha_{10} EPA_{it} + \alpha_{11} TREND_t \\ & + \Sigma\varphi_i + \varepsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} FERROR(Y)_{it} = {} & \beta_0 + \beta_1 CDP\_SCORE_{it} + \beta_2 CSR\_REPORT_{it-1} + \beta_3 ASSURANCE_{it} \\ & + \beta_4 FIRM\_AGE_{it} + \beta_5 LVAREARN_{it} + \beta_6 FFIN_{it} + \beta_7 LOSS_{it} \\ & + \beta_8 ROA_{it} + \beta_9 MARKET\_SHARE_{it} + \beta_{10} MGMT\_FCST_{it} \\ & + \beta_{11} LAT_{it} + \beta_{12} BTM_{it} + \beta_{13} LEV_{it} + \beta_{14} EPA_{it} + \beta_{15} LITIGATION_{it} \\ & + \beta_{16} LANANO_{it} + \beta_{17} LFHORIZON_{it} + \beta_{18} TREND_t + IMR \\ & + \Sigma\varphi_i + \varepsilon_{it} \end{aligned} \tag{3}$$

In Equation (3), our variable of interest, *CDP_SCORE*, measures a firm's carbon disclosure and performance quality. We incorporate control variables linked to analyst forecasts and firms' environmental reporting (Muslu et al. 2019; Peters and Romi 2014; Matsumura et al. 2014; Dhaliwal et al. 2012).

We include CSR report issuance (*CSR_REPORT*) and external assurance (*ASSURANCE*), expecting negative coefficients for both (Muslu et al. 2019; Dhaliwal et al. 2012). Additionally, we incorporate firm age (*FIRM_AGE*) (Roberts 1992), earnings per share volatility (*LVAREARN*) (Dichev and Tang 2009), financial opaqueness (*FFIN*), loss indicator (*LOSS*), profitability (*ROA*), market share (*MARKET_SHARE*), management forecasts (*MGMT_FCST*), firm size (*LAT*), book-to-market ratio (*BTM*), and leverage (*LEV*). Furthermore, we consider industry-specific reporting requirements (*EPA*), litigation risk (*LITIGATION*), analyst coverage (*LANANO*), forecast horizon (*LFHORIZON*), a time trend (*TREND*), and industry dummies (φ_i). We provide definitions for all variables in Appendix A.

IV. SAMPLE, DATA, AND EMPIRICAL RESULTS

Sample, Data, and Descriptive Statistics

We utilize BI ESG and Compustat data for S&P 500 firms from 2009 to 2020. We manually gather instrumental and CSR-related variables and verify firms' headquarters states.[9] We collect environmental liability and carbon

[7] In our sample, 23 firms did not respond to the CDP survey throughout 2009 to 2020. Therefore, we observe forecast accuracy for these firms lacking CDP scores.
[8] We obtain the inverse Mills ratio (*IMR*) from the first-stage regression and incorporate it into all subsequent regressions.
[9] We manually confirm the headquarters location of each firm using the "Company Information" section on the SEC EDGAR website.

TABLE 1

Sample Development

	No. of Firm-Years
Initial S&P 500 companies in BI ESG from 2009 to 2020	6,292
Less:	
Observations with insufficient data in Compustat to calculate control variables	(169)
Observations with missing I/B/E/S analysts forecasts	(240)
Observations with missing instrumental variables	(312)
Sample in Heckman's first-stage model of Equation (2)	5,571
Observations with missing *CDP_SCORE* in BI ESG	(1,688)
Sample in Heckman's second-stage model of Equation (3)	3,883

This table outlines a breakdown of our sample selection procedure starting from all S&P 500 firms covered in the BI ESG section and lists the number of firm-year observations dropped in each step of our sample selection procedure.

emission-related contexts through text analysis of eXtensible Business Reporting Language (XBRL) tags. Table 1 outlines our sample selection process. The final sample for our first-stage (second-stage) Heckman model comprises 5,571 (3,883) firm-year observations for 523 (500) firms.

We Winsorize continuous variables at the 1st and 99th percentiles. Table 2, Panel A (B) reports statistics for variables in the first-stage (second-stage) Heckman regression. Mean (median) values for *FERROR(0)*, *FERROR(1)*, and *FERROR(2)* are 0.348 (0.123), 1.601 (0.634), and 2.548 (1.052), respectively. As expected, forecast error increases with longer horizons. Untabulated correlation coefficients show a significant negative correlation (1 percent level) between CDP score and all three forecast error variables.

CDP Score and Analyst Forecast Accuracy

Table 3 presents regression results for the Heckman two-stage selection model. Panel A indicates that three out of four instrumental variables significantly correlate with a firm's CDP participation in the first-stage estimation (Equation (2)). Panel B shows consistently negative and significant coefficients for *CDP_SCORE* across all columns in the second-stage estimation (Equation (3)).[10,11] The absolute values of the coefficients show that an increase of *CDP_SCORE* by one unit leads to the most substantial decrease in *FERROR(2)* by 0.201, followed by 0.173 for *FERROR(1)*, and 0.069 for *FERROR(0)*. Economically, a one-unit improvement in *CDP_SCORE* corresponds to reductions of 7.9 percent, 10.8 percent, and 19.8 percent in the respective sample means of forecast errors. The significant improvement in the current-year forecast likely results from analysts precisely incorporating existing climate-control activities, which have an immediate impact in the short term and gradually manifest in the long term.

Panel B shows several control variables significantly affecting forecast accuracy, consistent with prior research (Muslu et al. 2019; Dhaliwal et al. 2012). Specifically, coefficients of *FIRM_AGE*, *LVAREARN*, *FFIN*, *LOSS*, *ROA*, *MGMT_FCST*, *LEV*, *LITIGATION*, and *TREND* are generally significant, suggesting that forecast accuracy declines with firm age, earnings volatility, financial opacity, loss indicator, financial leverage, and litigation risk, but improves with profitability, management forecast frequency, and temporal trend.[12,13]

Overall, Table 3 demonstrates a significant association between superior CDP disclosure and performance and improved forecast accuracy up to two years before earnings announcements, addressing our first research

[10] Matching forecast accuracy and the CDP score in the same fiscal year ensures analysts access the previous year's CDP score. Untabulated results confirm consistent findings when using lagged *CDP_SCORE*.

[11] In untabulated tests, we categorize the sample into three groups based on *CDP_SCORE* tiers: *LOW_CDPSCORE* (if *CDP_SCORE* is 1 or 2), *MID_CDPSCORE* (if 3 or 4), and *HIGH_CDPSCORE* (if 5). We estimate Equation (3) by substituting *CDP_SCORE* with the respective variables. Results indicate higher forecast accuracy for firms in the high-tier but not in the low-tier group. We appreciate the suggestion of this test by an anonymous reviewer.

[12] Significantly negative coefficients for *CDP_SCORE*, *MGMT_FCST*, and *TREND* underscore their importance in forecast accuracy. We investigate potential differences in their impact compared to the CDP score. Untabulated results confirm no significant difference.

[13] The nonsignificant *IMR* coefficient suggests that self-selection is not necessarily a concern. Additional tests using a noninstrumental variable approach show consistent findings. However, the research design does not fully rule out the possibility that higher internal information quality might affect the quality of carbon disclosures and the accuracy of analysts' forecasts. We appreciate the valuable insights from anonymous reviewers.

TABLE 2

Descriptive Statistics

Panel A: Variables in Heckman's First-Stage Model of Equation (2)

	n	Mean	Std. Dev.	10th	Q1	Median	Q3	90th
CDP_PART	5,571	0.824	0.381	0.000	1.000	1.000	1.000	1.000
BLUE_STATE	5,571	0.662	0.473	0.000	0.000	1.000	1.000	1.000
DJINDEX	5,571	0.197	0.398	0.000	0.000	0.000	0.000	1.000
GREEN	5,571	33.091	29.158	0.000	0.000	36.400	59.200	71.700
RELIGIOUS	5,571	24.502	10.921	10.000	14.000	24.000	32.000	40.000
MKT_SHARE	5,571	0.054	0.090	0.003	0.006	0.016	0.057	0.151
MGMT_FCST	5,571	2.415	2.887	0.000	0.000	0.000	5.000	6.000
LAT	5,571	9.542	1.522	7.698	8.472	9.410	10.496	11.638
BTM	5,571	0.441	0.337	0.095	0.215	0.378	0.602	0.875
LEV	5,571	0.288	0.174	0.062	0.158	0.278	0.398	0.513
EPA	5,571	0.308	0.462	0.000	0.000	0.000	1.000	1.000

Panel B: Variables in Heckman's Second-Stage Model of Equation (3)

	n	Mean	Std. Dev.	10th	Q1	Median	Q3	90th
FERROR(0)	3,883	0.348	0.736	0.027	0.055	0.123	0.294	0.731
FERROR(1)	3,883	1.601	3.115	0.122	0.256	0.634	1.596	3.535
FERROR(2)	3,883	2.548	4.757	0.209	0.443	1.052	2.525	5.703
CDP_SCORE	3,883	3.012	1.347	1.000	2.000	3.000	4.000	4.000
CSR_REPORT	3,883	0.541	0.498	0.000	0.000	1.000	1.000	1.000
ASSURANCE	3,883	0.098	0.297	0.000	0.000	0.000	0.000	0.000
FIRM_AGE	3,883	37.863	18.578	14.000	22.000	39.000	53.000	64.000
LVAREARN	3,883	0.915	0.523	0.372	0.532	0.792	1.185	1.562
FFIN	3,883	0.081	0.273	0.000	0.000	0.000	0.000	0.000
LOSS	3,883	0.104	0.305	0.000	0.000	0.000	0.000	1.000
ROA	3,883	0.052	0.063	−0.001	0.018	0.047	0.085	0.131
MKT_SHARE	3,883	0.060	0.096	0.004	0.008	0.020	0.069	0.170
MGMT_FCST	3,883	2.530	2.845	0.000	0.000	1.000	5.000	6.000
LAT	3,883	9.905	1.429	8.220	8.868	9.786	10.771	11.844
BTM	3,883	0.432	0.347	0.082	0.197	0.361	0.593	0.880
LEV	3,883	0.298	0.169	0.077	0.171	0.291	0.404	0.519
EPA	3,883	0.304	0.460	0.000	0.000	0.000	1.000	1.000
LITIGATION	3,883	0.240	0.427	0.000	0.000	0.000	0.000	1.000
LANANO	3,883	3.218	0.510	2.565	2.944	3.296	3.555	3.807
LFHORIZON	3,883	4.312	0.551	3.401	4.220	4.522	4.595	4.710

Panel A presents the descriptive statistics on analyst forecast accuracy, carbon disclosure and performance score, and control variables. Panel B presents the descriptive statistics of variables in cross-sectional and additional tests.
All the variables are defined in Appendix A.

question (RQ1).[14,15] This finding supports the SEC's guidelines (2024) to require climate-related disclosure in registrants' filings and annual reports. The rules mandate disclosing GHG emissions metrics (Scopes 1 and 2 emissions)

[14] To illustrate the added value of CDP over CSR reports, we conduct several tests (untabulated). First, we replicate the findings of Dhaliwal et al. (2012) and Muslu et al. (2019). The results initially align with previous findings, showing a significantly negative coefficient of *CSR_REPORT* (narratives of CSR reports). However, after incorporating *CDP_SCORE*, the coefficients of *CDP_SCORE* and narratives of CSR reports remain significantly negative, whereas *CSR_REPORT* loses significance. Second, we test the robustness of our results within a subset of 1,642 observations lacking both CSR standalone reports and carbon-related disclosures in 10-Ks but exclusively containing CDP information. Our findings remain robust in this confined sample.

[15] To discern the impact of carbon-related disclosures versus carbon emission levels, we examine the robustness of our findings by including emissions intensity (the sum of Scopes 1 and 2 emissions scaled by total assets) and the change in emissions intensity (current year minus previous year's Scopes 1 and 2 emissions scaled by total assets) as additional control variables in Equation (3). Our untabulated tests suggest that carbon-related disclosures, rather than carbon emission levels, predominantly influence analyst forecast accuracy.

TABLE 3

Analyst Forecast Accuracy and CDP Score: Heckman Selection Approach

Panel A: First-Stage Selection Regression of Equation (2)

	Dependent Variable =
	CDP_PART
BLUE_STATE	0.043
	(0.81)
DJINDEX	1.063***
	(7.81)
GREEN	0.015***
	(12.24)
RELIGIOUS	0.013***
	(5.56)
MKT_SHARE	−0.658*
	(−1.93)
MGMT_FCST	0.015*
	(1.68)
LAT	0.278***
	(10.71)
BTM	−0.055
	(−0.63)
LEV	−0.323**
	(−2.16)
EPA	0.060
	(0.94)
TREND	0.252***
	(24.44)
Industry indicators	Yes
Observations	5,571
Pseudo R^2	0.367

Panel B: Second-Stage Regressions of Equation (3)

	Dependent Variable =		
	FERROR(0)	***FERROR(1)***	***FERROR(2)***
CDP_SCORE	−0.069*	−0.173**	−0.201**
	(−1.74)	(−2.42)	(−2.17)
CSR_REPORT	−0.069	0.063	0.046
	(−0.84)	(0.38)	(0.21)
ASSURANCE	−0.070	0.172	0.577
	(−1.32)	(0.82)	(1.62)
FIRM_AGE	0.002	0.013**	0.021**
	(0.52)	(2.17)	(1.99)
LVAREARN	0.445**	1.440***	2.062***
	(2.32)	(4.67)	(5.81)
FFIN	0.447*	0.825**	1.628***
	(1.71)	(2.16)	(2.80)
LOSS	0.746***	3.198***	5.122***
	(2.79)	(6.45)	(7.16)
ROA	0.717	−5.235*	−7.864**
	(0.49)	(−1.81)	(−2.21)

(continued on next page)

TABLE 3 (continued)

	Dependent Variable =		
	FERROR(0)	*FERROR(1)*	*FERROR(2)*
MKT_SHARE	−0.413	0.845	1.194
	(−1.00)	(0.78)	(0.73)
MGMT_FCST	−0.053***	−0.152***	−0.192***
	(−4.58)	(−6.41)	(−5.87)
LAT	0.066	−0.149	−0.334**
	(0.84)	(−1.32)	(−2.39)
BTM	0.289	0.997	1.998*
	(0.79)	(1.42)	(1.91)
LEV	0.920**	2.542***	4.200***
	(2.34)	(3.47)	(3.56)
EPA	−0.029	−0.283	−0.285
	(−0.22)	(−0.95)	(−0.73)
LITIGATION	0.272*	0.841***	1.094***
	(1.86)	(2.63)	(2.69)
LANANO	−0.515*	−0.541	−0.166
	(−1.93)	(−1.44)	(−0.43)
LFHORIZON	0.165*	−0.113	−0.268
	(1.94)	(−0.79)	(−1.47)
TREND	−0.035**	−0.115***	−0.175***
	(−2.28)	(−3.41)	(−4.08)
IMR	−0.209	−0.456	−0.362
	(−1.09)	(−1.07)	(−0.58)
Industry indicators	Yes	Yes	Yes
Observations	3,883	3,883	3,883
Adjusted R^2	0.082	0.199	0.258

*, **, *** Indicate statistical significance at the 0.1, 0.05, and 0.01 levels (two-tailed), respectively.
Panel A presents the results for the Heckman first-stage selection regression of a firm's CDP participation decision. Panel B presents the results for the Heckman second-stage regressions of analyst forecast accuracy on CDP score. The model includes an unreported intercept. The z-statistics (t-statistics) reported in parentheses are computed using standard errors clustered by firm.
All the variables are defined in Appendix A.

and attesting to emissions metrics (phase-in assurance) by following a consistent structure to aid investors in better understanding reporting and assessing financial impacts resulting from climate-related risks (KPMG 2024).

Cross-Sectional Analyses: Disclosed Climate Risk Exposure

We investigate whether the association between *CDP_SCORE* and analyst forecast accuracy varies based on firms' disclosure of climate-related risk exposures (RQ2). We introduce interaction terms between *CDP_SCORE* and climate risk exposure proxies (*PHYS_RISKEXP*, *REG_RISKEXP*, and *ENV_10KDISC*) into Equation (3). The first two variables are based on Bloomberg/CDP characteristics, and the third is based on financial reporting characteristics. Physical risk arises from extreme weather changes impacting firms' operations and supply chains, potentially increasing operating expenses and reducing revenues. Regulation risk involves potential policy and legal changes, including scrutiny of services (products) and obligations to reduce emissions or face charges (CDP Report 2019).[16] Subject to environmental laws and regulations, some firms estimate compliance or remediation costs and document environmental obligations in footnote 10 of their annual reports. We classify these as climate risks, comprising physical and regulatory risks stemming primarily from climate change, as well as environmental risks encompassing issues like air and water pollution.[17]

[16] See details on https://www.cdp.net/en/research/global-reports/global-climate-change-report-2018/climate-report-risks-and-opportunities
[17] The transition risks in the SEC are actual or potential negative impacts on a registrant's business, attributable to regulatory, technological, and market changes. The regulation risk in CDP is considered a narrow scope of transition risk and it is the closest available proxy.

We include each measure and its interaction term with *CDP_SCORE* in Equation (3). The results in Table 4 indicate a consistently negative and significant coefficient of the interaction term in eight of nine models across Panels A–C. Moreover, the sum of coefficients of *CDP_SCORE* and the interaction term is negative and statistically significant in all regressions. This finding suggests that improved carbon disclosure and performance positively impact forecasts by incorporating climate-related risk exposures into financial implications. Our findings suggest that the main results are attributable to firms that have disclosed climate risk exposure, thereby validating the SEC (2024) in requiring registrants to disclose material climate-related risks and activities to mitigate such risks. Under the rules, firms must address the impacts of climate-related risks (e.g., physical risk, transitional or mitigation activities, associated risks) on financial statements if the aggregate amounts exceed a threshold percentage ($\geq$1 percent), but no disclosure requirement if the aggregate amounts are less than the threshold.

Additional Analyses

Timing of CDP Participation

To examine whether managers' participation in the CDP survey affects forecast accuracy, we compare forecast accuracy of the same firm before and after participation. This approach mitigates concerns about omitted variable bias. Our analysis comprises 5,185 firm-years, with 925 (4,260) observations before (after) observations.[18] In Table 5, Panel A, all three forecast accuracy measures are significantly higher in the post-participation group compared to the pre-participation group. In Panel B, the coefficients of the indicator variable (*POST_PART*) are negative and significant, indicating that participating in the CDP survey positively affects forecast accuracy.

We further examine whether forecast accuracy differs between first-year and subsequent-year participants by dividing post-participants into two groups: 256 first-year and 4,004 subsequent-year participants. In Panel C, *SUBSEQ_PART* has a significantly negative coefficient, whereas *FIRST_PART* is negative but insignificant. Forecast accuracy is better for subsequent-year participants than nonparticipants, with no significant difference observed for first-year counterparts. The results have practical implications: (1) Firms' CDP survey is subjective and fragmented, requiring time for analysts to unpack and map relevant information into earnings forecasts. Analysts improve their proficiency in utilizing CDP information over time. (2) Firms recognize that other market participants (e.g., creditors, rating agencies, institutional investors) have incorporated climate-related risks into decision-making.[19] Therefore, they should take a proactive approach toward sustainable growth.

Specificity of Carbon-Related Disclosures in Annual Reports

We develop a specificity measure of carbon-related disclosure in 10-Ks through text analysis, focusing on specific keywords.[20] This measure, named *EMISSION_10KCOUNT*, counts the frequency of phrases related to emission-specific risks or operational actions. Hope et al. (2016) suggest that more specific risk-factor disclosures lead to improved fundamental risk assessment by analysts.

In Equation (3), we substitute *CDP_SCORE* with *EMISSION_10KCOUNT*. The untabulated results show a negative and significant coefficient of *EMISSION_10KCOUNT*, consistent with Hope et al. (2016), indicating that more specific disclosures lead to higher accuracy. Our evidence suggests that detailed carbon-related information positively correlates with analysts' understanding of financial impacts from climate disclosure, endorsing the SEC (2024) to integrate specific quantitative and qualitative (narrative) climate-related information into 10-Ks. This integration aims to help stakeholders comprehend how climate-related risk factors could affect the firms they engage with.

V. CONCLUSION AND FUTURE RESEARCH

This study investigates the dilemma firms encounter in disclosing carbon information at varying levels of detail. Financial analysts assist investors in comprehending these disclosures. Our findings show that superior carbon disclosure and performance positively impact earnings forecast accuracy for the current and future years, primarily due to firms disclosing climate-related risk exposures.

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[18] We remove 386 firm-year observations (5,571 observations minus 5,185 observations) involving firms that remain nonparticipating, participating, or switch between the two statuses.

[19] Since 2020, Moody's Investors Service has begun to assess carbon transition risks and opportunities that drive changes in revenues, costs, and capital deployment.

[20] The dictionary of keywords is formed using RAKE-NLTK algorithm in Python. Available at: https://medium.datadriveninvestor.com/rake-rapid-automatic-keyword-extraction-algorithm-f4ec17b2886c

American Accounting Association

TABLE 4

Moderating Effect of Disclosed Climate Risk Exposure

Panel A: Physical Risk Exposure Disclosure in the CDP

	Dependent Variable =		
	FERROR(0)	*FERROR(1)*	*FERROR(2)*
CDP_SCORE (A)	−0.007	0.045	0.016
	(−0.30)	(0.54)	(0.15)
CDP_SCORE × *PHYS_RISKEXP* (B)	−0.085*	−0.254**	−0.272*
	(−1.66)	(−2.22)	(−1.85)
PHYS_RISKEXP	0.313	0.499	0.607
	(1.62)	(1.24)	(1.21)
p-value for testing (A) + (B) < 0	0.979	0.994	0.994
Control variables in Equation (3)	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes
Observations	3,566	3,566	3,566
Adjusted R^2	0.091	0.191	0.247

Panel B: Regulation Risk Exposure Disclosure in the CDP

	Dependent Variable =		
	FERROR(0)	*FERROR(1)*	*FERROR(2)*
CDP_SCORE (A)	−0.063	0.063	0.000
	(−1.29)	(0.81)	(0.00)
CDP_SCORE × *REG_RISKEXP* (B)	−0.019	−0.234**	−0.327**
	(−0.24)	(−2.07)	(−1.99)
REG_RISKEXP	0.083	0.523	0.890
	(0.29)	(1.31)	(1.56)
p-value for testing (A) + (B) < 0	0.940	0.981	0.999
Control variables in Equation (3)	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes
Observations	3,560	3,560	3,560
Adjusted R^2	0.100	0.275	0.252

Panel C: Environmental Liability Disclosure in 10-Ks

	Dependent Variable =		
	FERROR(0)	*FERROR(1)*	*FERROR(2)*
CDP_SCORE (A)	−0.002	−0.047	−0.060
	(−0.23)	(−1.21)	(−1.09)
CDP_SCORE × *ENV_10KDISC* (B)	−0.048**	−0.216**	−0.370**
	(−2.14)	(−2.19)	(−2.42)
ENV_10KDISC	0.100	0.580	1.147**
	(1.22)	(1.64)	(2.12)
p-value for testing (A) + (B) < 0	0.991	0.998	0.999
Control variables in Equation (3)	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes
Observations	3,858	3,858	3,858
Adjusted R^2	0.215	0.270	0.300

*, ** Indicate statistical significance at the 0.1 and 0.05 levels (two-tailed), respectively.
This table presents the results for the Heckman second-stage regressions of analyst forecast accuracy on CDP score conditioning on firms' disclosed climate risk exposure. The model includes an unreported intercept. The z-statistics (t-statistics) reported in parentheses are computed using standard errors clustered by firm.
All the variables are defined in Appendix A.

TABLE 5

Timing of CDP Participation

Panel A: Forecast Accuracy Differences in the Pre- and Post-Participation Periods

	***POST_PART* = 0 (n = 925)**		***POST_PART* = 1 (n = 4,260)**		**Testing the Differences**	
	Mean	**Median**	**Mean**	**Median**	**t-stat**	**z-stat**
FERROR(0)	0.513	0.201	0.361	0.130	5.44***	8.25***
FERROR(1)	2.514	0.985	1.732	0.676	5.92***	8.52***
FERROR(2)	4.193	1.691	2.832	1.132	6.60***	8.42***

Panel B: Regression of Forecast Accuracy on Post-Participation

	Dependent Variable =		
	FERROR(0)	***FERROR(1)***	***FERROR(2)***
POST_PART	−0.056**	−0.589***	−1.144***
	(−1.99)	(−3.18)	(−4.02)
Control variables in Equation (3)	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes
Observations	5,185	5,185	5,185
Adjusted R^2	0.216	0.258	0.289

Panel C: Regression of Forecast Accuracy on First-Year and Subsequent-Year Participations

	Dependent Variable =		
	FERROR(0)	***FERROR(1)***	***FERROR(2)***
FIRST_PART	−0.039	−0.405*	−0.401
	(−0.80)	(−1.79)	(−0.95)
SUBSEQ_PART	−0.058**	−0.613***	−1.242***
	(−2.03)	(−3.20)	(−4.28)
Control variables in Equation (3)	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes
Observations	5,185	5,185	5,185
Adjusted R^2	0.216	0.258	0.290

*, **, *** Indicate statistical significance at the 0.1, 0.05, and 0.01 levels (two-tailed), respectively.
Panel A presents a univariate comparison of analyst forecast accuracy between pre- and post-participation periods. Panel B presents the results for the Heckman second-stage regressions of analyst forecast accuracy on *POST_PART*. Panel C presents the results for the Heckman second-stage regressions of analyst forecast accuracy on *FIRST_PART* and *SUBSEQ_PART*. The model includes an unreported intercept. The z-statistics (t-statistics) reported in parentheses are computed using standard errors clustered by firm.
All the variables are defined in Appendix A.

Although our research offers valuable insights, it comes with caveats. The improvement in internal information quality, achieved through enhanced management guidance in implementing carbon-related disclosure processes, may contribute to higher accuracy of analyst forecasts. Hence, factors beyond the CDP score could influence our results. To address this, we control for management earnings forecasts and employ the Heckman two-stage selection model to tackle potential endogeneity issues, which may not be completely ruled out. For example, Matsumura et al. (2014) suggest a selection bias in their CDP respondents for 2006–2008. One explanation for the differences in our findings is our longer sample period, particularly as CDP participation has become more prevalent over time. Nevertheless, we caution against drawing causal conclusions and urge further exploration.

Our study indicates that managers should prioritize long-term climate strategies by offering transparent climate-related information and maintaining control over disclosure procedures, which ultimately reflect in financial reporting and are crucial to investors. The responsibilities of the board to oversee climate-related risks should not be understated.

These suggestions align with the SEC's rules for registrants to disclose comprehensive material climate-related risks and emissions metrics in a consistent structure (e.g., GHG Protocol, TCFD).

In today's regulatory landscape, it is challenging for firms to leverage efforts to comply with a mixture of climate legislations to streamline the implementation of various rules, not to mention the hurdles market participants face in interpreting such information. Meanwhile, business professionals express concern about data quality during the shift from voluntary to mandatory reporting (Deloitte 2024). Given the challenges of this transition, firms should carefully consider the extent of details, disclosure format, and suitable section(s) in filings, allowing for gradual progress. We call for regulators' continuous attention to the feedback from the business community and general public on the new rules to balance between mandated disclosure details to protect investors and related burden on the firms from the costly disclosure and/or assurance process.

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APPENDIX A

Variable Definitions

Variable	Definition	Source
Variables in Main Tests		
ASSURANCE	An indicator variable that takes the value of 1 if a CSR report has external assurance and 0 otherwise. (http://responsibilityreports.com)	Manual collections
BLUE_STATE	An indicator variable that takes the value of 1 if a firm's headquarters is in a blue state and 0 otherwise. A blue state is defined as a state that is carried by the Democratic Party in at least three out of the four presidential elections held in 2020, 2016, 2012, and 2008. (http://uselectionatlas.org)	Manual collections

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APPENDIX A (continued)

Variable	Definition	Source
BTM	The book-to-market ratio. [#ceq / (#prcc_f × #csho)]	Compustat
CDP_PART	An indicator variable that takes the value of 1 if a firm participates in the CDP climate change survey for a given year and 0 otherwise.	BI ESG
CDP_SCORE	The firm's CDP score represents its level of carbon disclosure and performance defined by the CDP, ranging from 1 to 5.	BI ESG
CSR_REPORT	An indicator variable that takes the value of 1 if a firm issues CSR report for a given year and 0 otherwise. (http://responsibilityreports.com)	Manual collections
DJINDEX	An indicator variable that takes the value of 1 if a firm is included in the Dow Jones Sustainability Index for a given year and 0 otherwise. (http://spglobal.com)	Manual collections
EPA	An indicator variable that takes the value of 1 if a firm operates in an industry required to report its GHG to the EPA by the GHG Mandatory Reporting Rule (EPA 2009) based on NAICS codes and 0 otherwise.	Compustat
FERROR(Y) ($Y = 0, 1, 2$)	The firm's absolute value of average analyst forecast errors scaled by the stock price at the beginning of the year.	I/B/E/S
FFIN	An indicator variable that takes the value of 1 if a firm has accruals higher than the industry-year mean value and 0 otherwise.	Authors' calculation
FIRM_AGE	The number of years since the firm's initial appearance in Compustat.	Compustat
GREEN	A firm's green score in *Newsweek Magazine*, ranges between 0 and 100 and is based on the firm's environmental impact, initiation of green policies, and reputation. (http://newsweek.com)	Manual collections
LANANO	The natural logarithm of the number of analysts following.	I/B/E/S
LAT	The natural logarithm of a firm's total asset (#at) at the end of the year.	Compustat
LEV	Leverage ratio, calculated as short-term debt plus long-term debt scaled by total asset. [(#dltt + #dlc) / #at]	Compustat
LFHORIZON	The natural logarithm of the median forecast horizon (the number of days between the earnings announcement date and forecast date) of analyst forecasts.	I/B/E/S
LITIGATION	An indicator variable that takes the value of 1 if a firm operates in biotechnology (SIC 2833–2836), computers (3570–3577, 7370), electronics (3600–3674), and retailing (5200–5961) industries and 0 otherwise.	Compustat
LOSS	An indicator variable that takes the value of 1 if a firm reports negative earnings (#ib) for a given year and 0 otherwise.	Compustat
LVAREARN	The natural logarithm of the time-series standard deviation of earnings per share (#epspx) over the past ten years; we require at least three years of complete data to construct this variable.	Compustat
MGMT_FCST	The number of management forecasts issued over the fiscal year.	I/B/E/S
MKT_SHARE	Sales of a firm (#sale) divided by the total sales in the industry (based on the two-digit SIC) and year.	Compustat
RELIGIOUS	The religion ranking of a firm's headquarters state ranges between 0 and 51 and is calculated as the proportion of the number of religious adherents in the firm's headquarters state to the state's total population in 2010. (http://theARDA.com)	Manual collections
ROA	Net income scaled by total assets. (#ib / #at)	Compustat
TREND	Time trend variable which has a value of 0 to 11, corresponding to 12 years of our sample.	Authors' calculations
Variables in Additional Tests		
ENV_10KDISC	An indicator variable that takes the value of 1 for a firm to report environmental liabilities (using the U.S. GAAP Financial Reporting	SEC Edger

(continued on next page)

APPENDIX A (continued)

Variable	Definition	Source
	Taxonomy XBRL tags) as described in footnote 10 in the 10-K reports and 0 otherwise.	
FIRST_PART	An indicator variable that takes the value of 1 if it is the first year for a firm to participate in the CDP and 0 otherwise. (http://responsibilityreports.com)	Manual collections
PHYS_RISKEXP	An indicator variable that takes the value of 1 if a firm identifies itself exposed to climate change physical risk and 0 otherwise.	BI ESG
POST_PART	An indicator variable that takes the value of 1 for the years since a firm's initial participation in the CDP (from the first year onward), and 0 otherwise. (http://responsibilityreports.com)	Manual collections
REG_RISKEXP	An indicator variable that takes the value of 1 if a firm identifies itself exposed to climate change regulatory risk and 0 otherwise.	BI ESG
SUBSEQ_PART	An indicator variable that takes the value of 1 for the years after a firm's initial participation in the CDP (from the second year onward) and 0 otherwise. (http://responsibilityreports.com)	Manual collections