Walking the walk or just talking the talk? Analyzing the predictive value of voluntary carbon disclosures

Simon Anetsmann[a] • Stefan Trück[b] • Marco Wilkens[c]

This Version: October 2022

Abstract While corporate social reporting (CSR) and voluntary carbon disclosure become more mainstream, research in the realm of discretionary carbon reporting mostly focusses on its determinants, whereas there is little-known knowledge on its informational value and its effects. Applying theoretical lenses from the management and legitimacy view of environmental disclosure as well as insights from impression management, we revisit the relation between carbon disclosure and performance, extending prior studies by considering disclosure quality. Based on a global sample of CDP participants from 2010 to 2019, we examine the impact of carbon disclosure and its quality on subsequent changes in carbon performance, while accounting for the hard-to-quantify nature of CSR reports by utilizing computer-based linguistic analysis to detect opportunistic reporting behavior. Evidencing that better carbon disclosure performance does not invoke reductions in carbon emission intensity, we argue that disclosure is driven by legitimacy reasons. We further find that increased opportunistic reporting behavior weakly indicates worse future performance, even more pronounced if companies are subject to less stakeholder pressure and regulations.

Keywords: Voluntary carbon disclosure • Carbon performance • Textual analysis • Predictive value • Carbon Disclosure Project • Impression management

JEL Classification: D83, G14, G24, M14, Q55, Q56

---

[a] Simon Anetsmann, Technical University of Munich, University of Augsburg, Email: simon.anetsmann@tum.de
[b] Stefan Trück, Department of Actuarial Studies and Business Analytics, Macquarie University, Australia, Email: stefan.trueck@mq.edu.au
[c] Marco Wilkens, University of Augsburg, Faculty of Business Administration and Economics, Chair of Finance and Banking, Email: marco.wilkens@wiwi.uni-augsburg.de

1. Introduction

Driven by a rise of mandatory as well as voluntary carbon trading, voluntary carbon disclosure surged in recent years (Kolk, Levy & Pinkse, 2008). This advance is further accelerated by public debates centering around a hypothesized positive effect of carbon disclosure (Hahn, Reimsbach & Schiemann, 2015), following the propagated mantra "what gets measured can be managed" (Topping, 2012). Likewise, stakeholders show an increased demand for environmental disclosure (Kolk, Levy & Pinkse, 2008), as can be seen by an increasing extent of corporations responding to the Carbon Disclosure Project (CDP), reaching more than 4,000 companies globally in 2019 (CDP, 2020a). Moreover, carbon disclosure research receives growing attention caused by regulatory developments, such as emission-trading scheme (ETS) introductions, and the establishment of carbon output as an additional corporate risk factor (Hahn, Reimsbach & Schiemann, 2015).

Despite all that, Hahn, Reimsbach and Schiemann (2015) emphasize that the effect of carbon disclosure is still uncertain. Accounting for the fact that CDP is used as the most frequent source of carbon emissions data, with many researchers presuming the data to be reliable (Stanny, 2018), assessing the initiative's data reliability is particularly important. Accordingly, we address this research gap by assessing the informational value of carbon disclosure made through CDP regarding future carbon performance, considering disclosure quality, derived via advanced textual analysis, as an additional explanatory variable.

While the management school argues that carbon disclosure leads to an enhancement of emission monitoring and management (Burritt & Schaltegger, 2010), a more critical view sees environmental reporting as a legitimation exercise and not an effective mechanism for performance change (Stanny, 2013). Further, this study applies theoretical insights on impression management, assuming that disclosure can be driven by the opportunistic motive to strategically introduce bias into the reporting (Merkl-Davies & Brennan, 2007).

Answering to mixed evidence potentially caused by shortcomings of previous research on the relation between environmental reporting and performance, as voiced by Doan and Sassen (2020), the study's sample is neither restricted to specific countries nor industries and its longitudinal approach enables to make inferences about carbon performance developments in the long run. In contrast to prior works, the study uses the current measure of carbon disclosure performance, the CDP's performance band, and compliments findings which are thus far mostly based on the former, discontinued disclosure score (e. g. Matisoff, 2013; Qian & Schaltegger, 2017). Following Velte, Stawinoga and Lueg's (2020) warning to be aware of greenwashing, selective disclosure and information overload practices within carbon reporting, we include the potential impact of impression management. Therefore, we assess disclosure quality through state-of-the-art computer-based analysis techniques which promise an objective quantification of disclosure quality (Muslu et al., 2019), in contrast to more common methods like content analysis (Hahn, Reimsbach & Schiemann, 2015).

Applying a lead-lag panel data analysis of CDP data reaching from 2010 to 2019, covering multiple countries as well as industries, this study investigates the changes in carbon emission intensity following to companies' responses to CDP questionnaires and the receipt of disclosure scores from the intermediary. Using CDP performance bands as a proxy for disclosure performance as well as a quality measure derived via computer-based text analysis, we observe supporting evidence that carbon disclosure through CDP is not indicative of future carbon emission intensity improvements, but rather used for legitimation purposes. Further, the results underline the necessity to account for decreased disclosure quality and reduced informational value invoked by impression management tendencies.

Our study contributes to the current state of literature in three ways. First, the findings add to investigations assessing the usefulness of environmental reporting within the domain of environmental, social, and governance scores as a broader frame-giving concept. As such, this paper evaluates the current performance band of CDP, which is considered to be provided by one of the most reliable rating agencies within environmental reporting and scoring (Wong, Brackely & Petroy, 2019). Since many studies that focus on the value relevance of environmental reporting are adjacent to the presumed link between environmental disclosure and performance, we contribute indirectly to research on the financial impact of carbon disclosure by giving indications whether CDP's performance band can be considered material information or not. Second, the study contributes to existing, inconclusive evidence concerning the effect of CDP disclosure on subsequent carbon performance, as a niche of the more thoroughly examined link between environmental disclosure and performance. As such, we revisit and extend findings of Matisoff (2013) and Qian and Schaltegger (2017) by applying more extensive samples and methodological alterations. Third and last, this paper adds to a growing field of research that assesses the informational value of text within corporate reporting and other market-relevant sources by using computer-aided text analysis (Zhang, Stone & Xie, 2019). More specifically, we expand extant studies on linguistic analysis of corporate social responsibility (CSR) reporting and in particular compliment findings of Fabrizio and Kim (2019), being the only scholars to apply text analysis within the framework of impression management for the examination of CDP narratives.

The further outline of the paper is structured as follows. Section 2 establishes existing literature that discusses the impact of environmental disclosure on environmental performance as a starting point, to then drill down more specifically to the scarce findings on the relation between carbon disclosure and performance. Further, research concerning the use of impression management and its effects regarding disclosure within CSR are introduced. Taken together theoretical insights from these different fields assist to develop the hypotheses for our study. Section 3 elaborates on the construction of a score to quantify disclosure quality, while the subsequent Section 4 discusses the research approach as well as the data and variables used. The ensuing analysis and its results are described together with several additional tests in Section 5, before the paper ends with summarizing main findings, stating implications, and discussing limitations as well as pointing out avenues for future research in Section 6.

2. Literature review

The question "Does it pay to be green" (Hart & Ahuja, 1996) and the corresponding link between environmental and corporate financial performance has been extensively in the focus of business and environmental research. Nevertheless, investigations yield different results, as findings are dependent on the respective ecological issues and environmental performance measurements observed. Specifying the issue to climate change and the metric under investigation to carbon performance, Busch and Hoffmann find a positive link between environmental performance and financial performance (Busch & Lewandowski, 2018).

In the meantime, carbon disclosure, often considered the centerpiece of public discussions on climate change due to its hypothesized effect on corporate and environmental performance, is widely under-researched. Only recently the topic gained significant momentum due to political developments, like the ratification of the Kyoto Protocol, and the growing availability of data. However, most work conducted is on the determinants of disclosure, i. e. which company is more likely to disclose, whereas the effects of carbon disclosure, on an ecologic as well as economic basis, are merely investigated (Hahn, Reimsbach & Schiemann, 2015).

While some scholars engaged in similar questions over the years, mainly shedding light on carbon disclosure's reflection ability of true underlying performance, scarce evidence exists on a potential impact on carbon performance following the act of disclosure (Qian & Schaltegger, 2017).

Departing from a common ground of investigation, insights on the link between environmental disclosure and performance serve as a starting point. As presumed by the "outside-in" management view (Schaltegger & Wagner, 2006), sustainability reporting as a response to external expectations can be used internally as a planning tool to develop incentives or pressure and enhance the related measurement and management practices. Finally, this would lead to improvements in performance (Burritt & Schaltegger, 2010).

On the other hand, based on legitimacy theory, disclosure may be solely used to receive a license to operate, i. e. to legitimize the continued operations of the firm vis-à-vis to corporate outsiders (Cormier, Magnan & van Velthoven, 2005). Therefore, environmental reporting would purely serve as a legitimation device and not an effective mechanism for substantial performance change (Stanny, 2013).

Last, accounting for the descriptive characteristics of environmental reporting, consisting mainly of verbal information instead of numerical metrics, it may be used as an impression management tool (Cho, Roberts & Patten, 2010). Such strategically shaped disclosure, also referred to as greenwashing in the context of environmental reporting, impairs the extent to which disclosure reflects actual environmental performance, as firms disseminate misleading environmental information (Mahoney et al., 2013).

2.1. The "outside-in" view – disclose to improve

Assuming that firms initially provide information due to societal demand, the managerial approach to environmental performance development holds that stakeholder communication and disclosure in response to public pressure leads to enhanced measurement activities and consequently advances sustainability performance (Burritt & Schaltegger, 2010). This view was coined by Schaltegger and Wagner (2006) as an "outside-in" path to corporate sustainability, as public expectations are assessed by corporates in order to be capable of deriving performance measures for the company (Qian & Schaltegger, 2013). As such, the view supports the notion that environmental disclosure mirrors expectations and values of stakeholders and helps to diffuse them into the corporate environment to invoke change and improvements (Boons & Strannegård, 2000).

Following Topping (2012), based on the mantra “what gets measured gets managed” and due to increased strategic relevance of carbon emissions, it is eventually assumed that carbon reporting leads to gains in efficiency in the management of emissions and consequently to an improvement of carbon performance (Tang & Demeritt, 2018).

Along this line of thought, Qian and Schaltegger (2013) use a CDP sample of Global 500 companies during the years 2008 to 2011 and find that companies with more thorough disclosure show lower carbon intensities in subsequent years. Looking at a sample of the same CDP years, they also observe preceding good carbon disclosure to be positively linked to changes in carbon emission intensity (Qian & Schaltegger, 2017). While evidencing contrary results for non-energy-intensive companies, Tang and Demeritt (2018) report that UK-firms within energy-intensive sectors are capable of pointing at tangible improvements in carbon performance following carbon reporting. Alsaifi (2021) contributes results consistent with the “outside-in” view, applying an instrumental variable two-stage approach, finding that carbon disclosure scores of FTSE350 firms for the period from 2007 to 2015 are associated to lower carbon intensity.

Based on this line of argumentation, the following hypothesis can be formulated:

H1: Carbon performance is positively affected by preceding carbon disclosure through the CDP.

2.2. The “legitimacy” view – disclose to conform

Grounded within socio-politics, formulating that economics cannot be isolated from politics, society and institutions giving frame to it (Gray, Kouhy & Lavers, 1995), legitimacy theory assumes disclosure to be determined by a function of social and political pressures that corporations are encountered with (Clarkson et al., 2008). Legitimacy, considered a status rather than a process, can only be prevalent if a company’s value construct is in accordance with the values of the system that it belongs to and is endangered if any case of discrepancy between the two exists, either factual or only unrealized (Lindblom, 1994).

An existence threat caused by lacking legitimacy can express itself in legal, economic, or other social sanctions. Therefore, firms will act to maintain their perceived legitimacy by changing their output and operations to conform to expectations of the public, by attempting to shape the public perception of what legitimacy is, or by means of communication that emphasize legitimate actions of the firm (Dowling & Pfeffer, 1975). In this light, disclosure is assumed to be a legitimacy tool and would neither mirror nor have a positive impact on performance, but only demonstrates the adherence to social norms and regulations demanding it. As such, it is rather a ritualistic deed driven by a compliance culture consistent with a "tick-box attitude" (Tang & Demeritt, 2018).

Confirming a potential legitimation purpose of carbon disclosure, Matisoff (2013) uses propensity score matching to find that corporate disclosure through mandatory reporting schemes in the US is not connected to a decrease in emissions or emission intensity, whereas CDP participation is even associated with an increase in carbon dioxide (CO_2) intensity. In the same vein, He, Tang and Wang (2013), observe a negative relation of CDP's disclosure score of S&P 500 firms in 2010 with subsequent carbon performance. Applying a mixed-method approach Tang and Demeritt (2018), confirm that UK-listed firms under a mandatory reporting scheme outside of energy-intensive sectors do not report to achieve enhanced output of emissions, but for legitimacy reasons. Using Bloomberg's environmental disclosure score within a simultaneous equations model to circumvent endogeneity risks, Hassan and Romilly (2018) investigate a multi-year sample of global scope, observing that worse environmental performance is precedented by increased disclosure.

Following this line of evidence, better carbon disclosure is linked to maintaining legitimacy (Luo, 2019), while future carbon performance is not significantly affected by it. Therefore, based on the legitimacy view, the subsequent hypothesis is posed:

H2: Carbon performance is not or negatively affected by preceding carbon disclosure through the CDP.

2.3. The "greenwashing" view – disclose to impress

While pressure from organizational outsiders, consistent with socio-political theories, is assumed to affect the corporate disclosure-choice, it may not necessarily bring forth complete and unbiased information (Liesen et al., 2015). Based on the fact that environmental reporting is mostly discretional, disclosure can easily be used for the sole purpose of legitimation, as companies are free to share biased information or selectively communicate to the outside world as they see fit (Gray & Bebbington, 2000), with some companies only disclosing substantially enough to circumvent a closer examination by public (Stanny, 2013).

Further, environmental reporting's predominantly descriptive, hard-to-quantify nature opens the door to purposely shape what and how is being disclosed (Cho, Roberts & Patten, 2010), enabling the establishment of legitimacy and the constitution of a positive public image (Hopwood, 2009). Accordingly, disclosure can be driven by an opportunistic motive and serves an impression management tool which enables strategic introduction of bias into the reporting (Merkl-Davies & Brennan, 2007). Finding its roots in social psychology impression management is concerned with "… how individuals present themselves to other to be perceived favorably" (Hooghiemstra, 2000 p. 60).

Grounded on a thorough analysis of accounting research narratives, Merkl-Davies and Brennan (2007) propose the existence of various strategies for managerial impression management, characterized either by the attempt to conceal information or by the strategic attribution of organizational outcomes. Strategies of the prior mentioned branch emphasize good news, whereas bad news are obfuscated, and make use of thematic or rhetorical manipulation of verbal information. The latter approach aims at entitling the company with positive events while shifting away responsibility for negative news.

Consistent with the suggested framework, this paper focusses on the manipulation of CSR disclosure exclusively via two avenues of impression management, namely (i) the obfuscation of bad news by reading ease manipulation and (ii) the emphasis on good news by thematic manipulation.

The prior avenue is concerned with the reading difficulty of narratives which serves as a proxy for intended obfuscation (Merkl-Davies & Brennan, 2007). Obfuscation itself can be defined as the intentional reduction of message clarity if report preparers wish to disclose less about certain facts, such as poor corporate performance, and is a manipulative writing technique that serves to confuse or distract readers (Courtis, 2004). Supporting the obfuscation hypothesis, i. e. corporations are likely to be more forthcoming in disclosures if they performed well (Li, 2008), Wang, Hsieh and Sarkis (2018) report a positive relation between readability of CSR reports and corporate social performance (CSP). Du and Yu (2020) not only back this claim by examining inter alia the changes in readability of CSR disclosure related to subsequent CSP using ratings of Kinder, Lydenberg, Domini (KLD), but also establish a positive relation between an improvement in readability and cumulative abnormal returns as well as abnormal trading volume. Following a similar research agenda, Muslu et al. (2019) incorporate readability into a disclosure score and contribute evidence that among other factors higher readability of CSR reports leads to more accurate analyst forecasts. Fabrizio and Kim (2016), so far the only scholars to investigate the linguistics used in CDP narratives, propose that the initiative's scores carry information about subsequent greenhouse gas (GHG) emissions for firms with a lower Fog index, i. e. when CDP reports are more readable. In the same vein, they find that CDP report preparers use more obfuscation if they wish to lessen the negative impact of lower CDP scores (Fabrizio & Kim, 2019).

The latter avenue is grounded on the hypothesis that management is reluctant to share bad news and consequently either refrains from reporting it at all or not as extensively as good news (Merkl-Davies & Brennan, 2007). In the realm of environmental reporting the selective disclosure of positive while holding back negative information is often referred to as greenwashing (Lyon & Maxwell, 2011). Due to stakeholder dependence on corporate communication and the hardship to directly evaluate corporate environmental performance themselves, it constitutes a common phenomenon in environmental reporting (Bowen & Aragon-Correa, 2014). Cho, Roberts and Patten (2010) report that firms instrumentalize biased language in form of a more optimistic and less certain tone in order to depict their environmental performance more favorably. Accordingly, they find a negative relation between tone and subsequent CSP, measured via the KLD score. Incorporating tone as positivity and negativity into an aggregate disclosure quality score, Muslu et al. (2019) associate positivity with lower disclosure quality and relate it to higher analyst forecast errors.

Along the lines of the framework, we expect the manipulation of verbal information in disclosure to be consciously biased, resulting in less reliable data, which can be defined as lacking quality and materiality (Global Reporting Initiative, 2013). Accounting for the notion that impression management is more likely a response to negative organizational outcomes (Merkl-Davies & Brennan, 2007), companies that fall short of a pursued benchmark are particularly motivated to manage impressions (Cho, Roberts & Patten, 2010).

Accordingly, it is hypothesized that companies sharing carbon disclosure of lower informational quality, applying more impression management, will show a subsequent carbon performance that is not congruent with preceding reporting, or put differently:

H3: Carbon performance is negatively affected by lower preceding disclosure quality.

3. Quantifying disclosure quality

Voluntary CSR disclosure, and as such the carbon emission reports of CDP, differentiate themselves from financial reporting, as they are not subject to regulatory frameworks and since CSR reporting relies widely on hard-to-quantify, descriptive content (Du & Yu, 2020). This implies that voluntary disclosure can only then carry informational value and be useful for decision-making if the information provided is reliable, i. e. if it possesses a certain quality (Andrew & Cortese, 2011a).

Instead of determining quality by one of the common approaches, namely employing a content analysis or simply applying the CDP disclosure score as an indicator for quality (Hahn, Reimsbach & Schiemann, 2015), the quality of disclosure is derived by examining the textual properties of the report narratives. As such, we employ insights extracted by a growing field of research that examines the informational value of text within corporate reporting and other market-relevant sources using computer-aided text analysis (CATA), which is backed by current technological developments and enabled through growing availability of data (Zhang, Stone & Xie, 2019).

Taking into account that CDP's questionnaires are based on quantitative as well as qualitative questions that evaluate the disclosers' progress towards good environmental management as communicated via their survey responses (CDP, 2019a, 2019b), the deliberate provision of information may be driven by opportunism, meaning that firms may engage in impression management (Cormier & Magnan, 2015). This phenomenon is potentially further facilitated through the fact that CDP respondents are free to selectively choose what information sets to share (Andrew & Cortese, 2011b) and due to the lack of verification of provided data (CDP, 2019b). Answering to these caveats of the reports, CATA promises a more objective analysis of disclosure quality while enabling the evaluation of large samples (Muslu et al., 2019).

Applying insights from the textual analysis of narratives within the realm of environmental reporting and CSR, a disclosure quality score of CDP reports using the following components is derived:

1. *Tone:* Accounting for potential opportunistic reporting behavior and greenwashing tendencies, leading to disclosure of proportionally more positive than negative environmental information (Lyon & Maxwell, 2011), firms disclosing more negative aspects are expected to be more credible. In concordance with prior empirical evidence

(Cho, Roberts & Patten, 2010; Muslu et al., 2019), CDP reports with more positivity (POS) and less negativity (NEG) are considered to be of lower disclosure quality. The overall tone (TONE) is evaluated by using the commonly applied word list of financial positive and negative words created by Loughran and McDonald (2011) that mitigates noise by considering the business context of certain words, such as "liability", to avoid wrong detection of negative or positive words due to the nature of corporate reporting. Applying a so-called bag-of-words approach (Davis et al., 2015), TONE is eventually calculated as the matches of positive words over the section's total words minus the matches of negative words, corrected for respective instances that have been negated within their closer surrounding.

2. *Readability:* Following the obfuscation hypothesis, firms produce less readable reports to hide bad performance (Li, 2008), whereas good performers are assumed to increase transparency to signal their doing (Muslu et al., 2019). So, if firms with more readable CDP reports intend to obfuscate less, their reports can be considered more transparent and therefore of higher quality. An established set of formulae employed in CATA quantifies readability by approximating a text's complexity considering average sentence length, average syllables per word as well as the proportion of polysyllabic words (Smeuninx, Clerck & Aerts, 2020). Applying the SMOG (Simple Measure of Gobbledygook) index, formerly used to denote texts with the required years of formal education for full comprehension (McLaughlin, 1969), the readability of the reports is measured. Eventually, answers with higher SMOG scores indicate lower report quality and greater impression management tendencies.
3. *Length:* Also anchored in obfuscation theory, length of disclosure is considered. Following Muslu et al. (2019), disclosure length is separated from text complexity to circumvent a confounding effect. Therefore, the residuals, called RESWORDS, from the regression of text length on the respective section's SMOG score are considered. Expecting good performers to be more forthcoming (Li, 2008), longer texts are considered to be composed by good performers with no intention to hide information and vice versa.

The parts of the CDP questionnaire that are used to construct the corpus, a term to refer to a sample of linguistic data that is analyzed via computer-based analytical techniques for pattern recognition and language analysis (Anthony, 2013), are based on sections that encourage a substantial textual response, so that meaningful quality measures can be ensured. The respective indicators are derived separately per observed question and year and then averaged yearly per measurement component and firm.

Further, the three components are then transformed to uniformly distributed variables ranging from 0 to 1 by ranking the companies yearly into centiles, before an aggregated quality score (IMPRESSION) is built. Firms with lower reporting quality are expected to apply more impression management and greenwashing and will have a higher score. As such, a higher score is indicated by more positivity and less readable disclosure that is less extensive.

Details on the process of textual analysis, the computation of score components and the composition of the aggregate score are described in Appendices 1 and 2.

4. Research design

4.1. Sample selection and sample distribution

The empirical analysis is based on carbon information collected through disclosure to the CDP for the period from 2010 to 2019. On the behalf of investors and stakeholders the CDP sends annual climate change questionnaires to targeted companies globally and uses voluntarily provided information to score firms on their progress towards environmental stewardship. It motivates measurement and management of risks and opportunities connected to climate change and constitutes the biggest repository of carbon disclosure data worldwide (CDP, 2020b), finding application in numerous studies examining the phenomenon of carbon reporting (e. g. Matisoff, 2013; Qian & Schaltegger, 2017; Fabrizio & Kim, 2019).

As can be seen in Table 1 the CDP observations are constituted of 14,363 firm-year observations over the course of ten years, forming an unbalanced panel data set with almost 50% of data stemming from the US, the UK, Japan, and Canada. The distribution of disclosers by ICB industry in Table 2 is dominated by firms of the industrial and consumer discretionary sector, accounting for more than a quarter of the total sample. Table 3 and 4 show on the one hand the temporal distribution of public CDP respondents and on the other hand the distribution by performance score. While the prior points at a rising tendency of firms to disclose, the latter indicates that more than 50% of all companies rated received the grading “B” or better.

4.2. Research model

The analysis builds up on a panel data approach allowing to control for unobservable firm heterogeneities. Equation 1 serves to examine the effect of carbon disclosure on subsequent carbon emission intensity change and is used to make inferences about H1 and H2, while conclusions about H3 are based on Equation 2, capturing the impact of impression management and decreased disclosure quality standalone on performance change, as well as Equation 3, using the variable together with disclosure performance.

$$\Delta \mathrm{CARBON}_{it+1} = \alpha_i + \beta \mathrm{CDP\_SCORE}_{it} + \gamma \Delta \mathrm{Controls}_{it} + \delta \mathrm{FE}_i + \varepsilon_{it} \quad (1)$$

$$\Delta \mathrm{CARBON}_{it+1} = \alpha_i + \theta \mathrm{IMPRESSION}_{it} + \gamma \Delta \mathrm{Controls}_{it} + \delta \mathrm{FE}_i + \varepsilon_{it} \quad (2)$$

$$\Delta \mathrm{CARBON}_{it+1} = \alpha_i + \beta \mathrm{CDP\_SCORE}_{it} + \theta \mathrm{IMPRESSION}_{it} + \gamma \Delta \mathrm{Controls}_{it} \quad (3)$$

$$+ \delta \mathrm{FE}_i + \varepsilon_{it}$$

In the described models ΔCARBON for firm i is the change in carbon emission intensity from year t to t+1. Following Busch and Hoffmann (2011) , the measure of emission intensity is derived by dividing the sum of emissions of scope 1 and scope 2 by a firm's net sales. Winsorizing the changes at 2% and 98% mitigates the impact of outliers in the measurements.

CDP_SCORE is the performance score given by CDP to mirror the detail as well as completeness of disclosure, corporations' awareness of climate issues, their environmental management methods, and the effort to develop towards exemplary environmental-conscious business conduct. Questions are evaluated across four successive levels called "Disclosure", "Awareness", "Management" and "Leadership", representing progressive steps towards environmental stewardship, with the respective letter scores reaching from "Disclosure" as "D" to "Leadership" denoted with "A" (CDP, 2019b). Earlier versions of the score further included the letter "E" for companies that had only started to disclose environmental information (Giannarakis, Zafeiriou & Sariannidis, 2017). The performance letters are recoded to numerical values, reaching from 1 to 5, where "A" equals 5. IMPRESSION is the derived quality score indicating impression management and greenwashing tendencies ranging from 0, indicating higher quality and less opportunistic reporting intentions, to 3. Since we aim at investigating the change induced by companies' current reporting, i. e. the most recent performance score and disclosure quality, CDP_SCORE and IMPRESSION are not used as change variables.

Control variables are based on earlier studies assessing the impact of environmental disclosure on environmental performance. Since SIZE has been a commonly controlled aspect in prior studies, we include total assets as a proxy. As suggested by Clarkson et al. (2011), larger firms are not only inclined to invest more in advanced, clean technology due to increased access to resources, but also since they face higher risks of litigation by being more prominent and by being confronted with higher public pressure (Luo, Tang & Lan, 2013). Leverage (LEV), as total debt over total assets, and profitability (ROA), as net income before extraordinary items over total assets, are used to control for the availability of financial resources, exploitable for financing of carbon disclosure and emission reductions. In the same vein, GROWTH, calculated as the change in net sales from the prior to the current year, is included, since growing companies are expected to use funds rather for economic expansion than for corporate greening (Luo, Tang & Lan, 2013). On the contrary, capital intensity (CAP), as capital expenditures divided by total assets, controls for companies that invest more in new, potentially more efficient equipment and technologies, leading to enhanced environmental performance. Based on the same assumption, asset newness proxied via the ratio of net property, plant and equipment (PPE) to gross PPE is used as NEW (Clarkson et al., 2008).[d] The changes of all control variables are calculated as percentage changes from the prior to the current year. Additionally, all change variables are winsorized at 2% and 98%, respectively, to mitigate the impact of outliers in the data.

The models apply a lead-lag method to account for the fact that changes in carbon performance may lack behind the respective act of carbon disclosure. Accordingly, the panel data is effectively reduced to nine years of observations. An overview of all variables used as well as details on their respective measurement can be found in Table 5.

5. Empirical results

5.1. Descriptive statistics

First, the overall carbon disclosure profile is summarized in Table 6 for all firms within the CDP sample from 2010 to 2019 with full carbon emissions and reporting data, corresponding to 5,460 firm-year instances.

As depicted in the table, the mean CARBON is 1.356, with big outliers as indicated by its very high standard deviation and low median at 0.037. Accordingly, the average company emits 1,356 kg per 1,000 $ of net sales, with some corporations beyond the 95th percentile, emitting

[d] Similarly, research and development expenses could be included to proxy advances in technology that could lead to greener operations. Since its inclusion drastically reduces observations, we follow Delmas et al. (2015) and refrain from incorporating the measure.

higher amounts per sales. With a mean carbon disclosure performance of 3.925 companies' disclosure ratings are on average on the upper end, as earlier indicated by the distributional properties of the performance score. Generally, the range from the 5th to the 95th percentile is rather low with values reaching from 3 to 5, pointing at the fact that most companies that agree to publish their emission data receive good scores. The sample's quality score IMPRESSION is close to a normal distribution with a mean of 1.470 and a standard deviation of 0.487 with no notable skewness. Figures 1 to 4 further illustrate the carbon emission profiles of firms, based on (i) carbon emission intensity and (ii) carbon emission intensity change as well as (a) per CDP score and (b) per equally sized quantiles of IMPRESSION. As shown by the box plots, neither CDP_SCORE nor IMPRESSION are clearly indicative of lower carbon emission intensities in t+1. A similar picture is drawn by the plots depicting emission intensity changes per score category, with the subtle indication that emission intensity per CDP_SCORE may increase due to the increased occurrence of outliers.

Table 7 presents the descriptive statistics for all variables used in the study, encompassing all financial change variables included in the estimation for control purposes. Due to the non-completeness of companies' financial records as well as the lead-lag approach, the sample is effectively reduced to 2,811 firm-year observations. Results show that the average ΔCARBON is 0.026, suggesting that the average company increases its carbon emission intensity. However, the respective median shows a reduction of carbon emission intensity, with -0.022 corresponding to a 2.2% reduction, again indicating the existence of outliers that more drastically increased their emission output relatively to sales. CDP_SCORE is concentrated at the upper end of its value range, indicating rather good performance ratings, while IMPRESSION stays widely normally distributed. The results further reveal that firms within the sample grew on average by 3.8% per year throughout the observed period. However, the average company decreased its sales growth by 76.3% a year. Looking at the respective median, with -67.2%, draws a similar picture giving indications that the sample reduced its growth throughout the observed period, pointing at a potential maturing process of companies. Further, values at the 5th and 95th percentile as well as the large standard deviation reveal the existence of outliers on both ends of the distribution. A mean ΔLEV of 6.1% suggests that average firms employed increasingly less equity over the years, while mean and median values of ΔROA, with 23.8% and 2.1% growth, point at enhanced profitability of observed companies, with some firms being increasing profitability far more than the sample average. Looking at ΔCAP, a mean increase of 7.8% is revealed, indicating the corporate tendency to invest increasingly more in equipment. However, ΔNEW shows mean and median values hovering close to zero, showing that firms did not necessarily decrease overall equipment age.

5.2. Correlation coefficients

The findings of the correlation test of the variables that are included in the estimation models are shown in Table 8. While ΔCARBON shows a rather low correlation to all control variables, significant Pearson coefficients ρ of 0.061 and 0.031 with CDP_SCORE and IMPRESSION, respectively, indicate a positive correlation of the variables, supported through similar findings of the Spearman correlation. It is further remarkable that CDP_SCORE and IMPRESSION are significantly, positively correlated with a ρ of 0.106 (0.125 for Spearman correlation). None of the control variables exhibits a high, significant correlation to each other, letting assume that multicollinearity is no issue.

5.3. Multivariate analysis

Empirical results of the models applied are presented in Tables 9 to 11. Mitigating a potential bias in model selection, originating from precarious assumptions in the often relied upon Hausman test (Woolridge, 2002), we apply random and fixed effect models to investigate the relation between carbon disclosure performance and quality and subsequent carbon intensity.

All results considered, the "outside-in" management view of the effect of carbon disclosure on carbon performance finds no support. On the contrary, it can be shown that better carbon disclosure performance rather amplifies carbon emission intensity in the following year, underpinning notions made by advocates of the legitimacy theory, supporting findings of Matisoff (2013) and Hassan and Romilly (2018). , indicating an increase of 3.4% in carbon emission intensity per CDP_SCORE. Similar results are observed for the effect of IMPRESSION in Table 10, leading to significant results at the 10% level for random and year and/or industry fixed effects. Observing the impact of both variables together in Table 11, the effects remain for CDP_SCORE, while coefficients of IMPRESSION lose their significance, yet still predict a positive relation. Based on these findings, H1 grounded on the legitimacy view can be supported, whereas H2, stating that enhanced disclosure performance leads to decreased emission intensity, is rejected. Moreover, H3 can partially be confirmed, since decreased disclosure quality proxied via IMPRESSION can be associated with following increases in emission intensity.

Furthermore, the control variables ΔSIZE and ΔCAP noticeably affect ΔCARBON, confirming observations of Qian and Schaltegger (2017). As can be followed in Table 11, random and industry fixed effect models indicate with a significance level of 10% that companies gaining size reduce their emission intensity. This implies that bigger companies have the possibility to produce and sell more relative to their emission output, underlining that they possess more efficient operations driven by economies of scale. ΔCAP is significantly associated with lower subsequent emission intensities throughout all models at the 10% level and for year and year as well as country fixed effects even at the 5% level. Accordingly, it seems that companies spending higher amounts for capital expenditures are more likely capable of managing emissions, potentially driven by investments in technologically advanced, greener equipment. All other financial variables are not significantly contributing to ΔCARBON.

5.4. Additional analysis

Three additional sets of tests related to (i) sample composition, (ii) the definition of carbon performance and (iii) methodological issues are undertaken to investigate the relation more thoroughly.

To answer to potential differences due to year, industry, or country driven specifics, different sub-samples are employed. First, the sample is divided into two periods (2010-2014 and 2015-2019) to account for time trends. With 1,621 and 1,190 firm-year observations, respectively, the set of tests depicted in Tables 12 and 13 yields that before 2015 CDP_SCORE gave a slight indication about future carbon performance, with negative, however not significant coefficients. However, the years from 2015 to 2019 indicate the same effect that is seen for the complete sample, only slightly more pronounced, which suggests that disclosure to the CDP has become with increasing likelihood rather a vehicle for legitimation. Also, the impact of IMPRESSION builds up from the years before 2015 to more recent times, underlining a potential opportunistic tendency that is however not statistically significant. Second, we account for industry factors through the dummy variable ENV_SENS, coded 1 for the sectors energy, materials or utilities, and 0 otherwise, as these are commonly considered environmentally-sensitive industries, and split the sample accordingly (Deegan & Gordon, 1996). Companies operating in the first-mentioned category are expected to be watched more closely by stakeholders and are potentially imposed to higher political costs (Cho & Patten, 2007). Following among others Qian and Schaltegger (2017), the increased public scrutiny leads to amplified exposure to carbon risks, motivating the fact to differentiate between the two. Tables 14 and 15 use samples reduced to 581 and 2,230 firm-year observations that belong to ENV_SENS=1, and 0 otherwise, showing that CDP_SCORE's effect is widely alike for both samples as well as when compared to the complete sample. Noticeable is that IMPRESSION contributes to a bigger extent to a positive ΔCARBON for non-environmentally-sensitive corporations, providing support that such firms are more likely to employ opportunistic reporting behavior, as they are subject to less severe scrutiny by stakeholders. Third, for the construction of sub-samples based on country characteristics firms operating either in common law countries or in countries with national ETS in place are considered. As shown by La Porta et al. (1998) common law countries (see Appendix 3 for overview) tend to have stronger legal protection of stakeholders and creditors, leading to predict that firms in those countries are more transparent, i. e. they more likely disclose truthfully (Luo, Tang & Lan, 2013). As such, Tables 16 and 17, constituted of 1,443 observations of civil and 1,368 of common law countries, point at a difference in legitimation and opportunistic tendencies. While firms based in countries governed by common law show no indication of using disclosure to legitimate themselves or even shape their impression willfully, companies that are subject to civil law ruling possess CDP_SCORES that indicate an increase in emission intensity, like evidenced for the full sample. More particularly still, those firms are more likely to apply impression management and greenwashing prior to poor environmental performance, as indicated by positive, significant IMPRESSION coefficients at the 10% level for industry as well as industry and country fixed effects. Similar tendencies are observed for samples split according to whether companies' headquarters are based in countries with a national ETS in place or not (see Appendix 4 for overview), since firms are more incentivized to decrease emission output if they face direct costs in form of carbon prices imposed by the schemes (Luo, Tang & Lan, 2013). Tables 18 and 19 based on samples without and with ETS, respectively, underline that CDP_SCORE and IMPRESSION do not contribute to a significant change in emission intensity if firms operate under the influence of a trading scheme, whereas the missing financial incentive in countries without ETS spurs opportunistic disclosure, observed via IMPRESSION, and leads to the fact that CDP_SCORES are rather indicative of future emission intensity growth.

Answering to potential differences in how carbon performance is measured, since different measurements may lead to diverging results (Busch & Lewandowski, 2018; Doan & Sassen, 2020), ΔCARBON is split into changes in intensity of scope 1 and scope 2 emissions, respectively. Since only first mentioned are regulated by mandatory schemes within certain countries on a corporate level and companies are obliged to control them (Matisoff, Noonan & O'Brien, 2013), firms may have greater power to influence the intensity of such direct, self-produced CO_2 emissions, whereas the second, referring to indirectly emitted CO_2, may less likely be within their reach of impact. Emphasized by Tables 20 and 21, IMPRESSION has no influence on either, i. e. emission intensity changes of scope 1 or scope 2. In contrast to this, CDP_SCORE is only exerting a significant positive effect on the change in scope 1 intensity, indicating that scope 1 emissions increase if they follow to good prior carbon disclosure performance. This suggests that CDP disclosure is rather used as a legitimation device, especially for self-procured, direct emissions, than to promote real changes and improvements in firms' own operations.

Allowing for a greater time lag, additional models described in Equations 4 to 6 capture the changes in carbon emission intensity over two periods, i. e. from the current year to t+2.

$$\Delta \mathrm{CARBON}_{it+2} = \alpha_i + \beta \mathrm{CDP\_SCORE}_{it} + \gamma \Delta \mathrm{Controls}_{it} + \delta \mathrm{FE}_i + \varepsilon_{it} \qquad (4)$$

$$\Delta \mathrm{CARBON}_{it+2} = \alpha_i + \theta \mathrm{IMPRESSION}_{it} + \gamma \Delta \mathrm{Controls}_{it} + \delta \mathrm{FE}_i + \varepsilon_{it} \qquad (5)$$

$$\Delta \mathrm{CARBON}_{it+2} = \alpha_i + \beta \mathrm{CDP\_SCORE}_{it} + \theta \mathrm{IMPRESSION}_{it} + \gamma \Delta \mathrm{Controls}_{it} \qquad (6)$$

$$+ \delta \mathrm{FE}_i + \varepsilon_{it}$$

As can be seen in Tables 22 to 24, allowing for a greater time lag, namely from t to t+2, does not yield meaningful results. However, ΔGROWTH consistently adds to the reduction of emission intensity, with significant coefficients at the 5% and 10% level except for year and country fixed effects (see Table 24). This leads to infer that in the long run a positive sales growth is indicative of carbon emission reductions, as economically successful companies may be more likely to reduce their carbon footprints which supports prior results of Qian and Schaltegger (2017).

Last, due to the risk of endogeneity arising from the potential joint determination of CDP participation and environmental performance (Choi & Luo, 2020), we follow the example of prior scholars, such as Li, Eddie and Liu (2014), and correct for a self-selection bias inherent in the decision to voluntary disclose to CDP by applying a Heckman approach (1979). It uses a full information maximum likelihood approach by estimating the disclosure-choice model jointly with the regression of interest within one equation system (Tucker, 2010). The sample of global firms that is required for the disclosure-choice model is constructed via Refinitiv Eikon Datastream and is described in Appendix 5. The disclosure-choice model itself, estimating the probability to disclose to CDP, is based on findings on determinants of environmental disclosure (e. g. Clarkson, 2008; Stanny & Ely, 2008; Prado-Lorenzo et al., 2009; Stanny, 2013; Luo, Tang & Lan, 2013; Matsumara, Prakash & Vera-Muñoz, 2014) and is introduced in detail in Appendix 6. Applying the Heckman correction, as can be seen in Table 25, mostly confirms prior results. As such, CDP_SCORE is associated with higher emission intensities, significant at the 10% level with random effects, industry, country or industry and country fixed effects, while IMPRESSION shows the before observed weak positive, but not significant association with an increase in carbon intensity. However, Chi^2 statistics of the Wald test of independence show that the correction for the self-selection bias is only necessary for models using year or year and industry fixed effects (significant at 5% level) as well as random effects or industry fixed effects (significant at 10% level).

Tying the findings of the supplementary tests together with the results of the main analysis supports that carbon disclosure leads to no substantial improvement of carbon performance. On the contrary, it is mostly used as a legitimation tool, with slight indication of bad performers following more opportunistic reporting behavior, as indicated through IMPRESSION. As emphasized by the investigation of different sub-samples, there seems to be a development towards less predictive power of the scores, since good CDP scores were rather associated with an increase than decrease of carbon emission intensity in recent years. Further, the combination of results hints at the fact, that companies are more likely to apply opportunistic reporting in form of greenwashing and use disclosure more likely to legitimize their operations if they are faced with lower risks of sanctions through stakeholders. As such, the missing economic incentives seem to discourage carbon intensity improvements and rather encourage impression management if companies do not operate in countries governed by common law or that have no ETS in place or simply if they belong to non-carbon-intensive sectors that are subject to less public attention. These findings provide empirical support for Tang and Demeritt's (2018) insights based on interviews, claiming that only the existence of regulation in the UK nudge carbon-intensive industries towards leveraging information received through carbon disclosure to improve their footprint.

6. Conclusion

Borne by the growing attention received by the voluntary carbon disclosure initiative CDP and the reliance of many research undertakings on the reliability of the intermediary's data, this study fills a thus far present research gap by shedding light on the informational value of CDP disclosure concerning its predictive power of future carbon performance. In view of the circumstance that much of the public debate about climate change evolves around the assumed positive impact of disclosure on environmental performance, such an investigation appears to be imperative, particularly since most scholars in the field rather seek to answer questions relating the less critical determinants of disclosure.

So far, the few studies conducted to elaborate on the changes in emission intensity subsequent to carbon disclosure yield mixed evidence, potentially caused by different measures and samples. Nevertheless, they are based on common theoretical frames either shaped by the "outside-in" management view which posits that measuring and disclosing emissions is a first step towards ameliorating carbon-related business conduct or the legitimacy view, assuming disclosure to be a tool to solely answer to pressure exerted by stakeholder, thus invoking no carbon improvements. Further, we complement those views by the aspect of impression management, theorizing that low quality disclosure, proxied via computer-based linguistic analysis of disclosure narratives, is indicative of impression management and greenwashing intents. Consequently, it impairs the informational value of CDP scores, which eventually leads to the fact that for more opportunistic reporters the CDP score is even less indicative of future carbon performance.

Through the analysis of all CDP respondents from the years 2010 to 2019, constituting a multi-country, cross-sectional and longitudinal sample, we observe that the current carbon performance measure provided by CDP is not indicative of future carbon emission intensity improvements. More specifically, this study finds good CDP scores to empirically have a rather amplifying effect on following carbon footprints, underlining the notion of disclosure being more likely a legitimacy tool than a catalyst for improvements. Further, the results cautiously support the fact that decreased disclosure quality and more greenwashing tendencies can be observed prior to increases in emission output. Those findings can be supported by additional tests based on carbon measurements of scope 1 and scope 2, respectively, and accounting for self-selection bias inherent in the voluntary CDP participation. For companies that are expected to be less likely subject of increased public and political attention or stakeholder pressure, weakened economic incentives seemingly discourage substantial changes in corporate carbon-conduct. Hence, firms do not walk the talk if they are not operating under regulations imposed by ETS or if they are not experiencing increased scrutiny by either belonging to carbon-intensive industries or originating from common law countries. On the contrary, empirical results even weakly support that they are more inclined to report opportunistically by producing low-quality reports to cover potential bad performance, contributing to observations made by Fabrizio and Kim (2019).

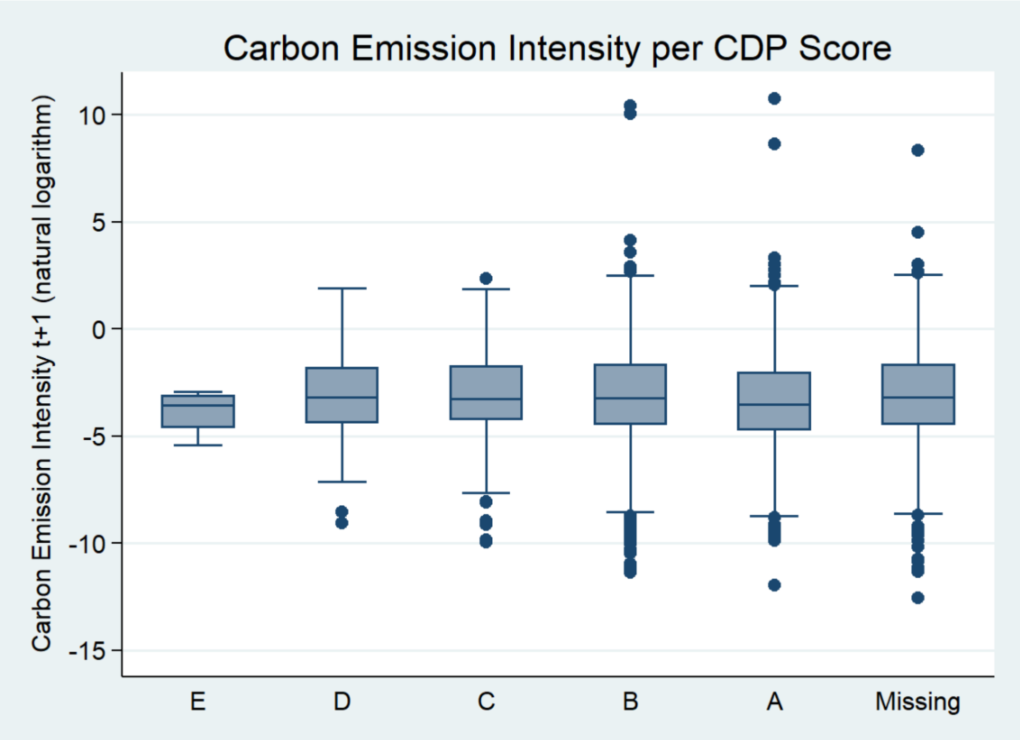
Following these findings, several implications can be drawn. Foremost, it is revealed that motivators for carbon emission improvements are seemingly dominated by external factors, implying that if companies do not perceive pressure through regulations or stakeholders, the chances of carbon improvements are slim. Accordingly, it seems that corporates themselves still see disclosure as a reactive rather than proactive exercise, missing the chance to leverage insights gained through the disclosure. This further insinuates that real change might require stricter regulations across all industries and countries. For policy makers this suggests that globally more binding carbon reporting regulations can serve the necessary impetus to nudge companies towards using disclosure as a motivation to improve carbon footprints, as actually intended by the current disclosure initiatives. At the same time, the findings subtly suggest that CDP itself needs to re-evaluate whether their scores in order to match their self-acclaimed purpose of recognizing and acknowledging leadership towards exceptional environmental conduct with good scores. As such, their scoring may be ameliorated by giving more weight to verifiable long-term improvement of carbon emission intensity and by being aware of potential biases in narratives, introduced through impression management and greenwashing, to enhance scores' informational and predictive values. In this context, it seems particularly troublesome if investors and stakeholders alike rely on the aggregated score awarded by CDP, believing that the performance bands yield material information and leverage them among other uses data for valuation purposes. Last, the findings imply that studies investigating a potential financial impact of disclosure, considering the reliability and materiality of carbon disclosure as a given pre-requisite, should exercise caution when using CDP's performance band as a source of information.

When interpreting the results of this study, certain limitations may need to be considered. Although we neither limit the analysis to specific geographies nor industries and cover a longer period than most other investigations, our study's sample relies on relatively large, publicly traded companies, as those are mostly targeted to respond to the CDP questionnaire and take part in the program. Further, despite grounding the analysis on justified measures and controls, we may face limitations regarding proxies that were not included in our models. Being aware of the benefits of extending a lead-lag analysis on the effect of environmental disclosure over longer time periods (Horváthová, 2010), the thus far limited data did not allow an investigation of a lagged effect of more than two years. Last, deriving disclosure quality via text analysis yields per se an objective approach, is however dependent on certain aspects facing potential shortcomings. As such, the linguistic analysis is based on word lists created for financial documents (Loughran & McDonald, 2016). Despite their common application, they may not consider the CSR-context of words used and may therefore potentially introduce noise in the measurement and not correctly account for the nature of the reports (Du & Yu, 2020). Additionally, the text analysis is based on sub-sections of the questionnaire that may not be representative of the whole reporting behavior and therefore of overall impression management tendencies and disclosure quality.

Providing empirical evidence that disclosure performance scores provided by CDP do not invoke subsequent improvements in carbon emissions, our study gives only indications about the impact of public attention and stakeholder pressure on the link between disclosure and performance and their specific relations to legitimation as well as greenwashing tendencies. Future research endeavors may investigate the effect of carbon disclosure and its quality in conjunction with public visibility of companies. Further, taking into consideration that measuring disclosure quality is a cumbersome process, additional research may not only further develop the quantification of disclosure quality, opportunistic reporting behavior and as such impression management and greenwashing intents through explorative, computer-based analysis, such as Bayesian networks, but could also consider other corporate information sources of environmental reporting to gain a more holistic insight into the matter.

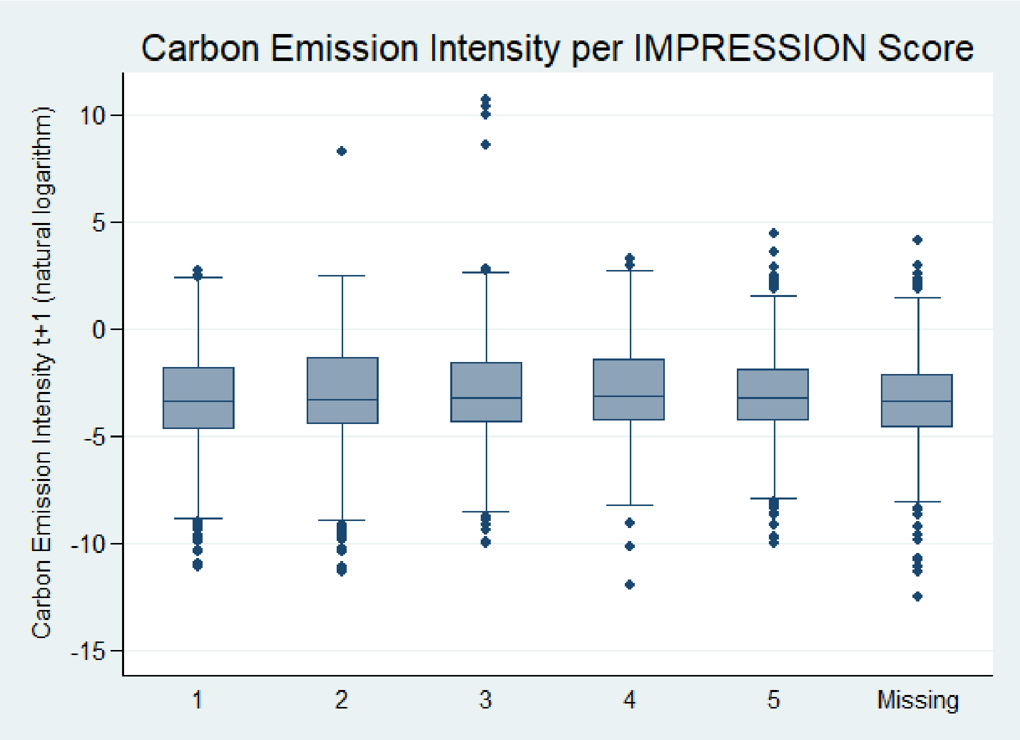
Figures and tables

Figure 1 – Carbon emission intensity (t+1) per CDP score



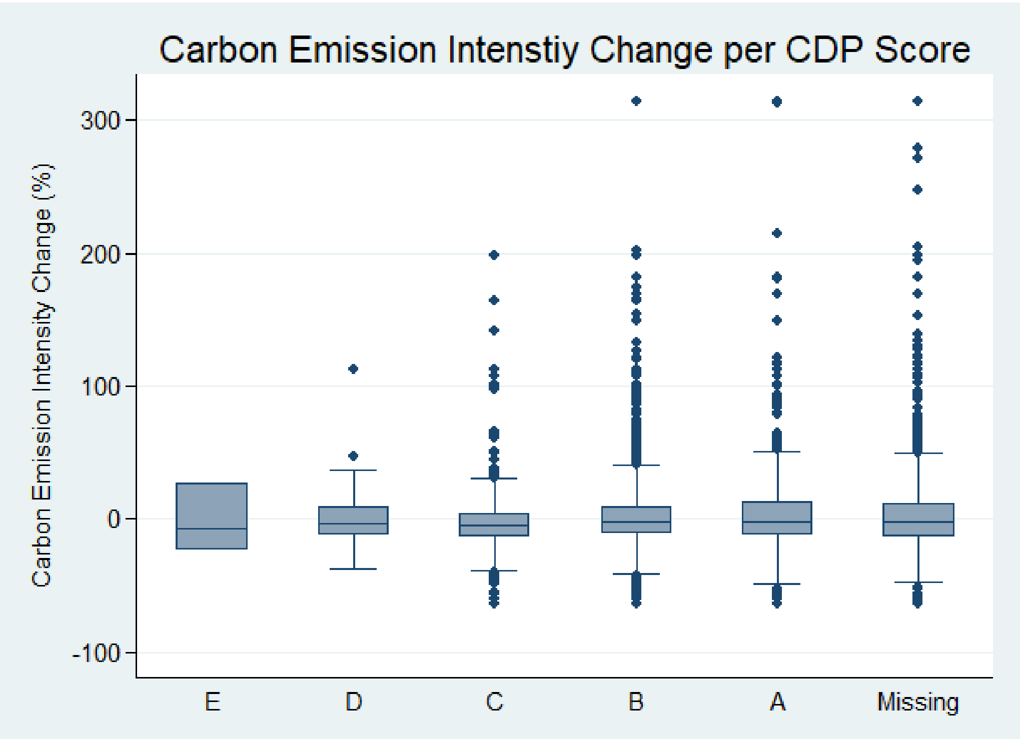
Notes: The figure depicts the natural logarithm of carbon emission intensity of t+1, calculated as scope 1 and scope 2 emissions per 1,000 $ of net sales, per CDP score category of t, ranging from "E" to "A".

Figure 2 – Carbon emission intensity (t+1) per IMPRESSION score



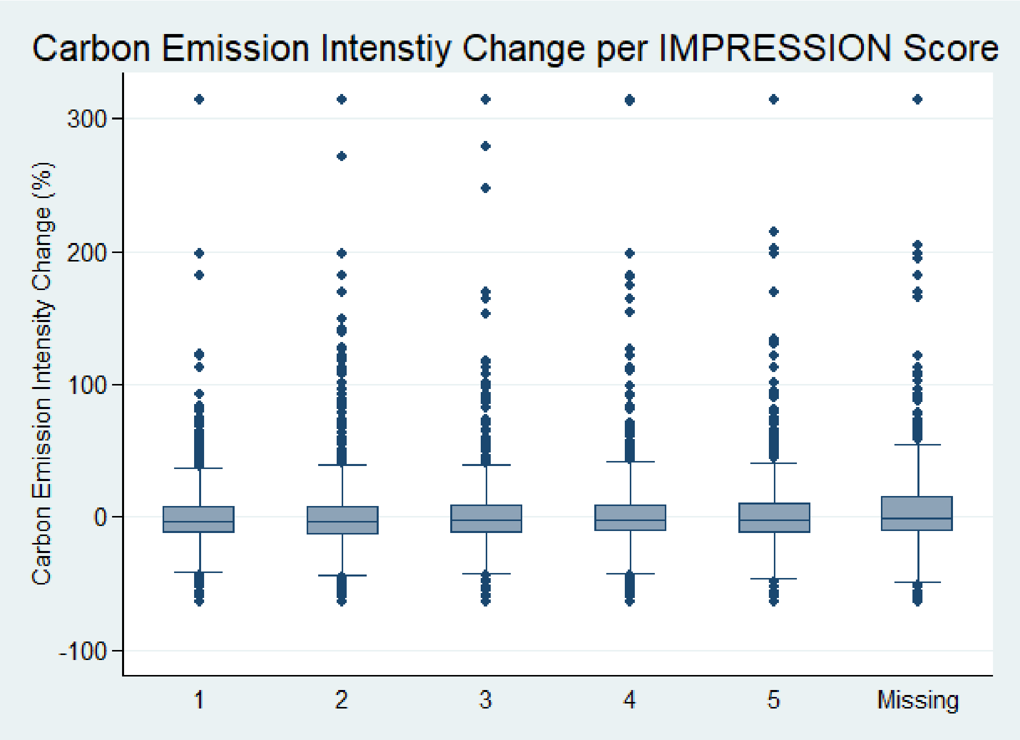
Notes: The figure depicts the natural logarithm of carbon emission intensity of t+1, calculated as scope 1 and scope 2 emissions per 1,000 $ of net sales, per IMPRESSION score category of t, based on five quantiles of equal size.

Figure 3 – Carbon emission intensity change per CDP score



Notes: The figure depicts the change of carbon emission intensity from t to t+1, calculated as the percentage change of scope 1 and scope 2 emissions per 1,000 $ of net sales, per CDP score category of t, ranging from “E” to “A”.

Figure 4 – Carbon emission intensity change per IMPRESSION score



Notes: The figure depicts the change of carbon emission intensity from t to t+1, calculated as the percentage change of scope 1 and scope 2 emissions per 1,000 $ of net sales, per IMPRESSION score category of t, based on five quantiles of equal size.

Table 1 – CDP sample observations per country

Country	Frequency	Percent	Cumulative
USA	3,031	21.10	21.10
United Kingdom	1,745	12.15	33.25
Japan	1,604	11.17	44.42
Canada	665	4.63	49.05
South Africa	607	4.23	53.28
France	606	4.22	57.49
Australia	523	3.64	61.14
Germany	506	3.52	64.66
Sweden	424	2.95	67.61
Switzerland	409	2.85	70.46
Korea	383	2.67	73.13
Spain	317	2.21	75.33
Brazil	313	2.18	77.51
Finland	287	2.00	79.51
Italy	269	1.87	81.38
Norway	248	1.73	83.11
Netherlands	215	1.50	84.61
Denmark	177	1.23	85.84
India	172	1.20	87.04
Turkey	148	1.03	88.07
Taiwan	145	1.01	89.08
Ireland	101	0.70	89.78
Na	526	3.66	93.44
Other	942	6.56	100.00
Total	14,363	100.00	

Notes: The table presents the geographical distribution of the CDP sample based on countries, showing absolute frequency, percentage as well cumulative percentage.

Table 2 – CDP sample observations per ICB industry name

ICB Industry Name	Frequency	Percent	Cumulative
Industrials	2,352	16.38	16.38
Consumer Discretionary	1,704	11.86	28.24
Financials	1,601	11.15	39.39
Basic Materials	1,061	7.39	46.78
Consumer Staples	946	6.59	53.37
Technology	894	6.22	59.59
Utilities	675	4.70	64.29
Energy	652	4.54	68.83
Health Care	640	4.46	73.29
Telecommunications	481	3.35	76.64
Real Estate	477	3.32	79.96
Na	2,880	20.04	100.00
Total	14,363	100.00	

Notes: The table presents the sectoral distribution of the CDP sample based on ICB industry codes, showing absolute frequency, percentage as well cumulative percentage.

Table 3 – CDP sample observations per year

Project Year	Frequency	Percent	Cumulative
2010	616	4.29	4.29
2011	969	6.75	11.04
2012	1,207	8.40	19.44
2013	1,271	8.85	28.29
2014	1,420	9.89	38.17
2015	1,629	11.34	49.52
2016	1,821	12.68	62.19
2017	1,925	13.40	75.60
2018	1,640	11.42	87.02
2019	1,865	12.98	100.00
Total	14,363	100.00	

Notes: The table presents the yearly distribution of the CDP sample based on project year, showing absolute frequency, percentage as well cumulative percentage.

Table 4 – CDP sample observations per performance score

Performance Score	Frequency	Percent	Cumulative
A	1,225	8.53	8.53
A-	1,522	10.60	19.13
B	4,487	31.24	50.37
B-	214	1.49	51.86
C	3,947	27.48	79.34
C-	76	0.53	79.86
D	2,255	15.70	95.56
D-	136	0.95	96.51
E	501	3.49	100.00
Total	14,363	100.00	

Notes: The table presents the distribution of the CDP sample based on performance score, showing absolute frequency, percentage as well cumulative percentage.

Table 5 – Overview of variable measurements

Variable	Abbreviation	Source	Description
Carbon emission intensity	CARBON	Refinitiv Eikon Datastream	Calculated as the sum of scope 1 and scope 2 emissions reported to CDP (in t+1) scaled by net sales (item WC01001); winsorized at 2% and 98%
Disclosure performance score	CDP_SCORE	CDP reports from 2010 to 2019	Performance score collected from CDP reports; originally ranging from "E" to "A" it was recoded to numerical values from 1 (="E") to 5 (="A")
Disclosure quality score	IMPRESSION	Text analysis of CDP reports	Disclosure quality score indicating impression management tendencies retrieved via text analysis
Total assets	SIZE	Refinitiv Eikon Datastream	Measured as total assets (item WC029999); winsorized at 2% and 98%
Leverage	LEV	Refinitiv Eikon Datastream	Measured as total debt to total assets (item WC08236); winsorized at 2% and 98%
Return on assets	ROA	Refinitiv Eikon Datastream	Measured as net income to common shareholders (item WC01751) scaled by total assets (item WC08416); winsorized at 2% and 98%
Growth	GROWTH	Refinitiv Eikon Datastream	Measured as the annual percent change in net sales (item WC01001); winsorized at 2% and 98%
Capital intensity	CAP	Refinitiv Eikon Datastream	Measured as capital expenditures scaled by total assets (item WC08416); winsorized at 2% and 98%
Asset newness	NEW	Refinitiv Eikon Datastream	Measured as ratio of net property, plant and equipment (item WC02501) to gross property, plant and equipment (item WC02301); winsorized at 2% and 98%

Notes: The table presents the variables used for the study, their sources and a detailed description of the measurement or calculation.

Table 6 – Overview of carbon emissions and reporting profile

Variable	N	Mean	SD	P5	Median	P95
CARBON	5,460	1.356	76.840	0.001	0.0374	1.260
CDP_SCORE	5,460	3.925	0.643	3.000	4.000	5.000
IMPRESSION	5,460	1.469	0.487	0.681	1.455	2.273

Notes: The table presents descriptive statistics of carbon emission intensity and reporting variables. N = number of observations; SD= standard deviation; P5 and P95 = 5th and 95th percentile of the variables, respectively. Please see detailed variable definitions in Table 5.

Table 7 – Descriptive statistics

Variable	N	Mean	SD	P5	Median	P95
∆CARBON	2,811	0.026	0.345	-0.331	-0.022	0.422
CDP_SCORE	2,811	3.957	0.641	3.000	4.000	5.000
IMPRESSION	2,811	1.466	0.474	0.707	1.455	2.242
∆SIZE	2,811	0.038	0.134	-0.135	0.026	0.259
∆LEV	2,811	0.061	0.458	-0.313	-0.008	0.551
∆ROA	2,811	0.238	1.111	-0.625	0.021	1.653
∆GROWTH	2,811	-0.763	4.414	-6.742	-0.672	4.798
∆CAP	2,811	0.078	0.555	-0.432	0.000	0.763
∆NEW	2,811	-0.002	0.076	-0.084	-0.009	0.100

Notes: The table presents descriptive statistics of the variables of the study. N = number of observations; SD= standard deviation; P5 and P95 = 5th and 95th percentile of the variables, respectively. Please see detailed variable definitions in Table 5.

Table 8 – Correlation coefficients

Variable (N = 2,811)	ΔCARBON	CDP_SCORE	IMPRESSION	ΔSIZE	ΔLEV	ΔROA	ΔGROWTH	ΔCAP	ΔNEW
ΔCARBON	1								
CDP_SCORE	0.061*	1							
IMPRESSION	0.031*	0.106*	1						
ΔSIZE	-0.026	-0.025*	0.003	1					
ΔLEV	0.011	-0.036*	-0.034*	0.130*	1				
ΔROA	0.015	-0.035*	-0.004	0.014*	-0.050*	1			
ΔGROWTH	-0.018	0.018	0.003	0.013*	0.006*	-0.013*	1		
ΔCAP	0.004	-0.014	0.007	0.075*	0.086*	0.055*	-0.003	1	
ΔNEW	-0.006	-0.0398*	-0.015	0.147*	0.143*	-0.005	0.004	0.253*	1

Notes: The table presents Pearson correlation coefficients of the variables of this study. N = number of observations. * represents the significance level at $p < 0.05$ (two-tailed). Please see detailed variable definitions and sources in Table 5.

Table 9 – The effects of carbon disclosure performance on subsequent carbon intensity change

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.034**	0.015	0.033***	0.035***	0.014	0.035***	0.014	0.014
	(3.29)	(1.45)	(3.32)	(3.33)	(1.45)	(3.40)	(1.33)	(1.39)
ΔSIZE	-0.117*	-0.028	-0.108	-0.091	-0.016	-0.087	0.000	0.007
	(-2.14)	(-0.48)	(-1.96)	(-1.61)	(-0.27)	(-1.53)	0.00	(0.11)
ΔLEV	0.011	0.007	0.011	0.012	0.006	0.013	0.008	0.008
	(0.68)	(0.43)	(0.63)	(0.72)	(0.37)	(0.75)	(0.47)	(0.47)
ΔROA	0.001	0.002	0.001	-0.001	0.002	-0.001	0.000	0.000
	(0.13)	(0.32)	(0.16)	(-0.12)	(0.34)	(-0.10)	(0.05)	(0.08)
ΔGROWTH	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	(-1.80)	(-1.43)	(-1.78)	(-1.41)	(-1.42)	(-1.43)	(-1.07)	(-1.09)
ΔCAP	-0.026*	-0.029*	-0.025*	-0.029*	-0.028*	-0.028*	-0.033**	-0.032**
	(-2.19)	(-2.52)	(-2.10)	(-2.43)	(-2.42)	(-2.39)	(-2.79)	(-2.74)
ΔNEW	0.055	0.022	0.042	0.032	0.006	0.023	-0.002	-0.013
	(0.44)	(0.18)	(0.34)	(0.24)	(0.05)	(0.18)	(-0.02)	(-0.11)
Constant	-0.100**	-0.028	-0.100**	-0.105**	0.009	-0.149*	-0.060	-0.033
	(-2.58)	(-0.72)	(-2.60)	(-2.64)	(0.21)	(-2.08)	(-1.34)	(-0.46)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,962	2,962	2,959	2,962	2,959	2,959	2,962	2,959
R^2	0.012	0.029	0.011	0.033	0.033	0.034	0.055	0.056

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance on carbon intensity change from t to t+1 via Equation 1: $\boldsymbol{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at p < 0.10, p < 0.05, and p < 0.01, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 10 – The effects of carbon disclosure quality on subsequent carbon intensity change

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
IMPRESSION	0.029*	0.029*	0.026*	0.014	0.026*	0.013	0.014	0.013
	(2.36)	(2.43)	(2.12)	(1.22)	(2.16)	(1.11)	(1.23)	(1.11)
ΔSIZE	-0.133**	-0.058	-0.129*	-0.108*	-0.050	-0.108*	-0.025	-0.023
	(-2.60)	(-1.06)	(-2.51)	(-2.06)	(-0.91)	(-2.05)	(-0.45)	(-0.41)
ΔLEV	0.006	0.002	0.005	0.007	0.000	0.006	0.002	0.001
	(0.44)	(0.11)	(0.34)	(0.46)	0.00	(0.40)	(0.11)	(0.05)
ΔROA	0.000	0.001	0.000	0.000	0.001	-0.001	0.000	0.000
	(0.04)	(0.22)	(0.03)	(-0.07)	(0.20)	(-0.11)	(0.06)	(0.03)
ΔGROWTH	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.13)	(-0.92)	(-1.23)	(-0.72)	(-1.01)	(-0.78)	(-0.48)	(-0.54)
ΔCAP	-0.012	-0.015	-0.010	-0.013	-0.012	-0.013	-0.016	-0.015
	(-0.58)	(-0.68)	(-0.49)	(-0.61)	(-0.56)	(-0.58)	(-0.72)	(-0.67)
ΔNEW	0.080	0.060	0.068	0.063	0.046	0.056	0.039	0.031
	(0.63)	(0.49)	(0.54)	(0.48)	(0.37)	(0.43)	(0.31)	(0.24)
Constant	-0.003	-0.006	0.001	0.019	0.019	-0.031	-0.025	-0.006
	(-0.16)	(-0.33)	(0.07)	(1.04)	(0.75)	(-0.49)	(-1.22)	(-0.10)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	3,140	3,140	3,140	3,140	3,140	3,140	3,140	3,140
R^2	0.004	0.028	0.009	0.046	0.033	0.047	0.071	0.072

Notes: Random and fixed effects models are used to test the impact of carbon disclosure quality on carbon intensity change from t to t+1 via Equation 2: $\mathbf{\Delta CARBON_{it+1} = \alpha_i + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 11 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.026*	0.009	0.026*	0.031**	0.009	0.031**	0.012	0.012
	(2.52)	(0.85)	(2.56)	(2.81)	(0.87)	(2.88)	(1.08)	(1.15)
IMPRESSION	0.019	0.022	0.015	0.004	0.018	0.002	0.007	0.006
	(1.52)	(1.76)	(1.26)	(0.28)	(1.49)	(0.16)	(0.56)	(0.44)
ΔSIZE	-0.125*	-0.033	-0.121*	-0.106	-0.024	-0.104	-0.010	-0.007
	(-2.33)	(-0.57)	(-2.20)	(-1.92)	(-0.42)	(-1.88)	(-0.18)	(-0.12)
ΔLEV	0.000	-0.005	-0.001	0.000	-0.007	0.000	-0.005	-0.005
	(-0.01)	(-0.36)	(-0.10)	(0.01)	(-0.48)	(0.02)	(-0.35)	(-0.37)
ΔROA	0.000	0.001	0.000	-0.002	0.001	-0.002	-0.001	-0.001
	(-0.05)	(0.09)	(-0.03)	(-0.32)	(0.10)	(-0.32)	(-0.21)	(-0.20)
ΔGROWTH	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	(-1.85)	(-1.48)	(-1.86)	(-1.43)	(-1.50)	(-1.47)	(-1.06)	(-1.10)
ΔCAP	-0.030*	-0.032**	-0.029*	-0.031*	-0.031*	-0.030*	-0.034**	-0.033*
	(-2.34)	(-2.61)	(-2.25)	(-2.34)	(-2.49)	(-2.30)	(-2.63)	(-2.57)
ΔNEW	0.093	0.062	0.081	0.074	0.045	0.067	0.042	0.031
	(0.73)	(0.50)	(0.63)	(0.56)	(0.37)	(0.50)	(0.33)	(0.24)
Constant	-0.100*	-0.038	-0.095*	-0.094*	-0.008	-0.138	-0.076	-0.046
	(-2.35)	(-0.94)	(-2.26)	(-2.18)	(-0.18)	(-1.89)	(-1.66)	(-0.63)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,811	2,811	2,811	2,811	2,811	2,811	2,811	2,811
R^2	0.013	0.033	0.012	0.035	0.037	0.036	0.059	0.060

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\mathbf{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 12 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies for the years 2010-2014

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	-0.012	-0.001	-0.010	-0.014	-0.001	-0.012	-0.006	-0.004
	(-1.00)	(-0.13)	(-0.87)	(-1.22)	(-0.13)	(-1.11)	(-0.57)	(-0.41)
IMPRESSION	0.018	0.010	0.012	0.000	0.005	0.000	-0.006	-0.006
	(1.26)	(0.71)	(0.93)	0.00	(0.38)	(-0.02)	(-0.38)	(-0.42)
ΔSIZE	-0.178**	-0.141*	-0.170*	-0.120	-0.121	-0.113	-0.073	-0.062
	(-2.58)	(-2.03)	(-2.41)	(-1.62)	(-1.70)	(-1.48)	(-0.96)	(-0.80)
ΔLEV	0.016	0.015	0.016	0.014	0.013	0.015	0.011	0.011
	(1.00)	(0.93)	(0.98)	(0.86)	(0.83)	(0.90)	(0.70)	(0.72)
ΔROA	0.005	0.005	0.005	0.004	0.006	0.004	0.004	0.005
	(0.52)	(0.56)	(0.59)	(0.43)	(0.64)	(0.46)	(0.46)	(0.49)
ΔGROWTH	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	(-1.36)	(-1.05)	(-1.36)	(-0.94)	(-1.03)	(-0.98)	(-0.65)	(-0.67)
ΔCAP	-0.010	-0.008	-0.008	-0.014	-0.006	-0.014	-0.014	-0.013
	(-0.63)	(-0.46)	(-0.48)	(-1.00)	(-0.36)	(-1.00)	(-0.90)	(-0.85)
ΔNEW	-0.100	-0.107	-0.118	-0.147	-0.131	-0.156	-0.155	-0.169
	(-1.01)	(-1.11)	(-1.19)	(-1.45)	(-1.32)	(-1.51)	(-1.53)	(-1.64)
Constant	0.067	0.032	0.063	0.096*	0.059	0.068	0.015	0.045
	(1.38)	(0.74)	(1.39)	(2.10)	(1.26)	(1.13)	(0.35)	(0.75)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	1,621	1,621	1,621	1,621	1,621	1,621	1,621	1,621
R^2	0.015	0.030	0.026	0.082	0.044	0.086	0.095	0.100

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\boldsymbol{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 13 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for the years 2015-2019

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.060**	0.024	0.059**	0.071**	0.023	0.069**	0.032	0.030
	(2.80)	(1.25)	(2.85)	(2.98)	(1.22)	(2.97)	(1.49)	(1.42)
IMPRESSION	0.035	0.042	0.032	0.025	0.040	0.022	0.032	0.029
	(1.28)	(1.52)	(1.17)	(0.90)	(1.44)	(0.76)	(1.15)	(1.04)
ΔSIZE	-0.034	0.085	-0.035	-0.060	0.087	-0.062	0.053	0.053
	(-0.35)	(0.82)	(-0.36)	(-0.60)	(0.84)	(-0.62)	(0.51)	(0.51)
ΔLEV	-0.030	-0.036	-0.032	-0.027	-0.038	-0.028	-0.033	-0.034
	(-1.30)	(-1.54)	(-1.34)	(-1.19)	(-1.60)	(-1.19)	(-1.43)	(-1.43)
ΔROA	-0.012	-0.009	-0.013	-0.014	-0.010	-0.016*	-0.011	-0.013
	(-1.87)	(-1.47)	(-1.90)	(-1.95)	(-1.50)	(-2.02)	(-1.59)	(-1.65)
ΔGROWTH	-0.002	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.83)	(-0.58)	(-0.81)	(-0.68)	(-0.56)	(-0.66)	(-0.44)	(-0.41)
ΔCAP	-0.051*	-0.054**	-0.051*	-0.046*	-0.055**	-0.047*	-0.050*	-0.051*
	(-2.47)	(-2.75)	(-2.48)	(-2.12)	(-2.75)	(-2.16)	(-2.38)	(-2.42)
ΔNEW	0.382	0.318	0.388	0.371	0.321	0.378	0.306	0.312
	(1.38)	(1.18)	(1.39)	(1.26)	(1.19)	(1.27)	(1.07)	(1.08)
Constant	-0.262**	-0.140	-0.255**	-0.286**	-0.102	-0.308*	-0.073	-0.126
	(-2.98)	(-1.74)	(-2.97)	(-3.03)	(-1.13)	(-2.58)	(-0.82)	(-0.99)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	1,190	1,190	1,190	1,190	1,190	1,190	1,190	1,190
R^2	0.050	0.043	0.025	0.049	0.048	0.053	0.071	0.075

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\mathbf{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 14 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies in environmentally-sensitive industries

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.044*	0.034	0.041*	0.044*	0.030	0.044*	0.032	0.031
	(2.28)	(1.66)	(2.11)	(2.19)	(1.45)	(2.21)	(1.42)	(1.44)
IMPRESSION	0.001	-0.006	-0.006	-0.040	-0.014	-0.050	-0.045	-0.058
	(0.03)	(-0.28)	(-0.32)	(-1.39)	(-0.71)	(-1.81)	(-1.40)	(-1.88)
ΔSIZE	-0.300*	-0.125	-0.297*	-0.310**	-0.117	-0.306**	-0.121	-0.113
	(-2.56)	(-1.02)	(-2.38)	(-2.75)	(-0.92)	(-2.63)	(-0.95)	(-0.88)
ΔLEV	0.087*	0.071	0.085*	0.077*	0.066	0.074	0.063	0.057
	(2.22)	(1.81)	(2.11)	(1.97)	(1.62)	(1.85)	(1.59)	(1.39)
ΔROA	-0.011	-0.012	-0.011	-0.011	-0.013	-0.010	-0.012	-0.012
	(-1.65)	(-1.87)	(-1.66)	(-1.70)	(-1.91)	(-1.60)	(-1.95)	(-1.86)
ΔGROWTH	0.001	0.003	0.001	0.002	0.003	0.001	0.003	0.003
	(0.57)	(1.14)	(0.52)	(0.61)	(1.10)	(0.60)	(1.08)	(1.08)
ΔCAP	-0.120***	-0.117***	-0.118***	-0.120***	-0.113***	-0.119***	-0.118***	-0.116***
	(-4.05)	(-3.97)	(-4.00)	(-3.94)	(-3.88)	(-3.91)	(-3.86)	(-3.81)
ΔNEW	0.264	0.249	0.222	0.193	0.199	0.181	0.163	0.143
	(1.14)	(1.18)	(0.98)	(0.94)	(0.98)	(0.90)	(0.89)	(0.80)
Constant	-0.123	-0.080	-0.101	-0.065	-0.028	-0.203**	-0.058	-0.103
	(-1.76)	(-1.11)	(-1.41)	(-0.88)	(-0.37)	(-2.67)	(-0.71)	(-1.29)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	581	581	581	581	581	581	581	581
R^2	0.048	0.082	0.055	0.111	0.092	0.114	0.145	0.150

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\mathbf{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at p < 0.10, p < 0.05, and p < 0.01, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 15 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies in non-environmentally-sensitive industries

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.024*	0.005	0.024*	0.029*	0.006	0.030*	0.009	0.010
	(1.98)	(0.45)	(2.08)	(2.26)	(0.53)	(2.39)	(0.75)	(0.84)
IMPRESSION	0.024	0.028	0.021	0.015	0.026	0.014	0.019	0.018
	(1.62)	(1.92)	(1.46)	(1.04)	(1.76)	(0.98)	(1.33)	(1.29)
ΔSIZE	(0.083)	(0.008)	(0.075)	(0.054)	0.002	(0.051)	0.022	0.027
	(-1.36)	(-0.12)	(-1.22)	(-0.86)	(0.04)	(-0.80)	(0.33)	(0.40)
ΔLEV	(0.009)	(0.012)	(0.010)	(0.008)	(0.014)	(0.009)	(0.012)	(0.013)
	(-0.64)	(-0.86)	(-0.72)	(-0.58)	(-0.97)	(-0.59)	(-0.84)	(-0.86)
ΔROA	0.004	0.005	0.005	0.002	0.006	0.003	0.003	0.004
	(0.48)	(0.59)	(0.55)	(0.26)	(0.66)	(0.30)	(0.36)	(0.40)
ΔGROWTH	-0.003*	-0.003*	-0.003*	(0.003)	-0.003*	(0.003)	(0.002)	(0.002)
	(-2.22)	(-2.07)	(-2.19)	(-1.73)	(-2.05)	(-1.73)	(-1.56)	(-1.55)
ΔCAP	(0.021)	(0.024)	(0.021)	(0.022)	(0.023)	(0.022)	(0.026)	(0.025)
	(-1.53)	(-1.76)	(-1.48)	(-1.54)	(-1.69)	(-1.53)	(-1.81)	(-1.79)
ΔNEW	0.068	0.034	0.065	0.043	0.029	0.041	0.009	0.006
	(0.45)	(0.23)	(0.43)	(0.27)	(0.20)	(0.26)	(0.06)	(0.04)
Constant	-0.102*	(0.038)	-0.101*	-0.108*	(0.044)	(0.017)	(0.090)	0.044
	(-2.04)	(-0.80)	(-2.07)	(-2.12)	(-0.91)	(-0.29)	(-1.65)	(0.76)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,230	2,230	2,230	2,230	2,230	2,230	2,230	2,230
R^2	0.009	0.031	0.010	0.032	0.033	0.032	0.055	0.056

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\mathbf{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 16 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies in civil law countries

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.045**	0.021	0.043*	0.048**	0.019	0.048**	0.020	0.020
	(2.68)	(1.22)	(2.58)	(2.63)	(1.13)	(2.64)	(1.04)	(1.09)
IMPRESSION	0.034	0.035	0.036*	0.007	0.037*	0.006	0.007	0.007
	(1.89)	(1.93)	(2.00)	(0.32)	(2.04)	(0.30)	(0.34)	(0.33)
ΔSIZE	-0.108	0.057	-0.105	-0.085	0.062	-0.077	0.094	0.104
	(-1.24)	(0.58)	(-1.19)	(-0.94)	(0.63)	(-0.84)	(0.90)	(0.99)
ΔLEV	-0.013	-0.020	-0.015	-0.015	-0.021	-0.016	-0.022	-0.023
	(-0.69)	(-1.03)	(-0.78)	(-0.78)	(-1.12)	(-0.83)	(-1.18)	(-1.22)
ΔROA	-0.009	-0.007	-0.009	-0.009	-0.007	-0.010	-0.007	-0.008
	(-1.46)	(-1.09)	(-1.58)	(-1.52)	(-1.14)	(-1.78)	(-1.21)	(-1.39)
ΔGROWTH	-0.002	-0.002	-0.003	-0.003	-0.002	-0.003	-0.003	-0.003
	(-1.41)	(-1.28)	(-1.39)	(-1.58)	(-1.26)	(-1.59)	(-1.47)	(-1.47)
ΔCAP	-0.034	-0.038	-0.035	-0.040	-0.039	-0.039	-0.044*	-0.043*
	(-1.60)	(-1.89)	(-1.62)	(-1.80)	(-1.92)	(-1.79)	(-2.12)	(-2.11)
ΔNEW	-0.007	-0.039	-0.015	-0.010	-0.047	-0.019	-0.052	-0.061
	(-0.06)	(-0.37)	(-0.13)	(-0.09)	(-0.44)	(-0.17)	(-0.48)	(-0.55)
Constant	-0.168**	-0.078	-0.163*	-0.138*	-0.089	-0.218*	-0.109	-0.110
	(-2.58)	(-1.24)	(-2.51)	(-2.00)	(-1.28)	(-2.17)	(-1.41)	(-1.09)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	1,443	1,443	1,443	1,443	1,443	1,443	1,443	1,443
R^2	0.022	0.045	0.018	0.033	0.050	0.038	0.066	0.070

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\mathbf{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at p < 0.10, p < 0.05, and p < 0.01, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 17 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies in common law countries

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.010	0.001	0.012	0.012	0.003	0.013	0.002	0.003
	(0.89)	(0.10)	(1.00)	(1.03)	(0.25)	(1.06)	(0.20)	(0.24)
IMPRESSION	0.004	0.007	0.001	-0.001	0.004	-0.001	0.003	0.003
	(0.25)	(0.46)	(0.09)	(-0.05)	(0.24)	(-0.06)	(0.21)	(0.18)
ΔSIZE	-0.116	-0.073	-0.108	-0.148*	-0.062	-0.140	-0.103	-0.094
	(-1.61)	(-1.01)	(-1.48)	(-2.07)	(-0.85)	(-1.92)	(-1.45)	(-1.30)
ΔLEV	0.017	0.014	0.017	0.015	0.013	0.016	0.011	0.012
	(0.87)	(0.72)	(0.90)	(0.72)	(0.68)	(0.79)	(0.56)	(0.59)
ΔROA	0.008	0.007	0.008	0.005	0.008	0.006	0.004	0.006
	(0.64)	(0.60)	(0.71)	(0.43)	(0.65)	(0.54)	(0.38)	(0.47)
ΔGROWTH	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000
	(-0.93)	(-0.78)	(-0.77)	(-0.50)	(-0.63)	(-0.40)	(-0.37)	(-0.27)
ΔCAP	-0.027	-0.031*	-0.024	-0.023	-0.027	-0.022	-0.027	-0.026
	(-1.95)	(-2.15)	(-1.76)	(-1.70)	(-1.91)	(-1.65)	(-1.94)	(-1.86)
ΔNEW	0.217	0.198	0.198	0.227	0.173	0.222	0.210	0.201
	(0.79)	(0.72)	(0.71)	(0.81)	(0.62)	(0.78)	(0.75)	(0.71)
Constant	-0.044	-0.013	-0.048	-0.041	0.069	-0.036	-0.033	0.081
	(-0.81)	(-0.24)	(-0.86)	(-0.79)	(1.17)	(-0.41)	(-0.62)	(0.88)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	1,368	1,368	1,368	1,368	1,368	1,368	1,368	1,368
R^2	0.017	0.029	0.021	0.029	0.042	0.038	0.051	0.059

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\boldsymbol{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at p < 0.10, p < 0.05, and p < 0.01, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 18 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies in countries without national ETS

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.037**	0.011	0.040**	0.042**	0.014	0.043**	0.014	0.015
	(2.81)	(0.81)	(2.96)	(3.13)	(1.05)	(3.11)	(1.07)	(1.10)
IMPRESSION	0.023	0.033*	0.018	0.006	0.027	0.007	0.017	0.017
	(1.34)	(1.97)	(1.08)	(0.39)	(1.69)	(0.42)	(1.04)	(1.07)
ΔSIZE	-0.170*	-0.096	-0.154	-0.122	-0.074	-0.123	-0.044	-0.044
	(-2.07)	(-1.12)	(-1.80)	(-1.39)	(-0.83)	(-1.37)	(-0.48)	(-0.46)
ΔLEV	0.009	0.007	0.006	0.010	0.003	0.009	0.008	0.006
	(0.38)	(0.28)	(0.26)	(0.45)	(0.13)	(0.40)	(0.33)	(0.26)
ΔROA	0.005	0.006	0.005	0.001	0.006	0.002	0.002	0.003
	(0.55)	(0.66)	(0.57)	(0.11)	(0.68)	(0.18)	(0.20)	(0.27)
ΔGROWTH	-0.004	-0.003	-0.004	-0.003	-0.003	-0.003	-0.002	-0.002
	(-1.94)	(-1.73)	(-1.96)	(-1.39)	(-1.73)	(-1.39)	(-1.13)	(-1.14)
ΔCAP	-0.027	-0.031	-0.027	-0.030	-0.030	-0.030	-0.035	-0.034
	(-1.36)	(-1.60)	(-1.32)	(-1.45)	(-1.52)	(-1.45)	(-1.70)	(-1.68)
ΔNEW	0.190	0.144	0.167	0.133	0.116	0.132	0.082	0.081
	(0.67)	(0.51)	(0.59)	(0.44)	(0.41)	(0.44)	(0.27)	(0.27)
Constant	-0.142*	-0.054	-0.146*	-0.135*	-0.011	0.036	-0.037	0.154
	(-2.30)	(-0.89)	(-2.36)	(-2.23)	(-0.16)	(0.37)	(-0.57)	(1.52)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	1,486	1,486	1,486	1,486	1,486	1,486	1,486	1,486
R^2	0.015	0.031	0.023	0.046	0.041	0.051	0.065	0.070

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\boldsymbol{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 19 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change for companies in countries with national ETS

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.013	0.007	0.011	0.018	0.005	0.019	0.012	0.012
	(0.81)	(0.47)	(0.67)	(1.03)	(0.30)	(1.05)	(0.67)	(0.67)
IMPRESSION	0.001	-0.007	-0.004	0.000	-0.011	-0.008	-0.010	-0.016
	(0.05)	(-0.39)	(-0.23)	(-0.02)	(-0.63)	(-0.41)	(-0.46)	(-0.77)
ΔSIZE	-0.081	0.042	-0.086	-0.088	0.045	-0.092	0.034	0.037
	(-1.22)	(0.57)	(-1.28)	(-1.32)	(0.62)	(-1.37)	(0.47)	(0.51)
ΔLEV	-0.010	-0.018	-0.009	-0.009	-0.017	-0.008	-0.016	-0.016
	(-0.60)	(-1.15)	(-0.56)	(-0.51)	(-1.14)	(-0.45)	(-1.03)	(-1.00)
ΔROA	-0.006	-0.006	-0.007	-0.005	-0.006	-0.006	-0.004	-0.006
	(-0.75)	(-0.66)	(-0.82)	(-0.62)	(-0.74)	(-0.77)	(-0.53)	(-0.67)
ΔGROWTH	-0.001	0.000	-0.002	-0.001	0.000	-0.001	0.000	0.000
	(-0.73)	(0.16)	(-0.94)	(-0.65)	(-0.03)	(-0.86)	(0.28)	(0.11)
ΔCAP	-0.035*	-0.041**	-0.037**	-0.033*	-0.042**	-0.035*	-0.040**	-0.041**
	(-2.47)	(-2.77)	(-2.63)	(-2.34)	(-2.88)	(-2.46)	(-2.67)	(-2.74)
ΔNEW	0.031	0.033	0.025	0.032	0.023	0.025	0.037	0.025
	(0.41)	(0.47)	(0.32)	(0.41)	(0.32)	(0.32)	(0.51)	(0.34)
Constant	-0.033	-0.002	-0.019	-0.052	0.024	-0.074	-0.118	-0.022
	(-0.58)	(-0.04)	(-0.32)	(-0.84)	(0.40)	(-0.86)	(-1.80)	(-0.25)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	1,325	1,325	1,325	1,325	1,325	1,325	1,325	1,325
R^2	0.011	0.061	0.015	0.017	0.069	0.025	0.070	0.077

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+1 via Equation 3: $\boldsymbol{\Delta CARBON_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 20 – The effects of carbon disclosure performance and quality on subsequent scope 1 emission intensity change

Variables	(1) - random ΔSCOPE1	(2) - fixed ΔSCOPE1	(3) - fixed ΔSCOPE1	(4) - fixed ΔSCOPE1	(5) - fixed ΔSCOPE1	(6) - fixed ΔSCOPE1	(7) - fixed ΔSCOPE1	(8) - fixed ΔSCOPE1
CDP_SCORE	0.038**	0.020	0.037**	0.036**	0.020	0.038**	0.016	0.017
	(2.95)	(1.45)	(2.80)	(2.79)	(1.41)	(2.84)	(1.11)	(1.19)
IMPRESSION	0.012	0.015	0.009	-0.003	0.013	-0.007	0.004	0.000
	(0.90)	(1.11)	(0.63)	(-0.23)	(0.88)	(-0.49)	(0.28)	(0.01)
ΔSIZE	-0.192*	-0.132	-0.183*	-0.194*	-0.130	-0.196*	-0.141	-0.143
	(-2.55)	(-1.71)	(-2.42)	(-2.53)	(-1.67)	(-2.54)	(-1.79)	(-1.79)
ΔLEV	0.004	0.004	0.003	0.004	0.001	0.002	0.003	0.001
	(0.23)	(0.27)	(0.17)	(0.24)	(0.09)	(0.14)	(0.18)	(0.08)
ΔROA	-0.008	-0.007	-0.010	-0.008	-0.008	-0.009	-0.006	-0.007
	(-1.28)	(-1.12)	(-1.51)	(-1.26)	(-1.26)	(-1.42)	(-0.97)	(-1.13)
ΔGROWTH	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(-0.76)	(-0.55)	(-1.04)	(-0.37)	(-0.65)	(-0.47)	(-0.04)	(-0.12)
ΔCAP	-0.010	-0.013	-0.010	-0.012	-0.013	-0.014	-0.016	-0.017
	(-0.80)	(-1.05)	(-0.80)	(-0.93)	(-1.04)	(-1.04)	(-1.21)	(-1.31)
ΔNEW	0.104	0.090	0.095	0.106	0.076	0.100	0.089	0.083
	(0.96)	(0.83)	(0.89)	(0.94)	(0.71)	(0.91)	(0.79)	(0.75)
Constant	-0.112*	-0.047	-0.101	-0.082	-0.046	-0.185**	-0.041	-0.109
	(-2.03)	(-0.85)	(-1.84)	(-1.56)	(-0.77)	(-2.85)	(-0.65)	(-1.58)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934
R^2	0.008	0.019	0.012	0.039	0.024	0.043	0.053	0.056

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on scope 1 carbon intensity change from t to t+1 via the modified Equation 3: $\mathbf{\Delta SCOPE1_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 21 – The effects of carbon disclosure performance and quality on subsequent scope 2 emission intensity change

Variables	(1) - random ΔSCOPE2	(2) - fixed ΔSCOPE2	(3) - fixed ΔSCOPE2	(4) - fixed ΔSCOPE2	(5) - fixed ΔSCOPE2	(6) - fixed ΔSCOPE2	(7) - fixed ΔSCOPE2	(8) - fixed ΔSCOPE2
CDP_SCORE	0.016	0.000	0.018	0.021	0.002	0.023	0.003	0.006
	(1.27)	(-0.03)	(1.45)	(1.62)	(0.17)	(1.83)	(0.24)	(0.46)
IMPRESSION	0.019	0.025	0.017	0.011	0.022	0.012	0.018	0.018
	(1.25)	(1.65)	(1.14)	(0.73)	(1.49)	(0.78)	(1.13)	(1.14)
ΔSIZE	-0.004	0.083	0.011	0.007	0.102	0.019	0.098	0.113
	(-0.05)	(0.99)	(0.14)	(0.09)	(1.21)	(0.24)	(1.20)	(1.36)
ΔLEV	-0.014	-0.018	-0.014	-0.010	-0.018	-0.009	-0.014	-0.014
	(-0.77)	(-0.98)	(-0.74)	(-0.55)	(-0.97)	(-0.48)	(-0.77)	(-0.73)
ΔROA	0.001	0.001	0.001	0.000	0.001	0.000	0.000	0.000
	(0.10)	(0.07)	(0.13)	(0.02)	(0.10)	(0.06)	(-0.02)	(0.01)
ΔGROWTH	-0.003*	-0.003	-0.003*	-0.002	-0.003	-0.003	-0.002	-0.002
	(-2.07)	(-1.82)	(-2.05)	(-1.65)	(-1.79)	(-1.65)	(-1.38)	(-1.38)
ΔCAP	-0.018	-0.020	-0.016	-0.016	-0.017	-0.015	-0.019	-0.017
	(-1.28)	(-1.43)	(-1.12)	(-1.14)	(-1.25)	(-1.04)	(-1.35)	(-1.22)
ΔNEW	0.024	0.000	0.009	0.012	-0.019	0.002	-0.016	-0.028
	(0.17)	(-0.00)	(0.06)	(0.08)	(-0.13)	(0.01)	(-0.11)	(-0.19)
Constant	-0.059	-0.004	-0.064	-0.069	0.010	0.012	-0.040	0.099
	(-1.12)	(-0.08)	(-1.26)	(-1.29)	(0.18)	(0.07)	(-0.64)	(0.60)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799
R^2	0.002	0.018	0.009	0.023	0.024	0.028	0.038	0.070

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on scope 2 carbon intensity change from t to t+1 via the modified Equation 3: $\mathbf{\Delta SCOPE2_{it+1} = \alpha_i + \beta CDP\_SCORE_{it} + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 22 – The effects of carbon disclosure performance on subsequent carbon intensity change (t+2)

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.009	0.021	0.019	0.013	0.023	0.015	0.018	0.020
	(0.38)	(0.95)	(0.89)	(0.59)	(1.08)	(0.68)	(0.78)	(0.93)
ΔSIZE	0.123	0.120	0.130	0.217	0.186	0.241*	0.269*	0.302*
	(1.04)	(1.02)	(1.09)	(1.82)	(1.53)	(1.96)	(2.21)	(2.43)
ΔLEV	0.036	0.037	0.033	0.039	0.032	0.037	0.038	0.035
	(1.25)	(1.30)	(1.16)	(1.46)	(1.14)	(1.38)	(1.45)	(1.35)
ΔROA	0.017	0.017	0.019	0.015	0.019	0.016	0.014	0.015
	(1.46)	(1.42)	(1.51)	(1.26)	(1.51)	(1.31)	(1.23)	(1.31)
ΔGROWTH	-0.006*	-0.006*	-0.007**	-0.006*	-0.006*	-0.006*	-0.005	-0.005
	(-2.30)	(-2.29)	(-2.62)	(-2.12)	(-2.33)	(-2.22)	(-1.84)	(-1.92)
ΔCAP	-0.029	-0.019	-0.016	-0.030	-0.015	-0.026	-0.030	-0.025
	(-1.25)	(-0.90)	(-0.74)	(-1.20)	(-0.69)	(-1.03)	(-1.23)	(-1.02)
ΔNEW	-0.184	-0.136	-0.182	-0.248	-0.193	-0.282	-0.254	-0.295
	(-1.14)	(-0.84)	(-1.13)	(-1.50)	(-1.22)	(-1.76)	(-1.57)	(-1.88)
Constant	0.033	-0.022	-0.015	0.008	0.062	-0.035	-0.072	0.029
	(0.34)	(-0.25)	(-0.17)	(0.09)	(0.66)	(-0.19)	(-0.78)	(0.16)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,112	2,112	2,110	2,112	2,110	2,110	2,112	2,110
R^2	0.01	0.022	0.022	0.075	0.038	0.082	0.091	0.099

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance on carbon intensity change from t to t+2 via Equation 4: $\boldsymbol{\Delta CARBON_{it+2} = \alpha_i + \beta CDP\_SCORE_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 23 – The effects of carbon disclosure quality on subsequent carbon intensity change (t+2)

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
IMPRESSION	0.019	0.027	0.019	-0.013	0.022	-0.012	-0.011	-0.010
	(0.74)	(1.09)	(0.78)	(-0.54)	(0.89)	(-0.53)	(-0.47)	(-0.45)
ΔSIZE	0.103	0.065	0.089	0.181	0.124	0.203	0.226	0.252*
	(0.92)	(0.54)	(0.74)	(1.52)	(0.98)	(1.66)	(1.84)	(2.00)
ΔLEV	0.018	0.023	0.021	0.022	0.021	0.023	0.021	0.021
	(0.56)	(0.74)	(0.67)	(0.71)	(0.68)	(0.75)	(0.71)	(0.72)
ΔROA	0.014	0.013	0.015	0.013	0.014	0.014	0.012	0.013
	(1.16)	(1.09)	(1.18)	(1.12)	(1.14)	(1.15)	(1.07)	(1.12)
ΔGROWTH	-0.005	-0.005	-0.006*	-0.005	-0.005*	-0.005	-0.004	-0.004
	(-1.93)	(-1.84)	(-2.31)	(-1.75)	(-2.03)	(-1.86)	(-1.44)	(-1.55)
ΔCAP	0.025	0.041	0.047	0.030	0.050	0.035	0.033	0.038
	(0.64)	(1.04)	(1.17)	(0.69)	(1.23)	(0.79)	(0.73)	(0.85)
ΔNEW	-0.118	-0.078	-0.131	-0.170	-0.127	-0.198	-0.168	-0.201
	(-0.69)	(-0.47)	(-0.79)	(-0.95)	(-0.78)	(-1.12)	(-0.96)	(-1.17)
Constant	0.057	0.039	0.047	0.093*	0.102	-0.001	0.031	0.058
	(1.46)	(1.04)	(1.29)	(2.49)	(1.79)	(-0.00)	(0.73)	(0.34)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,297	2,297	2,297	2,297	2,297	2,297	2,297	2,297
R^2	0.002	0.020	0.020	0.093	0.035	0.098	0.109	0.114

Notes: Random and fixed effects models are used to test the impact of carbon disclosure quality on carbon intensity change from t to t+2 via Equation 5: $\boldsymbol{\Delta CARBON_{it+2} = \alpha_i + \theta IMPRESSION_{it} + \gamma \Delta Controls_{it} + \delta FE_i + \varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at p < 0.10, p < 0.05, and p < 0.01, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 24 – The effects of carbon disclosure performance and quality on subsequent carbon intensity change (t+2)

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
CDP_SCORE	0.005	0.018	0.015	0.018	0.021	0.019	0.024	0.027
	(0.21)	(0.78)	(0.68)	(0.74)	(0.95)	(0.84)	(1.03)	(1.19)
IMPRESSION	0.008	0.004	-0.002	-0.027	-0.004	-0.029	-0.029	-0.032
	(0.32)	(0.16)	(-0.09)	(-1.20)	(-0.19)	(-1.34)	(-1.28)	(-1.45)
ΔSIZE	0.120	0.130	0.132	0.217	0.192	0.236	0.274*	0.301*
	(0.99)	(1.08)	(1.07)	(1.77)	(1.53)	(1.86)	(2.20)	(2.35)
ΔLEV	0.031	0.031	0.028	0.034	0.026	0.032	0.031	0.028
	(0.98)	(1.01)	(0.90)	(1.16)	(0.84)	(1.09)	(1.10)	(0.99)
ΔROA	0.016	0.017	0.019	0.014	0.019	0.015	0.014	0.015
	(1.33)	(1.36)	(1.44)	(1.17)	(1.42)	(1.21)	(1.13)	(1.18)
ΔGROWTH	-0.007*	-0.006*	-0.008**	-0.006*	-0.007*	-0.007*	-0.005	-0.005*
	(-2.40)	(-2.41)	(-2.79)	(-2.23)	(-2.51)	(-2.36)	(-1.94)	(-2.07)
ΔCAP	-0.024	-0.013	-0.011	-0.023	-0.009	-0.019	-0.021	-0.017
	(-1.03)	(-0.60)	(-0.52)	(-0.93)	(-0.39)	(-0.80)	(-0.89)	(-0.71)
ΔNEW	-0.177	-0.133	-0.177	-0.243	-0.185	-0.272	-0.247	-0.283
	(-1.09)	(-0.82)	(-1.10)	(-1.46)	(-1.18)	(-1.69)	(-1.51)	(-1.80)
Constant	0.030	-0.023	-0.003	0.024	0.053	-0.027	-0.079	0.014
	(0.30)	(-0.24)	(-0.03)	(0.25)	(0.53)	(-0.15)	(-0.81)	(0.08)
Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	2,014	2,014	2,014	2,014	2,014	2,014	2,014	2,014
R^2	0.009	0.025	0.021	0.077	0.041	0.083	0.096	0.104

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon intensity change from t to t+2 via Equation 6: $\Delta\mathbf{CARBON_{it+2}} = \boldsymbol{\alpha_i} + \boldsymbol{\beta}\mathbf{CDP\_SCORE_{it}} + \boldsymbol{\theta}\mathbf{IMPRESSION_{it}} + \boldsymbol{\gamma}\Delta\mathbf{Controls_{it}} + \boldsymbol{\delta}\mathbf{FE_i} + \boldsymbol{\varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Please see detailed variable definitions and data sources in Table 5.

Table 25 – The effects of carbon disclosure performance and quality on subsequent carbon emission intensity change including Heckman correction

Variables	(1) - random ΔCARBON	(2) - fixed ΔCARBON	(3) - fixed ΔCARBON	(4) - fixed ΔCARBON	(5) - fixed ΔCARBON	(6) - fixed ΔCARBON	(7) - fixed ΔCARBON	(8) - fixed ΔCARBON
Carbon emission intensity change model								
CDP_SCORE	0.022*	0.003	0.022*	0.028*	0.003	0.028*	0.008	0.008
	(1.99)	(0.28)	(2.02)	(2.47)	(0.29)	(2.52)	(0.73)	(0.76)
IMPRESSION	0.016	0.018	0.013	0.003	0.015	0.001	0.006	0.004
	(1.29)	(1.47)	(1.07)	(0.21)	(1.22)	(0.09)	(0.43)	(0.31)
ΔSIZE	-0.136*	-0.043	-0.131*	-0.111*	-0.035	-0.110*	-0.016	-0.013
	(-2.52)	(-0.75)	(-2.40)	(-2.01)	(-0.60)	(-1.97)	(-0.27)	(-0.22)
ΔLEV	0.000	-0.005	-0.001	0.000	-0.007	0.000	-0.005	-0.005
	(0.02)	(-0.35)	(-0.07)	(0.01)	(-0.48)	(0.02)	(-0.36)	(-0.40)
ΔROA	-0.001	0.000	-0.001	-0.002	0.000	-0.002	-0.002	-0.002
	(-0.13)	(-0.00)	(-0.10)	(-0.36)	(0.01)	(-0.36)	(-0.26)	(-0.26)
ΔGROWTH	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	(-1.83)	(-1.50)	(-1.85)	(-1.44)	(-1.53)	(-1.49)	(-1.09)	(-1.14)
ΔCAP	-0.030*	-0.033**	-0.029*	-0.031*	-0.031*	-0.030*	-0.034**	-0.033**
	(-2.40)	(-2.67)	(-2.29)	(-2.38)	(-2.54)	(-2.34)	(-2.68)	(-2.61)
ΔNEW	0.098	0.066	0.086	0.078	0.050	0.070	0.046	0.036
	(0.77)	(0.54)	(0.68)	(0.60)	(0.41)	(0.54)	(0.36)	(0.28)
Constant	-0.086*	-0.077	-0.059	-0.132	-0.052	-0.119	-0.105	-0.093
	(-1.97)	(-1.69)	(-1.25)	(-1.81)	(-1.08)	(-1.57)	(-1.46)	(-1.26)

Table 25 (continued)

Disclosure-choice model (CDP_DISC)								
CSR	1.219***	1.219***	1.219***	1.220***	1.219***	1.220***	1.220***	1.220***
	(25.84)	(25.84)	(25.83)	(25.83)	(25.84)	(25.83)	(25.84)	(25.84)
CDP_DISC_{t-1}	2.905***	2.905***	2.905***	2.906***	2.905***	2.906***	2.906***	2.906***
	(54.47)	(54.48)	(54.47)	(54.52)	(54.48)	(54.52)	(54.54)	(54.54)
SIZE	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(8.28)	(8.28)	(8.28)	(8.26)	(8.28)	(8.26)	(8.26)	(8.26)
LEV	0.473***	0.473***	0.472***	0.471***	0.473***	0.471***	0.471***	0.471***
	(4.27)	(4.28)	(4.27)	(4.26)	(4.28)	(4.26)	(4.26)	(4.26)
ROA	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
	(1.06)	(1.06)	(1.06)	(1.05)	(1.06)	(1.05)	(1.05)	(1.05)
DIV	0.124	0.124	0.125	0.127	0.125	0.127	0.126	0.127
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
CAP	-0.105	-0.104	-0.105	-0.104	-0.104	-0.104	-0.103	-0.103
	(-1.45)	(-1.44)	(-1.45)	(-1.44)	(-1.44)	(-1.44)	(-1.43)	(-1.43)
GROWTH	-0.652***	-0.652***	-0.653***	-0.651***	-0.653***	-0.651***	-0.651***	-0.651***
	(-5.93)	(-5.93)	(-5.93)	(-5.92)	(-5.93)	(-5.92)	(-5.91)	(-5.92)
NEW	0.189***	0.189***	0.189***	0.187***	0.189***	0.188***	0.187***	0.187***
	(4.67)	(4.68)	(4.66)	(4.63)	(4.67)	(4.63)	(4.62)	(4.62)
ETS	0.069	0.070	0.069	0.067	0.070	0.067	0.067	0.067
	(1.77)	(1.78)	(1.77)	(1.71)	(1.78)	(1.71)	(1.71)	(1.71)
COMMON	6.878	6.879	6.870	6.892	6.866	6.891	6.888	6.884
	(1.29)	(1.29)	(1.29)	(1.29)	(1.29)	(1.29)	(1.29)	(1.29)
DISC_PRO	-2.911***	-2.913***	-2.909***	-2.910***	-2.912***	-2.910***	-2.911***	-2.911***
	(-22.01)	(-22.04)	(-22.00)	(-22.01)	(-22.02)	(-22.01)	(-22.03)	(-22.02)
Constant	1.219***	1.219***	1.219***	1.220***	1.219***	1.220***	1.220***	1.220***
	(25.84)	(25.84)	(25.83)	(25.83)	(25.84)	(25.83)	(25.84)	(25.84)

Table 25 (continued)

Year	No	Yes	No	No	Yes	No	Yes	Yes
Industry	No	No	Yes	No	Yes	Yes	No	Yes
Country	No	No	No	Yes	No	Yes	Yes	Yes
Observations	117,803	117,803	117,803	117,803	117,803	117,803	117,803	117,803
Uncensored	2,811	2,811	2,811	2,811	2,811	2,811	2,811	2,811
Log Likelihood	-4,073	-4,037	-4,068	-4,036	-4,032	-4,034	-4,000	-3,998
Chi²	3.29*	4.96**	2.93*	0.95	4.70**	1.02	2.01	2.25

Notes: Random and fixed effects models are used to test the impact of carbon disclosure performance and quality on carbon emission intensity change from t to t+1 including a Heckman correction approach.
Therefore, Equation 3 $\Delta\mathbf{CARBON_{it+1}} = \boldsymbol{\alpha_i} + \boldsymbol{\beta}\mathbf{CDP\_SCORE_{it}} + \boldsymbol{\theta}\mathbf{IMPRESSION_{it}} + \boldsymbol{\gamma}\Delta\mathbf{Controls_{it}} + \boldsymbol{\delta}\mathbf{FE_i} + \boldsymbol{\varepsilon_{it}}$ is jointly estimated with Equation 7 $\mathbf{Pr}\,(\mathbf{CDP\_DISC_{it}}) = \boldsymbol{\alpha_i} + \boldsymbol{\beta_1}\mathbf{CSR\_REP_{it}} + \boldsymbol{\beta_2}\mathbf{CDP\_DISC_{it-1}} + \boldsymbol{\beta_3}\mathbf{SIZE_{it}} + \boldsymbol{\beta_4}\mathbf{LEV_{it}} + \boldsymbol{\beta_5}\mathbf{ROA_{it}} + \boldsymbol{\beta_6}\mathbf{DIV_{it}} + \boldsymbol{\beta_7}\mathbf{GROWTH_{it}} + \boldsymbol{\beta_8}\mathbf{CAP_{it}} + \boldsymbol{\beta_9}\mathbf{NEW_{it}} + \boldsymbol{\beta_{10}}\mathbf{COMMON_{it}} + \boldsymbol{\beta_{11}}\mathbf{ETS_{it}} + \boldsymbol{\beta_{12}}\mathbf{DISC\_PROP_{it}} + \boldsymbol{\gamma}\mathbf{FE_i} + \boldsymbol{\varepsilon_{it}}$. Z-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). The Z-statistics are based on clustered standard errors. Chi² is the Wald test of independence statistics and tests for the null hypothesis that there is no self-selection. Please see detailed variable definitions and data sources in Table 5.

Appendices

Appendix 1 Details on the corpus construction

The sections that form part of the corpus are chosen based on the extensiveness of the required textual response and cover the following aspects: (i) introduction, (ii) risk and opportunities and (iii) strategy. While these questions not only remain mostly unchanged throughout the sample years, academics like Fabrizio and Kim (2016) or Schieman and Sakhel (2019) also rely on parts of these for text analysis purposes.

The following exemplary questions are used for the questionnaire of 2019:

(i) Introduction (C0.1: *"Give a general description and introduction to your organization."*)

(ii) Risk and Opportunities (C2.2d: "*Describe your process(es) for managing climate-related risks and opportunities."*)

(iii) Strategy (C3.1c: *"Explain how climate-related issues are integrated into your business objectives and strategy."*)

After preprocessing of the Excel-reports we use the R-package "tm" to create three corpora for each year, resulting in a total of 30 corpora for further analysis. An overview of the corpora, i. e. the number of companies per section, their text responses' mean characters as well as their standard deviations, can be found in the table below:

Table 26 – Overview of corpora characteristics

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Introduction	N	1,499	1,547	1,711	1,784	1,825	1,896	1,959	1,999	1,804	2,013
	Mean (Char)	1,110	1,324	1,246	1,488	1,567	1,585	1,634	1,662	1,921	2,030
	SD (Char)	1,043	1,078	1,151	1,170	1,165	1,178	1,198	1,228	1,331	1,402
	Thereof missing	117	41	41	28	17	11	10	19	1	4
Risk	N	1,499	1,547	1,711	1,784	1,825	1,896	1,959	1,999	1,804	2,013
	Mean (Char)	1,456	1,894	2,248	2,616	1,152	1,215	1,253	1,288	2,454	2,763
	SD (Char)	1,287	1,913	2,071	2,299	719	703	696	692	1,594	1,731
	Thereof missing	71	222	242	238	240	205	172	166	12	10
Strategy	N	1,499	1,547	1,711	1,784	1,825	1,896	1,959	1,999	1,804	2,013
	Mean (Char)	1,473	2,245	2,838	3,399	3,507	3,631	3,794	3,948	3,766	3,788
	SD (Char)	1,378	2,250	2,422	2,852	2,566	2,577	2,545	2,581	2,381	2,396
	Thereof missing	85	243	245	236	193	202	176	139	5	8

Notes: The table presents the characteristics of corpora based on the three sections “Introduction”, “Risk” and “Strategy” for the years 2010 to 2019. N = number of text instances per section and year; Mean (Char) = mean count of characters per section; SD (Char) = standard deviation of characters per section.

Appendix 2 Overview of score components

Table 27 – Overview of score components

Component	Source	Approach	Calculation
TONE	Loughran and McDonald (2018)	Applying a bag-of-words approach, counting matches, and correcting for negated negative/positive words with look-around function	Ratio of positive matched words minus the ratio of negative matched words per section word count
SMOG	McLaughlin (1969)	Formula: $\mathrm{SMOG} = 1.043 \times [(\text{number of polysyllables}) \times \left(\frac{30}{\text{number of sentences}}\right)]^{\frac{1}{2}} + 3.129$	Via formula for each section
RESWORDS	Muslu et al. (2019)	Residuals from the regression: $\ln(\mathrm{words})_{it} = \alpha_i + \beta \mathrm{SMOG}_{it} + \gamma \mathrm{YEAR}_i + \delta \mathrm{INDUSTRY}_i + \varepsilon_{it}$	Via regression for each section
Aggregate score calculation			
IMPRESSION	Own approach	Summing up centile ranks of TONE, SMOG and RESWORDS	$\mathrm{IMPRESSION} = \mathrm{TONE} + \mathrm{SMOG} + (1 - \mathrm{RESWORDS})$

Notes: The table represents all score components and their construction rules. For all score components only companies providing more than 100 words across the investigated text sections are considered to ensure a sufficient basis for text analysis, while other instances are manually filtered out. Further, each score component is first calculated per text section and then averaged per year and company.

Table 28 – Descriptive statistics of score components

Score Component	N	Mean	SD	P5	Median	P95
TONE	10,823	0.014	0.010	0.000	0.014	0.030
SMOG	10,823	18.412	1.766	15.810	18.340	21.360
RESWORDS	10,823	0.006	0.680	-1.371	0.183	0.840

Notes: The table presents descriptive statistics of the score components. N = number of observations; SD= standard deviation; P5 and P95 = 5th and 95th percentile of the variables, respectively. Please see detailed variable definitions in Table 27.

Table 29 – Correlation coefficients of score components

	TONE	SMOG	RESWORDS
TONE	1	-0.003	0.113*
SMOG	-0.013	1	-0.005
RESWORDS	0.076*	-0.015	1

Notes: The table presents correlation coefficients of the score components. Pearson (Spearman) correlation coefficients are in the lower (upper) triangle. * represents the significance level at $p < 0.05$ (two-tailed). Please see detailed variable definitions and sources in Table 27.

Examples of SMOG score:

Auckland International Airport (13.82): *Auckland Airport has a five year sustainability action plan in place. This includes targets to reduce emission per passenger by 10% by 2012 and to reduce total carbon footprint by 5% by 2012. Performance against targets is reported annually and disclosed on the company's website.*

Ausenco Limited (27.37): *Group business strategies link with actions described for "risks" and "opportunities" by setting business emission reduction targets, monitoring of public policy changes, maintaining a leadership in emerging technologies and engaging in external communications with stakeholders (Clients, regulators, financial sector and local communities) in all projects undertaken.*

Appendix 3 Overview of common law countries

Table 30 – Common law countries in alphabetical order

Country (A-M)	Country (M-Z)
Australia	Mauritius
Bangladesh	Namibia
Bermuda	New Zealand
Botswana	Nigeria
Canada	Pakistan
Cayman Islands	Philippines
Cyprus	Palestinian Territory
Ghana	Singapore
Hong Kong	South Africa
Jersey	Sri Lanka
India	Tanzania
Ireland	Uganda
Israel	United Kingdom
Kenya	United States
Malawi	Zambia
Malaysia	Zimbabwe

Notes: The table presents common law countries based on La Porta et al. (1998).

Appendix 4 Overview of national ETS

Table 31 –Operating national ETS in alphabetical order

Country	Name of Scheme	Launch Year
Australia	Carbon Pricing Mechanism	2012
European Union (27 members)	EU ETS	2005
Iceland	EU ETS	2008
Kazakhstan	Kazakhstan Emissions Trading Scheme	2013
Korea	Korea Emissions Trading Scheme	2015
Liechtenstein	EU ETS	2008
New Zealand	New Zealand ETS	2010
Norway	EU ETS	2008
Switzerland	Swiss ETS	2008
United Kingdom	CRC Energy Efficiency Scheme	2010

Notes: The table presents operating national ETS based on the International Carbon Action Partnership (2020).

Appendix 5 Heckman sample construction and sample distribution

Considering the sample construction procedure of Hou, Karolyi and Kho (2011) as well as Schmidt et al. (2019), a screening of publicly listed companies worldwide is employed to construct a sample for the Heckman correction approach. Only companies that had been listed prior to 2010, which corresponds to before the start of the CDP sample period from 2010 to 2019, are included. Further, only primary, major, and active public companies remain within the sample. Additionally, to avoid any biases due to liquidity constraints of the respective equities only firms contributing to the upper 99% of market capitalization per country and year are used. Accordingly, the Heckman sample has been reduced from 243,509 to 240,492 firm-year observations whose distribution can be seen in the following Tables 32 to 34.

Table 32 – Heckman sample observations per country

Country	Frequency	Percent	Cumulative
USA	50,011	20.80	20.80
Japan	26,288	10.93	31.73
India	23,070	9.59	41.32
China	15,427	6.41	47.73
Taiwan	10,262	4.27	52.00
Korea	9,750	4.05	56.06
Canada	7,354	3.06	59.11
United Kingdom	6,965	2.90	62.01
Hong Kong	6,632	2.76	64.77
Malaysia	5,421	2.25	67.02
Germany	4,307	1.79	68.81
Australia	4,180	1.74	70.55
France	4,001	1.66	72.21
Thailand	3,790	1.58	73.79
Pakistan	3,378	1.40	75.19
Singapore	3,358	1.40	76.59
Vietnam	3,280	1.36	77.95
Indonesia	2,804	1.17	79.12
Israel	2,445	1.02	80.14
Other	47,769	19.86	100.00
Total	240,492	100.00	

Notes: The table presents the geographical distribution of the Heckman sample based on countries, showing absolute frequency, percentage as well cumulative percentage.

Table 33 – Heckman sample observations per ICB industry name

ICB Industry Name	Frequency	Percent	Cumulative
Industrials	24,333	10.12	10.118
Consumer Discretionary	38,683	16.08	26.20
Basic Materials	17,774	7.39	33.59
Technology	8,006	3.33	36.92
Financials	42,939	17.85	54.78
Consumer Staples	11,941	4.97	59.74
Health Care	47,690	19.83	79.57
Real Estate	13,615	5.66	85.23
Energy	20,903	8.69	93.93
Telecommunications	6,461	2.69	96.61
Utilities	6,218	2.59	99.20
Na	1,929	0.80	100.00
Total	240,492	100.00	

Notes: The table presents the sectoral distribution of the Heckman sample based on ICB industry names, showing absolute frequency, percentage as well cumulative percentage.

Table 34 – Heckman sample observations per year

Project Year	Frequency	Percent	Cumulative
2010	24,050	10.00	10.00
2011	23,899	9.94	19.94
2012	23,632	9.83	29.76
2013	23,944	9.96	39.72
2014	24,172	10.05	49.77
2015	23,641	9.83	59.60
2016	24,093	10.02	69.62
2017	24,617	10.24	79.86
2018	24,251	10.08	89.94
2019	24,193	10.06	100.00
Total	240,492	100.00	

Notes: The table presents the yearly distribution of the CDP sample based on project year, showing absolute frequency, percentage as well cumulative percentage.

Appendix 6 Disclosure-choice model and description of variables

Equation 7 utilizes the Heckman sample of CDP participants and non-participants and estimates the probability of voluntary disclosure using the following probit model, based on insights by Matsumara, Prakash and Vera-Muñoz (2014) arguing that the decision is mainly driven by a corporate cost-benefit analysis:

$$\mathrm{Pr}\ (\mathrm{CDP\_DISC_{it}}) = \alpha_i + \beta_1 \mathrm{CSR\_REP_{it}} + \beta_2 \mathrm{CDP\_DISC_{it-1}} + \beta_3 \mathrm{SIZE_{it}} \tag{7}$$

$$+\beta_4 \mathrm{LEV_{it}} + \beta_5 \mathrm{ROA_{it}} + \beta_6 \mathrm{DIV_{it}} + \beta_7 \mathrm{GROWTH_{it}} + \beta_8 \mathrm{CAP_{it}} + \beta_9 \mathrm{NEW_{it}}$$

$$+\beta_{10} \mathrm{COMMON_{it}} + \beta_{11} \mathrm{ETS_{it}} + \beta_{12} \mathrm{DISC\_PROP_{it}} + \gamma \mathrm{FE_i} + \varepsilon_{it}$$

where CDP_DISC for firm i in year t is an indicator variable corresponding to 1 if a company publicly shares carbon information through CDP, and 0 otherwise.

Due to a potential economy of scale in information production (Clarkson et al., 2008), companies disclosing other information voluntarily are more inclined to share emission information (Matsumura, Prakash & Vera-Muñoz, 2014). Accordingly, CSR_REP is used as a binary indicator that is 1 if firms publish voluntarily CSR reports and 0 otherwise. Similarly, the lagged disclosure decision $\mathrm{CPP\_DISC}_{t-1}$ is included in the model, as findings show that responding becomes routine and participants of the previous year are highly likely to respond the current year's questionnaire (Stanny, 2013).

Further, the model includes control variables for firm characteristics. SIZE is expected to positively impact disclosure choice, as larger companies are not only experiencing increased scrutiny by stakeholders (Stanny & Ely, 2008), but also face lower costs for disseminating voluntary disclosure (Clarkson et al., 2008). Based on Agency Theory, companies with a highly leveraged capital structure, indicated through LEV, are more inclined to disclose information to reduce information asymmetries and agency costs (Clarkson et al., 2008; 2009). Financially less constrained firms, proxied via return on assets as ROA and the dividend payout ratio DIV, possess more financial resources to invest in carbon reduction and will disclose such doing (Luo, Tang & Lan, 2013). On the other hand, the resource availability of growing company, controlled for with

GROWTH, is constrained and may lead to lower investments in GHG reporting (Luo, Tang & Lan, 2013). If companies do invest in newer clean technologies, they may wish to share this positive news with stakeholders. Following this theory, higher capital intensity ratios, CAP, are predictive of corporations with more modern equipment which then aspire to signal such through disclosure. In the same vein NEW is used, indicating the newness of equipment (Clarkson et al., 2008).

To control for country- and industry-specifics further variables are included. As shown by La Porta et al. (1998) common law countries tend to have stronger legal protection of stakeholders and creditors, leading to predict that firms in those countries are more transparent, i. e. they are more likely to disclose (Luo, Tang & Lan, 2013). Therefore, COMMON is included as an indicator variable. Arguing that firms that are directly imposed to costs in form of carbon prices are more motivated to not only decrease emissions but to report them as well, it is assumed that corporations in regions with an established ETS are more likely to disclose (Luo, Tang & Lan, 2013). Accordingly, ETS is used as an additional control. Capturing the propensity of certain industries to be more willing to share information, DISC_PRO measures the proportion of firms per industry and year that participate in the CDP. A higher proportion of disclosers in an industry will increase perceived pressure on non-disclosers to do alike and to emit their data to circumvent sanctions or bad perceptions by stakeholders outside of the corporation (Matsumura, Prakash & Vera-Muñoz, 2014). Moreover, industry and year dummies are incorporated into the model to account for industry-specific differences and potential time trends affecting the decision to disclose. To avoid distortions due to outliers in the data, all financial variables are winsorized at 2% and 98%. A more detailed description of all disclosure-choice model variables can be found in Table 35 below.

Table 35 – Variables of disclosure-choice model

Variable	Abbreviation	Source	Description
CDP disclosure	CDP_DISC	CDP reports from 2010 to 2019	Indicator variable (0 or 1) whether firm disclosed to CDP
CSR report	CSR_REP	Refinitiv Eikon Datastream	Indicator variable (0 or 1) whether firm published a CSR report (item CGVSDP026)
Lagged CDP disclosure	CDP_DISC_{t-1}	CDP reports from 2010 to 2019	Indicator variable (0 or 1) whether firm disclosed in prior year
Total assets	SIZE	Refinitiv Eikon Datastream	Measured as total assets (item WC029999); winsorized at 2% and 98%
Leverage	LEV	Refinitiv Eikon Datastream	Measured as total debt to total assets (item WC08236); winsorized at 2% and 98%
Return on assets	ROA	Refinitiv Eikon Datastream	Measured as net income to common shareholders (item WC01751) scaled by total assets (item WC08416); winsorized at 2% and 98%
Dividend payout	DIV	Refinitiv Eikon Datastream	Measured as the sum of dividends paid to common and preferred shareholders (item WC04551) scaled by net income before extraordinary items (item WC01551); winsorized at 2% and 98%
Capital intensity	CAP	Refinitiv Eikon Datastream	Measured as capital expenditures scaled by total assets (item WC08416); winsorized at 2% and 98%
Growth	GROWTH	Refinitiv Eikon Datastream	Measured as the annual percent change in net sales (item WC01001); winsorized at 2% and 98%

Table 35 (continued)

Equipment age	NEW	Refinitiv Eikon Datastream	Measured as the ratio of net property, plant and equipment (item WC02501) to gross property, plant and equipment (item WC02301); winsorized at 2% and 98%
Common law country	COMMON	La Porta et al. (1998)	Indicator variable (0 or 1) for common law country (see Appendix 3)
ETS	ETS	ICAP (2020)	Indicator variable (0 or 1) for national ETS (see Appendix 4)
Disclosure proportion	DISC_PRO	CDP reports from 2010 to 2019	Calculated as proportion of firms in a given year and industry that disclose to CDP
Fixed effect	FE	Refinitiv Eikon Datastream	Year and industry (item ICBIN) dummies to account for the respective fixed effects

Notes: The table presents the variables used for the disclosure-choice model, their sources and a detailed description of the measurement or calculation.

Publication bibliography

Alsaifi, Khaled (2021): Carbon disclosure and carbon performance: Evidence from the UK's listed companies. In *Management Science Letters*, pp. 117–128.

Andrew, Jane; Cortese, Corinne (2011a): Accounting for climate change and the self-regulation of carbon disclosures. In *Accounting Forum* 35 (3), pp. 130–138.

Andrew, Jane; Cortese, Corinne (2011b): Carbon disclosures: Comparability, the Carbon Disclosure Project and the Greenhouse Gas Protocol. In *Australasian Accounting, Business and Finance Journal* 5 (4), pp. 5–18.

Anthony, Laurence (2013): A critical look at software tools in corpus linguistics. In *Linguistic Research* 30 (2), pp. 141–161.

Boons, Frank; Strannegård, Lars (2000): Organizations Coping with Their Natural Environment. In *International Studies of Management & Organization* 30 (3), pp. 7–17.

Bowen, Frances; Aragon-Correa, J. Alberto (2014): Greenwashing in Corporate Environmentalism Research and Practice. In *Organization & Environment* 27 (2), pp. 107–112.

Burritt, Roger L.; Schaltegger, Stefan (2010): Sustainability accounting and reporting: fad or trend? In *Accounting, Auditing & Accountability Journal* 23 (7), pp. 829–846.

Busch, Timo; Hoffmann, Volker H. (2011): How Hot Is Your Bottom Line? Linking Carbon and Financial Performance. In *Business & Society* 50 (2), pp. 233–265.

Busch, Timo; Lewandowski, Stefan (2018): Corporate Carbon and Financial Performance: A Meta-analysis. In *Journal of Industrial Ecology* 22 (4), pp. 745–759.

CDP (2019a): CDP Climate Change 2019 Questionnaire. Available online at https://guidance.cdp.net/en/guidance?cid=8&ctype=theme&idtype=ThemeID&incchild=1&microsite=0&otype=Questionnaire&tags=TAG-597%2CTAG-605%2CTAG-599 [checked on: 11/26/2020].

CDP (2019b): Scoring Introduction 2020. Available online at b8f65cb373b1b7b15feb-c70d8ead6ced550b4d987d7c03fcdd1d.r81.cf3.rackcdn.com/cms/guidance_docs/pdfs/000/000/233/original/Scoring-Introduction.pdf?1524216279 [checked on: 11/1/2020].

CDP (2020a): Search and view past CDP responses. Available online at https://www.cdp.net/en/responses?utf8=%E2%9C%93&queries%5Bname%5D= [checked on: 11/26/2020].

CDP (2020b): What we do. CDP. Available online at https://www.cdp.net/en/info/about-us/what-we-do [checked on: 1/11/2021].

Cho, Charles H.; Patten, Dennis M. (2007): The role of environmental disclosures as tools of legitimacy: A research note. In *Accounting, Organizations and Society* 32 (7-8), pp. 639–647.

Cho, Charles H.; Roberts, Robin W.; Patten, Dennis M. (2010): The language of US corporate environmental disclosure. In *Accounting, Organizations and Society* 35 (4), pp. 431–443.

Choi, Bobae; Luo, Le (2020): Does the market value greenhouse gas emissions? Evidence from multi-country firm data. In *The British Accounting Review*, p. 100909.

Clarkson, Peter M.; Li, Yue; Richardson, Gordon D.; Vasvari, Florin P. (2008): Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. In *Accounting, Organizations and Society* 33 (4-5), pp. 303–327.

Clarkson, Peter M.; Li, Yue; Richardson, Gordon D.; Vasvari, Florin P. (2011): Does it really pay to be green? Determinants and consequences of proactive environmental strategies. In *Journal of Accounting and Public Policy* 30 (2), pp. 122–144.

Cormier, Denis; Magnan, Michel (2015): The Economic Relevance of Environmental Disclosure and its Impact on Corporate Legitimacy: An Empirical Investigation. In *Business Strategy and the Environment* 24 (6), pp. 431–450.

Cormier, Denis; Magnan, Michel; van Velthoven, Barbara (2005): Environmental disclosure quality in large German companies: Economic incentives, public pressures or institutional conditions? In *European Accounting Review* 14 (1), pp. 3–39.

Courtis, John K. (2004): Corporate report obfuscation: artefact or phenomenon? In *The British Accounting Review* 36 (3), pp. 291–312.

Davis, Angela K.; Ge, Weili; Matsumoto, Dawn; Zhang, Jenny Li (2015): The effect of manager-specific optimism on the tone of earnings conference calls. In *Review of Accounting Studies* 20 (2), pp. 639–673.

Deegan, Craig; Gordon, Ben (1996): A Study of the Environmental Disclosure Practices of Australian Corporations. In *Accounting and Business Research* 26 (3), pp. 187–199.

Delmas, Magali A.; Nairn-Birch, Nicholas; Lim, Jinghui (2015): Dynamics of Environmental and Financial Performance. In *Organization & Environment* 28 (4), pp. 374–393.

Doan, My Hanh; Sassen, Remmer (2020): The relationship between environmental performance and environmental disclosure: A meta-analysis. In *Journal of Industrial Ecology* 24 (5), pp. 1140–1157.

Dowling, John; Pfeffer, Jeffrey (1975): Organizational Legitimacy: Social Values and Organizational Behavior. In *The Pacific Sociological Review* 18 (1), pp. 122–136.

Du, Shuili; Yu, Kun (2020): Do Corporate Social Responsibility Reports Convey Value Relevant Information? Evidence from Report Readability and Tone. In *Journal of Business Ethics* 31 (2).

Fabrizio, Kira; Kim, Eun-Hee (2016): Voluntary Disclosure and Information Intermediaries: Evidence from the Carbon Disclosure Project. In *Academy of Management Proceedings* 2016 (1), p. 15005.

Fabrizio, Kira R.; Kim, Eun-Hee (2019): Reluctant Disclosure and Transparency: Evidence from Environmental Disclosures. In *Organization Science* 30 (6), pp. 1207–1231.

Giannarakis, Grigoris; Zafeiriou, Eleni; Sariannidis, Nikolaos (2017): The Impact of Carbon Performance on Climate Change Disclosure. In *Business Strategy and the Environment* 26 (8), pp. 1078–1094.

Global Reporting Initiative (2013): The G4 Sustainability Reporting Guidelines: Reporting Principles and Standard Disclosure. GRI. Amsterdam. Available online at https://respect.international/wp-content/uploads/2017/10/G4-Sustainability-Reporting-Guidelines-Implementation-Manual-GRI-2013.pdf [checked on: 1/10/2021].

Gray, Rob; Bebbington, Jan (2000): Environmental accounting, managerialism and sustainability: Is the planet safe in the hands of business and accounting? In, vol. 1. Bingley: Emerald (MCB UP) (Advances in Environmental Accounting & Management), pp. 1–44.

Gray, Rob; Kouhy, Reza; Lavers, Simon (1995): Corporate social and environmental reporting. In *Accounting, Auditing & Accountability Journal* 8 (2), pp. 47–77.

Gunning, Robert (1952): The Technique of Clear Writing. New York: McGraw-Hill.

Hahn, Rüdiger; Reimsbach, Daniel; Schiemann, Frank (2015): Organizations, Climate Change, and Transparency. In *Organization & Environment* 28 (1), pp. 80–102.

Hart, Stuart L.; Ahuja, Gautam (1996): Does it pay to be green? An empirical examination of the relationship between emission reduction and firm performance. In *Bus. Strat. Env.* 5 (1), pp. 30–37.

Hassan, Omaima A.G.; Romilly, Peter (2018): Relations between corporate economic performance, environmental disclosure and greenhouse gas emissions: New insights. In *Bus. Strat. Env.* 27 (7), pp. 893–909.

He, Yu; Tang, Qingliang; Wang, Kaitian (2013): Carbon disclosure, carbon performance, and cost of capital. In *China Journal of Accounting Studies* 1 (3-4), pp. 190–220.

Heckman, James J. (1979): Sample Selection Bias as a Specification Error. In *Econometrica* 47 (1), p. 153.

Hooghiemstra, Reggy (2000): Corporate Communication and Impression Management – New Perspectives Why Companies Engage in Corporate Social Reporting. In *Journal of Business Ethics* 27 (1/2), pp. 55–68.

Hopwood, Anthony G. (2009): Accounting and the environment. In *Accounting, Organizations and Society* 34 (3-4), pp. 433–439.

Horváthová, Eva (2010): Does environmental performance affect financial performance? A meta-analysis. In *Ecological Economics* 70 (1), pp. 52–59.

Hou, Kewei; Karolyi, G. Andrew; Kho, Bong-Chan (2011): What Factors Drive Global Stock Returns? In *Review of Financial Studies* 24 (8), pp. 2527–2574.

International Carbon Action Partnership (2020): ETS MAP. Available online at https://icapcarbonaction.com/en/ets-map [checked on: 12/1/2020].

Kolk, Ans; Levy, David; Pinkse, Jonatan (2008): Corporate Responses in an Emerging Climate Regime: The Institutionalization and Commensuration of Carbon Disclosure. In *European Accounting Review* 17 (4), pp. 719–745.

La Porta, Rafael; Lopez-de-Silanes, Florencio; Shleifer, Andrei; Vishny, Robert W. (1998): Law and Finance. In *Journal of political economy* 106 (6), pp. 1113–1155.

Li, Feng (2008): Annual report readability, current earnings, and earnings persistence. In *Journal of Accounting and Economics* 45 (2-3), pp. 221–247.

Li, Yongqing; Eddie, Ian; Liu, Jinghui (2014): Carbon emissions and the cost of capital: Australian evidence. In *Review of Accounting and Finance* 13 (4), pp. 400–420.

Liesen, Andrea; Hoepner, Andreas G.; Patten, Dennis M.; Figge, Frank (2015): Does stakeholder pressure influence corporate GHG emissions reporting? Empirical evidence from Europe. In *Accounting, Auditing & Accountability Journal* 28 (7), pp. 1047–1074.

Lindblom, Cristi K. (1994): The implications of organizational legitimacy for corporate social performance and disclosure. In : Critical Perspectives on Accounting Conference.

Loughran, Tim; McDonald, Bill (2011): When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. In *The Journal of Finance* 66 (1), pp. 35–65.

Loughran, Tim; McDonald, Bill (2016): Textual Analysis in Accounting and Finance: A Survey. In *Journal of Accounting Research* 54 (4), pp. 1187–1230.

Loughran, Tim; McDonald, Bill (2018): LoughranMcDonald_SentimentWordLists_2018. Available online at https://sraf.nd.edu/textual-analysis/resources/#LM%20Sentiment%20Word%20Lists [checked on: 12/2/2020].

Luo, Le (2019): The influence of institutional contexts on the relationship between voluntary carbon disclosure and carbon emission performance. In *Accounting & Finance* 59 (2), pp. 1235–1264.

Luo, Le; Tang, Qingliang; Lan, Yi-Chen (2013): Comparison of propensity for carbon disclosure between developing and developed countries. In *Accounting Research Journal* 26 (1), pp. 6–34.

Lyon, Thomas P.; Maxwell, John W. (2011): Greenwash: Corporate Environmental Disclosure under Threat of Audit. In *Journal of Economics & Management Strategy* 20 (1), pp. 3–41.

Mahoney, Lois S.; Thorne, Linda; Cecil, Lianna; LaGore, William (2013): A research note on standalone corporate social responsibility reports: Signaling or greenwashing? In *Critical Perspectives on Accounting* 24 (4-5), pp. 350–359.

Matisoff, Daniel C. (2013): Different rays of sunlight: Understanding information disclosure and carbon transparency. In *Energy Policy* 55, pp. 579–592.

Matisoff, Daniel C.; Noonan, Douglas S.; O'Brien, John J. (2013): Convergence in Environmental Reporting: Assessing the Carbon Disclosure Project. In *Business Strategy and the Environment* 22 (5), pp. 285–305.

Matsumura, Ella Mae; Prakash, Rachna; Vera-Muñoz, Sandra C. (2014): Firm-Value Effects of Carbon Emissions and Carbon Disclosures. In *The Accounting Review* 89 (2), pp. 695–724.

McLaughlin, Harry G. (1969): SMOG Grading - a New Readability Formula. In *Journal of Reading* 12 (8), pp. 639–646.

Merkl-Davies, Doris M.; Brennan, Niamh M. (2007): Discretionary disclosure strategies in corporate narratives: incremental information or impression management? In *Journal of accounting literature* 27, pp. 116–196.

Muslu, Volkan; Mutlu, Sunay; Radhakrishnan, Suresh; Tsang, Albert (2019): Corporate Social Responsibility Report Narratives and Analyst Forecast Accuracy. In *Journal of Business Ethics* 154 (4), pp. 1119–1142.

Prado-Lorenzo, José-Manuel; Rodríguez-Domínguez, Luis; Gallego-Álvarez, Isabel; García-Sánchez, Isabel-María (2009): Factors influencing the disclosure of greenhouse gas emissions in companies world-wide. In *Management Decision* 47 (7), pp. 1133–1157.

Qian, Wei; Schaltegger, Stefan (2013): Perform to disclose or disclose to perform: Which drives which. In *Governance and Sustainability* 30 (4), pp. 14–20.

Qian, Wei; Schaltegger, Stefan (2017): Revisiting carbon disclosure and performance: Legitimacy and management views. In *The British Accounting Review* 49 (4), pp. 365–379.

Schaltegger, Stefan; Wagner, Marcus (2006): Integrative management of sustainability performance, measurement and reporting. In *IJAAPE* 3 (1), p. 1.

Schiemann, Frank; Sakhel, Alice (2019): Carbon Disclosure, Contextual Factors, and Information Asymmetry: The Case of Physical Risk Reporting. In *European Accounting Review* 28 (4), pp. 791–818.

Schmidt, Peter S.; von Arx, Urs; Schrimpf, Andreas; Wagner, Alexander F.; Ziegler, Andreas (2019): Common risk factors in international stock markets. In *Financial Markets and Portfolio Management* 33 (3), pp. 213–241.

Smeuninx, Nils; Clerck, Bernard de; Aerts, Walter (2020): Measuring the Readability of Sustainability Reports: A Corpus-Based Analysis Through Standard Formulae and NLP. In *International Journal of Business Communication* 57 (1), pp. 52–85.

Stanny, Elizabeth (2013): Voluntary Disclosures of Emissions by US Firms. In *Business Strategy and the Environment* 22 (3), pp. 145–158.

Stanny, Elizabeth (2018): Reliability and Comparability of GHG Disclosures to the CDP by US Electric Utilities. In *Social and Environmental Accountability Journal* 38 (2), pp. 111–130.

Stanny, Elizabeth; Ely, Kirsten (2008): Corporate environmental disclosures about the effects of climate change. In *Corp. Soc. Responsib. Environ. Mgmt.* 15 (6), pp. 338–348.

Tang, Samuel; Demeritt, David (2018): Climate Change and Mandatory Carbon Reporting: Impacts on Business Process and Performance. In *Business Strategy and the Environment* 27 (4), pp. 437–455.

Topping, Nigel (2012): How Does Sustainability Disclosure Drive Behavior Change? In *Journal of Applied Corporate Finance* 24 (2), pp. 45–48.

Tucker, Jennifer. W. (2010): Selection Bias and Econometric Remedies in Accounting and Finance Research. In *Journal of accounting literature* 29, pp. 31–57.

Velte, Patrick; Stawinoga, Martin; Lueg, Rainer (2020): Carbon performance and disclosure: A systematic review of governance-related determinants and financial consequences. In *Journal of Cleaner Production* 254.

Wang, Zhihong; Hsieh, Tien-Shih; Sarkis, Joseph (2018): CSR Performance and the Readability of CSR Reports: Too Good to be True? In *Corporate Social Responsibility and Environmental Management* 25 (1), pp. 66–79.

Wong, Christina; Brackely, Aiste; Petroy, Erika (2019): Rate the Raters 2019: Expert Views on ESG Ratings. SustainAbility. Available online at https://sustainability.com/wp-content/uploads/2019/02/sustainability-rate-the-raters-2019.pdf [checked on: 10/20/2020].

Woolridge, Jeffrey M. (2002): Econometric analysis of cross section and panel data. Massachusets Institute of Technology.

Zhang, Michael Chuancai; Stone, Dan N.; Xie, Hong (2019): Text Data Sources in Archival Accounting Research: Insights and Strategies for Accounting Systems' Scholars. In *Journal of Information Systems* 33 (1), pp. 145–180.