Climate-related Disclosures, Disclosure Quality and Information Asymmetry

ABSTRACT

This study examines whether corporate climate-related disclosures during earnings conference calls affect information asymmetry and how the use of deceptive language conditions this relationship. We utilize textual analysis to measure the climate-related disclosures and the frequency of deceptive language used by executives during earnings conference calls from S&P 500 firms covering the period of 2005-2022. Controlling for the overall deceptiveness of executives in financial disclosures, we find a significant negative association between climate-related disclosures and information asymmetry. Additional analysis shows that the use of deceptive language negatively moderates the above relationship, meaning increased information asymmetry for firms providing a higher amount of climate-related disclosures and using more deceptive language. In a sub-sample analysis, we further find that the negative impact of deceptive language on the relationship between climate-related disclosures and information asymmetry is more pronounced in firms with better environmental performance. These findings provide new insights on when and how climate-related disclosures and their quality affect the information asymmetry.

Key words: Climate-related disclosures, Deceptive language, earnings conference calls, information asymmetry, environmental performance.

1. Introduction

With severe global climate changes and rising business risks therefrom, corporate climate-related disclosures are becoming increasingly important to stock market investors. Prior literature suggests that climate-related disclosures (henceforth "CRDs" only) contain material information for investors (Matsumura et al., 2024; Schiemann & Sakhel, 2019) and investors incorporate climate-related risks and opportunities in their investment decisions (Flammer et al., 2021; Ilhan et al., 2023; Matsumura et al., 2024). By reducing the information gap between the management and investors, CRDs can reduce investor incentives to seek private information regarding the firm climate-related risks and opportunities. That is, CRDs can reduce information asymmetry. However, a large part of climate-related risks and opportunities might relate to propriety information, which might prevent executives to provide sufficient disclsoures on material risks and opportunities (Matsumura et al., 2024). Consequently, private trading and information processing costs might increase, leading to increased information asymmetry. In contrast, a higher amount of CRDs might create a perception of higher risks preventing investors from trading, bearing negative implications for information asymmetry (Schiemann & Sakhel, 2019). Despite these contrasting views, extant literature provides limited evidence on the casual relationship between CRDs and information asymmetry. In this study, we investigate whether and how CRDs during earnings conference calls affect information asymmetry.

Earnings conference calls are one of the key sources of up-to-date corporate disclosures. By providing value-relevant information, conference calls reduce information asymmetry between investors and management (Brown et al., 2004). During this interactive disclosure session, executives disseminate critical information regarding firm performance and prospects (Lee, 2016; Mayew & Venkatachalam, 2012). Prior literature provide evidence that voluntary financial disclosures in earnings conference call reduce information asymmetry (Brown & Hillegeist, 2007; Brown et al., 2004; Tasker, 1998). Besides financial disclosures, executives also provide other material information at earnings conference calls, such as firm climate-related risks and opportunities (Liu et al., 2024;

Sautner et al., 2023). Recent literature suggests that CRDs during earnings conference calls are associated with higher green innovation (Sautner et al., 2023), faster leverage adjustment (Zhou & Wu, 2023) and stock liquidity commonality (Liu et al., 2024). Moreover, it is found that a higher climate risk exposure disclosed through CRDs during earning calls leads to reduction in firm value (Li et al., 2024). Despite the rising importance of CRDs and increasing pressure on firms for such disclosures, there is limited evidence on whether CRDs affect the firm information asymmetry that affects investor trading behavior and firm cost of capital (Brown & Hillegeist, 2007). We aim at answering this critical research question by investigating the impacts CRDs at conference earnings calls on information asymmetry. We further consider how a contextual factor like disclosure quality measured by deceptive language in CRDs affects the above relationship.

Corporate CRDs at earnings conference calls are susceptible to the use of deceptive language by executives particularly for two reasons, e.g., (i) the interactive nature of earnings conference calls and (ii) the innate uncertainties in climate-related risks and opportunities. Being an interactive disclosure setting and having the latitude of wider linguistic choice, deceptive language in CRDs during earnings conference calls is easier to use but harder to detect (Vrij, 1994). That is, executives have greater scope for using deceptive language in earnings conference calls. Moreover, corporate climate-related risks and opportunities are subject to natural uncertainties, creating commensurate difficulties for investors to detect the deceptive language in CRDs (Fiedler et al., 2021; Hain et al., 2022; Kim et al., 2022). Therefore, executives might take the opportunity to mislead investors through deceptive disclosures to reap benefits in stock markets. Linguistic cues such as general references, extreme emotions, hesitations and uncertainties stemming from deceivers' emotions, cognitive efforts and lack of embracement are regarded as signs of language deception (Larcker & Zakolyukina, 2012). Consistent with this, prior literature provides evidence that executives use deceptive language in financial disclosures at earnings conference calls (Allee et al., 2021; Hope & Wang, 2018; Larcker & Zakolyukina, 2012). Executives might use similar strategies to hide climate-related risks or exaggerate opportunities to create a favorable image of environmental sustainability among investors.

Arguably, whether or not deceptive language affects CRDs and information asymmetry relationship depends on investor ability to discern that deception (Bochkay et al., 2020). An ex-ante prediction of the impact of deceptive language on the information value of CRDs is challenging. First, investors might not form any judgment about the quality of CRDs based on the deceptive language perceiving it a normal human linguistic habit. That is, deceptive language might be insignificant in the relationship between CRDs and information asymmetry. Second, if investors can detect the deceptive language, it will jeopardize the information content of CRDs and hence increase information asymmetry (Hope & Wang, 2018). Finally, investors might be misled by the deceptive language, meaning they might trust the deception as a genuine disclosure. Consequently, they are likely to engage in more active treading leading to increased stock illiquidity, which will strengthen the CRDs-information asymmetry relationship. As such, the direction and strength of the association between CRDs and information asymmetry can be contingent upon the use of deceptive language in CRDs and how investors perceive that deception. Therefore, we argue that, besides investigating the impact of CRDs on information symmetry, it is also critical to know how the quality of CRDs proxied by deceptive language affects such causal relationships.

To investigate the potential impact of CRDs on information asymmetry and how deceptive language affects such relationships, we conduct a textual analysis of CRDs at earnings conference calls and employ an event-period analysis of stock illiquidity from S&P 500 firms over 2005-2022. Controlling the overall deceptiveness of financial disclosures, we provide evidence that CRDs is negatively associated with stock illiquidity and positively related to trading volume within 0–3 and 0-25 trading days. That is, CRDs lead to higher stock liquidity, meaning reduced information asymmetry for firms with higher CRDs. These findings suggest that CRDs during the earnings conference calls disseminate value-relevant information and reduce the information gap between the management and investors. Consequently, they engage in more active trading of the share of the firms with higher CRDs. In addition, we find that deceptive language in CRDs increases stock illiquidity for firms with higher CRDs. These findings suggest that investors perceive a higher volume of CRDs of firms with higher deceptive language as an indication of poor-quality disclosure. Consequently, whereas the existing shareholders might want to sell out the shares faster, the potential investors might not be motivated enough to buy those shares. Alternatively, both existing and potential investors might hold trading those shares due to higher information processing time, causing delayed engagement in trading activities and decreased liquidity. In further analysis, we find that this negative impact of deceptive language on the information value of CRDs is more pronounced in firms with better environmental performance. In other words, when a firm has higher CRDs and better environmental performance, the use of deceptive language imposes increased punishment on those firms by further decreasing stock liquidity. These findings indicate that the use of deceptive language not only jeopardizes the information content of CRDs but also undermines good environmental performance by creating a substantial doubt about the substance of that performance.

This study contributes to the existing literature in the following ways. First, the existing literature on CRDs during earnings conference calls, albeit spares in number, is limited to the impact higher climate risk exposure on firm strategic responses to the risk and its valuation impact. For instance, prior studies show that higher climate risk exposure leads to higher job creation and green innovation (Sautner et al., 2023), faster adjustment of leverage (Zhou & Wu, 2023) and lower market valuation (Li et al., 2024). Also, a high climate risk exposure is found to positively affect stock liquidity commonality (Liu et al., 2024). However, there is limited evidence on how investor trading behavior is affected by the CRDs during earnings conference calls. More particularly, there is little evidence on whether or not such CRDs during earnings conference calls provide additional information to investors to reduce information asymmetry, except for Schiemann and Sakhel (2019) who have a limited focus on the firm physical risk exposure disclosed through CDP survey response. In this study, however, we focus on corporate climate-related risk and opportunity disclosures during earnings conference call to investigate whether and how such disclosures reduce information asymmetry among investors. Unlike Schiemann and Sakhel (2019), our measure of CRDs capture both physical and transition risks and opportunities. Therefore, we provide a more comprehensive measure of CRDs to show their information value to investors. Moreover, during earnings conference calls, executives have a broader scope to discuss their climate-related risks and opportunities in more detail compared to CDP survey response. Similarly, investors and analysts can ask for further information and clarification about firm climate risks and opportunities during earnings conference calls. Information asymmetry can increase firm cost of capital, and it is important to know whether CRDs during earnings conference calls reduce information asymmetry. We provide evidence that CRDs during earnings conference calls reduce information asymmetry. Thus, we not only contribute to the literature on CRDs during earnings by providing new evidence on information content of such disclosures but also extend the existing evidence on CRDs and information asymmetry relationship from an interactive disclosure setting.

Second, existing literature on CRDs are largely focused on the quantity of CRDs during earning conference calls (Hope & Wang, 2018; Li et al., 2024; Liu et al., 2024; Zhou & Wu, 2023). However, a higher disclosure might come with poor disclosure quality when management uses such disclosure strategically to alter investor perceptions. As such, disclosure quantity and quality might be endogenously determined. Yet, there is a scarcity of literature on how disclosure quality of CRDs earning conference call might affect information content of CRDs during earnings conference calls. CRDs during earnings conference calls are susceptible to the use of deceptive language for the innate natural uncertainties in climate-related risks and opportunities (Gneezy, 2005). These uncertainties might mask a deceptive language in CRDs from investors and thus they might trust a deceptive disclosure as a genuine one (Hain et al., 2022; Kim et al., 2022). Moreover, the interactive nature of earnings conference call provide a wider latitude of linguistic choice making a deception harder to be detected (Vrij, 1994). Thus, executives have a greater room for misguiding investors by using deceptive language in CRDs during earning conference calls. Arguably, such poor disclosure should undermine the information usefulness of CRDs. In contrast, it might be also possible that investors are misled by executives through deceptive language, leading to an increased positive perception, and hence decreased illiquidity. Therefore, it important to know whether deceptive language conditions the impact of CRDs during earnings conference calls on information asymmetry. We fill this critical gap in literature by providing evidence that deceptive language negatively moderates the relation between CRDs and information asymmetry. In other words, a poor-quality disclosure caused by deceptive language leads to a higher information asymmetry for firms with higher CRDs. Moreover, we find that this impact is further strongly pronounced in firms with better environmental performance, indicating that for a deceptive firm with higher CRDs and better environmental performance, investors might even take further processing time to verify the environmental performance such firms in addition to verifying the disclosure itself. Consequently, when a higher CRDs couple with higher deceptive language in a firm with good environmental performance, information asymmetry further increases. In other words, besides diminishing the decision usefulness of CRDs, deceptive language also reduces the credibility of a good environmental performance.

The rest of this paper is structured as follows. Section 2 presents a literature review and the development of our hypotheses. The research model, sample and data used in our empirical model are explained in Section 3. Finally, we analyze our results in Section 4 and conclude the paper in Section 5.

2. Literature Review and Hypothesis Development

2.1 Prior Literature

2.1.1 Climate-related Disclosure and Information Asymmetry

In recent years, investor attention to global climate change and commensurate investment risks has increased. Consequently, demand for a transparent disclosure of corporate climate-related has also increased (Flammer et al., 2021; GIA, 2020; Ilhan et al., 2023). Similarly, regulatory changes are taking place to ensure a transparent disclosure of corporate climate-related financial risks and opportunities (IRA 2022; TCFD, 2017). In line with these, there has been a gradual increase in the corporate disclosures of climate-related financial risks and opportunities (Demaria & Rigot, 2021;

Lei et al., 2023; Sautner et al., 2023; Unda & Foerster, 2022). Prior literature suggests that corporate climate-related disclosures conveys material information about the firm financial risks and opportunities (Ilhan et al., 2023; Matsumura et al., 2024; Schiemann & Sakhel, 2019; Solomon et al., 2011). Moreover, investors consider these disclosures the complement to financial disclosures for efficient investment (Ilhan et al., 2023) and incorporate them into various financial decisions, such as asset pricing (Li & Zhang, 2023), measuring bond spread (Javadi & Masum, 2021) and credit pricing (Delis et al., 2019). Prior studies provide evidence that public disclosure of firm sustainability/CSR performance reduces information asymmetry (Cho et al., 2013; Cui et al., 2018). Similarly, it is found the disclosure of firm climate risks reduces information asymmetry (Schiemann & Sakhel, 2019) and increases market-level stock liquidity commonality (Liu et al., 2024). Schiemann and Sakhel (2019) focus on the impact of disclosures of physical risks through CDP survey on firm-level information asymmetry. In addition, recent evidence suggests that corporate climate-related disclsoures during earnings conference calls are associated with firms' strategic response to risks exposure and firm valuation. For instance, Sautner et al. (2023) find that a higher climate risk exposure leads to increased green innovation and job creation. They used corporate climate-related disclosure during earnings conference calls as a proxy for climate risk exposure. In a similar vein, Zhou and Wu (2023) find that a higher climate risk exposure during earnings conference calls leads to a faster adjustment to firm leverage. They argue that higher climate-related disclosures mitigate agency problems and increase information efficiency.

However, a larger part of firm climate-related risk and opportunities might be of proprietary nature (Hain et al., 2022; Ilhan et al., 2023; Matsumura et al., 2024; Schiemann & Sakhel, 2019). Therefore, management might opt not to provide sufficient disclosure of material risks and opportunities, leading to an increased information gap between management and investors. In other words, this insufficient disclosure is likely to increase information asymmetry by increasing the private trading and information processing costs (Brown & Hillegeist, 2007; Bushee et al., 2018; Cohen et al., 1981). Recent investigation by Li et al. (2024) provides evidence that higher climate risk disclosures during earnings conference calls leads to discounted firm valuation, more particularly for the firms not proactively responding to climate change risks. Similarly, Liu et al. (2024) examine how climate-related disclosures in earnings conference calls positively affect the market-level stock liquidity commonality by increasing financial constraints and operation risks. Altogether, we find mixed evidence on the impact of climate-related disclosures. However, it is still unaddressed in literature whether climate-related disclsoures affect the firm information environment which affects the investors' trading behavior. Therefore, in this study we aim at filling this void in literature by investigating how corporate climate-related disclosures during earnings conference calls affect firm-level information asymmetry.

2.1.2 Disclosure Quality and Information Asymmetry

Besides disclosure quantity, quality of disclosure is equally important for investors to make informed investment decisions. Arguably, a higher amount of disclosure devoid of quality might be more harmful for investors. As such, information asymmetry among investors might be significantly affected by disclosure quality (Brown & Hillegeist, 2007). Although, in recent years the voluntary disclosure of climate-related risks has increased, the extant literature shows that corporate climate-related disclosure quality has remained questionable. A number of prior studies express concern about the incompleteness of corporate climate-related disclosures, where firms provide a partial disclosure of different aspects of climate-related risks and opportunities. For instance, firms are found to avoid the disclosure of emissions, sources of emissions, consumption of energy and usage of renewable energy (Liesen et al., 2015; Sullivan & Gouldson, 2012). Similarly, prior literature finds that corporate climate-related disclosures are biased and selective where firms focus more on nonmaterial information rather than critical and material risk-related information (Bingler et al., 2022; Demaria & Rigot, 2021). Not only that, firms with poor environmental performance are found to manipulate the language and tone of disclosures to create a favorable image of better environmental sustainability (Cho et al., 2010). Finally, there is growing evidence of corporate greenwashing where firms falsify their environmental disclosures to maintain environmental legitimacy (Doan & Sassen, 2020; Du, 2015; Mateo-Márquez et al., 2022).

While investors consider climate-related disclosures material and incorporate them in decision making (Flammer et al., 2021; Ilhan et al., 2023; Javadi & Masum, 2021), these kinds of misleading disclosures might significantly jeopardize investor judgment about the firm actual risks and opportunities. As such, a misleading disclosure might create doubt in investor mind about the firm environmental sustainability, leading to increased information processing cost and delayed response. That is, poor quality disclosure might undermine the positive effects of disclosure by increasing asymmetry among investors. However, there is a dire lack of evidence in literature on how a misleading disclosure of corporate climate-related risks and opportunities might affect investor response to such disclosures. In this study, we investigate this critical research question by providing evidence on how deceptive climate-related disclosures during earnings conference calls affect the relationship between climate-related disclosures and information asymmetry.

2.1.3 Conference Calls Language, Disclosure Quality and Information Asymmetry

Earnings conference calls have become an increasingly important medium of disclosures through which firms convey value relevant information to the market (Bowen et al., 2002; Miller & Skinner, 2015; Price et al., 2012). However, being an informal and interactive disclosure channel, management has a greater latitude for manipulating their language during earnings conference calls (Bushee et al., 2018; DeLisle et al., 2021). Executives' linguistic choice during earnings conference calls might reflect their disclosure choice. Prior studies suggest that executive disclosure language is related to the quality of information disclosed during earnings conference calls (Mayew & Venkatachalam, 2012). As such, the management's intention to provide honest or dishonest disclosures affects their disclosure language. Given the interactive nature disclosure, it can be more important how executives say something than what they say during earnings conference calls (Mayew & Venkatachalam, 2012). Prior literature shows that investors react to the soft signal conveyed by executives' language in conference call disclosures (De Amicis et al., 2021; Mayew &

Venkatachalam, 2012; Price et al., 2012). For example, it is found that event period stock returns are affected by disclosure tone and vagueness (De Amicis et al., 2021; Price et al., 2012), positive affect (Mayew & Venkatachalam, 2012) and linguistic complexity (Bochkay et al., 2020). In a similar vein, prior literature also provides evidence on how conference call disclosure language affects the event period information asymmetry proxied by stock illiquidity. It is documented that disclosure tone increases event-period stock liquidity by inducing investors to engage in more active trading (Bochkay et al., 2019; Price et al., 2012). With a more specific focus, Bushee et al. (2018) investigate whether and how linguistic complexity elicits market reactions to affect stock illiquidity. Particularly, they aim at documenting the impact of linguistic complexity on information asymmetry, which they measure by the Amihud illiquidity ratio. Their findings show that within 0-25 trading days, illiquidity has a significant positive association with disclosure complexity, meaning complex language impedes investor decisions. Thus, they hold trading following a complex disclosure at earnings conference calls. Contemporaneous to this study, Hope and Wang (2018) examine how the deceptive language used by the executives from firms reporting a large loss (i.e., big bath) affects information asymmetry. Through a textual analysis of the executive language during earnings conference calls, they identify whether an executive is deceptive. Employing several proxies of information asymmetry, e.g., Amihud illiquidity ratio, trade volume, and bid-ask spread, they find that big bath taken by the deceptive executives are perceived more negatively by the investors. They document that stock illiquidity significantly increases for a firm with deceptive disclosures at earnings conference calls. We extend this line of literature by investigating whether deceptive language in climate-related disclosures during earnings conference calls elicit similar or different reactions.

Given the recent rise in investor attention to corporate climate risks and demand for transparent CRDs, management might respond through voluntary climate-related disclosures, which might, in turn, be affected by the incentives form management behind the disclosure (Schiemann & Sakhel, 2019). From a stakeholder perspective, a firm might diligently provide higher and better-quality disclosure climate-related risks and opportunities. However, from legitimacy perspective, management might engage in more strategic disclosure of firm climate-related risks and opportunities to safeguard environmental legitimacy. As such, deceptive CRDs might be a strategic tool for management to positively shape the perception of investors about firm environmental sustainability. Arguably, whether information asymmetry is increased or decreased by deceptive language depends on how such disclosures affect the belief and interpretation of investors. Moreover, uncertainties in and low-verifiability of CRDs might further affect investor perception about information content of deceptive CRDs. Altogether, deceptive CRDs might have substantial impact on the relationship between climate-related disclosures and information asymmetry. Therefore, investigating this contextual factor is important. In the following section, we construct our hypotheses.

2.2 Hypothesis Development

2.2.1 Climate-related Disclosures and Information Asymmetry

Economic theory suggests that disclosure of information can cause a reduction in information asymmetry in both direct and indirect ways. Disclosures leads to a direct reduction in information asymmetry by reducing private trading done based on private information. Similarly, disclosures cause an indirect reduction in information asymmetry through reducing the motivation of investors to search for private information (Brown et al., 2004; Diamond, 1985). In support of this theory, prior literature provide evidence that voluntary disclosure of financial and non-financial information through both written and interactive disclosure channels reduce information asymmetry (Brown et al., 2004; Cho et al., 2013; Cui et al., 2018; Schiemann & Sakhel, 2019). Accordingly, in general, climate-related risks and opportunities disclosure during earnings conference calls should decrease information asymmetry among investors. Investors consider climate change risks as material risks and thus require relevant disclosures to make well informed decisions (Ilhan et al., 2023; Matsumura et al., 2024). Although, certain aspects of firm climate-related risks and opportunities might be publicly available, such as carbon performance and regulatory changes, a larger part might be proprietary in nature and hardly becomes publicly available, such as physical risks and adaptation strategies (Ilhan et al., 2023; Schiemann & Sakhel, 2019). Therefore, an insufficient disclosure of the firm climate risks and opportunities might widen the information gap between management and investors, resulting in higher private trading and higher information procession cost. In other words, a higher amount climate-related disclosures should decrease the information asymmetry among stock market investors. Consistent with these arguments, we posit a negative association between climate-related disclosure quantity and information asymmetry and propose our hypothesis 1 as follows:

H1: Corporate climate-related disclosure quantity during earnings conference calls is negatively associated information asymmetry.

However, it might be argued that disclosure of climate-related risks and opportunities might increase uncertainties among investors which might instead increase information asymmetry (Brown et al., 2009; Schiemann & Sakhel, 2019). A higher disclosure might cause investors to perceive a higher climate risk, resulting in a delayed reaction (Li et al., 2024). Moreover, investors might be unaware of the potential implications of certain climate-related risks and opportunities on their investment (risk and returns) leading to higher information processing time and delayed reactions (Kim et al., 2022). Similarly, a higher volume of disclsoures might be a consequence of executives' intention to greenwash. Prior studies suggest that management might try to manipulate the perceptions of investors through providing extensive disclosures (Cho & Patten, 2007; Rodrigue et al., 2013). Arguably, such disclsoures should not be true reflection of the firm's climate-related risks and opportunities, increasing the time needed for investors to process the information. Given these contrasting arguments, the impact of climate-related disclosures during earnings conference call on information asymmetry is an open empirical question.

2.2.2 The Role Disclosures Quality

In previous section, we argue that climate-related disclosures will decrease information asymmetry. However, a key contextual factor that might affect the above relationship is the quality of disclosures. Whether or not a higher amount of disclosure comes with better quality depends on the motivation of the management behind such disclosures. A higher amount of disclosures might be an indication of poor disclosure quality (Berrone et al., 2017; Bui et al., 2020; Clarkson et al., 2011). That is, management might provide an extensive disclosure to manage investor perceptions, especially when they are not performing well in terms of environmental sustainability. As such, for the perception management, executives might leverage the use of deceptive language while discussing climate-related risks and opportunities during earnings conference calls. In doing so, they might try to overstate the perceived opportunities and understated the risks related to climate change, jeopardizing the quality of disclosures. Arguably, such deceptive language is likely to obfuscate investors about the actual information content of CRDs, causing higher information asymmetry. Hope and Wang (2018) provide evidence that deceptive langue in financial disclosures during earnings conference calls increase the information asymmetry that is caused by management big bath. In contrast, management is likely to provide higher amount of disclosure along with a better quality when they have better information to disclose, meaning they are less likely to use deceptive language to ensure a better disclosure quality. A better disclosures quality can enable investors to make better informed decisions and can attract more investors in the capital market (FASB, 2024; ISSB 2023). Investor Recognition Hypothesis suggests that when investors recognize a business for its transparent business practices, they will form favourable perceptions about that business, and consequently, are more like to invest in that business (Merton, 1987). In other words, quality disclosures might increase the visibility of the firms to capital market investors and/or can decrease the processing cost of the publicly available information, meaning increased level of stock trading. Prior literature provide evidence that disclosure quality reduces information asymmetry among investors (Brown & Hillegeist, 2007; Cheng et al., 2020; Fuhrmann et al., 2017). Brown and Hillegeist (2007) argue that a good quality disclosure can not only increase the uninformed trading (liquidity trading) but also reduces tendency of informed trading. As such, a good quality public disclosure can become a perfect substitute for private information. Therefore, we argue that when a larger disclosure couples with better quality, the information asymmetry should be further reduced. That is, the negative relationship between climate-related disclosures and information asymmetry should be more (less) pronounced in firms with better (poor) disclosure quality. Thus, our hypothesis 2 is proposed as follows:

H2: Deceptive language in climate-related disclosure will weaken the negative association between climate-related disclosure quantity and information asymmetry.

However, it can be argued that deceptive language in CRDs is likely strengthen the negative impact of CRDs on information asymmetry. Executives might be aware that investors are less likely to detect their deceptive language in CRDs due natural uncertainties in climate-related risks and opportunities and disclosure setting being interactive (Gneezy, 2005; Vrij, 1994). A such, deceptive language in CRDs can be an intentional choice by management, and accordingly, they might frame their CRDs with a heightened level of deceptive language to hide the actual picture of firm's climate-related risks or to inflate the potential opportunities. If investors are unable to detect such deceptive language and are misled by deceptive CRDs, they are likely to consider the firm as more environmentally sustainable and the disclosed information as value relevant. Consequently, both the potential and existing shareholder are likely to feel more confident to engage in more active trading of the deceptive firm. Thus, deceptive language might strengthen the negative relationship between climate-related disclosure quantity and information asymmetry. These conflicting arguments urges an empirical investigation of the impact of deceptive language on the relationship between climate-related disclosure quantity and information asymmetry.

3. Research Design

3.1 Data and Sample

Our initial sample covers S&P 500 firms from 2005 to 2022, comprising a total 63,576 firm-quarter observations.[1] We collect the quarterly conference call transcripts from Seeking Alpha, which is one of the biggest and most up-to-date databases for conference call transcripts (Allee &

[1] In our initial sample, we include all firms in the S&P 500 list from 2005-2022 and find 883 unique firms. Over the period, some of these firms have been delisted from the S&P 500 index.

DeAngelis, 2015; Bochkay et al., 2020). Conference call transcripts in Seeking Alpha are available from 2005. Daily stock price, trade volume, bid-ask price and other financial data is collected from DataStream. Institutional ownership and analysts following data are collected from the FactSet and I/B/E/S, respectively. Environmental performance and corporate governance data is retrieved from Refinitiv ESG. Finally, we collect deceptive financial disclosures and analysts present data from conference call transcripts. We merge conference call disclosures with financial data by using firm RICs, followed by a manual check ensuring that firms match. We present the sample section process in Table 1. Within the initial sample of 63,576 firm-quarter observations for firms hosting earning conference calls, 48,238 observations are associated with firm-quarter that do not provide any climate-related discussions during earnings conference calls, leaving 5,338 firm-quarter observations with CRDs.[2] After removing the observations with missing GICS code (532), missing daily price data (377) and missing financial control variables (35), 4,394 firm-quarter observations are used in the final sample for regression analysis.

[Insert Table 1 Here]

Panel A of Table 2 shows the sample distribution by industry, which indicates that our sample consists of firms from all industry groups, with about 25.83% of firms from the utilities sector and 17.61% from the industrials sector who are more likely to provide climate-related discussions at earnings conference calls. Further, Panel B of Table 2 shows the sample distribution by year, indicating that there is a steady growth in corporate CRDs in conference calls since 2014, reaching a peak at 697 firm-quarter observations in 2021.

[Insert Table 2 Here]

[2] The 63,576 firm-quarter observations are determined based on the 883 unique firms over 18 years.

3.2 Variables and Empirical Model

3.2.1 Dependent Variable

To measure information asymmetry, we follow Hope and Wang (2018) and Bushee et al. (2018) to take the natural logarithm of the mean Amihud Illiquidity ratio (*ILLI*). In addition, we employ various alternative measures for stock illiquidity as follows. We take the natural logarithm transformation of the sum of daily dollar trade volume (*STRD*). Also, we measure the information asymmetry by average daily bid-ask spread (*BAS*). We measure these three proxies of information asymmetry (illiquidity) over 0-3 trading days and 0-25 trading days. In addition to these, we employ the percentile rank of the illiquidity measures e.g., percentile rank of *ILLI* (*PR_ILLI)* and illiquidity for a relatively longer time horizons (0-45 days and 0-60 days) in the validation test of the baseline results.

3.2.2 Independent Variables

We measure corporate climate-related disclosure quantity during earnings conference calls (*CRDQ*) by the quarterly frequency climate-related bigrams in earnings conference calls. The measurement of *CRDQ* is calculated in two steps. First, we utilize Sautner et al. (2023)'s climate-related risks and opportunities bigrams using Python program to extract the climate-related discussions from conference call transcripts (see Appendix I for the bigrams lists). We combine Sautner et al. (2023)'s four bigram lists and eliminate the overlapping bigrams between the four categories to obtain seventy-eight (78) unique bigrams to identify climate-related discussions from conference call transcripts. Second, after extracting climate-related disclosures, we count the frequency of climate-related bigrams. Then we follow Sautner et al. (2023) to divide the frequency of climate-related bigrams with the total number of bigrams to measure the independent variable *CRDQ*.

To test our Hypotheses 2, i.e., the moderating impact of climate-related disclosure quality, we use the frequency of deceptive language (*FDL*) in climate-related discussions during earnings conference calls as a proxy for the disclosure quality. We do this measurement in following steps. First, we utilize Larcker and Zakolyukina (2012)'s taxonomy of deceptive language to identify the deceptive languages used in climate-related discussions by executives (see Appendix II for the taxonomy of deceptive language). This taxonomy of deceptive language is based on psychological theories linking deception to linguistic behavior and is built up by applying a well-developed and frequently used psychosocial dictionary named Linguistic Inquiry and Word Count (LIWC). In addition to LIWC word categories, Larcker and Zakolyukina (2012) manually investigate conference call transcripts to find out the linguistic pattern of deceptive executives and develop additional six categories of words that are related to deceptive executive language during conference calls. We utilize LIWC-2022 software to count the frequency of deceptive language in each of the word categories. Second, following Hope and Wang (2018), we count the sum of deceptive words in each category that are positively related to deceptions and those negatively related to deceptions (i.e., words show genuine) separately, and then subtract the latter from the former one to obtain the net frequency of deceptive language used in every quarterly conference call transcript. Finally, we take the indicator value 1 for *FDL* if the frequency of deceptive language is greater than the quarterly industry median; 0 otherwise.

Besides, to test our Hypotheses 2, we divide our sample firms into subsamples by good vs poor environmental performance. We utilize environmental pillar scores (ENSCORE) provided by Refintiv as a proxy for firm environmental performance. Then, we construct the categorical variable *ENDUM* which equals to the indicator value 1 if the environmental pillar scores for a firm in a fiscal quarter is greater than the industry media; 0 otherwise.

3.2.3 Empirical Model

To examine the effect of deceptive CRDs on information asymmetry, we follow Bushee et al. (2021) to develop the following OLS regression model to investigate our research questions:

$$\text{IA}_{itq} = \alpha + \beta_1\text{CRD}_{itq} + \beta_2\text{DISPERSION}_{itq} + \beta_3\text{SALEGRO}_{itq} + \beta_4\text{LEVER}_{itq} + \beta_5\text{LOSS}_{itq} + \beta_6\text{RETURN}_{itq} + \beta_7\text{SIZE}_{itq} + \beta_8\text{SPEIT}_{itq} + \beta_9\text{SURP}_{itq} + \beta_{10}\,\text{BEAT}_{it} + \beta_{11}\text{ANALYST}_{itq} + \beta_{12}\text{BTM}_{itq} + \beta_{13}\text{ROACHN}_{itq} + \beta_{14}\text{OUTSH}_{itq} + \beta_{15}\text{LENCRD}_{itq} + \beta_{16}\text{LENFIND}_{itq} + \beta_{17}\text{FINDUM}_{itq} + \beta_{18}\text{GENREF}_{itq} + \beta_{19}\text{SHVAL}_{itq} + \beta_{20}\text{EXTPOS}_{itq} + \beta_{21}\text{EXTNEG}_{itq} + \beta_{22}\text{TONPRI}_{itq-1} + \beta_{23}\text{TONFIN}_{itq} + Industry + Year + \varepsilon_{itq} \quad \ldots (1)$$

where for a firm i in the year t and quarter q, $CRDQ$ is the frequency of climate-related bigrams, *IA* is the information asymmetry proxied by stock illiquidity measured by Amihud illiquidity ratio *(ILLI),* sum of daily trading volume in dollar amount *(STRD)* and average daily bid-ask spread (*BAS)* over 0-3 and 0-25 trading days. A higher value of *ILLI* and *BAS* means higher information asymmetry (lower liquidity), whereas a higher value of *STRD* indicates a lower information asymmetry (higher liquidity). Therefore, our Hypothesis 1 is supported if the coefficients on *ILLI* and *BAS* are negative but positive for *STRD*.

The error terms are represented by ε_{itq}. Industry and year fixed effects are also included in the regression, as indicated by *Industry* and *Year (Gallego-Álvarez et al., 2015).*[3] The OLS regression method is used with clustering the standard errors at firm level to mitigate serial correlation in intra-firm residuals over time (Gong et al., 2011). All continuous variables are winsorized at 1st and 99th percentiles to mitigate the impact of outliers. Full variable definition table is provided in Appendix III.

3.2.4 Control Variables

We follow Bushee et al. (2018) and Hope and Wang (2018) to include the following control variables in the regression model. To control the impact of firm-level financial variables, we include the natural logarithm of total assets (*SIZE*), standard deviation of the analysts' consensus earnings forecast scaled by the quarter beginning stock price (*DISPERSION*), growth in sales revenue (*SALGRO*), firm leverage total debt scaled by total assets (*LEVER*), indicator variable for firms

[3] For industry fixed effect, we build on the GICS six-digit industry codes retrieved from Refinitiv.

reporting a loss (*LOSS*), buy-and-hold return over the quarter (*RETURN*), special items scaled by the market value of equity (*SPEIT*), the ratio of the book value of equity to the market value of equity (*BTM*), indicator variable if the firms' earnings beat analysts' consensus forecasts by a penny or loss (*BEAT*), consensus forecast error scaled by market value of equity at the beginning of the quarter (*SURP*), change in return on assets (*ROACHN*) and log natural of the number of shares outstanding (*OUTSH*).

In addition to financial indicators, we include the number of analysts following the firm (*ANALYST*) to control the impact of external analysts on the capital market information environment. *ANALYST* signifies the presence of potentially more informed and sophisticated market participants (Bhushan, 1989; Brown et al., 2004). Prior studies document that *ANALYST* reduces the conference call uncertain tones (Allee et al., 2021) and information asymmetry (Brown et al., 2004).

Further, we include the indicator variable for deceptiveness in overall financial disclosures (*FINDUM*) and the tone of executive financial disclosures (*TONFIN*) to isolate the impact of financial disclosures deception for the CRDs deception. We add general references (*GENREF*), shareholder value (*SHVAL*), extreme positive words (*EXTPOS*) and extreme negative words (*EXTNEG*) in the CRDs section as well as the prior quarter overall tone in the financial disclosures (*TONPRI*) to control executives' overall linguistic habits.

4. Empirical Results

4.1 Descriptive Statistics and Univariate Analysis

Table 3 presents descriptive statistics for variables used for testing our hypotheses. The mean value of *ILLI, STRD* and *BAS* over 0-3 days window after the taking the natural logarithm transformation are -3.512, 19.191 and 0.063, respectively. Over 25 trading days, the mean values are -3.491, 20.887 and 1.56, respectively. These statistics reveal that firms have a comparatively higher liquidity following the earnings conference calls. These statistics are comparable with the prior literature by Bushee et al. (2018). An industry break-down of the average illiquidity measures shows that the communication service industry has the lowest illiquidity followed by the consumer staples industry with an average value of *ILLI03 (ILLI25)* at -4.92 (-4.88) and -4.31 (-4.39), respectively (untabulated). The mean value of *CRDQ* is 5.80, indicating that on average climate-related bigrams appear in the earnings conference calls for 6 times. We further observe that the consumer staples has the highest mean value for *CRDQ* followed by the communication industry with a mean value of 6.87 and 6.81, respectively (untabulated). The mean value of *FDL* and *FINDUM* are 0.499 and 0.497, suggesting that compared to the industry median, half of the sample firms use more deceptive language in their climate-related disclosures and financial disclosures during earnings conference calls.

[Insert Table 3 Here]

The descriptive statistics of control variables show that firms providing CRDs are generally large firms (mean 23.81) with a lower leverage (0.569). The mean value of *DISPERSION*, *BEAT* and *SURPRISE* with 0.079, 0.021 and 0.476, respectively, suggests that the sample firms have relatively stable earnings and little variation from the analyst forecasts, which resembles the prior study by (Bushee et al., 2018). The mean value for *RETURN* is 3.76. The mean value of *LOSS* at 0.076 suggests that only 7.6% of the sample firms report a loss in the fiscal quarter. The average value of *ROACHN* and *SALGRO* at 0.434% and 3.41%, respectively, indicating a moderate level of growth of the financial performance. The mean value of *ANALYST* at 2.53 after taking the natural logarithm reflects a comparatively stronger external monitoring by analysts compared to the prior literature (Bushee et al., 2018). *TONFIN* has a mean value of 61.403, indicating that a substantially higher number of positive words are used by executives during earnings conference calls compared to the negative words. The means value of *GENREF, SHVAL, EXTPOS* and *EXTNEG* are 0.048, 0.004, 0.592 and 0.166, respectively. Finally, our sample firms have an average value for *ENDUM* at 0.504, showing that more than half of the firms have better environmental performance compared to their industry peers.

Table 4 presents the Pearson correlation matrix among *ILLI*, *CRDQ* and other independent variables. Our independent variable *CRDQ* has a significant negative correlation with *ILLI*, which suggests that newer value relevant information is disclosed by the executives through climate-related disclosures during the earnings conference call. Consequently, the information gap between the management and investors reduces, leading to lower illiquidity (information asymmetry). A negative correlation of *ILLI* with *TONFIN* and *LENCRD* provides similar evidence that CEO's positive tone and more climate-related disclosures help reduce the information gap between investors and management. We further observe that *ILLI* has a significant negative correlation with *ROACHN*, *SIZE* and *ANALYST*, which indicate that firms with better financial performance, better resource backup and higher external monitoring have lower information asymmetry (lower illiquidity). Similarly, a significant positive association of *RETRUN* with *ILLI* indicate that firms with higher buy-and-hold returns over that quarter has less information asymmetry. In contrast to these, we observe a significant positive correlation of *ILLI* with *LEVER, LOSS and BTM.* These findings indicate that illiquidity is higher in firms with higher dependence on debt financing, higher reported loss and higher growth potential. None of the correlation coefficients exceeds 0.70. Further, from untabulated results, we observe that all the predictor variables in our model have a VIF value lower than 4. Altogether, we can eliminate the multicollinearity concerns in our model.

[Insert Table 4 Here]

4.2 Results from Tests for Hypothesis 1

Table 5 presents our regression results on how firm-level information asymmetry (*ILLI*, *STRD* and *BAS*) is impacted by the corporate climate-related disclosures during earnings conference calls (*CRDQ*). Panel A of Table 5 presents the results for a short window ranging over 0-3 trading days, whereas Panel B of Table 5 shows the results for a relatively longer window ranging over 0-25 trading days. In Panel A of Table 5, the coefficients of *CRDQ* for *ILLI* (β = - 0.00755; *t*-statistics = -2.129) in Column (1) and for *STRD* (β =0.00674; *t*-statistics = 1.972) in Column (2) are significantly negative and positive, respectively. Similarly, in Panel B of Table 5, the coefficients of *CRDQ* for *ILLI* (β = -

0.00610; *t*-statistics = - 1.723) in Column (1) and for *STRD* (β =0.00762; *t*-statistics = 2.336) in Column (2) are significantly negative and positive, respectively. These findings indicate that *CRDQ* decreases stock illiquidity and increases the stock trade volume following earnings conference calls. More particularly, the negative association of *ILLI* and *STRD* with *CRDQ* suggests that corporate climate-related disclosures during earnings conference calls provide useful information relevant to the firm future value and performance. Therefore, the perceived information gap between the management and investors decreases, meaning a reduced level of information asymmetry as suggested by decreased Amihud illiquidity. Our results further imply that the disclosure of corporate climate-related risks and opportunities increases investor confidence in the firm and consequently, both the potential and existing shareholders engage in more active trading of those shares, leading to increased trading volume. Similarly, potential investors might be more willing to pay the price asked by the current shareholders. Therefore, stock turnover increases and for a given level of trade volume, accumulation of a big return becomes less likely. Overall, our results suggests that information asymmetry decreases following the disclosure of corporate climate-related risks and opportunities during earnings conference calls. More specifically, one standard deviation rise in climate-related disclosures during conference calls decreases (increases) the *ILLI* (*STRD*) by 1.25 % (0.20%) over 0-3 trading days, indicating the economic significance of our results for an average firm.

Although the coefficients of *CRDQ* for *BAS* in Column (3) of both Panel A and B in Table 5 are negative, they are statistically insignificant, suggesting that bid-ask spread is not affected by the *CRDQ*. One possible explanation for this weaker result could be that bid-ask spread is largely dependent on the transactions costs and microstructure of the market, which might not be affected by firms climate-related performance or disclosures in the short-run (Cohen et al., 1981; Copeland & Galai, 1983; Glosten & Harris, 1988). For instance, (gaining from) sellers' immediacy might be less affected by a public disclosure made through the disclosure of the firm climate-related risks and opportunities. In addition, for the market makers, corporate climate-related disclosures might not appear highly relevant to the short-term value of the firms (Jain et al., 2016), leading to lower association with bid-ask spread. Moreover, market makers can safeguard themselves from information asymmetry by simultaneous manipulation of bid and ask price together with the quoted depths of those prices, making bid-ask spread less sensitive to new information released through CRDs during earnings conference calls. Consequently, although investors positively react to a higher volume of climate-related disclsoures through higher trading, the bid-ask spread remains relatively unaffected.

Overall, we find consistent evidence of the negative association between information asymmetry and *CRDQ*, indicating that climate-related risk and opportunity disclosure during conference calls reduces the information gap between the management and investors. Therefore, investors are more likely to engage in active trading of the shares of firms with higher *CRDQ*. These findings support our Hypothesis 1 that *CRDQ* is negatively associated with information asymmetry. Our findings are consistent with the existing literature which suggest that information asymmetry is reduced by public disclosure of climate-related physical risks (Schiemann & Sakhel, 2019) and sustainability performance (Cho et al., 2013; Cui et al., 2018). In the rest of the analyses, we provide results and discussions for *ILLI03* and *ILLI025.*

[Insert Table 5 Here]

4.3 Robustness Tests

In this section, we provide the results of the robustness tests for our baseline findings. First, we examine the sensitivity of our findings to the alterative specifications of the baseline model. Next, we investigate the robustness of our results to endogeneity by conducting a Two-stage Least Squares (2SLS) test.

4.3.1 Alternative Measure for Dependent, Independent and Control Variables

We conduct several sensitivity tests to check the robustness of our baseline results. First, we check the sensitivity of our results to the alternative measurement of our independent variable (*CRDQ*). To do this, we re-estimate the baseline regression equation with two alternative measures of *CRDQ*, e.g., (i) the length of climate-related disclosures (*LENCRD*) measured by the natural logarithm of total word count of climate-related disclosures and (ii) the ratio of climate-related disclosure and financial disclosure word count during conference calls (*PCTCRD*). Panel A of Table 6 presents our results for the alterative measure of *CRDQ* for 0-3 trading days and 0-25 trading days, respectively. Column (1) and (2) and Column (3) and (4) present results for *LENCRDQ* and *PCTCRDQ* over 0-3 trading days and 0-25 trading days, respectively. As indicated in Column (1) and (3), the coefficients of *ILLI03* on *LENCRDQ and PCTCRDQ* are negative and statistically significant. That is, the alternative measures of climate-related disclosures using *LENCRD* and *PCTCRD* produce results that are consistent with our baseline results in Table 5. Then, we re-estimate our baseline regressions by using two alternative measures of dependent variables *ILLI03 and ILLI025, e.g.,* by (i) taking the percentile rank of illiquidity of over 0-3 and 0-25 days, e.g., *PR_ILLI03* and *PR_ILLI025* and (ii) taking a longer time horizon for illiquidity at 45 days (*ILLI45)* and 60 (*ILLI060)* days. Panel B of Table 6 presents the results of our regressions using these alternative specifications of the dependent variables. Column (1) and (2) present results for *PR_ILLI03 and PR_ILLI025* and Column (3) and (4) present results *ILLI45* and *ILLI060*, respectively. As indicated by the results in Column (1), the coefficient of *CRDQ* on *PR_ILLI03* is negative and statistically significant, meaning *CRDQ* reduces illiquidity over 0-3 trading days. Similarly, the coefficients of *CRDQ* on *ILLI45* and *ILLI060* in Column (3) and (4) are negative and statistically significant, which suggest that the negative association *CRDQ* and stock illiquidity persists over a longer time horizon until 60 days. Altogether, our baseline results are robust to the alternative specification of both the independent and dependent variables.

[Insert Table 6 Here]

We also perform a battery of sensitivity tests to validate our baseline results by manipulating the control variables (untabulated). First, we add the percentage of institutional ownership (*INSTOWN*) to our baseline regressions to check if controlling these more sophisticated groups of investors bring any change to our baseline results. Institutional owners are more knowledgeable about the market and have greater access to private information (Brown & Hillegeist, 2007). In contrast, institutional investors are also considered an important component of the firms information environmental and corporate governance bearing relevance to information asymmetry (Liu et al., 2024). Untabulated results show that after controlling for *INSTOWN,* our baseline findings remain unchanged. Second, we investigate whether controlling for firm corporate governance affects our results. We add corporate governance pillar scores (*CGSCORES*) provided by the Refintiv ESG as a proxy for good governance quality. Arguably, better corporate governance should be more capable a better disclosure environment and investor protection. Untabulated results suggest that our main results still hold after controlling corporate governance quality. Finally, we re-run our baseline regressions after adding quarter fixed effects. Since our data is quarterly data, quarter variations cannot be eliminated. From our re-estimated results, we observe that our baseline results remain unaltered after adding quarter fixed effects (Untabulated).

4.3.2 Endogeneity Test: Two Stage Least Squares

To address the endogeneity concerns, we use firm environmental performance proxied by the Refintiv *ENSCORE* as instrumental variable for *CRDQ* in a two-stage least squares regression (2SLS) regressions. Firm environmental performance is likely to have a signification positive association with their *CRDQ*. Arguably, a firm with better environmental performance is likely to be more inclined to provide more discussion about its risks and opportunities to distinguish itself from the poor performers, according to stakeholder theory. On the other hand, legitimacy theory suggest that firms with poor environmental performance are likely to withdraw disclosures or provide a poor quality disclosure. Prior literature suggest that environmental performance has significant association with environmental disclosures in annual reports and sustainability reports (Bui et al., 2020; Giannarakis et al., 2017). As such, environmental performance can affect the level of information asymmetry through affecting the level of disclosure and hence, justifies an ideal instrumental variable for *CRDQ* during earnings conference call.

We provide our 2SLS regression results on Panel A of Table 7. Columns (1) and (2) provide 2SLS results for *ILLI03* and *ILLI025*, respectively. The coefficients of *CRDQ* on *ILLI03* and *ILLI025* in Columns (1) and (2) are negative and statistically significant. Thus, our 2SLS estimations provide results that are consistent with our baseline results and alleviate the endogeneity concerns caused by reverse causality. Besides these 2SLS results, we also perform additional tests to check the strength and potential under-identification of *ENSCORE* as an IV for *CRDQ* (Xu et al., 2021). We present the results in Panel B of Table 7. The test results indicate that the F-value is 36.35 and statistically significant. Moreover, the minimum Eigen value statistics is 21.24, which falls far outside the critical values of 2SLS size of nominal 5% Wald test and LIML size of nominal 5% Wald test, rejecting the null hypothesis of weak IV. In other words, *ENSCORE* proves a strong instrumental variable for CRDs.

4.4 Tests for Hypotheses 2

4.4.1 Tests for Hypothesis 2: Role of Deceptive Language in Climate-related Disclosures

In Hypothesis 2, we propose that climate related disclosure quality measured by the executives' deceptive language in climate-related disclosures during earnings conference calls will negatively moderate the association between *CRDQ* and information asymmetry. We argue that deceptive language will increase uncertainty among investors and might increase the information processing costs delaying stock market trading (Bushee et al., 2018). To measure the impact of deceptive language in climate-related disclosures, we take the categorical variable *FDL* which equals to 1 if the frequency of deceptive language in climate-related disclosures is greater than the quarterly industry median; 0 otherwise.

We present the estimation results in Column (1) to (2) of Table 8. The test variable is the interaction of *CRDQ×FDL*, capturing the moderating impacts of higher deceptive language on the relationship of *CRDQ* with information asymmetry. As shown by the Column (1), the coefficients of the interaction term *CRDQ×FLD* is positive and significant for *ILLI03* (β = -0.00680; *t*-statistics = 1.685), supporting H2 that the negative association between *CRDQ* and information asymmetry is negatively moderated by the use of deceptive language in climate-related disclosures during earnings conference calls. In other words, the use of deceptive language in climate-related disclosures increases the information asymmetry that is otherwise reduced by *CRDQ*. These results further suggest that use of deceptive language in climate-related disclosures decreases investor confidence about the trustworthiness of firm climate-related disclosures and their usefulness. Therefore, investor activeness in trading the shares decreases, leading to an accumulation of abnormally high return for a given level of trade volume. One interesting observation is that in Column (1), the coefficient of *FDL* on *ILLI025* is negative and statistically significant ($\beta = -0.00680$; t-statistics = 1.685), which might indicate a disclosure effect of the deceptive disclosures. In other words, investors might initially think a deceptive disclosure as genuine one and thus engage in trading activities more actively. However, when such higher deception occurs with a higher level of disclosures, investors might feel more uncertain about the information content of the disclosure. Overall, these results are consistent with the prior literature by Brown and Hillegeist (2007) and Fuhrmann et al. (2017) who provide evidence that poor quality of disclosures increases information asymmetry. More particularly, our evidence supports and complements the previous findings by Hope and Wang (2018) who document that deceptive language in financial disclosures in earnings conference calls increase information asymmetry. However, as indicated in Column (2), the coefficient of *CRDQ×FLD* on *ILLI025* is statistically insignificant, providing no support to our H2. One potential reason could be due to a longer time horizon, which might neutralize investor negative perceptions about the disclosure quality via other factors, like firm financial performance and higher returns. Also, it might be possible that over time investor judge the quality of disclosures is affected by other contextual factors, for instance firm environmental performance. Therefore, in the following section, we analyse how a good or poor environmental performance might alter the interaction of effect *CRDQ* and *FDL* on information asymmetry.

4.4.2 Difference between Good vs Poor Environmental Performance

Firm environmental performance can be a highly relevant contextual factor that might affect investor perceptions of the usefulness climate-related disclosures of firm that contain a higher level of deceptive language. More specifically, firm environmental performance might alter investor perception about the deceptive language in climate-related disclosures during earning conference call. For example, for a firm with better environmental performance, investors might be more inclined to accept the deceptive language as a genuine information, as par the signalling theory. Thus, the negative conditioning impact of *FDL* on the association between *CRDQ* and information asymmetry might weaken. In contrast, a better environmental performance and higher level of deceptive followed by a higher deceptive language in climate-related disclosures might create substantial doubt about a firm environmental performance. Consequently, the information asymmetry caused by deceptive language is likely to be higher for firms with better environmental performance than poor environmental performance. To resolve this dispute, we investigate whether the conditioning effect of *FLD* varies between good vs poor environmental performance firms. We create a categorical variable *ENDUM,* which equals to 1 if the firm has a greater environmental pillar scores than the industry median; 0 otherwise.

We present the estimation results in Column (1) to (4) of Table 9. The test variable is the interaction of *DCRD×FDL*, capturing the moderating impacts of higher deceptive language on the association between *CRD* and *IA*. Further, our sample is divided into two groups, e.g.*, ENDUM=1*, for good environmental performance and *ENDUM=0* for poor environmental performance. As indicate in Table 9, for good environmental performance firms (*ENDUM=1*), the coefficients of the interaction term *CRD×FDL* for *ILLI03* (β =0.01474; *t*-statistics = 2.617) in Column (1) and for *ILLI025* (β =0.0992; *t*-statistics = 1.990) in Column (3), respectively, are positive and significant. However, for poor environmental performance firms (*ENDUM=0*), we observe that in Columns (2) and (4), the coefficient of the interaction term *CRD×FDL* are negative and statistically insignificant. Altogether, these results suggest that information asymmetry caused by deceptive language in climate-related disclosures becomes stronger for firms with better environmental performance. In other words, investors becomes more suspicious about the firm environmental performance and climate-related disclosure information content when such disclosures contain a higher level of deceptive language. More interesting, in this subsample analysis, we find that the negative moderating impact of *FDL* becomes significant for 0-25 days trading window which was otherwise insignificant in section 4.4.1.[4] Thus, our results suggests, when a firms with good environmental performance provide higher amount of deceptive disclosures, it induces investors to further verify the firm good environmental performance along with verifying the disclsoures. This increased level of information asymmetry might be facilitated by nature of environmental performance itself. Certain aspects of environmental performance such as carbon emission and product innovation might be publicly available. However, other aspect like impact on biodiversity and resource uses might not be publicly available and hence might be costlier to process. As such, investor confidence in both firm environmental performance and climate-related disclosures reduces due to increased level of deceptive language, causing higher information time for both the performance and disclsoures. Consequently, trading activities gets delayed, meaning a lesser liquidity. Therefore, although *CRDQ* itself reduces information asymmetry, deceptive disclosures imposes punishment by decreased liquidity for higher disclosure firms and such punishment is more pronounced for firms with better environmental performance scores. Overall, we find further support our hypothesis 2. Also, these results consistent with recent literature by Schiemann and Sakhel (2019) who suggest that contextual factors are need to be considered in analysing the relationship between climate-related disclosure and information asymmetry. In this study, we are contextual both disclosure quality and environmental performance and find evidence that these factors are highly relevant in the association between climate-related disclosures and information asymmetry.

[4] Besides, we employ an alternative measure of deceptive climate-related disclosures by using the word count per sentence (WPS) to test the robustness of our results. Extant literature suggest that deceptive disclosures are likely to contain shorter sentences (Larcker & Zakolyukina, 2012).

5. Conclusion and Policy Implications

Using a sample of S&P 500 firms from 2005 to 2022, this study investigates how corporate climate-related disclosures during earnings conference calls affect information asymmetry. We find consistent evidence climate-related disclosures during earnings conference calls disseminates information relevant to firm future prospects and performance. Thus, climate-related disclosures are found to reduce information asymmetry. In additional analysis, we find that deceptive language in climate-related disclosures during earnings conference calls increases information asymmetry for firms with a higher volume of climate-related disclosures. These findings suggest that investors perceive a higher volume of disclosures of firms with higher deceptive language as an indication of poor-quality disclosure. Consequently, the perceived information gap between the management and investors increase, leading to decreased liquidity. We also find that this negative impact of deceptive language on the information value of CRDs is more pronounced in firms with better environmental performance. That means, when a firm has higher CRDs and better environmental performance, the use of deceptive language further increases information asymmetry, meaning deceptive language also undermines the firm environmental performance by requiring further information processing time for investors. These findings indicate that the use of deceptive language deceptive language is a double-edged sword for firms with higher climate-related disclosures and better environmental performance.

Overall, our results suggest that investors care about firm climate-related disclosures during earnings conference calls and find such disclosures as decision useful. Thus, a higher disclosure reduces information asymmetry. Our results suggests that poor disclosure quality reduces the decision usefulness of climate-related disclosures although they contain material information for investors. Therefore, with a higher amount of deceptive language, information asymmetry increases for firms with a higher volume of disclosures. Finally, our results suggest that poor quality disclosure are further harmful for firms with better environmental performance than firms with poor environmental performance. That is, poor quality disclosure can undermine even a good environmental performance by creating doubt in the mind of investors. By providing evidence on such poor-quality climate-related disclosures during conference calls and their impact on investor trading behavior, our study responds to recent concerns from regulators and investors about the quality of climate-related disclosures and need to improve the quality of such disclosures (FASB, 2024; TCFD, 2017)). Another implication of our study is that it urges the board of directors to ensure that corporate climate-related disclosure quality are ensured while disseminating those disclosures to public. Moreover, executives should be careful about their language, especially about those that might indicate that executives are trying to be deceptive, while discussing climate-related risks and opportunities during earnings conference calls. Finally, policy changes regarding environmental disclosures are required, particularly in interactive disclosure settings so that there is a smoother flow of better-quality disclosures to the capital market investors. Therefore, policymakers should provide guidelines for appropriate climate-related disclosures (language and contents) by executives during earnings conference calls to ensure the stability of capital market.

We acknowledge the following limitations of this study. First, although we are analyzing the language of executives in an interactive setting to determine the impact of deceptive climate-related disclosures on information asymmetry, we have no access to the interactive physical postures and gestures, which could provide a better insight into our analysis. Also, psychological theories used in this study suggest that the language of deceivers can capture their deception. However, in our setting, we were unable to capture linguistic cues like hesitations and pauses. Second, our sample firms are the biggest U.S. firms which are subject to higher socio-economic and regulatory pressures. Thus, our findings could be generalized only for large U.S. firms.

References

Allee, K. D., & DeAngelis, M. D. (2015). The structure of voluntary disclosure narratives: Evidence from tone dispersion. *Journal of Accounting Research*, *53*(2), 241-274. https://doi.org/10.1111/1475-679x.12072

Allee, K. D., Do, C., & Sterin, M. (2021). Product market competition, disclosure framing, and casting in earnings conference calls. *Journal of Accounting and Economics 72*(1), 101405. https://doi.org/10.1016/j.jacceco.2021.101405

Berrone, P., Fosfuri, A., & Gelabert, L. (2017). Does greenwashing pay off? Understanding the relationship between environmental actions and environmental legitimacy. *Journal of Business Ethics*, *144*(2), 363-379. https://doi.org/10.1007/s10551-015-2816-9

Bhushan, R. (1989). Collection of information about publicly traded firms: Theory and evidence. *Journal of Accounting and Economics*, *11*(2-3), 183-206. https://doi.org/10.1016/0165-4101(89)90005-0

Bingler, J. A., Kraus, M., Leippold, M., & Webersinke, N. (2022). Cheap talk and cherry-picking: What climatebert has to say on corporate climate risk disclosures. *Finance Research Letters*, *47*(2), 102776. https://doi.org/10.1016/j.frl.2022.102776

Bochkay, K., Chychyla, R., & Nanda, D. (2019). Dynamics of CEO disclosure style. *The Accounting Review*, *94*(4), 103-140. https://doi.org/10.2308/accr-52281

Bochkay, K., Hales, J., & Chava, S. (2020). Hyperbole or reality? Investor response to extreme language in earnings conference calls. *The Accounting Review*, *95*(2), 31-60. https://doi.org/10.2308/accr-52507

Bowen, R. M., Davis, A. K., & Matsumoto, D. A. (2002). Do conference calls affect analysts' forecasts? *The Accounting Review*. https://doi.org/10.2308/accr.2002.77.2.285

Brown, S., & Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies*, *12*, 443-477. https://doi.org/10.1007/s11142-007-9028-1

Brown, S., Hillegeist, S. A., & Lo, K. (2004). Conference calls and information asymmetry. *Journal of Accounting and Economics 37*(3), 343-366. https://doi.org/10.1016/j.jacceco.2004.02.001

Brown, S., Hillegeist, S. A., & Lo, K. (2009). The effect of earnings surprises on information asymmetry. *Journal of Accounting and Economics*, *47*(3), 208-225. https://doi.org/10.1016/j.jacceco.2008.12.002

Bui, B., Houqe, M. N., & Zaman, M. (2020). Climate governance effects on carbon disclosure and performance. *The British Accounting Review*, *52*(2), 100880. https://doi.org/10.1016/j.bar.2019.100880

Bushee, B. J., Gow, I. D., & Taylor, D. J. (2018). Linguistic complexity in firm disclosures: Obfuscation or information? *Journal of Accounting Research*, *56*(1), 85-121. https://doi.org/10.1111/1475-679x.12179

Cheng, H., Huang, D., & Luo, Y. (2020). Corporate disclosure quality and institutional investors' holdings during market downturns. *Journal of Corporate Finance*, *60*, 101523. https://doi.org/10.1016/j.jcorpfin.2019.101523

Cho, C. H., & Patten, D. M. (2007). The role of environmental disclosures as tools of legitimacy: A research note. *Accounting, Organizations and Society*, *32*(7-8), 639-647. https://doi.org/10.1016/j.aos.2006.09.009

Cho, C. H., Roberts, R. W., & Patten, D. M. (2010). The language of US corporate environmental disclosure. *Accounting, Organizations and Society*, *35*(4), 431-443. https://doi.org/10.1016/j.aos.2009.10.002

Cho, S. Y., Lee, C., & Pfeiffer Jr, R. J. (2013). Corporate social responsibility performance and information asymmetry. *Journal of Accounting and Public Policy*, *32*(1), 71-83. https://doi.org/10.1016/j.jaccpubpol.2012.10.005

Clarkson, P. M., Overell, M. B., & Chapple, L. (2011). Environmental reporting and its relation to corporate environmental performance. *Abacus*, *47*(1), 27-60. https://doi.org/10.1111/j.1467-6281.2011.00330.x

Cohen, K. J., Maier, S. F., Schwartz, R. A., & Whitcomb, D. K. (1981). Transaction costs, order placement strategy, and existence of the bid-ask spread. *Journal of Political Economy*, *89*(2), 287-305. https://doi.org/10.1086/260966

Copeland, T. E., & Galai, D. (1983). Information effects on the bid-ask spread. *The journal of finance*, *38*(5), 1457-1469.

Cui, J., Jo, H., & Na, H. (2018). Does corporate social responsibility affect information asymmetry? *Journal of Business Ethics*, *148*, 549-572. https://doi.org/10.1007/s10551-015-3003-8

De Amicis, C., Falconieri, S., & Tastan, M. (2021). Sentiment analysis and gender differences in earnings conference calls. *Journal of Corporate Finance*, *71*, 101809. https://doi.org/10.1016/j.jcorpfin.2020.101809

Delis, M. D., De Greiff, K., & Ongena, S. (2019). *Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans*. (EBRD Working Paper No. 231). European Bank. https://doi.org/10.2139/ssrn.3451335

DeLisle, R. J., Grant, A., & Mao, R. (2021). *Does ESG decrease information asymmetry? Evidence from earnings conference call tones and subsequent returns*. (Working paper). Available at: https://www.efmaefm.org/0efmameetings/efma%20annual%20meetings/2021-leeds/papers/efma%202021_stage-2049_question-full%20paper_id-330.Pdf. (Accessed 30 June 2022)

Demaria, S., & Rigot, S. (2021). Corporate environmental reporting: Are French firms compliant with the Task Force on Climate Financial Disclosures' recommendations? *Business Strategy and the Environment*, *30*(1), 721-738. https://doi.org/10.1002/bse.2651

Diamond, D. W. (1985). Optimal release of information by firms. *The journal of finance*, *40*(4), 1071-1094. https://doi.org/10.1111/j.1540-6261.1985.tb02364.x

Doan, M. H., & Sassen, R. (2020). The relationship between environmental performance and environmental disclosure: A meta-analysis. *Journal of Industrial Ecology*, *24*(5), 1140-1157. https://doi.org/10.1111/jiec.13002

Du, X. (2015). How the market values greenwashing? Evidence from China. *Journal of Business Ethics*, *128*(3), 547-574. https://doi.org/10.1007/s10551-014-2122-y

FASB. (2024). *Investor Outreach Report*. https://www.fasb.org/page/ShowPdf?path=FASB_Investor_Outreach_Report_2024.pdf&title=2024%20FASB%20Investor%20Outreach%20Report

Fiedler, T., Pitman, A. J., Mackenzie, K., Wood, N., Jakob, C., & Perkins-Kirkpatrick, S. E. (2021). Business risk and the emergence of climate analytics. *Nature Climate Change*, *11*(2), 87-94. https://doi.org/10.1038/s41558-020-00984-6

Flammer, C., Toffel, M. W., & Viswanathan, K. (2021). Shareholder activism and firms' voluntary disclosure of climate change risks. *Strategic Management Journal* *42*(10), 1850-1879. https://doi.org/10.1002/smj.3313

Fuhrmann, S., Ott, C., Looks, E., & Guenther, T. W. (2017). The contents of assurance statements for sustainability reports and information asymmetry. *Accounting and Business Research*, *47*(4), 369-400. https://doi.org/10.1080/00014788.2016.1263550

Gallego-Álvarez, I., Segura, L., & Martínez-Ferrero, J. (2015). Carbon emission reduction: The impact on the financial and operational performance of international companies. *Journal of Cleaner Production*, *103*, 149-159. https://doi.org/10.1016/j.jclepro.2014.08.047

GIA. (2020). *Climate change risk disclosure: A practical guide to reporting against ASX corporate governance council's corporate governance principles and recommendations*. Governace Institue of Australia.

https://higherlogicdownload.s3.amazonaws.com/GOVERNANCEPROFESSIONALS/a8892c7c-6297-4149-b9fc-378577d0b150/UploadedImages/govinst_climate_change_guide.pdf

Giannarakis, G., Zafeiriou, E., & Sariannidis, N. (2017). The impact of carbon performance on climate change disclosure. *Business Strategy and the Environment*, *26*(8), 1078-1094. https://doi.org/10.1002/bse.1962

Glosten, L. R., & Harris, L. E. (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics*, *21*(1), 123-142. https://doi.org/10.1016/0304-405X(88)90034-7

Gneezy, U. (2005). Deception: The role of consequences. *American Economic Review*, *95*(1), 384-394. https://doi.org/10.1257/0002828053828662

Gong, G., Li, L. Y., & Wang, J. J. (2011). Serial correlation in management earnings forecast errors. *Journal of Accounting Research*, *49*(3), 677-720. https://doi.org/10.1111/j.1475-679X.2011.00407.x

Hain, L. I., Kölbel, J. F., & Leippold, M. (2022). Let's get physical: Comparing metrics of physical climate risk. *Finance Research Letters*, *46*(5), 102406. https://doi.org/10.1016/j.frl.2021.102406

Hope, O.-K., & Wang, J. (2018). Management deception, big-bath accounting, and information asymmetry: Evidence from linguistic analysis. *Accounting, Organizations and Society*, *70*, 33-51. https://doi.org/10.1016/j.aos.2018.02.004

Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, *36*(7), 2617-2650. https://doi.org/10.1093/rfs/hhad002

IRA , U. S. D. o. t. T. (2022). Inflation Reduction Act. https://home.treasury.gov/policy-issues/inflation-reduction-act

ISSB , I. S. S. B. (2023). *ISSB issues inaugural global sustainability disclosure standards*. https://www.ifrs.org/news-and-events/news/2023/06/issb-issues-ifrs-s1-ifrs-s2/

Jain, A., Jain, P. K., & Rezaee, Z. (2016). Value-relevance of corporate social responsibility: Evidence from short selling. *Journal of Management Accounting Research*, *28*(2), 29-52. https://doi.org/10.2308/jmar-51439

Javadi, S., & Masum, A. A. (2021). The impact of climate change on the cost of bank loans. *Journal of Corporate Finance*, *69*, 102019. https://doi.org/10.1016/j.jcorpfin.2021.102019

Kim, J.-B., Wang, C., & Wu, F. (2022). The real effects of risk disclosures: Evidence from climate change reporting in 10-Ks. *Review of Accounting Studies*, *28*(4), 2271-2318. https://doi.org/10.1007/s11142-022-09687-z

Larcker, D. F., & Zakolyukina, A. A. (2012). Detecting deceptive discussions in conference calls. *Journal of Accounting Research*, *50*(2), 495-540. https://doi.org/10.1111/j.1475-679X.2012.00450.x

Lee, J. (2016). Can investors detect managers' lack of spontaneity? Adherence to predetermined scripts during earnings conference calls. *The Accounting Review*, *91*(1), 229-250. https://doi.org/10.2308/accr-51135

Lei, L., Zhang, D., Ji, Q., Guo, K., & Wu, F. (2023). A text-based managerial climate attention index in China. *Finance Research Letters*, *55*(7), 103911. https://doi.org/10.1016/j.frl.2023.103911

Li, Q., Shan, H., Tang, Y., & Yao, V. (2024). Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, *37*(6), 1778-1830. https://doi.org/10.1093/rfs/hhad094

Li, Y., & Zhang, Z. (2023). Corporate climate risk exposure and capital structure: Evidence from Chinese listed companies. *Finance Research Letters*, *51*, 103488. https://doi.org/10.1016/j.frl.2022.103488

Liesen, A., Hoepner, A. G., Patten, D. M., & Figge, F. (2015). Does stakeholder pressure influence corporate GHG emissions reporting? Empirical evidence from Europe. *Accounting, Auditing & Accountability Journal* *28*(7), 1047-1074. https://doi.org/10.1108/AAAJ-12-2013-1547

Liu, Z., Gao, X., Xu, H., & Xu, W. (2024). Climate change exposure and stock liquidity commonality: International evidence. *Pacific-Basin Finance Journal*, *86*, 102440. https://doi.org/10.1016/j.pacfin.2024.102440

Mateo-Márquez, A. J., González-González, J. M., & Zamora-Ramírez, C. (2022). An international empirical study of greenwashing and voluntary carbon disclosure. *Journal of Cleaner Production 363*, 132567. https://doi.org/10.1016/j.jclepro.2022.132567

Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2024). Climate-risk materiality and firm risk. *Review of Accounting Studies*, *29*(1), 33-74. https://doi.org/10.1007/s11142-022-09718-9

Mayew, W. J., & Venkatachalam, M. (2012). The power of voice: Managerial affective states and future firm performance. *The journal of finance*, *67*(1), 1-43. https://doi.org/10.1111/j.1540-6261.2011.01705.x

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

Miller, G. S., & Skinner, D. J. (2015). The evolving disclosure landscape: How changes in technology, the media, and capital markets are affecting disclosure. *Journal of Accounting Research*, *53*(2), 221-239. https://doi.org/10.1111/1475-679x.12075

Price, S. M., Doran, J. S., Peterson, D. R., & Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, *36*(4), 992-1011. https://doi.org/10.1016/j.jbankfin.2011.10.013

Rodrigue, M., Magnan, M., & Cho, C. H. (2013). Is environmental governance substantive or symbolic? An empirical investigation. *Journal of Business Ethics*, *114*(1), 107-129. https://doi.org/10.1007/s10551-012-1331-5

Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449-1498. https://doi.org/10.1111/jofi.13219

Schiemann, F., & Sakhel, A. (2019). Carbon disclosure, contextual factors, and information asymmetry: The case of physical risk reporting. *European Accounting Review*, *28*(4), 791-818. https://doi.org/10.1080/09638180.2018.1534600

Solomon, J. F., Solomon, A., Norton, S. D., & Joseph, N. L. (2011). Private climate change reporting: an emerging discourse of risk and opportunity? *Accounting, Auditing & Accountability Journal*, *24*(8), 1119-1148. https://doi.org/10.1108/09513571111184788

Sullivan, R., & Gouldson, A. (2012). Does voluntary carbon reporting meet investors' needs? *Journal of Cleaner Production 36*, 60-67. https://doi.org/10.1016/j.jclepro.2012.02.020

Tasker, S. C. (1998). Bridging the information gap: Quarterly conference calls as a medium for voluntary disclosure. *Review of Accounting Studies*, *3*, 137-167. https://doi.org/0.1023/a:1009684502135

TCFD. (2017). *Recommendations of the Task Force on Climate-related Financial Disclosures. Available at: https://www.fsb-tcfd.org/publications/. (Accessed 10 June 2022)*. T. o. C.-r. F. Disclosures.

Unda, L., & Foerster, A. (2022). Climate risk disclosure, compliance and regulatory drivers: A textual tone analysis. *Company and Securities Law Journal*, *39*(1), 47-72. https://doi.org/10.3316/agispt.20220315063428

Vrij, A. (1994). The impact of information and setting on detection of deception by police detectives. *Journal of Nonverbal Behavior*, *18*(2), 117-136. https://doi.org/10.1007/Bf02170074

Xu, L., Fan, M., Yang, L., & Shao, S. (2021). Heterogeneous green innovations and carbon emission performance: evidence at China's city level. *Energy Economics*, *99*, 105269. https://doi.org/10.1016/j.eneco.2021.105269

Zhou, Z., & Wu, K. (2023). Does climate risk exposure affect corporate leverage adjustment speed? International evidence. *Journal of Cleaner Production*, *389*, 136036. https://doi.org/10.1023/a:1009684502135

Appendix I: Sautner, et al. (2023)'s Climate-related Risk and Opportunity Bigrams

Initial Bigrams to Search other Bigrams					
air pollution	electric vehicle	new energy	air quality	energy climate	ozone layer
air temperature	energy conversion	renewable energy	biomass energy	energy efficient	sea level
carbon dioxide	energy environment	sea water	carbon emission	environmental sustainability	snow ice
carbon energy	extreme weather	solar energy	carbon neutral	flue gas	solar thermal
carbon price	forest land	sustainable energy	carbon sink	gas emission	water resource
carbon tax	GHG emission	water resources	clean air	global decarbonization	wave energy
clean energy	global warm	weather climate	clean water	greenhouse gas	wind energy
climate change	heat power	wind power	coaster area	Kyoto protocol	wind resource
coastal region	natural hazard				
Climate-related Opportunity Bigrams					
heat power	new energy	plug hybrid	rooftop solar	electric hybrid	
electric vehicle	renewable electricity	wind energy	solar farm	solar energy	
hybrid car	wave power	sustainable energy	renewable resource	renewable energy	
geothermal power	clean energy	wind power			
Regulatory Risk Bigrams					
greenhouse gas	gas emission	carbon tax	emission trade	energy independence	
carbon reduction	reduce emission	air pollution	carbon price	energy regulatory	
dioxide emission	carbon market	carbon emission	reduce carbon	nox emission	
environmental standard	EPA regulation	mercury emission	carbon dioxide		
Physical Risk Bigrams					
coastal area	forest land	storm water	water discharge	warm climate	
global warm	natural hazard	sea level	heavy snow	air water	
sea water	ice product	snow ice	nickel metal		

Appendix II: Larcker and Zakolyukina (2012)'s Taxonomy of Deceptive Language

Word Category	Relations	Words
References		
1st person singular pronouns	-	LIWC word category "I": I, me, mine, etc.
1st person plural pronouns	+	LIWC word category "we": we, us, our, etc.
3rd person plural pronouns	+	LIWC word category "they": they, their, etc.
Impersonal pronouns	+	LIWC word category "ipron": it, anyone*, nobody*, etc.
References to general knowledge	+	Larcker and Zakolyukina (2012)'s Self-generated Word Categories (Genknlref)
Positives/Negatives		
Assent	-	LIWC word category "assent": ok, agree, yes, etc.
Nonextreme positive emotions	-	LIWC word category "posemone": love, nice, accept, etc.
Extreme positive emotions	+	Larcker and Zakolyukina (2012)'s Self-generated Word Categories (Posemoextr)
Negations	+	LIWC word category "negate": no, not, never, etc.
Anxiety	+	LIWC word category "anx": worried, fearful, nervous, etc.
Anger	+	LIWC word category "anger": hate, kill, annoyed, etc.
Swear	+	LIWC word category "swear": screw*, hell, etc.
Extreme negative emotions	+	Larcker and Zakolyukina (2012)'s Self-generated Word Categories (Negemoextr)
Cognitive Process		
Certainty	-	LIWC word category "certain": always, never, etc.
Tentative	+	LIWC word category "tentat": maybe, perhaps, guess, etc.
Other Cues[5]		
Hesitations	-	Larcker and Zakolyukina (2012)'s Self-generated Word Categories (Hesit)
Shareholder value	-	Larcker and Zakolyukina (2012)'s Self-generated Word Categories (Shvalue)
Value creation	-	Larcker and Zakolyukina (2012)'s Self-generated Word Categories (Value)

[5] For this category of words, there are contrasting arguments in theory. For example, the cognitive effort perspective suggests that deceivers are likely to hesitate more, whereas the attempted control hypothesis suggests that deceivers will be less hesitant due to their control over speech. Furthermore, according to the attempted control perspective, deceivers will use lesser shareholder value and value creation words due to their future concern of adverse reactions, such as legal actions by investors. Larcker and Zakolyukina (2012)'s findings provide evidence in favour of attempted control perspective for these three groups of words. Therefore, in this study, we build on the attempted control perspective and argue that hesitations, shareholder value and value creation are negatively related to deceptions in CRDs.

Appendix III: Variables' Definition

Variable Name	Definition	Source
CRDQ	Climate-related bigrams used by executives in the earnings conference calls divided by the total number of bigrams.	Conference calls
FDL	Indicator value equals 1 if the frequency of deceptive language in climate-related disclosures in a conference call is greater than the quarterly industry median; 0 otherwise.	Conference calls
ILLI	The natural logarithm of the mean Amihud illiquidity ratio calculated by daily absolute return divided by dollar volume: 1,000,000×|ret|÷ (prc×vol).	DataStream
STRD	The natural logarithm of the sum of daily trade volume in dollar.	DataStream
BAS	Average daily bid-ask spread, which is calculated as 100 × (ask − bid)/[(ask + bid)/2].	DataStream
PR_ILLI	The percentile rank of illiquidity measured using the Amihud illiquidity ratio.	DataStream
DISPERSION	Standard deviation of analyst earnings forecast for the quarter scaled by price at the beginning of the quarter.	DataStream
LEVER	Total debt scaled by total assets.	DataStream
LOSS	Indicator value 1 if a firm reports a loss in the quarter; 0 otherwise.	DataStream
RETURN	Buy-and-hold return over the quarter.	DataStream
SIZE	The natural logarithm of total assets.	DataStream
SPEIT	Special items scaled by the total assets.	DataStream
SURP	Consensus forecast error scaled by the market value of equity.	DataStream
BEAT	Indicator variable equals 1 if actual earnings beat the analysts' consensus earnings forecast by a penny or less.	I/B/E/S
ANALYST	The natural logarithm of 1 plus the number of analysts following the firm. 0 for any period with missing data.	I/B/E/S
BTM	Book value of debt divided by market value of equity.	DataStream
ROACHN	Year-on-year change in return on assets.	DataStream
FINDUM	Indicator value equals1 if the frequency of deceptive language in financial disclosure in a conference call is greater than the quarter industry median; 0 otherwise.	Conference calls
TONPRI	The overall tone of the previous quarter's earnings conference calls financial disclosures.	Conference calls
TONFIN	Overall tone of financial disclosures calculated by deducting the negative tone form positive tone of financial disclosures.	

GENREN	The percentage frequency of general references used in the CRDs of each quarter earnings conference call.	Conference calls
SHVALU	The percentage frequency of shareholder value words used in the CRDs of each quarter earnings conference call.	Conference calls
EXTPOS	The percentage frequency of extremely positive words used in the CRDs of each quarter earnings conference call.	Conference calls
EXTNEG	The percentage frequency of extremely negative words used in the CRDs of each quarter earnings conference call.	Conference calls
CGSCORE	Corporate governance score (CGSCORE) provided by the Refinitiv ESG.	Refintiv ESG
ENDUM	Indicator variable equals 1 if the environmental pillar score for a firm is greater than the industry median; 0 otherwise.	Refintiv ESG
LENCRD	The natural logarithm of the total word counts in the climate-related disclosures during earnings conference calls.	Conference calls
LENFIND	Natural logarithm of the total word counts in the financial disclosures during earnings conference calls.	Conference calls

Table 1: Sample Selection Process

Criteria	Firm-quarter
Total firm-quarter observations	63,576
No CRDs in earnings conference calls	58,238
Climate-related disclosures found	5,338
Missing GICS code	532
	4,806
Missing daily price data	3,77
	4,429
Missing other control variables	35
Final firm-quarter observations	4,394

Note: This table shows the sample selection process.

Table 2: Sample Distribution by Industry and Year

Panel A: Sample Distribution by Industry			
Sector Name (GICS Code)	Frequency	Percent	Cumulative
Energy (10)	361	8.22	8.22
Materials (15)	458	10.42	18.64
Industrials (20)	774	17.61	36.25
Consumer discretionary (25)	450	10.24	46.5
Consumer staples (30)	141	3.21	49.7
Health care (35)	138	3.14	52.84
Financials (40)	288	6.55	59.4
Information Technology (45)	446	10.15	69.55
Communication services (50)	48	1.09	70.64
Utilities (55)	1,135	25.83	96.47
Real estate (60)	155	3.53	100
Total	4,394	100	

Panel B: Sample Distribution by Year			
Year	Frequency	Percent	Cumulative
2006	28	0.64	0.64
2007	71	1.62	2.25
2008	176	4.01	6.26
2009	187	4.26	10.51
2010	143	3.25	13.77
2011	177	4.03	17.8
2012	170	3.87	21.67
2013	191	4.35	26.01
2014	191	4.35	30.36
2015	180	4.1	34.46
2016	190	4.32	38.78
2017	235	5.35	44.13
2018	272	6.19	50.32
2019	351	7.99	58.31
2020	471	10.72	69.03
2021	697	15.86	84.89
2022	664	15.11	100
Total	4,394	100	

Note: Panel A of Table 2 presents the sample distribution by industry and Panel B of Table 2 presents the sample distribution by year. Total number of firm-quarter observation is 4,394. Utilities sector has the largest sample size with a firm-quarter observation of 1,135 and year 2021 has the largest sample size with a firm-quarter observation of 697.

Table 3: Descriptive Statistics of Key Variables

Variable	N	Mean	SD	p25	Median	p75
ILLI03	4394	-3.512	1.170	-4.234	-3.502	-2.804
ILLI025	4394	-3.491	1.143	-4.189	-3.523	-2.813
STRD03	4394	19.191	1.011	18.548	19.137	19.790
STRD025	4394	20.887	1.019	20.263	20.842	21.508
BAS03	4394	0.063	0.073	0.031	0.049	0.075
BAS025	4394	1.560	.962	1.063	1.388	1.825
CRDQ	4394	5.800	3.683	3.500	5.085	7.317
DISPERS	4394	0.073	0.170	0.020	0.037	0.078
LEVER	4394	0.569	1.101	0.147	0.327	0.702
SALGRO	4394	3.409	17.959	-5.145	2.440	10.667
SIZE	4394	23.811	1.229	22.940	23.818	24.588
LOSS	4394	0.076	0.265	0.000	0.000	0.000
RETURN	4394	3.763	16.638	-5.187	2.989	11.751
SUPR	4394	0.476	0.700	0.091	0.238	0.554
BTM	4394	0.465	0.348	0.230	0.409	0.625
SPEIT	4394	-0.045	0.953	-0.087	0.000	0.000
BEAT	4394	0.021	0.145	0.000	0.000	0.000
ROACHN	4394	0.434	5.574	-1.120	0.108	1.543
OUTSH	4394	19.671	1.118	18.909	19.597	20.317
ANALYST	4394	2.535	0.526	2.197	2.565	2.890
GENREF	4394	0.048	0.218	0.000	0.000	0.000
SHVAL	4394	0.004	0.034	0.000	0.000	0.000
EXTPOS	4394	0.592	0.800	0.000	0.290	0.940
EXTNEG	4394	0.166	0.408	0.000	0.000	0.000
LENCRD	4394	5.074	0.857	4.419	4.963	5.659
LENFIND	4394	8.572	0.072	8.561	8.585	8.605
TONFINN	4394	61.403	10.394	54.190	61.550	68.970
TONPRI	4394	61.349	10.456	54.040	61.455	68.920
FINDUM	4394	0.497	0.500	0.000	0.000	1.000
FDL	4394	0.499	0.500	0	0	1.000
ENDUM	3876	0.504	0.500	0	1.000	1.000

Notes: Panel A of table 3 presents the descriptive statistics for the key variables. N is the Number of observations; SD is the standard deviation; P25 and P75 are the 25th and 75th percentiles of the variables, respectively. Please see detailed variable definitions and sources in Appendix III.

Table 4: Pearson Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
(1) ILLI	1																							
(2) CRDQ	-0.05*	1																						
(3) DISPERS	-0.03	0.02	1																					
(4) LEVER	0.16*	0.004	0.06*	1																				
(5) SALGRO	-0.01	0.03	0.07*	-0.01	1																			
(6) SIZE	-0.6*	0.04*	0.05*	0.20*	-0.021	1																		
(7) LOSS	0.17*	0.001	0.11*	0.19*	-0.07*	-0.08*	1																	
(8) RETURN	-0.06*	0.02	0.02	-0.06*	0.011	-0.04*	0.05*	1																
(9) SUPR	-0.01	0.02	0.41*	0.08*	0.07*	0.10*	0.12*	-0.01	1															
(10) BTM	0.27*	-0.03	0.002	0.28*	-0.02	0.22*	0.11*	-0.13*	0.06*	1														
(11) SPEIT	0.01	0.01	0.01	0.002	-0.02	-0.01	0.11*	0.01	0.02	0.02	1													
(12) BEAT	0.02	-0.01	-0.04*	-0.02	-0.01	-0.08*	-0.01	-0.002	-0.10*	-0.03*	0.002	1												
(13) ROACHN	-0.07*	0.002	0.05*	-0.08*	0.04*	-0.02	-0.17*	0.01	0.03	-0.10*	-0.03*	0.01	1											
(14) OUTSH	-0.62*	0.03	-0.13*	0.08*	-0.01	0.69*	-0.03	0.02	-0.16*	0.01	-0.01	0.11*	0.03*	1										

(15) ANALYST	-0.33*	0.02	0.03*	-0.18*	0.08*	0.12*	-0.004	0.02	0.01	-0.21*	0.01	0.02	0.03	0.27*	1									
(16) GENREF	-0.05*	-0.06*	-0.02	0.01	-0.001	0.03*	-0.002	-0.01	-0.03	0.01	-0.01	0.01	-0.01	0.04*	0.01	1								
(17) SHVAL	-0.011	-0.04*	0.04*	-0.01	0.02	0.04*	0.02	0.02	0.04*	0.02	0.01	-0.003	0.01	0.04*	0.02	-0.002	1							
(18) EXTPOS	-0.016	-0.065*	-0.008	-0.003	-0.010	-0.032*	-0.011	-0.010	-0.039*	-0.048*	-0.003	0.037*	0.018	0.047*	0.065*	0.001	0.028	1						
(19) EXTNEG	-0.007	0.009	0.050*	-0.033*	0.015	-0.029	-0.031*	0.005	0.004	-0.039*	-0.023	-0.005	0.024	-0.014	0.052*	0.014	-0.016	0.006	1					
(20) LENCRD	-0.05*	-0.35*	-0.004	0.003	0.01	0.121*	-0.02	0.01	-0.001	0.05*	0.002	-0.02	0.01	0.04*	-0.13*	0.11*	0.11*	-0.02	-0.04*	1				
(21) LENFIND	-0.016	-0.004	0.03	0.01	0.01	0.01	0.05*	0.004	-0.001	-0.03	0.01	0.02	-0.003	0.05*	0.12*	0.03*	0.003	0.03*	0.04*	-0.01	1			
(22) TONFINN	-0.13*	0.06*	0.01	-0.11*	0.03*	0.10*	-0.10*	0.09*	0.03	-0.18*	-0.02	0.01	0.05*	0.02	0.12*	-0.02	-0.01	0.08*	0.002	0.02	-0.05*	1		
(23) TONPRI	-0.13*	0.03*	0	-0.110*	0.032*	0.068*	-0.094*	0.032*	0.039*	-0.179*	-0.013	0.003	0.077*	0.012	0.134*	-0.023	0	0.08*	0.003	0.03	-0.01	0.66*	1	
(24) FINDUM	0.01	-0.01	-0.01	0.01	-0.004	-0.02	0.02	0.02	0.01	-0.03	-0.01	-0.002	-0.02	-0.01	-0.01	0.003	0.01	0.02	0.04*	-0.02	0.18*	-0.01	0.02	1

Note: This table presents the Pearson (Spearman) correlation coefficients. *represents significance levels at < 0.05 (two-tailed). Please see detailed variable definitions and sources in Appendix III.

Table 5: Baseline Regression Results

Panel A: 0-3 Trading Days			
	(1)	(2)	(3)
VARIABLES	ILLI03	STRD 03	BAS03
CRDQ	-0.00755**	0.00674**	-0.00026
	(-2.129)	(1.972)	(-0.833)
DISPERSION	-0.25095***	0.42582***	0.00658
	(-3.946)	(3.226)	(0.972)
LEVER	0.18706***	-0.13543***	0.00947**
	(5.060)	(-6.448)	(2.422)
SALGRO	0.00009	0.00036	0.00011*
	(0.145)	(0.468)	(1.804)
SIZE	-0.60198***	0.44818***	-0.00896***
	(-17.249)	(12.301)	(-4.088)
LOSS	0.21826*	-0.11638	0.01334
	(1.792)	(-0.853)	(1.366)
RETURN	-0.00274***	0.00203**	0.00009
	(-3.325)	(2.552)	(0.819)
SURP	-0.02409	0.08084***	0.00293
	(-1.148)	(4.044)	(0.665)
BTM	1.03331***	-0.72593***	0.00652
	(11.281)	(-8.593)	(0.956)
SPEIT	-0.01027	-0.00173	-0.00000
	(-0.967)	(-0.209)	(-1.088)
BEAT	0.09718	-0.03598	-0.00450
	(1.107)	(-0.443)	(-0.930)
ROACHN	-0.00149	0.00560	0.00000
	(-0.465)	(1.508)	(0.021)
OUTSH	-0.16094***	0.18335***	-0.00026
	(-3.555)	(3.633)	(-0.115)
ANALYST	-0.36056***	0.40785***	-0.00522
	(-5.917)	(6.643)	(-1.106)
GENREF	-0.08457*	0.02041	-0.00118
	(-1.808)	(0.501)	(-0.339)
SHVAL	0.26913	0.05809	-0.00082
	(1.106)	(0.193)	(-0.045)
EXTPOS	-0.00644	-0.01510	-0.00011
	(-0.431)	(-1.041)	(-0.100)
EXTNEG	-0.01529	0.00758	0.00134
	(-0.502)	(0.281)	(0.547)
LENCRD	-0.04158**	0.04305**	0.00008
	(-2.256)	(2.273)	(0.064)
LENFIND	0.30791	-0.02590	0.00768
	(1.516)	(-0.190)	(0.616)
TONFIN	-0.00053	-0.00250	-0.00010
	(-0.318)	(-1.627)	(-0.624)
TONPRI	0.00080	-0.00203	0.00002

	(0.528)	(-1.471)	(0.163)
FINDUM	-0.02563	-0.01519	0.00190
	(-0.813)	(-0.573)	(0.748)
Constant	11.95723***	4.47904***	0.22184**
	(6.608)	(3.642)	(1.979)
Industry FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	4,394	4,394	4,394
R-squared	0.697	0.709	0.108

Panel B: 0-25 Trading Days

VARIABLES	ILLI025	STRD025	BAS025
CRDQ	-0.00601*	0.00762**	-0.00464
	(-1.723)	(2.336)	(-1.077)
DISPERSION	-0.22160***	0.45736***	0.55063*
	(-3.384)	(3.283)	(1.868)
LEVER	0.18480***	-0.13391***	0.17149***
	(5.174)	(-5.481)	(5.244)
SALGRO	0.00006	0.00052	0.00091
	(0.097)	(0.720)	(1.174)
SIZE	-0.60256***	0.46410***	-0.14920***
	(-16.503)	(12.886)	(-3.195)
LOSS	0.26844**	-0.10363	0.18488
	(2.207)	(-0.838)	(1.441)
RETURN	-0.00284***	0.00199***	0.00185
	(-3.892)	(2.646)	(1.216)
SURP	-0.01660	0.07602***	-0.02301
	(-0.804)	(3.966)	(-0.484)
BTM	1.05172***	-0.76504***	0.25936**
	(11.440)	(-9.257)	(2.089)
SPEIT	-0.00444	-0.00058	0.01371
	(-0.471)	(-0.074)	(0.736)
BEAT	0.06365	-0.11422	-0.13265
	(0.786)	(-1.348)	(-1.600)
ROACHN	-0.00147	0.00515	0.00378
	(-0.438)	(1.418)	(1.092)
OUTSH	-0.15944***	0.20244***	-0.02415
	(-3.414)	(4.125)	(-0.552)
ANALYST	-0.40224***	0.38040***	-0.22287**
	(-7.060)	(6.479)	(-2.010)
GENREF	-0.04973	0.01030	0.07227
	(-1.336)	(0.263)	(1.299)
SHVAL	0.09834	0.08100	-0.13756
	(0.453)	(0.283)	(-0.424)
EXTPOS	-0.00066	-0.00584	0.02942
	(-0.047)	(-0.421)	(1.134)
EXTNEG	-0.00514	0.00691	0.03598
	(-0.187)	(0.279)	(0.946)

LENCRD	-0.02376	0.04709**	-0.00857
	(-1.278)	(2.584)	(-0.319)
LENFIND	0.27833*	-0.05337	0.07225
	(1.877)	(-0.389)	(0.338)
TONFIN	-0.00057	-0.00233	-0.00437**
	(-0.368)	(-1.515)	(-2.196)
TONPRI	0.00128	-0.00171	0.00033
	(0.955)	(-1.316)	(0.183)
FINDUM	0.00498	-0.00798	0.04773
	(0.176)	(-0.307)	(1.131)
Constant	12.15875***	5.67899***	5.53087***
	(9.049)	(4.509)	(2.704)
Industry FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	4,394	4,394	4,394
R-squared	0.757	0.740	0.180

Notes: This table presents results for the baseline Ordinary Least Squares (OLS) regressions. Panel A presents results for 0-3 trading days, whereas the Panel B presents results for 0-25 trading days. Information asymmetry is proxied by *ILLI, STRD* and *BAS* over 0-3 days and 0-25 days, which are the dependent variables. Climate-related disclosures (*CRDQ*) is the independent variable which is measured by dividing the total number of climate-related bigrams by total number of bigrams in climate-related disclosures at earnings conference calls. Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). Please see detailed variable definitions and data sources in Appendix III.

Table 6: Alternative Measures of Climate-related Disclosures and Illiquidity

Panel A: Alternative Measure of *CRDQ*				
	LENCRD		PCTCRD	
VARIABLES	(1) ILLI03	(2) ILLI025	(3) ILLI03	(4) ILLI025
CRDQ	-0.02833*	-0.01463	-0.02833*	-0.01463
	(-1.717)	(-0.898)	(-1.717)	(-0.898)
DISPERSION	-0.24960***	30.58066**	-0.24960***	30.58066**
	(-3.882)	(2.225)	(-3.882)	-2.225
LEVER	0.18739***	0.15986***	0.18739***	0.15986***
	(5.010)	(4.529)	-5.01	-4.529
SALGRO	0.00005	-0.00028	0.00005	-0.00028
	(0.078)	(-0.406)	-0.078	(-0.406)
SIZE	-0.60410***	-0.60200***	-0.60410***	-0.60200***
	(-17.364)	(-16.673)	(-17.364)	(-16.673)
LOSS	0.21855*	0.19128*	0.21855*	0.19128*
	(1.789)	(1.804)	-1.789	-1.804
RETURN	-0.00275***	-0.00357***	-0.00275***	-0.00357***
	(-3.342)	(-4.345)	(-3.342)	(-4.345)
SURP	-0.02353	-0.04944**	-0.02353	-0.04944**
	(-1.123)	(-2.174)	(-1.123)	(-2.174)
BTM	1.03455***	1.00120***	1.03455***	1.00120***
	(11.206)	(11.071)	-11.206	-11.071
SPEIT	-0.01048	-0.00416	-0.01048	-0.00416
	(-0.989)	(-0.440)	(-0.989)	(-0.440)
BEAT	0.09679	0.06751	0.09679	0.06751
	(1.104)	(0.845)	-1.104	-0.845
ROACHN	-0.00150	-0.00218	-0.0015	-0.00218
	(-0.466)	(-0.655)	(-0.466)	(-0.655)
OUTSH	-0.16049***	-0.15562***	-0.16049***	-0.15562***
	(-3.530)	(-3.372)	(-3.530)	(-3.372)
ANALYST	-0.35786***	-0.39217***	-0.35786***	-0.39217***
	(-5.858)	(-6.932)	(-5.858)	(-6.932)
GENREF	-0.08285*	-0.04373	-0.08285*	-0.04373
	(-1.769)	(-1.160)	(-1.769)	(-1.160)
SHVAL	0.26664	0.00555	0.26664	0.00555
	(1.090)	(0.026)	-1.09	-0.026
EXTPOS	-0.00395	-0.00041	-0.00395	-0.00041
	(-0.264)	(-0.030)	(-0.264)	(-0.030)
EXTNEG	-0.01535	-0.01199	-0.01535	-0.01199
	(-0.503)	(-0.451)	(-0.503)	(-0.451)
LENFIND	0.30526	0.22921	0.30526	0.22921
	(1.496)	(1.565)	-1.496	-1.565
TONFIN	-0.00061	-0.00072	-0.00061	-0.00072

	(-0.370)	(-0.469)	(-0.370)	(-0.469)
TONPRI	0.00084	0.00188	0.00084	0.00188
	(0.557)	(1.376)	-0.557	-1.376
FINDUM	-0.02471	0.00334	-0.02471	0.00334
	(-0.780)	(0.116)	(-0.780)	-0.116
Constant	11.90284***	12.35982***	11.90284***	12.35982***
	(6.556)	(9.263)	-6.556	-9.263
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	4,394	4,394	4,394	4,394
R-squared	0.693	0.759	0.697	0.759

Panel B: Alternative Measure of Illiquidity

	Percentile Rank		Longer Horizon	
VARIABLES	PR_ILLI03	PR_ILLI025	ILLI045	ILLI060
CRDQ	-0.00169*	-0.00123	-0.00619*	-0.00612*
	(-1.780)	(-1.245)	(-1.799)	(-1.788)
DISPERSION	-0.04825**	-0.04548*	-0.23559***	-0.24741***
	(-2.009)	(-1.802)	(-3.341)	(-3.405)
LEVER	0.04252***	0.04236***	0.17937***	0.17751***
	-5.96	(6.086)	(5.161)	(5.110)
SALGRO	-0.00006	-0.00006	-0.00001	-0.00009
	(-0.384)	(-0.319)	(-0.013)	(-0.143)
SIZE	-0.16149***	-0.16642***	-0.59609***	-0.59191***
	(-17.156)	(-16.040)	(-16.173)	(-15.906)
LOSS	0.01778	0.03224	0.27281**	0.27870**
	-0.793	(1.397)	(2.206)	(2.236)
RETURN	-0.00064***	-0.00067***	-0.00259***	-0.00225***
	(-3.650)	(-4.179)	(-3.475)	(-2.988)
SURP	-0.00086	0.00127	-0.01743	-0.01806
	(-0.156)	(0.225)	(-0.866)	(-0.908)
BTM	0.26606***	0.27951***	1.04412***	1.03682***
	-12.906	(12.782)	(11.436)	(11.362)
SPEIT	-0.00272	-0.00066	-0.00342	-0.00175
	(-0.900)	(-0.232)	(-0.369)	(-0.194)
BEAT	0.01362	0.01476	0.06868	0.06097
	-0.638	(0.702)	(0.856)	(0.772)
ROACHN	0.00006	0.00005	-0.00099	-0.00095
	-0.07	(0.055)	(-0.290)	(-0.278)
OUTSH	-0.02545**	-0.02726**	-0.16504***	-0.16842***
	(-2.270)	(-2.283)	(-3.494)	(-3.542)
ANALYST	-0.09657***	-0.10911***	-0.41164***	-0.40591***
	(-6.804)	(-7.786)	(-7.188)	(-7.015)
GENREF	-0.01671	-0.00939	-0.02831	-0.02768
	(-1.298)	(-0.845)	(-0.740)	(-0.716)

SHVAL	0.10785*	0.03756	0.15739	0.12818
	-1.657	(0.508)	(0.688)	(0.556)
EXTPOS	-0.00132	0.00026	-0.00178	0.00140
	(-0.334)	(0.066)	(-0.126)	(0.098)
EXTNEG	-0.0092	-0.00512	-0.00887	-0.00615
	(-1.115)	(-0.643)	(-0.327)	(-0.227)
LENCRD	-0.00882*	-0.00376	-0.02837	-0.02803
	(-1.815)	(-0.709)	(-1.550)	(-1.529)
LENFIND	0.04872	0.01916	0.24257*	0.24439*
	-0.957	(0.462)	(1.660)	(1.699)
TONFIN	-0.00047	-0.00041	-0.00012	0.00004
	(-1.073)	(-0.945)	(-0.074)	(0.027)
TONPRI	0.00037	0.00040	0.00092	0.00071
	-0.919	(1.050)	(0.710)	(0.538)
FINDUM	-0.00434	0.00602	0.00598	0.00548
	(-0.504)	(0.736)	(0.214)	(0.196)
Constant	4.58103***	4.96915***	-1.34766	-1.40366
	-9.986	(13.152)	(-1.009)	(-1.064)
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	4,394	4,394	4,394	4,394
R-squared	0.629	0.693	0.761	0.763

Notes: This table presents results for the Ordinary Least Squares (OLS) regressions for the alternative measurement of independent and dependent variables. Panel A presents results for two alternative measures of the independent variable e.g., for *LENCRD* in column (1) and (2) and for *PCTCRD* in column (2) and (4) for *ILLI03* and *ILLI025*, respectively. *LENCRD* is the natural logarithm of the total number of words in climate-related disclosure, whereas *PCTCRD* is the ratio of climate-related disclosure word count over total word count in the financial disclosures in percentage form. Information asymmetry is proxied by *ILLI03* and *ILLI025*, respective. Panel B presents results for the alternative specification of the dependent variable measured by the percentile rank of illiquidity e.g., *PR_ILLI03* and *PR_ILLI025* in column (1) and (2), respectively and illiquidity over a longer time horizon e.g., *ILLI045* and *ILLI060* in column (3) and (4), respectively. Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). Please see detailed variable definitions and data sources in Appendix III.

Table 7: Two-stage Least Squares (2SLS) and IV Strength Tests

Panel A: 2SLS Results		
	(1)	(2)
VARIABLES	ILLI03	ILLI025
CRDQ	-0.17722*	-0.20934**
	(-1.935)	(-2.214)
DISPERSION	-0.29837***	-0.27165***
	(-4.142)	(-3.802)
LEVER	0.17454***	0.17045***
	(6.773)	(7.302)
SALGRO	0.00071	0.00093
	(0.754)	(0.917)
SIZE	-0.56190***	-0.54788***
	(-11.694)	(-11.158)
LOSS	0.12912	0.18248**
	(1.584)	(2.064)
RETURN	-0.00211**	-0.00228**
	(-2.211)	(-2.353)
SURP	-0.02468	-0.01747
	(-0.925)	(-0.635)
BTM	1.02801***	1.03100***
	(12.272)	(11.686)
SPEIT	-0.00302	0.00418
	(-0.210)	(0.277)
BEAT	0.11518	0.08405
	(1.022)	(0.756)
ROACHN	-0.00640**	-0.00665*
	(-1.969)	(-1.946)
OUTSH	-0.15772***	-0.16467***
	(-3.719)	(-3.756)
ANALYST	-0.36949***	-0.43599***
	(-5.455)	(-6.512)
GENREF	-0.10215*	-0.07812
	(-1.729)	(-1.413)
SHVAL	0.51849	0.30734
	(1.537)	(0.948)
EXTPOS	-0.07171*	-0.07213*
	(-1.861)	(-1.839)
EXTNEG	-0.04531	-0.02794
	(-1.139)	(-0.677)
LENCRD	-0.33852**	-0.38392**
	(-2.099)	(-2.327)
LENFIND	0.36854	0.36194
	(1.307)	(1.338)
TONFIN	0.00052	0.00116
	(0.245)	(0.547)
TONPRI	-0.00087	-0.00081

	(-0.429)	(-0.378)
FINDUM	-0.04756	-0.02357
	(-1.301)	(-0.639)
Constant	13.49372***	13.91270***
	(6.178)	(6.727)
Industry FE	yes	yes
Year FE	yes	yes
Observations	3,968	3,968
R-squared	0.451	0.389

Panel B: IV Strength Test

	Adjusted R-sq.	Partial R-sq	Robust R-sq	F
	0.0405	0.0292	0.0118	36.3521
Min. Eigen value statistics				21.24
Critical Values	10%	15%	20%	25%
2SLS size of nominal 5% Wald test	16.38	8.96	6.66	5.53
LIML size of nominal 5% Wald test	16.38	8.96	6.66	5.33

Notes: This table presents results for Two-stage least squares (2SLS) regressions to check the endogeneity of our baseline results. Panel A of Table 7 presents results of the 2SLS estimation. Columns (1) and (2) present results for a window of 0-3 trading days and 0-25 trading days, respectively. Information asymmetry proxied by *ILLI03* and *ILLI025* are the dependent variables. We use ivregress command to generate the 2SLS regression results. Panel B of Table 7 presents results for the IV strength test. We use Stata postestimation to generate the first stage regressions statistics to generate the minimum Eigen value statistics, critical values for 2SLS size of nominal 5% Wald test and LIML size of nominal 5% Wald test for 10% to 25% significance level. Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). Please see detailed variable definitions and data sources in Appendix III.

Table 8: Moderating Effect Deceptive Language in Climate-related Disclosures (FDL)

VARIABLES	(1) ILLI03	(2) ILLI025
CRDQ	-0.00630**	-0.00100
	(-1.988)	(-0.389)
FDL	-0.07899***	-0.02599
	(-2.858)	(-1.128)
CRDQ*FDL	0.00680*	-0.00032
	(1.685)	(-0.092)
DISPERSION	-0.13789**	-0.10092
	(-2.395)	(-1.378)
LEVER	0.03183***	0.02756**
	(2.895)	(2.526)
SALGRO	-0.00090*	-0.00097*
	(-1.741)	(-1.895)
SIZE	-0.88393***	-0.89927***
	(-33.927)	(-37.784)
LOSS	-0.04612	-0.00427
	(-0.609)	(-0.057)
RETURN	-0.00250***	-0.00260***
	(-4.651)	(-6.590)
SURP	-0.01680	-0.00723
	(-1.084)	(-0.533)
BTM	-0.06091	-0.05530
	(-0.976)	(-0.930)
SPEIT	-0.01769**	-0.01208*
	(-2.158)	(-1.944)
BEAT	-0.00848	-0.05267
	(-0.145)	(-0.971)
ROACHN	-0.00407**	-0.00420**
	(-2.092)	(-2.119)
OUTSH	0.00784	0.01961
	(0.301)	(0.800)
ANALYST	-0.14927***	-0.18536***
	(-3.912)	(-5.734)
GENREF	-0.05591	-0.02343
	(-1.521)	(-0.869)
SHVAL	0.17327	0.00301
	(0.961)	(0.019)
EXTPOS	-0.00688	-0.00223
	(-0.621)	(-0.254)
EXTNEG	0.00629	0.01675
	(0.280)	(0.909)
LENCRD	-0.01806	-0.00055
	(-1.411)	(-0.048)
LENFIND	0.16684	0.13483
	(0.875)	(1.089)

TONFIN	-0.00084	-0.00090
	(-0.654)	(-0.844)
TONPRI	0.00183	0.00233**
	(1.482)	(2.415)
FINDUM	-0.07843***	-0.05163***
	(-3.271)	(-2.785)
Constant	16.38341***	16.72178***
	(10.000)	(15.796)
Industry FE	yes	yes
Year FE	yes	yes
Observations	4,394	4,394
R-squared	0.803	0.875

Notes: This table presents results for the moderating impact of deceptive language in climate-related disclosures (*FDL*) on the association of *CRDQ* and *IA*. Columns (1) and (2) present results for a window of 0-3 trading days and 0-25 trading days, respectively. *FDL* is measured assigning a categorical value 1 if a firm's frequency of deceptive language in climate-related disclosures for in a quarter is more than the quarter industry median value; 0 otherwise. Information asymmetry proxied by *ILLI03* and *ILLI025* are the dependent variables. Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). Please see detailed variable definitions and data sources in Appendix III.

Table 9: Moderating Effect of FDL Subsampled by Environmental Performance

	ILLI03		ILLI025	
	(1)	(2)	(3)	(4)
VARIABLES	ENDUM=1	ENDUM=0	ENDUM=1	ENDUM=0
CRDQ	-0.00897*	-0.00544	-0.00466	-0.00005
	(-1.789)	(-1.124)	(-1.251)	(-0.013)
FDL	-0.13862***	-0.01808	-0.08766***	0.02404
	(-3.582)	(-0.384)	(-2.780)	(0.624)
CRDQ*FDL	0.01476***	-0.00036	0.00915**	-0.00626
	(2.617)	(-0.058)	(1.990)	(-1.134)
DISPERSION	-0.21451**	-0.11173	-0.18778**	-0.05931
	(-2.117)	(-1.276)	(-2.527)	(-0.629)
LEVER	0.02641***	0.04515	0.02240**	0.03831
	(2.917)	-1.229	(2.429)	(1.115)
SALESGR	-0.00028	-0.00146**	-0.00064	-0.00119*
	(-0.422)	(-1.988)	(-1.252)	(-1.653)
SIZE	-0.89059***	-0.88702***	-0.89204***	-0.88719***
	(-29.336)	(-28.238)	(-33.337)	(-29.272)
LOSS	-0.01512	-0.18612**	-0.00200	-0.10657
	(-0.224)	(-2.425)	(-0.031)	(-1.336)
RETURN	-0.00170**	-0.00250***	-0.00235***	-0.00221***
	(-2.095)	(-3.894)	(-4.184)	(-3.999)
SURP	0.00432	-0.02981	0.02250	-0.02796
	(0.234)	(-1.033)	(1.416)	(-1.189)
BTM	-0.05079	-0.02532	-0.00794	-0.03536
	(-0.879)	(-0.272)	(-0.148)	(-0.393)
SPEIT	-0.02345**	-0.00461	-0.01344	-0.00546
	(-2.295)	(-0.371)	(-1.618)	(-0.586)
S_BEAT	0.10355	-0.08569	0.06278	-0.11766
	(1.372)	(-0.978)	(0.816)	(-1.519)
ROA_CHN	-0.00504*	-0.00715***	-0.00440*	-0.00693**
	(-1.935)	(-2.966)	(-1.943)	(-2.540)
SH_OUT	0.03309	0.00186	0.03922	-0.00297
	(1.010)	-0.061	(1.389)	(-0.094)
ANALYST	-0.08315*	-0.12599***	-0.11169***	-0.19419***
	(-1.833)	(-2.736)	(-3.286)	(-4.794)
GENREF	-0.02449	-0.08245	0.01065	-0.06624
	(-0.475)	(-1.334)	(0.260)	(-1.414)
SHVAL	0.37365	-0.12987	0.17754	-0.34814
	(1.406)	(-0.412)	(0.999)	(-1.220)
EXTPOST	-0.03080*	-0.01254	-0.02431*	0.00553
	(-1.945)	(-0.756)	(-1.965)	(0.456)
EXTNEG	0.02395	-0.0341	0.04240*	-0.00789
	(0.786)	(-1.056)	(1.860)	(-0.291)

LENCRD	-0.01586	-0.04803***	0.01503	-0.03930**
	(-1.045)	(-2.718)	(1.141)	(-2.426)
LENFIND	0.28843	0.10021	0.28021	-0.00264
	(0.874)	-0.625	(1.388)	(-0.022)
TONFIN	-0.00098	-0.00161	-0.00072	-0.00154
	(-0.528)	(-0.842)	(-0.507)	(-0.959)
TONFINPRI	0.00283**	0.00034	0.00186*	0.00215
	(2.021)	-0.171	(1.827)	(1.435)
FINDUM	-0.01863	-0.13124***	-0.01775	-0.08967***
	(-0.651)	(-3.765)	(-0.915)	(-3.339)
Constant	14.73620***	17.35489***	14.62658***	18.29966***
	(5.118)	-12.625	(8.044)	(18.945)
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	1,952	1,924	1,952	1,924
R-squared	0.801	0.783	0.881	0.854

Notes: This table presents results for the moderating impact of deceptive language in climate-related disclosures (*FDL*) on the association of *CRDQ* and *IA* by dividing the sample into two groups based on environmental performance. Environmental performance is proxied by Refintiv environmental pillar scores and *ENDUM* is the categorical variable which equals 1 if a firms' ENSCORE is greater than the industry median; 0 otherwise. Columns (1) and (2) present results for a *ILLI03*, whereas Columns (3) and (4) present results for a *ILLI025* trading days, respectively. *FDL* is measured assigning a categorical value 1 if a firm's frequency of deceptive language in climate-related disclosures for in a quarter is more than the quarter industry median value; 0 otherwise. Information asymmetry proxied by *ILLI03* and *ILLI025* are the dependent variables. Industry fixed effects and year fixed effects are included. Standard errors are clustered at firm level. Robust t-statistics are in parentheses. *, **, and *** represent significance levels at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively (two-tailed). Please see detailed variable definitions and data sources in Appendix III.