Energy Policy 185 (2024) 113938

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

When attention to climate change matters: The impact of climate risk disclosure on firm market value

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ARTICLE INFO

Keywords:
Climate change
Risk disclosure
Firm value
Semantic network analysis
Semantic brand score
Text mining

ABSTRACT

Concerns about climate change and its potential economic impact have prompted policymakers and institutions to introduce standards and principles to encourage the disclosure of company risks related to climate change. Past research demonstrated that such disclosure positively impacts firm stock prices. This study analyzes the magnitude and significance of climate risk disclosures within 10-K and 10-Q reports of U.S. companies through the application of novel methods in text mining and social network analysis. Furthermore, it measures the level of attention directed towards climate change at the firm level by analyzing transcripts from earnings conference calls. The study contributes to the literature by investigating the effect of climate risk disclosure on firm market value and considering where such disclosure occurs. The findings demonstrate a positive relationship between climate risk disclosures and firm value. However, this relationship can turn negative when the attention to climate change intensifies. The results of this study are of particular relevance for practitioners and policymakers who are provided with a novel instrument to quantify the magnitude of climate change risk disclosure in textual data. Regulators can identify firms particularly exposed to climate change and create incentives for disclosure, especially when firms may be disincentivized to share information about climate change risks.

1. Introduction

Over the past decades, there has been a growing concern about climate change risks (Battiston et al., 2021; Bolton and Kacperczyk, 2021; Dowling, 2013; Hong et al., 2020). Investors incorporate climate risk exposure of their portfolio companies into their decision-making, and the majority of investors believe that climate risks have significant financial implications for companies and call for greater disclosure (Ceres, 2018; FinancialTimes, 2017, 2018, 2020; Krueger et al., 2020).

In response, policymakers and other institutions started introducing various standards and principles to incentivize the disclosure of climate change-related risks. For example, in 2010, the SEC introduced a principle-based approach for firms to self-identify climate-related risks material to their business in 10k reports.[1] In 2015, the Financial Stability Board created the TCFD to introduce a standard-based approach for firms to disclose specific information and metrics (FSB, 2015).

Despite the agreed-upon importance of climate change risks, little is known about the effect of companies' disclosure of such risks and the scenario in which such disclosure takes place (Connelly et al., 2011; Flammer et al., 2021; Vanacker et al., 2020). Scholarly attention has focused mainly on participation in voluntary initiatives and disclosure of greenhouse gas emissions (Bento and Gianfrate, 2020; Bu et al., 2022; Fisher-Vanden and Thorburn, 2011; Griffin et al., 2017; Hahn et al., 2015; Lewis et al., 2014; Marquis et al., 2016). However, the exposure to climate change risks is different from firms' carbon footprint and participation of firms in climate-related initiatives (Flammer et al., 2021). Climate change risks are broad and heterogeneous and can include transition risks, which are a combination of multiple shocks, and physical risks, which are directly attributable to catastrophic events related to climate change, such as flooding, heat waves, or biodiversity loss (Venturini, 2022).

In this study, we examine the effect of the disclosure of climate

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[1] Commission Guidance Regarding Disclosure Related to Climate Change, Rel. No. 33–9106 (Feb. 2, 2010) [75 FR 6290] (Feb. 8, 2010) ("2010 Climate Change Guidance").

https://doi.org/10.1016/j.enpol.2023.113938
Received 29 September 2023; Received in revised form 18 November 2023; Accepted 4 December 2023
Available online 13 December 2023

change risk exposure on firm market value. We analyze different categories of climate risks to see how they relate to firm market value in different ways. We further examine the scenario in which disclosure of climate change risks takes place. Specifically, we examine how this disclosure interacts with increased climate attention posed toward a firm. To the best of our knowledge, this is the first study that analyses the combined effect of climate change exposure using two different sources of textual documents (conference calls transcripts and firm reports).

To conduct the analysis, we analyze item 1A of companies' reports, where relevant risks for the business are disclosed, and we assess the magnitude of climate risks through the application of novel methods in text mining and social network analysis known as the Semantic Brand Score (SBS) (Fronzetti Colladon, 2018). Precisely, we quantify the significance and discourse centrality of climate risk disclosures within the 10-K and 10-Q reports of U.S. companies. Furthermore, we measure the level of attention directed towards climate change at the firm level by analyzing transcripts from earnings conference calls.

We find a general positive association between climate risk disclosure and firm market value (as measured by Tobin's Q). We find that such positive association holds for different types of exposure to climate risk. However, we also find that the association between climate risk disclosure and firm market value becomes negative when there is heightened attention on climate issues specifically directed at the firm, as indicated by an increase in the discussion of climate-related topics during conference calls.

This study contributes to different branches of literature. First, by examining the disclosure of firms' exposure to climate change risks, we complement the literature concerned with the disclosure of firms' actions that can have an environmental impact (Kim and Lyon, 2011; Lewis et al., 2014; Marquis et al., 2016). Second, we contribute to the literature that delves into the impact of risk disclosure on firms' financial and operational value by examining different kinds of risk and how they interact with climate attention (Jiang et al., 2021; Kölbel et al., 2022; Nguyen et al., 2023; Yoo and Managi, 2022). Finally, we contribute to the field of literature that addresses the so-called measurement problem by using a novel technique to quantify climate risk exposure and climate attention at the firm level (Giglio et al., 2021; Sautner et al., 2020).

This study provides practical insights for regulators and policymakers about methods for the quantitative analysis of large sets of unstructured data. Regulators can use the SBS to quantify the magnitude of climate change exposure and risk disclosure from textual documents. Additionally, policymakers should note that when a company is particularly exposed to climate change, investors may not reward increased risk disclosure. In this regard, regulators may want to intervene with safeguards and incentives to reward information sharing of climate change risk exposure. Indeed, disclosure of climate change risks may require more coercion in situations of higher uncertainty or attention directed toward the firm.

2. Literature review and hypothesis development

The primary objective of the Securities and Exchange Commission (SEC) is to encourage the sharing of information between investors and firms. Since 2005, due to SEC mandates, U.S. firms must disclose the most pertinent risk factors in their reports, providing quarterly updates. These risk factors must be clear, concise, and aimed at informing investors (Jeklin et al., 2016). By leveraging this information, market participants can more accurately assess the actual value of a company (Healy and Palepu, 2001).

Among the various possible risks disclosed in financial reports, we focus our attention on climate risk disclosure. The effect of climate risk disclosure to investors is not obvious; it can trigger two opposite mechanisms (Flammer et al., 2021). If disclosure reveals novel risk factors, it can increase investors' risk perceptions, leading to higher firm risk and lower valuation (Kothari et al., 2009; Kravet and Muslu, 2013).

On the other hand, increased transparency regarding a company's climate risk can lead to a higher valuation. The notion that greater transparency is associated with higher valuation has been extensively discussed in the accounting literature (Healy and Palepu, 2001).

We develop our first hypothesis, positing that climate risk disclosure will be positively associated with firm market value as a consequence of greater transparency. The reasoning stems from the fact that investors normally dislike uncertainty and are willing to pay more for companies that are less opaque. In this sense, greater transparency about climate change could be beneficial for investors since it eliminates doubt about a potentially significant source of risk.

We ground our first hypothesis on the following literature. First, studies in the literature that investigated the effect of climate risk disclosure on firm value describe a positive impact in the short term. Specifically, Flammer et al. (2021) found that companies that voluntarily disclose climate change risks experience abnormal returns in the short term compared to companies that do not disclose climate risks. In the same vein, Ioannou and Serafeim (2019) and Krueger (2015) document higher valuations following the mandatory disclosure of non-financial information. Lastly, Matsumura et al. (2018) found that climate change disclosure reduces a firm's cost of capital, leading to higher valuations. Furthermore, given the increased concern for climate change in recent years, at least in normal times, we expect investors to positively reward transparency about climate risk exposure (Maji and Kalita, 2022).

H1. Increased disclosure of climate risk is positively associated with firm market value.

In the second part of this study, we investigate the effect of climate disclosure under the condition of low or high climate change attention directed toward the firm that is disclosing climate-change-related risks. In other words, we examine what happens when a firm discloses climate change exposure in situations where investors pay more attention to climate change for that firm.

To quantify firm-level climate attention, we follow a recent branch of literature that employed text mining techniques for analyzing conference call transcripts (Sautner et al., 2020, 2021). Unlike 10-K reports, where firms have the discretion to disclose information selectively, conference calls offer more transparent information as financial analysts can ask questions and steer the discussions toward specific subjects. The measurement of the importance of a topic discussed during these meetings was revealed to be a good proxy of firm exposure to that topic (Hassan et al., 2020; Sautner et al., 2020).

By using earnings conference calls, we can quantify firms' individual exposure to a specific risk factor (climate change). We assume that when firms disclose climate-related risks in a scenario of intensified climate attention, the subsequent impact on their market value may not uniformly align with the positive trajectory observed under less attentive circumstances.

Heinle et al. (2018) found that greater disclosure may lead to lower valuations when a firm is particularly exposed to a specific risk factor. Sautner et al. (2020), using a similar measure of climate change uncertainty derived from conference calls, found a negative relationship with firm market value. Bennett et al. (2023) showed that higher scrutiny (as represented by focused climate talks) could constrain management's decisions or increase mistakes' costs and exposure to legal and regulatory actions, negatively affecting firm valuations. Lastly, Eugster et al. (2023) found that higher discussions about climate change during conference calls happen when risks are more relevant for the firm and that, in the U.S., stock prices decrease when climate talk increases.

Overall, we propose that increased climate change discussions during conference calls (possibly caused by uncertainty and exposure to climate change, higher scrutiny, or greater risk relevance, as explained by the above literature) can affect the relationship between climate risk disclosure and firm market value.

H2. Increased disclosure of climate risk in the presence of increased climate attention is negatively associated with firm market value.

3. Methodology and data

To address the relationship between climate risk information disclosure, climate attention, and company market value, we build on prior research, and we use different tools that incorporate elements from social network analysis and text mining (Fabiani et al., 2023; Fronzetti Colladon, 2020).

We measure climate risk disclosure in quarterly and annual reports of U.S. American firms using a tool derived from social network analysis applied in the context of text mining, the Semantic Brand Score (SBS). The SBS was first introduced by Fronzetti Colladon (2018) to capture brand importance in textual documents. A brand can be described as a single word (Nike, for example). Still, it can also be represented as a combination of n-grams to define a topic (for example, climate change). The SBS was used in different studies ranging from examining the impact of social awareness regarding energy storage (Fabiani et al., 2023) to impact investing (Toschi et al., 2023) and financial forecasting (Fronzetti Colladon, 2020). We use the SBS to quantify the relevance of climate change risks disclosed in companies' annual and quarterly reports from 2020 to 2022. Second, we use SBS to analyze conference call transcripts to assess the importance of climate change topics discussed between companies and call participants during meetings. This analysis allows us to quantify the attention posed by market participants to climate change-related topics concerning an entity (e.g., a firm).

3.1. Measuring semantic importance

The SBS is a measure that quantifies the semantic importance of a word or a concept (set of words) that appears in large text corpora. To do so, the SBS combines three different measures derived from the field of social network analysis: prevalence, diversity, and connectivity.

The SBS value for a word or concept is high when it is frequently mentioned in the text (high prevalence), it has heterogeneous and less common textual associations (diversity), and it is deeply embedded in the discourse (connectivity).

For the calculation of the SBS, a preliminary text pre-processing and transformation of the text documents into a network of co-occurring words is required. The procedure is detailed in the Appendix.

A word/concept often appearing in discourse will be more prevalent than another that appears less frequently. Consequently, prevalence is measured by the frequency of a term or set of terms in the text. In previous works, this measure was already used as a proxy for topic importance in text documents since it is easy and fast to compute (Sautner et al., 2020).

However, the drawback of relying exclusively on the number of times a term appears in a text to measure its relevance and centrality stems from the fact that high prevalence does not ensure high importance and memorability (Fronzetti Colladon, 2020).

For this reason, prevalence is complemented by diversity. Diversity captures the heterogeneity and degree of uniqueness of the words frequently associated with the concept/word that we are analyzing. Diversity is measured through the *distinctiveness centrality* metric (Fronzetti Colladon and Naldi, 2020), used in social network analysis and here applied to the semantic network derived from the text corpora. The higher the diversity, the more heterogeneous the semantic context in which a brand is used.

The last SBS dimension is connectivity, measured using *weighted betweenness centrality* (Brandes, 2001). Connectivity captures how often a brand serves as a bridge between all the other pairs of nodes (terms/concepts in the discourse). This measure is intended as a proxy of the brokerage power of a brand/concept, i.e., how much it connects words and topics that are not directly co-occurring (Fronzetti Colladon, 2018).

The SBS, our measure of semantic importance, is obtained by summing the normalized values of prevalence, diversity, and connectivity.

The use of the SBS enables us to quantify how much a topic/concept (e.g., a risk factor in our case) is mentioned and how much it is embedded in the discourse. Research has suggested that when a concept/brand has numerous associations and brokerage power in the semantic network, it becomes significantly more important than when referenced using always the same words (Fronzetti Colladon, 2018). Compared to other Natural Language Processing (NLP) techniques where the importance of a concept is calculated only by counting the number of times that the terms defining it appear in the text, the SBS allows us to acquire more information and gain deeper insights into the semantic importance of climate change in textual data.

3.2. Definition of climate-related terms

Given that climate change encompasses various arguments and topics (Sautner et al., 2020; Venturini, 2022), we built different vocabularies that capture distinct aspects of climate change and compute the SBS values for each. We refer to the terms that compose these clusters as climate-related terms (CRTs). To construct these clusters, we started by extracting the most relevant terms contained in the Intergovernmental Panel on Climate Change (IPCC) reports because they provide a comprehensive summary of the drivers of climate change, its impacts, future risks, and how adaptation and mitigation can reduce those risks[2] (Kölbel et al., 2022; Research, 2022). Subsequently, we organized, refined, and extended these initial keywords with the help of two experts (we provide details about this process in the Appendix). Five clusters emerged from the analysis: Climate Attention, Transition Risks, Physical Risks, Emissions, and Pollution (see Table A3 in the Appendix for a detailed description). Transition Risks captures climate change risks derived from future potential regulations impacting firms – such as shocks associated with regulatory costs, write-downs of carbon-intensive assets, reduced market share for companies slow to adapt to green transition, and potentially stranded assets. Physical Risks captures risks associated with potentially catastrophic events such as floods or hurricanes. Physical hazards can disrupt supply chains and damage facilities and equipment, potentially leading to higher insurance costs, business interruptions, and asset write-offs, which can have significant financial consequences for a company. Emissions focuses on GHG (greenhouse gas) emissions, while Pollution refers to topics associated with waste (plastic, nuclear, or chemical waste).

We performed the SBS analysis on two types of textual documents (firms' reports and conference call transcripts), using different clusters according to our finality. To gain insight into climate risk disclosure, we focused on item 1A in quarterly and annual reports of U.S. companies. This section, known as Risk Factors, provides crucial information about the most significant hazards companies face. Accordingly, we calculated the SBS values of Transition Risks, Physical Risks, Emissions, and Pollution on Item 1A. We also calculate the SBS value for the "Total Disclosure Index" created by merging the clusters of the four single risks to analyze the overall level of climate risk disclosure in reports.

The SBS analysis on item 1A serves as a reliable indicator of firms' exposure to various climate-related risks, as they are considered risks relevant to the business. Additionally, it offers quantitative insights into the disclosure and communication of these risks to stakeholders. Lastly, because of the nature of the SBS itself, we quantify not only how much risk is mentioned but also its embeddedness in the discourse, potentially leading to higher memorability (Fronzetti Colladon, 2018). This is particularly relevant given that information with higher semantic importance is probably easier to understand and remember, thus being likely to be incorporated into market prices (Ball, 1992; Bloomfield,

[2] For a complete description of the reports used to extract climate related terms (CRTs) please refer to Table A1 in the Appendix.

2002; Bonsall et al., 2014; Hirshleifer and Teoh, 2003).

To quantify market participants' attention to climate change, we used a different cluster than the previous ones, Climate Attention. This cluster extends beyond climate risks and also encompasses potential opportunities. Discussions between managers and investors during conference calls can involve more comprehensive conversations related to the macro theme of climate change. Besides risks and opportunities that firms face and that are relevant for them (and therefore disclosed in reports), such discussions can be linked to other climate change issues, such as global warming, green financing, carbon neutrality strategies, stakeholder engagement, or environmental partnerships. This cluster provides a broader perspective on the level of attention given to climate change by market participants.

3.3. Data

We collected data from different sources. In line with Sautner et al. (2020), transcripts of conference calls were collected from the Eikon database using Refinitiv street events. On the other hand, we collected 10-K and 10-Q reports from the SEC official website in line with past research (Azmi Shabestari and Romero, 2022; Li, 2008; Yu, 2005).

Regarding firm-level control variables, we collect data from Compustat North America at a quarterly frequency. We used different firm-level control variables that previous literature demonstrated to impact firm market performance (Fauver et al., 2017; Yoo and Managi, 2022).

In particular, we control for leverage obtained by dividing debt by total assets: including leverage as a control variable accounts for the influence of a firm's debt level on its value, as higher debt can impact risk and financial stability.

Cash is defined as cash divided by total assets. Including cash as a control variable accounts for the liquidity position of a firm, which can influence its ability to respond to financial shocks and investment opportunities, thereby affecting its value.

The degree of foreign exposure is proxied by the ratio of foreign currency adjustment and sales. Controlling for foreign exposure captures the effect of a firm's exposure to global markets, which can affect its market value through different economic and regulatory conditions.

Research and development is calculated as the ratio of R&D expenses to sales. At the same time, the level of investment is proxied by the ratio of capital expenditure over total assets. Incorporating research and development and capital expenditure reflects the firm's innovation efforts, which can impact its competitiveness, growth prospects, and value.

Lastly, firm size is proxied by the natural logarithm of sales. Controlling for size helps address the impact of a firm's scale on its value, as larger firms might have different risk profiles, market power, and resources compared to smaller firms.

Our dependent variable, Tobin's Q, is calculated as total assets minus book value of equity plus market value, divided by total assets. Numerous studies used this variable as a proxy for a firm's market value given that it takes into account both the market value of a firm's assets (its stock price) and the replacement cost of its assets, providing a more comprehensive measure of a firm's value compared to just using stock price alone (Coles et al., 2008; Doidge et al., 2004; Jiang et al., 2021; Yoo and Managi, 2022). Moreover, Tobin's Q captures a firm's long-term value, reflecting the market's perception of its future earning potential and growth prospects, making it suitable for studying the impact of climate risks, which often have longer-term effects.

In Table 1, we summarize the description of the control variables employed in our models. Column one reports the variables' names, and column two describes how each variable is calculated. After merging all the data from different sources, we return with a final dataset composed of 2013 different U.S. American firms and a total of 13652 firms-quarterly observations for three years ranging from 2020 to 2022. In Table 2 are reported mean, standard deviation, maximum, and minimum values of all the variables employed in our research.

Table 1
Description of the control variables.

Variable	Description
Size	The natural logarithm of company sales (SALEQ).
R&D	The ratio of R&D expenditure (XRDQ) to sales (SALEQ). If R&D expenditure is missing, we set the missing value to zero over quarter q.
Leverage	The sum of long-term debt (DLTTQ) and debt in current liabilities (DLCQ) divided by the book value of total assets (ATQ).
Cash	Cash and short-term investments (CHEQ) scaled by the book value of total assets (ATQ)
Foreign	Foreign currency adjustement sales (FCAQ) divided by sales (SALEQ)
Capital Expenditure	The annual level of capital expenditure (CAPXY) scaled by the book value of total assets (ATQ)

Table 2
Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Tobin's Q	2.462	2.229	.607	13.822
Size	5.353	2.316	−2.419	10.052
R&D	.815	5.135	0	51.209
Leverage	. 304	.241	0	1.22
Cash	.216	.0236	.001	.965
Foreign	0	.006	−0.034	.032
Capital Expenditure	.017	.023	0	.132
Climate Attention	.097	.293	0	4.736
Physical risks	.039	.091	0	2.325
Pollution	.001	.006	0	.318
Transition risks	.001	.004	0	.338
Emissions	.018	.121	0	3
Total Disclosure Index	.058	.165	0	3.175

Table 3
Impact of risk disclosure on firm market value.

	Model 1	Model 2	Model 3	Model 4
	Tobin's Q	Tobin's Q	Tobin's Q	Tobin's Q
Tobin's Q (lag)	1.026***	1.026***	1.027***	1.025***
Emissions (lag)	.113***			
Physical risks (lag)		.168**		
Pollution (lag)			1.852	
Transition risks (lag)				1.717**
Size	−.047*	−.047*	−.105	−.046*
R&D	.002	.002	.003	.002
Leverage	.102	.100	.097	.099
Cash	.297**	.300**	.302**	.301**
Foreign	−.033	−.017	.070	−.012
Days to 10k/10q publication	$.266*10^{-3}$	$.274*10^{-3}$	$.262*10^{-3}$	$.256*10^{-3}$
Capital Expenditure	−.062	−.056	−.132	−.071
Constant	.123	.124	.111	.120
N of Groups	2013	2013	2013	2013
Observations	13652	13652	13652	13652

Note. *p < .1; **p < .05; ***p < .01.

The average values for Tobin's Q, leverage, and size align with previous studies examining the financial performance of U.S. American firms (Gupta et al., 2022; Li et al., 2022). Focusing on our main explanatory variables, we observe that the mean values of the Climate Attention and Total Disclosure Index are notably higher compared to the SBS values of the individual risks. This is as expected, given that the aforementioned clusters take into account a large vocabulary of climate-related terms. Those two clusters are then followed by Physical risks and Emissions that are undoubtedly more central and likely to be disclosed in reports compared to transition risks and risks associated with Pollution.

3.4. Research design

Equation (1) presents the model employed to test our initial hypothesis. Among the various possible estimation techniques, we opted for the Maximum likelihood estimation method applied to dynamic panels proposed by Hsiao et al. (2002).

We incorporated in our model firm-fixed effects to control for unobserved time-invariant omitted variables and time-fixed effects to control for unobserved firm-invariant omitted variables. The dependent variable in this analysis is Tobin's Q, while the primary explanatory variables are the SBS values computed for each of the four brands outlined in Table 2:

$$Tobin's\ Q_{i,t} = \alpha + \gamma Tobin's\ Q_{i,t-1} + \beta SBS_{i,t-1} + \omega X_{i,t} + \theta_i + \vartheta_t + \epsilon_{i,t} \tag{1}$$

The control variables in equation (1) are denoted as $X_{i,t}$ and include proxies for size, research and development, capital expenditure, cash, foreign exposure, and leverage. Tobin's Q, represented as $Tobin's\ Q_{i,t}$ reflects the firm's value at a given time t. The main explanatory variables are lagged one period backward to account for reverse causality. θ_i and ϑ_t Represent the firm and time fixed effects, respectively, while $\epsilon_{i,t}$ represents the error term. We employed robust standard errors to address heteroskedasticity. Based on H1, we anticipate a positive and statistically significant β coefficient.

To test our second hypothesis, we incorporated an interaction term into the model. This interaction term combines the SBS for firm disclosure with the SBS used to measure climate attention in conference call transcripts. Equation (2) outlines the model employed to examine the second hypothesis:

$$\begin{aligned} Tobin's\ Q_{i,t} = {} & \alpha + \gamma Tobin's\ Q_{i,t-1} + \beta_1 SBSfull_{i,t-1} * CC_{i,t-1} + \beta_2 SBSfull_{i,t-1} \\ & + \beta_3 CC_{i,t-1} + \omega X_{i,t} + \theta_i + \vartheta_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

We incorporated the level of climate risk disclosure into our analysis using the $SBS\ full_{i,t-1}$ measure that represents the Total Disclosure Index, as reported in Table 2. In our second equation, we did not distinguish between different topics disclosed when we referred to the SBS value for climate risk disclosure. Instead, we computed a single SBS value for disclosure by summing the individual SBS values for each risk. Additionally, $CC_{i,t-1}$ represents the level of attention given to climate change by market participants, that is, the Climate Attention as described in Table 2.

4. Results and discussions

In Table 3, we investigate the impact of climate risk disclosure on Tobin's Q. Specifically, we consider different risks disclosed in firms' reports. Each column in the table displays the results for equation (1), with the only variation being the SBS measure. Accordingly, each column represents the effect of a distinct risk category.

Of the four risks analyzed, three of them report a positive and statistically significant beta coefficient (Emissions, Physical Risks, and Transition Risks), suggesting a positive association between disclosing such kinds of risks in quarterly and annual reports and firm market value. On the other hand, the beta coefficient for the SBS value calculated on Pollution is not statistically different from zero. Economically, a one standard deviation increase in the SBS value for Physical Risks is associated, on average, with a 1.51 percentage point increase in Tobin's Q. A one standard deviation increase in the SBS for Emissions clusters is associated with a 1.36 percentage point increase in Tobin's Q and a standard deviation increase in Transition Risks cluster is associated with 0.7 percentage points increase in Tobin's Q.

We draw two main conclusions from the results reported in Table 3. First, only three of the four risks analyzed seem to be positively associated with firm value (namely, Physical risks, Transition risks, and Emissions). On the contrary, Pollution is not. As previous literature has shown, physical, transition, and emission risks are widely known factors, more common and widespread than pollution risks (Venturini, 2022) – and, therefore, more likely to be reflected in firm market value. This result leaves room for further research to explore why some risks are reflected in market valuations while others are not.

Among the studies that investigated the effect of disclosing risk exposure, our results align with previous research that found a positive effect on market value (Campbell et al., 2014; Hope et al., 2016). On the other hand, we do not perfectly align with the results of Kravet and Muslu (2013), who found that textual risk disclosures increase investors' risk perceptions. However, in their study, they found that this effect is less pronounced for firm-level disclosures that deviate from those of other companies in the same industry and year. Climate change risk may be something that not all companies disclose. Moreover, the authors analyzed not only item 1A but the reports as a whole.

Our finding supports the literature that investigates the effect of disclosing non-financial information. For example, Griffin et al. (2012) used an event study to examine shareholders' responses to firms' voluntary disclosures about greenhouse gas emissions. They found that shareholders responded positively to the disclosures. Griffin et al. (2012) results are similar to our findings: disclosing information related to emissions seems to be positively associated with firm market value. In addition, Matsumura et al. (2014) documented that firm value is positively associated with carbon emissions and whether firms voluntarily disclose that information. Their findings suggest that investors view environmental disclosures as relevant for firm value, in line with our results.

Lastly, our findings match with the literature that investigates climate risk disclosure and its impact on firm value. Specifically, we align with Krueger et al. (2020). In their survey analysis, they show that institutional investors value and demand climate risk disclosures. We empirically provide evidence that climate risk disclosure is positively rewarded in terms of market value. Similarly, Matsumura et al. (2022) found a positive effect of disclosing climate risks, and Flammer et al. (2021) found that the stock market reacts positively to companies' climate risk disclosure following environmental shareholder activism, suggesting that investors value transparency with respect to firms' exposure to climate change risks.

Overall, it seems that climate risk disclosure in item 1A of firms' reports plays a role in affecting market value. This result goes in contrast with the ideas stating that risk disclosure is merely boilerplate (Nelson and Pritchard, 2007). On the opposite, it seems that investors, in normal situations, reward firm transparency and climate risk disclosure, as explained by the significance and positive coefficients in Table 3 and supported by previous literature (Flammer et al., 2021; Krueger et al., 2020; Matsumura et al., 2022).

In Table 4, we investigate the combined effect of risk disclosure and climate change attention on firm market value. We present three distinct models. Model 1 shows the regression of Tobin's Q on the Total Disclosure Index. As previously mentioned, this index is derived by summing the individual values of the four risk categories used in the Models from 1 to 4 of Table 3. Model 2 shows the regression of Tobin's Q on Climate Attention, and in Model 3, we add the interaction term between Climate Attention and the Total Disclosure Index.

We find that a standard deviation increase in the Total Disclosure Index is associated with a 1.92 percentage point increase in Tobin's Q. Such a result confirms our first hypothesis, suggesting that increased climate risk disclosure positively impacts firm value. Model 2 represents the regression of Tobin's Q against the SBS value for climate change attention calculated from conference call transcripts. The beta coefficient is positive and statistically significant. Increased climate change discussion (a one standard deviation increase in the SBS value) during conference calls is associated with a 3.36 percentage point increase in Tobin's Q. However, when we consider the interaction term (Model 3), we find that its beta coefficient is negative and statistically significant. This result suggests that the positive impact of climate risk disclosure is

Table 4
Interaction of risk disclosure with climate change attention.

	Model 1	Model 2	Model 3
	Tobin's Q	Tobin's Q	Tobin's Q
Tobin's Q (lag)	1.027***	1.032***	1.033***
Total Disclosure Index (Lag)	.120***		.156***
Climate Attention (Lag)		.116***	.121***
Total Disclosure Index * Climate Attention			−.064**
Size	−.047*	−.038	−.039
R&D	.001	.002	.002
Leverage	.102	.103	.104
Cash	.296**	.300**	.293**
Foreign	−.032	−.084	−.112
Capital Expenditure	−.048	−.036	.050
Days to 10k/10q publication	$.278*10^{-3}$		$.232*10^{-3}$
Days from conference call		$-.514*10^{-3}$**	$.472*10^{-3}$**
Constant	.124	.061	.074
N of groups	2013	2013	2013
Observations	13652	13652	13652

Note. *p < .1; **p < .05; ***p < .01.

reduced when there is increased climate attention posed toward the firm. In other words, in a scenario where climate attention significantly increases, the impact of climate risk disclosure can negatively impact firm value.

The results of these models align with Heinle et al. (2018), who modeled a theoretical relationship between asset prices, exposure to risk factors, and disclosure. Their model demonstrates that when firms have high factor-exposure uncertainty and reduce it through increased disclosure, the cost of capital may rise, resulting in a decrease in firm value. Similarly, Sautner et al. (2020) found that increased climate change talk during conference calls can negatively impact firm value due to increased uncertainty toward climate risk factors. Moreover, higher climate change disclosure, combined with more attention to climate change, can reinforce and confirm risk relevance for climate change (Eugster et al., 2023). Indeed, Eugster et al. (2023) showed that when managers engage in climate talk during earnings conference calls, climate matters are more relevant for a firm. Additionally, they found that for U.S. firms characterized by individualistic cultures and cultures characterized by short-term horizons, increased climate change discussions do not improve environmental behavior (such as CO2 emission reduction). Fig. 1 summarizes our results.

5. Policy implications and conclusions

Transparency through public filings is crucial for well-informed and efficiently functioning markets. Information plays a pivotal role in firms' operations and how markets value companies (Healy and Palepu, 2001). However, complying with and interpreting disclosures can be costly (Heinle and Smith, 2017).

Regulators and researchers stress the importance of companies providing investors with comprehensive information regarding their exposure to risk factors (Campbell et al., 2014). Ryan (1997) proposed that regulators incentivize the accounting profession to establish a dynamic accounting system that centers on risk exposures. Additionally, given the increased concern for climate change, there is increasing pressure on firms to disclose their exposure to it. In this scenario, it becomes crucial to understand how and what such increased disclosure impacts (Kravet and Muslu, 2013).

In this work, we investigate the effect of climate risk disclosure on firm market value for U.S. firms over a time span of three years. Risk disclosure was criticized in the past for being boilerplate (Nelson and Pritchard, 2007). However, our findings suggest that risk disclosure of climate change risks is valuable to investors (Flammer et al., 2021; Hope et al., 2016; Kravet and Muslu, 2013). While previous studies focused on general risk disclosure (Bao and Datta, 2014; Campbell et al., 2014; Kravet and Muslu, 2013), few investigated the effect of climate risk disclosure (Flammer et al., 2021; Matsumura et al., 2022). We complement the work of Flammer et al. (2021) and Matsumura et al. (2022), studying how climate risk disclosure can be related to firm market value. We complement their work by analyzing separately different kinds of risks disclosed by the company, showing how they differently affect firm value. Our first results hold while controlling for numerous variables, after employing time and firm fixed effect, after taking into account the lagged value of our dependent variable, and after controlling for its endogeneity. In addition, our results remain robust for different dictionaries used to analyze climate change disclosure (Total Disclosure Index, Physical Risks, Transition Risk, and Emissions).

In the second part of our investigation, we take into account that firm disclosure can have a differential impact depending on where it happens (Lester et al., 2006). Looking at the literature, the environment where disclosure takes place was little explored (Connelly et al., 2011; Vanacker et al., 2020). Moreover, to the best of our knowledge, no study analyzed the combined effect of climate change exposure at the firm level using both conference call transcripts and firm reports. In line with the model proposed by Heinle et al. (2018), we find that risk disclosure can have a negative effect on firm value in specific situations. Second, we complement the work of Eugster et al. (2023) by empirically demonstrating the effect of increased disclosure in the presence of increased climate change discussion during conference calls.

In light of the results of this study, we propose the following insights for practitioners and policymakers. Firstly, we show how the Semantic Brand Score can be leveraged to obtain quantitative insights starting from unstructured textual data. Regulators and policymakers can use the SBS to get quantitative information about how much a risk factor is central in a discourse by analyzing textual documents (including speech transcripts). Future studies could leverage the potentiality of the SBS, and in general of semantic network analysis, to further explore the effectiveness of risk disclosure, considering additional analyses, such as a qualitative exploration of the textual associations of disclosed risk factors.

Secondly, our results should encourage companies to engage in transparent and comprehensive climate risk disclosure. The observed positive correlation between climate risk disclosure and firm market value highlights the importance of communicating to investors climate change exposure. Accordingly, the confirmed evidence regarding the effectiveness of risk disclosure should compel regulators to establish specific standards for the disclosure of diverse business risks. Policymakers can play a pivotal role in developing standardized reporting frameworks that enable companies to communicate their climate-related risks and mitigation strategies effectively (Heinle and Smith,

Fig. 1. Main results.

2017).

However, our results also suggest that climate risk disclosure is not always beneficial. Companies may be more likely not to disclose climate change exposure in some situations. Policymakers should consider this aspect to avoid companies retaining information, especially when sharing them becomes of paramount importance (for example, when exposure to a factor increases). We suggest that by introducing incentives and safeguards, policymakers can prevent firms from avoiding disclosure, especially when the exposure to a risk factor is relevant and firms are under higher scrutiny.

Future research could further explore the relationship between climate risk disclosure and firm value by going deeper into the type and quality of risk disclosure. Several aspects could be considered, such as the features of the risks disclosed, their heterogeneity, and the way they are reported by companies in their reports. Factors related to readability or language complexity of climate change risks could be calculated from textual data to provide further insight to regulators, firms, and policymakers (Eugene Baker and Kare, 1992). Lastly, although we have tried to minimize the possibility of endogeneity or reverse causality, further research could strengthen our results by using alternative approaches, such as the instrumental variables approach or the difference-in-difference methodology, to reinforce a possible causal effect between climate risk disclosure and firm value.

Funding

This work was supported by the European Union's Horizon 2020 program under grant agreement number 764025 (SWS-HEATING).

CRediT authorship contribution statement

Roberto Vestrelli: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Andrea Fronzetti Colladon:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Anna Laura Pisello:** Conceptualization, Funding acquisition, Writing – review & editing.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used the software Grammarly in order to review and improve the use of English. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data availability

Authors do not have permission to share textual data. All other data will be made available upon reasonable request to the first author.

Acknowledgements

This work was supported by the European Union's Horizon 2020 program under grant agreement number 764025 (SWS-HEATING). The authors thank the ERC Starting Grant Project "HELIOS: the new generation of scalable urban heat mitigation by means of adaptive photoluminescent radiative cooling skins" (g.a. 101041255) funded by the European Research Council (ERC-StG-2021, HELIOS, G.A.101041255). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them. The authors are deeply grateful to Francesco Venturini for his help during the revision process of this manuscript.

Appendix

1. SBS analysis

This section explains in more detail the methodology behind the calculation of the Semantic Brand Score (SBS). We use the SBS to analyze climate change risk disclosure in Item 1A of annual and quarterly company reports and transcripts of earnings conference calls.

1.1. Data Collection and Cluster Construction

As explained in Section 3.2, the macro-theme of climate change encompasses different arguments and topics. Firms may disclose different risks related to climate change in their reports. For example, some firms may be more exposed to physical risks (flooding, earthquakes) because they are located in specific positions (such as coasts). In contrast, others may be more exposed to potential adverse regulations (firms with higher carbon emissions). Our analysis distinguishes four macro categories of risks that are likely to be disclosed in reports. Transition risks, physical risks, and risks related to pollution and GHG emissions.

On the other hand, conversations between managers and investors during conference calls can involve wider discussions related to the macro theme of climate change. Practically speaking, in addition to the risks and opportunities that firms face and that are relevant to them (and thus disclosed in reports), these discussions can be linked to climate change issues, such as global warming, green financing, carbon neutrality strategies, stakeholder engagement, or environmental partnerships.

For the arguments mentioned above, we built four clusters meant to assess the four types of risks and the magnitude of their disclosure in item 1A. In addition, being interested in measuring attention posed by participants to climate change during calls, we built another cluster that encompasses wider themes linked to climate change.

In order to obtain the terms that represent each cluster, we extracted an initial set of keywords from the IPCC reports. In previous studies, IPCC reports were already used as a source of textual documents to retrieve information and insights related to climate change risks and opportunities (Kölbel et al., 2022; Research, 2022). We included synthesis reports and special reports published after 2000. Table A1 shows the titles of these reports and their publication date. All the IPCC reports were collected from the IPCC's official website.

Table A1
IPCC Reports Analyzed

Title	Publication
Emissions scenarios	2000 March
Land use, land-use change, and forestry	2000 March

(*continued on next page*)

Table A1 (*continued*)

Title	Publication
Methodological and technological issues in technology transfer	2000 March
TAR Climate Change 2001: Synthesis Report	2001 October
Carbon dioxide capture and storage	2005 March
Safeguarding the ozone layer and the global climate system	2005 March
AR4 Climate Change 2007: Synthesis Report	2007 September
Renewable energy sources and climate change mitigation	2011 April
Managing the risks of extreme events and disasters to advance climate change adaptation	2012 March
AR5 Synthesis Report: Climate Change 2014	2014 October
Global warming of 1.5 °C	2018 October
Climate change and land	2019 August
The ocean and cryosphere in a changing climate	2019 September

To extract the most relevant terms from IPCC reports, we used the well-known Term Frequency-Inverse Document Frequency (TF-IDF) metric (Aizawa, 2003). After the collection of this initial set of keywords, two experts convened to select and organize them into meaningful clusters of climate change-related terms (CRTs). Based on the experts' domain expertise and aligned with past research (Fabiani et al., 2023; Hain et al., 2022; Piselli et al., 2022), these groups of keywords were carefully crafted by considering the primary themes in climate change-related topics and the content of the text to be analyzed. The Lexicon Augmenter tool available in the SBS BI app also supported the experts. This tool is able to expand an initial list of words by identifying synonyms, hyponyms, hypernyms, and related terms (such as "global warming" given the input term "climate change"). The tool uses the Wordnet lexical database (Miller, 1995) and pre-trained word embedding models.

After this process, we ended up with five different clusters (four used in the analysis of the disclosure of firms' climate change exposure and one for the analysis of climate attention in conference calls); they are described in Table A2.

Table A2
Considered CRTs: examples of keywords and general CRTs' description

CRTs	Example of Keywords	CRTs description
Transition risks	Gas regulation, environmental awareness, energy transition, low-carbon economy, green preference, sustainable choice	Terms used to identify shocks and risks related to the transition to a greener economy. These involve a shift in consumer preferences and future interventions or regulations.
Physical risks	Climate catastrophe, floods, glacier melt, climate disruptions	Terms used to identify risks associated with catastrophic and physical events related to climate change.
Emission	Emission rate, nitrogen oxide, greenhouse gas, CO2 emissions	Terms used to identify different kinds of emissions potentially contributing to climate change.
Pollution	Chemical waste, industrial waste, toxic waste, air contamination, contaminated soil	Terms used to identify risks associated with waste derived by industrial production.
Climate attention	Climate change, sustainability, climate impact, carbon footprint	Terms used to identify general climate change discussion in conference calls

1.2. Calculation of the SBS

This section aims to explain better how the Semantic Brand Score (Fronzetti Colladon, 2018) is calculated and the formulas behind it. As described in Section 3.1, the SBS is a measure that quantifies the semantic importance of a word or a concept (set of words) that appears in large text corpora. To do so, the SBS combines three different measures derived from the field of social network analysis: prevalence, diversity, and connectivity.

For the calculation of the SBS, a preliminary text preprocessing and transformation of the text documents into a network of co-occurring words is required. Text preprocessing is performed in different steps. We remove punctuation, stop-words, and special characters. We transform the whole text into lowercase and extract stems by eliminating the word affixes (Porter, 2006). Text preprocessing aims to reduce language complexity by retaining only the most significant words while preserving the meaning of the discourse. After this process, a network is constructed where each node represents a word, and nodes are connected by edges weighted by the frequency of word co-occurrences (see an example in Figure A1).

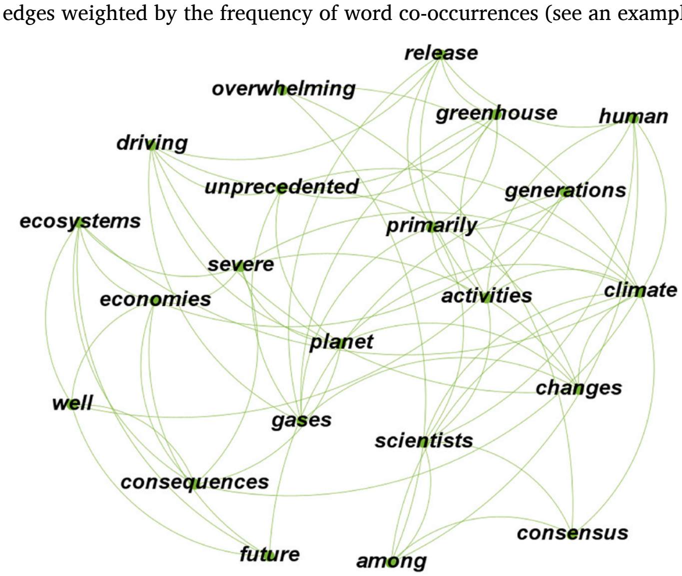

Fig. A1. Semantic Network of Words.

Representing the text as a network has two advantages. First, in this way, we are able to capture the relationships among words. Second, we can leverage tools and formulas from social network analysis and apply them to the analysis of textual data.

Prevalence is the number of times a risk category represented by the terms in our clusters appears in the text. Prevalence measures how frequently a brand/concept is mentioned in the text. A concept frequently mentioned is easier to remember and more recognizable (Keller, 1993). The prevalence of a particular set of words could ultimately influence the opinions and behaviors of the readers.

Diversity, the second component of the SBS indicator, measures the degree of heterogeneity of the semantic context in which a concept (set of terms) is used, emphasizing the richness and distinctiveness of its textual associations. Diversity is defined by the number and uniqueness of connections a cluster has in the co-occurrence network, and it is measured by the distinctiveness centrality metric introduced in Fronzetti Colladon and Naldi (2020). More precisely, in a graph of n nodes (words) and E edges (e.g.,1), the distinctiveness of node i is given by:

$$D_i=\sum_{j=1,j\neq i}^{n} log\frac{(n-1)}{g_j}I(w_{ij}>0)$$

Where W is the set of weights associated with each edge; g_j is the degree of node j, which is a neighbor of node i, and $I(\bullet)$ is an indicator function that equals one if there is an edge that connects nodes i and j with positive weight, w_{ij}.

The third dimension of the index is connectivity. Connectivity measures how much a cluster (or a set of words) is embedded in the discourse. It leverages a measure derived from social network analysis called betweenness centrality (Brandes, 2001; Freeman, 1979). Betweenness calculates how much a cluster appears between the network paths interconnecting the other words.

$$C_i=\sum_{j<k}\frac{d_{jk}(i)}{d_{jk}}$$

Where $\frac{d_{jk}(i)}{d_{jk}}$ is the proportion of shortest network paths connecting nodes j and k (measured by edge weights) that include node i. Finally, an index is constructed as a composite score by summing the normalized measures of prevalence, diversity, and connectivity discussed above. The normalization is performed through min-max normalization, considering the semantic network of each time period. This normalization process ensures that the final SBS values are scaled proportionally within the range of 0–3, facilitating a consistent and comparable representation across different periods.

2. *Robustness tests*

As additional robustness tests, we explore the relationship between climate risk disclosure and firm value using different proxies for it (dependent variables other than Tobin's Q). In Tables A3 and A3.1, we use market capitalization as a dependent variable measured by the total number of shares of the company multiplied by the share price. In Tables A4 and A4.1, we use the natural logarithm of share price.

Among the various possible estimation techniques, we opted for the Maximum likelihood estimation method applied to dynamic panels (Hsiao et al., 2002). We used this estimation technique for multiple reasons. First, it allows us to employ firm and time-fixed effects controlling for non-time varying factors within companies and factors that do not vary among companies for the same quarter. Second, given that we deal with quarterly observations, it is likely that the current value of our dependent variable could be affected by the value of the previous quarter; this can lead to biased results (Arellano and Bond, 1991; Nickell, 1981). To deal with this, we included the lagged value of the dependent variable in the right-hand side of the equation. However, the lagged variable will be endogenous by construction, leading, also in this case, to biased estimates (Li et al., 2021; Nickell, 1981). One of the most common methods employed in the literature to deal with dynamic panel data is the Arellano Bond estimator (Arellano and Bond, 1991). However, the generalized method of moments proposed in the Arellano Bond estimator is less efficient than the likelihood approach when dealing with lagged dependent variable endogeneity, both in terms of the bias and root mean square error of the estimators and the size and power of the test statistics (Hsiao et al., 2002). Therefore, we employed the quasi-maximum likelihood estimator for fixed effects dynamic panel data developed by Hsiao et al. (2002).[3]

Regarding the results, we highlight that in analyzing the relationship between climate risk disclosure and firm market value, the sign and the significance of the coefficients of Emissions, Physical Risks, and Pollution remain robust and consistent with our main analyses. On the contrary, the cluster that changes, only in terms of significance, is Transition Risks. When using Market capitalization and Share Price as dependent variables, the coefficient is not statistically significant.

Regarding our second hypothesis, in all the robustness tests, the sign and significance of both the interaction term and the Total Disclosure Index remain in line with our main analysis. All the proxies for the market value that we considered suggest a similar effect of disclosing climate exposure in the presence of high climate attention. As a last analysis, in Table A5, we report the results of the Granger Causality tests carried out to evaluate the connection between the SBS measures of climate risk disclosure and Tobin's Q. We select one lag according to the model selection criteria developed by Andrews and Lu (2001). This selection is also consistent with the number of lags used in our models. Each row of the table reports results for the null hypothesis that our main explanatory variable does not Granger cause the main dependent variable (Tobin's Q), and the null hypothesis that the main dependent variable does not Granger cause our main explanatory variable. According to the chi-squared value reported in column three, we find evidence that each of the climate risk disclosure variables analyzed Granger cause Tobin's Q. On the other hand, we do not find any evidence that Tobin's Q Granger causes climate risk disclosure, with the only exception being Pollution. Consistently with the main analysis, the pollution cluster has not proved to have a statistically significant impact on Tobin's Q.

[3] We estimated the model using the xtdpdqml command for Stata by Kripfganz (2016).

Table A3
Climate Risk Disclosure and Market Capitalization

	Model 1	Model 2	Model 3	Model 4
	Market Capitalization	Market Capitalization	Market Capitalization	Market Capitalization
Market Capitalization (lag)	.875***	.875***	.874***	.874***
Emissions (lag)	.119***			
Physical risks (lag)		.107***		
Pollution (lag)			.521	
Transition risks (lag)				−.055
Size	.080***	.080***	.118**	.080***
R&D	.002	.002	.002	.002
Leverage	−.292***	−.292***	−.293***	−.293***
Cash	.378***	.379***	.381***	.38***
Foreign	.016	.020	.030	.026
Days to 10k/10q publication	$.262*10^{-4}$	$.289*10^{-4}$	$.212*10^{-4}$	$.181*10^{-4}$
Capital Expenditure	−.511***	−.512***	−.535***	−.536***
Constant	2.173***	2.162***	2.193***	2.178***

Note. *p < .1; **p < .05; ***p < .01.

Table A3.1
Climate Risk Disclosure Climate Attention and Market Capitalization

	Model 1	Model 2	Model 3
	Market Capitalization	Market Capitalization	Market Capitalization
Market Cap (lag)	.875***	.877***	.878***
Total Disclosure Index (Lag)	. 095***		.125***
Climate Attention (Lag)		. 013	.121***
Total Disclosure Index * Climate Attention			−.064**
Size	.079***	.082***	.081***
R&D	.002	.002	.002
Leverage	−.291***	−.288***	−.287***
Cash	.377***	.378***	.373***
Foreign	.014	−.003	−.011
Capital Expenditure	−.492***	−.49***	−.439**
Days to 10k/10q publication	$.341*10^{-4}$		$.124*10^{-4}$
Days from conference call		$.250*10^{-4}$**	$.242*10^{-3}$**
Constant	2.157***	2.125***	2.098***

Note. *p < .1; **p < .05; ***p < .01.

Table A4
Climate Risk Disclosure and Share Price

	Model 1	Model 2	Model 3	Model 4
	Ln Price	Ln Price	Ln Price	Ln Price
Ln Price (lag)	.976***	.977***	.976***	.977***
Emissions (lag)	2.309**			
Physical risks (lag)		5.503**		
Pollution (lag)			45.893	
Transition risks (lag)				2.074
Eps	.87***	.87***	.871***	.873***
Size	.304	.318	.313	.313
R&D	0.00	0.00	0.00	0.00
Leverage	−1.649	−1.67	−1.696	−1.428
Cash	10.387***	10.445***	10.343***	10.551***
Foreign	−.004	−.004	−.004	−.004
Days to 10k/10q publication	−.003	−.003*	−.003	−.003
Capital Expenditure	−4.063	−3.685	−4.194	−4.478
Constant	−.966	−1.137	−.97	−1.143

Note. *p < .1; **p < .05; ***p < .01.

Table A4.1
Climate Risk Disclosure Climate Attention and Share Price

	Model 1	Model 2	Model 3
	Ln Price	Ln Price	Ln Price
Ln Price (lag)	.915***	.914***	.915***
Total Disclosure Index (lag)	3.064***		4.205***
Climate Attention (lag)		1.604*	2.19**

(*continued on next page*)

Table A4.1 (*continued*)

	Model 1	Model 2	Model 3
	Ln Price	Ln Price	Ln Price
Total Disclosure Index * Climate Attention			−3.581*
Eps	.868***	.861***	.858***
Size	.295	.372	.351
R&D	0	0	0
Leverage	−1.634	−1.55	−1.526
Cash	10.325***	10.366***	10.244***
Foreign	−.004	−.005	−.006
Capital Expenditure	−3.667	−4.169	−3.452
Days to 10k/10q publication	−.004*		−.004*
Days from conference call		.006*	.007*
Constant	−1.003	−1.798	−1.824

Note. *p < .1; **p < .05; ***p < .01.

Table A5
Granger Causality

Variable	Null Hypothesis	Chi2
Emissions	Emissions do not Granger cause Tobin's Q	30.75***
	Tobin's Q does not Granger cause Emissions	0.00
Physical risks	Physical risks do not Granger cause Tobin's Q	49.80***
	Tobin's Q does not Granger cause Physical risks.	0.21
Pollution	Pollution does not Granger cause Tobin's Q	934.50***
	Tobin's Q does not Granger cause Pollution	12.66***
Transition risks	Transition risks do not Granger cause Tobin's Q	1797.64***
	Tobin's Q does not Granger cause Transition risks	0.96
Total Disclosure Index	Total Disclosure Index does not Granger cause Tobin's Q	16.33***
	Tobin's Q does not Granger cause Total Disclosure Index	0.61

Note. *p < .1; **p < .05; ***p < .01.

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