Textual and AI-based Analysis of Climate Disclosures: Evidence from the European Energy Sector

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Abstract

As European companies face increasing pressure to align with sustainability reporting frameworks, recent analyses of corporate disclosures reveal uneven quality, with gaps in clarity, structure, and thematic integration. This paper examines the textual structure of climate-related financial disclosures in the European energy sector, focusing on their alignment with the Task Force on Climate-Related Financial Disclosures (TCFD) recommendations on governance, strategy, risk management, and metrics and targets. The analysis combines four layers: lexicometric diagnostics to assess readability and structure; AI-based BERT models to evaluate alignment; topic modeling to explore thematic organisation; and panel regressions to identify structural, financial, and cultural drivers. Results show that firms prioritize metrics and strategy over governance and risk management. Shorter, focused language improves alignment with risk disclosures, while lexical variety supports governance and strategy. Thematic analysis reveals fragmented climate narratives, suggesting limited maturity in integration. Regression results highlight that board gender diversity, ownership structure, ESG scores, EU taxonomy-aligned revenues, and cultural orientation are key drivers of TCFD alignment. These alignments are material, as each is significantly linked to firm valuation, indicating investors respond to depth and specificity of disclosures. Findings advance understanding of narrative climate disclosures and offer practical insights for assurance, benchmarking, and sustainability analysis.

Keywords: Climate-Related Financial Disclosures, AI, BERT, LDA, GNTM, Language-Enhanced Panel Regressions.

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1. Introduction

The growing urgency to address climate change has transformed corporate disclosures into a strategic domain where firms articulate their engagement with climate-related risks. Far from being uniform or purely regulatory, climate disclosures are shaped by linguistic choices, institutional structures, and sectoral pressures. Frameworks such as the Task Force on Climate-related Financial Disclosures (TCFD) provide a formalised structure for reporting climate risks and opportunities (TCFD, 2023), aiming to improve comparability and decision-usefulness across markets (Field, 2024). In particular, the emphasis placed on forward-looking metrics and strategic risk management has reshaped the landscape of sustainability reporting (Ameli et al., 2020), shifting the focus from reputational signalling to financial materiality.

Yet, despite the rise of disclosure frameworks, variation in the quality and content of climate reports remains persistent (Deloitte Finland, 2025; Deloitte France, 2025; CSR-Tools, 2024). Misalignment with the TCFD pillars continues to hinder the interpretability and comparability of corporate narratives (Steuer and Tröger, 2022). These misalignments are not neutral: they signal weaknesses in internal governance and preparedness, and they often result in market penalties such as higher risk premia or reputational costs (Staker et al., 2017; Chava, 2011). In this context, the European energy sector occupies a critical position. As both a contributor to and a potential mitigator of carbon emissions, it faces increasing scrutiny from regulators, investors, and civil society. Understanding how firms in this sector construct their climate narratives offers a window into broader dynamics of disclosure performance under institutional and economic pressure.

This study investigates the degree to which climate-related financial disclosures by European energy firms align with the TCFD framework, with particular attention to the pillars of governance, strategy, risk management, and metrics and targets. The approach combines four complementary layers of analysis. First, lexicometric indicators such as average word length, lexical diversity, and entropy are used to evaluate the readability and internal coherence of disclosures (Loughran and McDonald, 2014; Oradi et al., 2024). These metrics capture how firms manage complexity, either to clarify or to obscure their climate-related positioning (Chava et al., 2020; Brié et al., 2023; Sautner et al., 2023). Second, AI based models trained on TCFD recommendations, such as BERT models (Sanh et al., 2019), are used to assess the extent to which corporate disclosures cover the four TCFD pillars. Rather than measuring superficial similarity, these models identify context-aware textual correspondences between corporate reports and reference disclosures. Third, thematic modeling techniques, including Latent Dirichlet Allocation (LDA) and Graph Neural Topic Models (GNTM), explore the structure and maturity of reported topics (Blei et al., 2003; Shen et al., 2021). Finally, panel regression models identify structural and cultural determinants of alignment, examining the influence of board composition (Luo et al., 2023), ownership and financial traits (Eleftheriadis and Anagnostopoulou, 2015), national cultural dimensions (Hofstede and Minkov, 2010) and sustainable performance (Luo et al., 2023).

This multi-layered methodology enables a deeper understanding of both the form and function of climate reporting. The empirical findings highlight that alignment with TCFD is not reducible to communication strategy. Instead, it reflects an interplay of linguistic clarity, governance diversity, financial robustness, and cultural adaptability. Reports that demonstrate significant alignment with TCFD pillars, thematic coherence, and narrative accessibility are associated with board diversity, dispersed ownership, higher levels of ESG performance and EU taxonomy-aligned green revenues. Such alignment also contribute to firm valuation, reinforcing its material significance in the eyes of the market.

The contributions of this study are threefold. First, it demonstrates how AI-enhanced textual tools, such as BERT models, can systematically assess alignment with established reporting frameworks, offering greater diagnostic value than keyword-based methods. Second, it expands the application of topic models to examine disclosure maturity and structure, thus moving beyond content identification to interpretive mapping (Uthirapathy and Sandanam, 2023; Zhu et al., 2023). Third, it identifies the institutional and cultural conditions that shape disclosure performance and market relevance, offering practical levers for firms and policymakers seeking to improve the credibility and impact of sustainability reporting (Hoffman, 2015; Luo and Tang, 2016; Giannarakis et al., 2018; Luo et al., 2018).

The remainder of this paper is organized as follows. Section 2 reviews the literature on climate-related disclosures and methodological approaches to evaluating alignment. Section 3 presents the data and methodological framework. Section 4 reports and discusses the results. Section 5 examines their managerial implications. Section 6 concludes.

2. Related Literature

2.1. Regulatory Standards and Language in Climate Disclosures

In the context of filings with the U.S. Securities and Exchange Commission (SEC), companies are required to submit their financial statements in eXtensible Business Reporting Language (XBRL) format along with their traditional Hypertext Markup Language (HTML) or Portable Document Format (PDF). XBRL is a digital language used for communicating and exchanging business and financial data across various users (Weshah, 2024). This standard enables the automation and standardization of business information, thereby improving the transparency, accuracy, and accessibility of financial data. This requirement is intended to make financial information more accessible and easier to analyze for investors, analysts, and regulators. European companies are also concerned with these standards.

While XBRL is mandatory for financial statements under the European Single Electronic Format (ESEF), it is not specifically mandated for climate-related disclosures. However, european companies are increasingly encouraged to report on climate-related risks and opportunities, particularly in line with the TCFD recommendations (GECO, 2022; European Commission, 2023). These recommendations have been integrated into the International Financial Reporting Standards (IFRS) under the norm IFRS S2. The International Sustainability Standards Board (ISSB) has mandated IFRS S2, effective for annual reporting periods beginning on or after January 1, 2024. Figure 1 explores the TCFD framework's approach to climate-related disclosures (TCFD, 2018) and compares it with the current regulatory requirements of IFRS S2, which, while incorporating TCFD recommendations, impose more stringent disclosure obligations (IFRS Foundation, 2023). The comparison is structured around the TCFD four pillars: governance, strategy, risk management, and metrics and targets. The TCFD governance pillar emphasizes oversight of climate risks by boards and management, while IFRS S2 expands on this with more detailed disclosures on risk identification and integration. In the strategy pillar, TCFD outlines the need to describe the impacts of climate-related risks on business strategy and financial planning under different scenarios. IFRS S2, however, mandates more comprehensive details on how these strategies are incorporated into business plans.

For 'Metrics and Targets,' TCFD emphasizes the use of metrics, including Scope 1, 2, and 3 GHG emissions, while IFRS S2 requires more extensive reporting on these emissions and details on global climate agreements, carbon credit use, and decarbonization strategies. Assessing the alignment of European energy companies' climate disclosures with the TCFD pillars, now integrated into the IFRS S2 standards effective January 2024, calls for a thorough evaluation of current practices to improve transparency, support EU climate goals, and advance both sustainable energy practices and economic resilience.

2.2. Techniques for Assessing Disclosure Alignment

The sheer volume of modern textual data, often comprising millions of words, renders manual analysis both impractical and inefficient (Griffiths and Steyvers, 2004; Asmussen and Moller, 2019). Advanced computational methods are essential for transforming unstructured text into actionable insights, enabling a nuanced understanding of climate risk adaptation and mitigation trends (Benites-Lazaro et al., 2017, 2018; Bingler et al., 2022; Polyzos and Wang, 2022; Madzik et al., 2023; Uthirapathy and Sandanam, 2023). Leveraging computational linguistics metrics provides a robust foundation for analyzing climate-related disclosures, capturing the intricate dynamics of language shaped by context, authorship, and timing (Loughran and McDonald, 2016).

A core method for this type of analysis is cosine similarity, which provides a straightforward way to assess the degree of content similarity between a company's disclosures and the TCFD guidelines (Singhal, 2001; Loughran and McDonald, 2016). This approach can be strengthened by using efficient AI models such as MiniLM, which are designed for quick and accurate language processing and can handle large datasets effectively (Wang et al., 2020). AI language models such as Bidirectional Encoder Representations from Transformers (BERT) have recently revolutionized how text analysis (Devlin et al., 2019) is conducted in the context of regulatory compliance.

Table 1: TCFD Recommendations & IFRS S2 Climate-related Disclosures

	TCFD	IFRS S2
Governance	**Disclose the company's governance around climate-related risks and opportunities.** a) Describe the board's oversight of climate related risks and opportunities. b) Describe management's role in assessing and managing climate-related risks and opportunities.	**Understand the governance processes, controls and procedures used to monitor, manage, and oversee climate-related risks and opportunities.** a) IFRS S2 requires more detailed information b) IFRS S2 broadly consistent
Strategy	**Disclose the actual and potential impacts of climate-related risks and opportunities on the company's businesses, strategy, and financial planning where such information is material.** a) Describe the climate-related risks and opportunities the company has identified over the short, medium and long term. b) Describe the impact of climate-related risks and opportunities on the company's businesses, strategy, and financial planning. c) Describe the impact of the company's strategy, taking into consideration different climate-related scenarios, including a 2°C or lower scenario.	**Understand a company's strategy for managing climate-related risks and opportunities.** a) IFRS S2 requires identifying climate risks and opportunities using industry guidance, demanding detailed impact disclosures on the company's business and value chain. b) IFRS S2 necessitates comprehensive details on how these factors affect financial status, performance, and cash flows, with specific criteria for qualitative and quantitative data. Qualitative disclosure is permitted under conditions like significant measurement uncertainty. c) Aligned with TCFD, IFRS S2 doesn't set fixed scenarios for climate analysis but requires information on organizational resilience, strategy adaptation, and the methods and timing of scenario analysis, using reasonable and accessible information.
Risk Management	**Disclose how companies identifies, assesses, and manages climate-related risks.** a) Describe the company's processes for identifying and assessing climate-related risks. b) Describe the company's processes for managing climate-related risks. c) Describe how processes for identifying, assessing, and managing climate-related risks are integrated into the company's overall risk management.	**Understand the processes to identify, assess, prioritise and monitor climate-related risks and opportunities, including whether and how those processes are integrated into and inform the company's overall risk management process.** a) IFRS S2 mandates detailed disclosures, emphasizing the need for additional information on processes for identifying, assessing, prioritizing, and monitoring opportunities. b) IFRS S2 focuses on disclosing risk management processes specifically for climate-related risks and opportunities. c) IFRS S2 also requires disclosing how these processes are integrated into the company's overall risk management.
Metrics and Targets	**Disclose the metrics and targets used to assess and manage relevant climate-related risks and opportunities where such information is material.** a) Disclose the metrics used by the company to assess climate-related risks and opportunities in line with its strategy and risk management process. b) Disclose Scope 1, Scope 2, and if appropriate, Scope 3 greenhouse gas emissions (GHG) and the related risks. c) Describe the targets used by the company to manage climate-related risks and opportunities and performance against targets.	**Understand a company's performance in relation to its climate-related risks and opportunities, including progress towards any climate-related targets it has set, and any targets it is required to meet by law or regulation.** a) IFRS S2 mandates cross-industry and industry-specific metric disclosures aligned with TCFD guidance. b) IFRS S2 requires detailed GHG emissions reporting, covering Scope 1 and 2 emissions for various organizational entities and Scope 3 for financed emissions, including measurement specifics. It doesn't mandate gas disaggregation but may require it for materiality. c) Unlike TCFD, IFRS S2 requires reporting on the influence of global climate agreements on targets, their third-party validation, and detailed GHG target information, including carbon credit use and monitoring methods, emphasizing sectoral decarbonization approaches.

This table presents a comparative overview of the TCFD recommendations and IFRS S2 climate-related disclosure requirements. The content is organized along the four TCFD pillars: governance, strategy, risk management, and metrics and targets. It contrasts the principles-based orientation of TCFD with the more prescriptive IFRS S2 guidelines, reflecting a regulatory shift toward greater granularity, integration, and accountability. Source: TCFD (2018), IFRS Foundation (2023), and author adaptations.

BERT's architecture uses an 'attention' mechanism (Vaswani et al., 2017) to understand word relationships within their context, making it highly effective for evaluating complex texts (Chowdhery et al., 2023; Ferrando et al., 2024). Specifically, 'Climate' BERT models pre-trained on climate-specific content—including TCFD pillars—allow for a nuanced assessment of disclosures by measuring content coverage and adherence (Liu et al., 2019; Moreno and Caminero, 2021; Friederich et al., 2021; TCFD, 2023; Chava et al., 2020; Gutierrez-Bustamante and Espinosa-Lea, 2022; Brié et al., 2023). This capability ensures that each section of a disclosure is evaluated in relation to regulatory requirements, revealing strengths and gaps in the reporting.

DistilBERT (Sanh et al., 2019), a lighter variant of BERT, provides similar analytical capabilities with reduced computational requirements. This model is ideal for environments where processing power may be limited but comprehensive text analysis is still necessary. BERT and its variants provide robust tools for assessing content alignment by measuring how closely disclosures adhere to predefined regulatory content, and primarily focus on direct comparisons to specific training material. This approach effectively highlights which sections of a disclosure align or fall short based on a model's understanding of the TCFD and IFRS S2 guidelines. However, this content-based perspective can miss another important aspect of analysis: understanding the broader thematic landscape within disclosures.

Thematic exploration techniques takes a different approach by identifying the primary topics within the text itself. Rather than focusing on how much content matches predefined pillars, these methods uncover the main themes (topics). This shift in focus is particularly valuable for revealing how disclosures are structured and whether they inherently address key areas such as governance, strategy, risk management, and metrics and targets. If the identified themes naturally map to these pillars, it suggests that the disclosures align well with regulatory expectations.

Latent Dirichlet Allocation (LDA) (Blei et al., 2003) is a foundational method used for this type of analysis. LDA breaks down texts into distributions of topics by grouping related words, allowing researchers to determine which themes are most prevalent in a disclosure (Blei and Lafferty, 2007; Griffiths and Steyvers, 2004). This insight is useful for understanding what areas a company emphasizes in its climate reporting. For instance, LDA has been applied to analyze the presence of climate-related themes in social media and corporate communications, providing an overview of thematic coverage (Uthirapathy and Sandanam, 2023; Polyzos and Wang, 2022; Benites-Lazaro et al., 2018).

However, while LDA can identify dominant topics, it treats them as independent and fails to capture relationships between interconnected themes. This limitation can lead to a fragmented understanding of how various components of climate reporting interact within disclosures (Wheelock and Pachamanova, 2022; Blei et al., 2003). For example, discussing governance in isolation from strategy may not provide a complete view of how a company integrates climate risk management into its overall operations.

To overcome this limitation, Graph Neural Topic Models (GNTM) have been recently developed to represent words and topics as nodes and edges in a graph, capturing their relationships and dependencies (Zhu et al., 2023). By using GNTM, analysts can explore how different themes within a disclosure are interlinked, which helps determine whether the document presents an integrated, cohesive narrative (Wang et al., 2020; Shen et al., 2021). This approach is particularly beneficial when assessing alignment with TCFD, as it shows not just the presence of themes but how they support each other, creating a more connected and strategic disclosure (Zhu et al., 2023; Benites-Lazaro et al., 2018).

While content-focused models like BERT provide a direct measure of alignment based on coverage, thematic exploration with LDA and GNTM offers a complementary view by revealing the structure and interconnections of topics within disclosures. This combination of approaches ensures a comprehensive analysis, evaluating both explicit alignment and the underlying thematic coherence of climate-related reporting.

2.3. Determinants Influencing Climate Disclosure Alignment

Identifying variables influencing this alignment with TCFD recommendations is key to evaluating corporate climate-related reporting. Linguistic and contextual factors significantly shape the transparency and effectiveness of disclosures, with corporate language complexity and word ambiguity varying by context, timing, and authorship (Loughran and McDonald, 2016). Lexicometric measures such as average word length, lexical diversity, and entropy provide valuable insights into how companies construct their climate narratives (Chava et al., 2020; Brié et al., 2023; Sautner et al., 2023). These metrics reveal whether a report employs clear, accessible language or complex, technical jargon. Longer words may indicate a highly technical tone, potentially hindering stakeholder comprehension. Lexical diversity reflects vocabulary range, highlighting whether the text is varied and rich or repetitive (Zipf, 1935; Sigurd et al., 2004), while entropy evaluates structural coherence, shedding light on the uniformity and clarity of information presentation (Shannon, 1948).

Readability indices, such as Flesch-Kincaid (Flesch, 1948; Kincaid et al., 1975; Plavén-Sigray et al., 2017) and Gunning-Fog (Gunning, 1952; Strong, 1986), assess language complexity to determine whether reports are accessible or challenging to interpret. Easier-to-read reports enhance stakeholder understanding and trust, contributing to lower analyst dispersion and higher earnings forecast accuracy. Conversely, less readable disclosures may require greater analyst effort, potentially affecting trading and investment behaviors (Li, 2008; Biddle et al., 2009; Miller, 2010; Lawrence, 2013; Chen et al., 2023; Lehavy et al., 2011; De Franco et al., 2015; Rennekamp, 2012). Yan (2024) observed that detailed environmental disclosures improve readability and tone, thereby enhancing report quality, though not necessarily ensuring alignment with TCFD standards. While clarity is undoubtedly valuable, it must be evaluated alongside other factors to provide a comprehensive assessment of disclosure practices (Loughran and McDonald, 2014; Chen et al., 2023; Torchani et al., 2024).

Board characteristics significantly influence climate disclosure practices. Factors such as independent directors, diversity policies, and female representation shape how climate issues are prioritized and reported (Liao et al., 2015; Luo and Tang, 2016). Diverse and independent boards often promote more transparent and comprehensive reporting, reflecting governance structures that prioritize environmental considerations and align disclosures with TCFD recommendations (Giannarakis et al., 2018; Luo et al., 2023).

Financial variables like leverage and return on assets (ROA) provide valuable context for a company's climate disclosure practices (Eleftheriadis and Anagnostopoulou, 2015). Highly leveraged firms may prioritize transparency to maintain investor confidence, while firms with strong ROA often highlight sustainable investments to showcase their commitment to environmental and regulatory standards. These factors reveal how economic performance shapes the depth and focus of climate reporting.

Environmental performance also significantly influences climate disclosures, as firms with stronger performance tend to provide more transparent and comprehensive reports (Clarkson et al., 2008; Giannarakis et al., 2017; Jiang et al., 2023). Ding et al. (2023) highlight that higher carbon emissions prompt detailed disclosures as companies aim to show their proactive environmental management. Similarly, Jiang and Tang (2023) demonstrate that mandatory carbon reporting boosts voluntary disclosure, indicating that regulatory pressure fosters openness. Dawkins and Fraas (2011) further emphasize that companies with better environmental performance are more likely to align with frameworks like TCFD, showcasing their commitment to transparency. These insights underscore how environmental performance shapes the depth and quality of climate reporting.

Finally, cultural influences add an essential dimension to understanding the variability in climate disclosures across regions and industries. Hofstede and Minkov (2010) cultural dimensions—such as power distance, individualism, and uncertainty avoidance—illustrate how societal norms shape reporting practices (Luo and Tang, 2016; Luo et al., 2018). For instance, cultures with high uncertainty avoidance often emphasize detailed risk management, aligning with TCFD's focus on comprehensive disclosure. This context explains regional differences in climate reporting, reflecting how local expectations shape the communication of climate-related information.

This paper advances the analysis of climate-related disclosures by exploring alignment with TCFD recommendations through a multi-layered methodology. Building on prior research on content and readability, it integrates advanced AI tools such as Climate BERT to analyze alignment with TCFD pillars: governance, strategy, metrics and targets, and risk management. Thematic analysis using Latent Dirichlet Allocation (LDA) and Graph Neural Topic (GNT) models captures the depth, fragmentation, and coherence of climate narratives. Language-enhanced panel regressions further identify structural, financial, and cultural determinants of alignment, while also enabling the exploration of links between disclosure practices and market valuation. By linking disclosure content to governance structures and valuation signals, this paper provides a scalable foundation for assurance practices (Simnett et al., 2009) and demonstrates the informational relevance of climate narratives in market valuation.

3. Data and Methodology

The sample for this study comprises 28 major European energy companies that publish annual reports and climate-related disclosures. The companies were identified by systematically collecting all publicly listed energy firms headquartered in Europe that met the following inclusion criteria: (i) availability of annual reports and climate-related disclosures for the period 2020–2022, and (ii) reports accessible in English to ensure consistency in language analysis. The selection process used professional databases such as Refinitiv, Statista, and Xerfi 7000 to ensure sectoral and geographical diversity. The final sample reflects a broad cross-section of the European energy sector, including firms with different business models, from traditional oil and gas companies to renewable energy providers. The detailed list of companies and their abbreviations is provided in the Appendix, Table 9. All computations in this work were performed using Python. The list of variables used in the analysis, along with their definitions and data sources, is provided in Table 2.

Figure 1 outlines the methodology. The process begins with data collection and preprocessing (Step 1), where annual reports and climate disclosures from companies are gathered, and text data are standardized to remove irrelevant elements, setting the foundation for analysis. The next phase, initial linguistic analysis (Step 2), evaluates linguistic metrics to assess readability and structural coherence. Principal component analysis is conducted to evaluate and compare companies' reporting styles for the year 2022, providing an overview of how different firms approach their climate disclosures.

In content alignment assessment (Step 3), similarity measures are calculated to evaluate how well climate disclosures align with TCFD recommendations. They provide a baseline understanding by comparing the company's climate-related text against the consolidated content of TCFD's four pillars (Singhal, 2001; Loughran and McDonald, 2016; Polyzos and Wang, 2022).

The analysis was then augmented with a AI Based DistilBert model. This model was trained on the dataset introduced by Bingler et al. (2022), which comprises over 1,000 manually labeled text samples extracted from the annual and sustainability reports of more than 50 financial institutions. Each sample is annotated according to the four TCFD pillars: Governance, Strategy, Risk Management, and Metrics and Targets. DistilBERT, a

Table 2: List of Variables

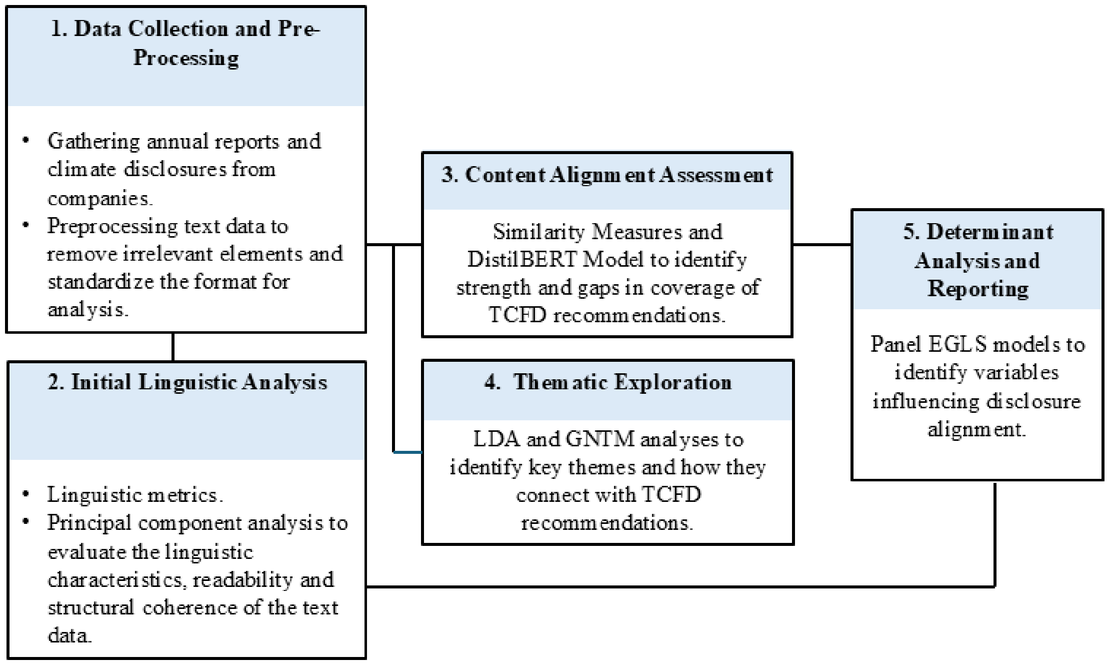
Category	Variable	Definition	Data Source
TCFD Pillars			Annual Reports
	GOV	TCFD pillar coverage percentage, assessed using climate DistilBert.	
	MET	Coverage percentage for 'Metrics and Targets'.	
	RSK	Coverage percentage for 'Risk Management'.	
	STR	Coverage percentage for 'Strategy'.	
Lexicometrics			Annual Reports
	WC	Total number of words in the document.	
	AWL	Average word length (characters/words).	
	LEX	Ratio of unique words to total words.	
	ENT	Average information per word.	
	SUR	Cosine similarity between documents.	
	SEM	Semantic similarity score using a language model.	
Board Characteristics			Refinitiv
	PBD	Board diversity policy presence. Includes gender and intercultural representation.	
	IND	Policy on board independence. Ensures an independent board structure.	
	FEM	Percentage of female board members.	
Financial Information			Refinitiv
	FF	Publicly tradable shares excluding major holders.	
	SH	Shares held by major shareholders.	
	ROA	Return on Assets.	
	LEV	Total Debt over Total Assets.	
	MB	Market to Book Ratio.	
Cultural Influences			Culture Factor Group
	PWD	Extent of acceptance of unequal power distribution.	
	INDIV	Degree of individualism versus group loyalty.	
	MAS	Preference for achievement (masculinity) or care (femininity).	
	UAV	Comfort level with uncertainty and ambiguity.	
	LTO	Focus on long-term future or short-term traditions.	
	INDUL	Degree of indulgence versus strict social norms.	
Sustainability Performance			Refinitiv
	ESG	ESG Score.	
	ETAX	Tier Green Revenue, EU Taxonomy.	

This table presents the full list of variables used in the analysis, with their definitions and corresponding data sources.

computationally lighter variant of BERT[1], leverages attention mechanisms to capture word relationships within their broader sentence-level context (Sanh et al., 2019; Vaswani et al., 2017).The climate-specific training allows the model to identify semantic similarities beyond exact lexical matches, enabling it to recognize conceptually equivalent expressions (e.g., "climate governance" and "board oversight of climate risks") (Bingler et al., 2022; Chava et al., 2020; Gutierrez-Bustamante and Espinosa-Lea, 2022; Brié et al., 2023).This model was subsequently employed to assess the degree of alignment with the four TCFD pillars:

[1]DistilBERT requires fewer computational resources than BERT while maintaining competitive accuracy levels (Friederich et al., 2021).

Figure 1: Research Methodology



This figure presents the step-by-step research design, from data collection and preprocessing to linguistic analysis, BERT-based content alignment assessment, thematic modeling, and determinant testing using panel regressions.

Governance, Strategy, Risk Management, and Metrics and Targets.

Thematic exploration (Step 4) involved applying Latent Dirichlet Allocation (LDA) and Graph Neural Topic Models (GNTM) to identify key themes within the disclosures and understand their connections [2].

The final step (Step 5) involved incorporating the BERT-generated alignment scores into a series of panel regression models. The first set of models uses each pillar-specific alignment score as the dependent variable to examine the firm-level determinants of disclosure alignment with that particular TCFD dimension. The second set of models assesses the economic relevance of these alignment scores by including them as explanatory variables in panel regressions where the market-to-book ratio serves as the dependent variable. This two-stage approach enables a systematic evaluation of both the drivers and the implications

[2]The Louvain community detection algorithm (Blondell et al., 2008) was used to confirm prominent topics and validate the thematic results derived from LDA, ensuring that the thematic content was relevant.

of climate disclosure alignment. The models are structured as follows:

$$\begin{aligned}\text{BertAlignment}_{it} =&\alpha + \beta_i(\text{Lexicometrics})_{it} \\ &+ \theta_i(\text{Board})_{it} + \zeta_i(\text{Financial Information})_{it} \\ &+ \mu_i(\text{Cultural Influences})_{it} + \kappa_i(\text{Sustainability Performance})_{it} + \epsilon_{it}\end{aligned} \tag{1}$$

Where BertAlignment refers to the alignment with the four TCFD pillars, as assessed by the DistilBERT model: Governance (GOV_{it}), Metrics and Targets (MET_{it}), Risk Management (RSK_{it}), and Strategy (STR_{it}). Lexicometric variables include word count (Wc), average word length (AWL), lexical diversity (LEX), and entropy (ENT). Board characteristics are represented by policies on board diversity (PBD), independence (IND), and the proportion of female members (FEM). Financial information encompasses free float (FF), shares held by major shareholders (SH), return on assets (ROA), and debt (DEB). Cultural influences are denoted by power distance (PWD), individualism (IND), masculinity (MAS), uncertainty avoidance (UAV), long-term orientation (LTO), and indulgence (IND). Sustainability Performance includes the ESG Score (ESG), which captures firm-level performance across three dimensions: environmental factors, social factors and governance factors. It also includes the share of green revenue in accordance with the EU Taxonomy (ETAX), defined as the proportion of a company's turnover derived from economic activities that substantially contribute to at least one of the EU's six environmental objectives[3], while respecting minimum social safeguards and doing no significant harm to other objectives. The model includes α as a constant and ϵ_{it} as the error term.

To evaluate the firm-level implications of alignment with the TCFD pillars (BertAlignment), the following models are estimated:

$$\text{MB}_{it} = \alpha + \beta_i(\text{BertAlignment})_{it} + \theta_1\text{LEV}_{it} + \theta_2\text{ROA}_{it} + \epsilon_{it} \tag{2}$$

Where MB refers to the market-to-book ratio; LEV is included to control for financial

[3]These objectives include: (1) climate change mitigation, (2) climate change adaptation, (3) sustainable use and protection of water and marine resources, (4) transition to a circular economy, (5) pollution prevention and control, and (6) protection and restoration of biodiversity and ecosystems.

risk, as higher debt can affect firm valuation by increasing perceived default risk, and ROA captures profitability, a key determinant of firm valuation. By including these controls, we ensure that the relationship between BertCoverage and MB reflects the impact of TCFD alignment, without being confounded by differences in risk or profitability.

The analysis begins with summary statistics[4], which are reported in Table 10 in the Appendix. Endogeneity concerns, particularly between lexicometric and BERT alignment scores, were examined using lagged variables, and Two-Stage Least Squares (2SLS) regression. No significant evidence of endogeneity were found. The presence of cross-sectional dependencies within the variables was checked using tests of Pesaran (2004). These tests clearly confirmed cross-sectional dependencies, leading to a preference for panel estimations that account for these effects. Stationarity tests of Pesaran (2007) were also performed. These tests rejected the null hypothesis of a unit root in all cases, justifying the estimation of all series at their level, expressed in logarithmic form.

The panel EGLS estimations under cross-section fixed effects was selected as the most relevant method, as the F-Statistics for each model reject the null hypothesis. The Hausman (1978) tests further ascertain the fixed effects model as the most appropriate for each case. The models' robustness is additionally supported by the absence of cross-section dependencies among the residuals. The robustness and validity of the estimated coefficients are rigorously examined in subsection 4.5. To this end, the analytical scope has been broadened to encompass quantile regression estimations (Koenker and Bassett jr., 1978) and robust least squares (Huber, 1973). In analyzing a small, diverse panel of European energy companies, Quantile Regression (QR) at the median ($\tau = 0.5$) and Robust Least Squares (RLS) offer robust insights. QR's focus on the median provides a central tendency measure less affected by outliers. This is particularly relevant in the energy sector (Uribe and Guillen, 2020) where operational scales and financial metrics can vary significantly. This complements Panel EGLS models, which, despite handling unobserved heterogeneity and cross-sectional differences, may not fully account for distributional effects. RLS further enhances robustness by down-weighting outliers (Baltagi, 2013), ensuring estimates reflect the sector's economic realities without bias

[4]Additional information such as detailed lexicometric scores, correlation matrices between variables, and other supplementary materials is available upon request.

from extreme values. Employing both QR and RLS offers a comprehensive, nuanced analysis, balancing the exploration of distributional effects and outlier management, thus providing a solid foundation for our empirical results.

4. Results and Discussion

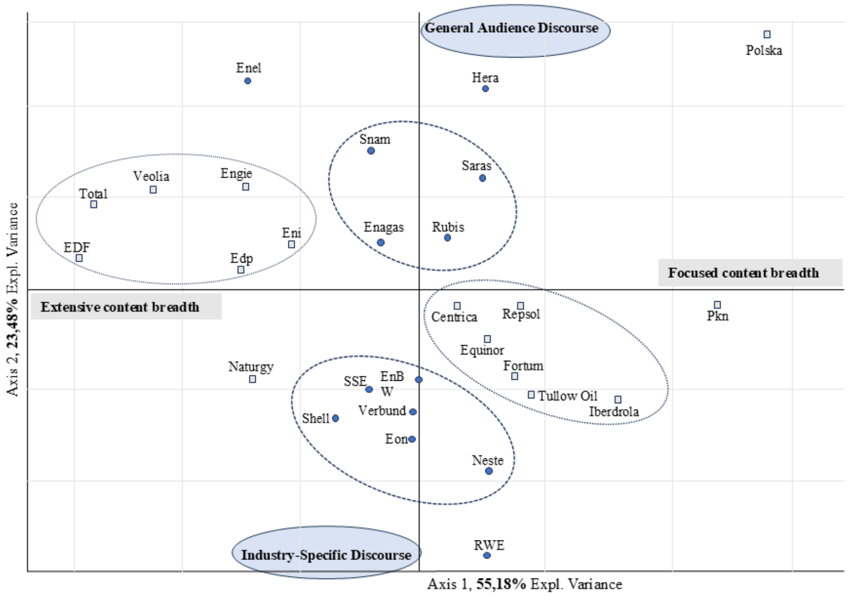
4.1. Readability

In the principal component analyses of lexicometric data from annual reports and climate-related disclosures (Figure 2 and 3), corpus richness metrics (e.g., page and word counts, lexical diversity) aligned strongly with the first axis, labeled 'Extensive Content Breadth/Focused Content Breadth'. This axis contrasts extensive content (larger documents with high lexical diversity) with focused content (concise and selective). The second axis, associated with average word length and readability indices (Flesch-Kincaid, Gunning-Fog), was termed 'General Audience Discourse/Industry-Specific Discourse'. General discourse shows lower word length and readability scores, while higher values indicate industry-specific language. The consistent readability scores observed across companies likely reflect standardized language norms imposed by disclosure requirements.

The entropy metric, assessing textual coherence, was significantly associated with both axes, indicating a strong organizational structure across all reports and confirming adherence to language norms. In Figure 2, reports on the left side of the graph were marked by extensive content (e.g., high page and word counts, lexical diversity), corresponding to the largest companies in the sample, often with broad activities, including nuclear power, which demands detailed disclosures. These reports showed higher synonym use and longer average word length, traditionally linked to lower readability, potentially complicating analysis and influencing investor behavior. This aligns with findings by Loughran and McDonald (2016), who emphasized the importance of considering the ambiguous nature of terms, which can vary significantly based on context, timing, and authorship. This highlights the importance of considering company-specific traits like size, ownership, and operational scope.

In the analysis of climate-related disclosures (Figure 3), a distinct pattern emerges, with most companies positioned in the left-hand triangle, indicating increased report complexity. This complexity appears as either greater lexical diversity with rich content or more

Figure 2: Annual Reports Lexicometrics, Principal Component Analysis, Year 2022.



This figure presents the results of a Principal Component Analysis on lexicometric variables extracted from the full annual reports in 2022. Axis 1 represents content breadth, while Axis 2 captures the discourse orientation, ranging from industry-specific to general-purpose communication. The positioning of firms reflects their reporting style and lexical structure. Square labels are linked to content breadth (Axis 1), while round labels relate to discourse style (Axis 2).

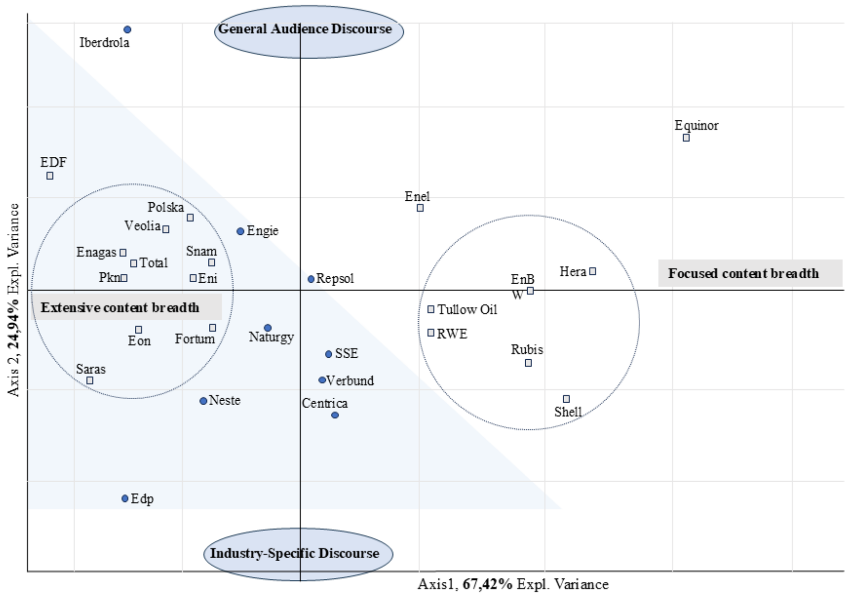
technical vocabulary with longer average word lengths, signifying specialized environmental communication and typically lower readability.

4.2. TCFD Alignment

4.2.1. Similarities with TCFD recommendations

To assess the alignment of these discourses with the TCFD recommendations, surface cosine similarity (Singhal, 2001) and semantic cosine similarity (Wang et al., 2020) with the TCFD guidelines were calculated. The results of these analyses are presented in Table 3.

Figure 3: Climate-Related Disclosures Lexicometrics, Principal Component Analysis, Year 2022.



This figure presents the Principal Component Analysis based on lexicometric variables extracted from climate-related disclosures in 2022. Axis 1 represents the breadth of content, while Axis 2 reflects the discourse orientation. Firms are positioned according to the structure, readability, and lexical diversity of their climate narratives. Square labels are linked to content breadth (Axis 1), while round labels relate to discourse style (Axis 2).

Table 3: Compliance with TCFD, Surface and Semantic Cosine Similarity (%), Year 2022.

Company	Surface	Semantic	Company	Surface	Semantic
Centrica	42,63	49,07	Pkn	24,32	56,13
Edf	32,23	67,93	Polska	27,68	61,76
Edp	30,32	55,4	Repsol	32,69	73,31
Enagas	33,42	62,88	Rubis	24,45	50,99
Enbw	23,58	56,5	Rwe	25,91	71,04
Enel	39,83	47,22	Saras	30,77	61,22
Engie	28,13	49,84	Shell	22,89	60,66
Eni	37,82	63,47	Snam	32,04	51,17
Eon	36,2	48,83	Sse	43,81	65,1
Equinor	18,32	67,17	Total	29,8	50,52
Fortum	38,11	70,55	Tullow	36,48	50,59
Hera	34,59	64,3	Veolia	28,69	61,54
Iberdrola	34,04	65,99	Verbund	27,49	63,77
Naturgy	31,4	56,6			
Neste	30,99	64,48	**Average**	**31,37**	**59,57**

This table presents the surface and semantic cosine similarity scores (%) between each company's climate-related disclosures and the TCFD recommendations for the year 2022. Surface similarity captures lexical alignment, while semantic similarity reflects conceptual alignment assessed using a mini LM model.

Table 3 reveals a significant disparity between surface and semantic cosine similarity scores, with surface scores being relatively low and semantic scores notably higher. This highlights the role of language models in effectively assessing text alignment with standards. This is further exemplified in the EDF Group's report, which details its commitments to addressing climate change:

> "Pursuant to this policy, the EDF group undertakes to evaluate the impacts of climate change on future and existing activities; adapt existing installations to make them less sensitive to climatic conditions and more resilient to extreme weather events; incorporate climate change scenarios in the design of new installations; adapt the Group's solutions, internal operations, and know-how in light of climate change; and take into account the ecosystemic dimension of climate change." Source: EDF Universal Registration Document, 2022, Section 3, p. 149.

When comparing EDF's report to the TCFD recommendations, lower surface similarity is noted due to reliance on exact word matches. For example, expressions like "evaluate the impacts of climate change" and "adapt existing installations" differ from the TCFD's phrasing. However, a language model captures the contextual alignment, recognizing that EDF's commitments align with TCFD goals such as climate impact assessment, resilience, and scenario incorporation, even with varied wording. This underscores the value of semantic similarity measures for accurate alignment assessment. Nevertheless, a language model's accuracy depends on the reference text used. The MiniLM model used here, trained on general content, can overestimate similarity compared to models trained with detailed content outlining TCFD's specific pillars. This variability may explain divergent findings in recent studies evaluating TCFD alignment. While some, like Chava et al. (2020) and Bingler et al. (2022, 2024), found low congruence between corporate disclosures and TCFD mandates, others such as Luccioni et al. (2020), Friederich et al. (2021), Moreno and Caminero (2021), Brié et al. (2023), and the TCFD itself (TCFD, 2023), reported stronger compliance.

4.2.2. Alignment to TCFD Recommendations

The AI-based DistilBERT model[5] offers enhanced analytical capacity for examining climate-related disclosures. Trained on the dataset of Bingler et al. (2022), the model classifies textual content by identifying relevant climate-related passages with a high degree of accuracy. It achieved an F1 score of 81.38%, a metric that balances precision and recall to reflect the model's ability to correctly detect relevant disclosures while minimizing both false

[5] During training, the model's performance improved steadily, as reflected in a decrease in the loss function, a standard measure of prediction error in machine learning. Specifically, the loss dropped from 1.004 in the first epoch to 0.7909 in the second, and further to 0.6756 in the third. This decline indicates that the model became increasingly accurate in identifying climate-related disclosures as training progressed.

positives and false negatives. For comparison, TCFD (2023) reported an aggregated F1 score of 73.18%.

DistilBERT results on the alignment of company reports with TCFD recommendations (Table 4) show varied scores across the four pillars. For governance, Engie and Eon have the highest alignment (42.08% and 44.14%). Enel has the highest alignment in risk management (79.68%), while Edp and EnBW perform strongly in metrics and targets (81.35% and 80.02%). Centrica shows the highest alignment in strategy (83.62%). Scores in the 'Others' category remain low across companies, typically below 1%. Overall, alignment is highest for strategy (41.06%) and metrics and targets (35.07%).

Compared to the international sample from TCFD (2023), European energy companies show higher alignment in strategy (41.06% vs. 34.08%) and metrics and targets (35.07% vs. 20.52%), while alignment in governance (10.57% vs. 28.43%) and risk management (12.77% vs. 16.95%) remains lower. These results indicate that European firms place greater emphasis on disclosing quantitative commitments and long-term strategic intentions, but fall short in integrating climate considerations into internal governance and risk oversight. Interestingly, the alignment scores for metrics and targets in the transport (36.50%) and agriculture (36.42%) sectors are closer to those of the European energy sector than to the global energy average. This convergence may reflect broader shifts in climate-related reporting practices that transcend sector boundaries. Overall, the findings highlight the relevance of sector-specific analysis while also revealing commonalities across pillars such as strategy and metrics and targets, regardless of industry or region.

Despite low alignment across TCFD pillars (Table 4), reports from 2021 and 2022 show a gradual improvement over time, consistent with TCFD (2023). Overall, these findings suggest that while companies increasingly address climate-related issues, alignment with detailed TCFD recommendations remains limited.

Table 4: Alignment of Climate Disclosures with TCFD Pillars (%), DistilBERT Model, Year 2022.

Company	Governance	Metrics and Targets	Risk Management	Strategy	Others
Centrica	2,9	9,3	3,85	83,62	0,33
EDF	6,66	10,11	7,9	74,96	0,37
Edp	0,79	81,35	1,86	15,65	0,34
Enagas	8,71	3,62	16,41	70,88	0,38
EnBW	0,77	80,02	5,93	12,75	0,52
Enel	16,33	1,42	79,68	2,29	0,28
Engie	42,08	3	50,25	4,3	0,36
Eni	0,8	65,7	12,71	20,25	0,54
Eon	44,14	11,04	11,74	32,39	0,69
Equinor	1,53	14,05	8,42	75,65	0,35
Fortum	1,34	38,71	3,63	55,79	0,54
Hera	2,8	79,5	7,24	9,81	0,66
Iberdrola	25,31	24,53	5,76	43,53	0,87
Naturgy	22,98	12,06	5,18	58,92	0,85
Neste	4,17	54,73	3,31	37,02	0,77
pkn	7,12	5,23	5,36	81,88	0,4
Polska	63,95	9,13	4,23	22,08	0,61
Repsol	2,06	77,32	1,81	18,36	0,46
Shell	1,64	56,42	4,82	36,52	0,6
Rubis	7,04	19,67	39,65	32,97	0,67
RWE	4,09	29,82	5,56	59,95	0,58
Saras	15,64	10,79	24	48,95	0,62
Snam	0,86	86,89	2,53	9,28	0,44
SSE	2,52	2,64	12,5	82,15	0,19
Total	3,36	15,22	13,78	67,27	0,37
TullowOil	0,6	66,45	8,08	24,54	0,34
Veolia	4,09	44,42	6,29	44,47	0,73
Verbund	1,71	68,99	5,19	23,71	0,4
Average DilstilBert	10.57	35.07	12.77	41.06	0.53
TCFD Bert					
Energy Sector	28.43	20.52	16.95	34.08	0
Transportation	30.15	36.50	15.52	17.81	0
Agriculture	25.71	36.42	15.89	21.96	0

This table reports the alignment (in percentage) of climate-related disclosures with the four TCFD pillars, estimated using a distilBERT model applied to a sample of European firms. The names of the European companies appear in the first column. The alignment scores indicate the proportion of content related to each TCFD pillar: governance, metrics and targets, risk management, strategy, and other information. The final rows provide the TCFD's own BERT-based alignment scores for an international sample of firms from the energy, transportation, and agriculture sectors, included here for comparison (TCFD, 2023).

4.3. Thematic Exploration

To identify primary topics of concern, a Latent Dirichlet Allocation (LDA) was performed on the aggregate set of climate disclosures from energy sector companies. The results are visually represented through an Intertopic Distance Map[6], where each topic is accompanied by a list of the top 30 words ranked by saliency (Chuang et al., 2012) and relevance (Sievert and Shirley, 2014). Chuang et al. (2012) developed a method to identify terms that are not only frequent but also distinctive and informative for a topic, while Sievert and Shirley (2014) emphasized the identification of discriminating terms unique to a specific topic. The full content for each topic is provided in Appendix, Table 11, and has been summarized

[6]Refer to Figure 4 in the Appendix for an intertopic distance map obtained via multidimensional scaling for Topic 1, including a short list of the most relevant terms. Additional results are available upon request.

into concise sentences. The main areas of concern in the sector include SCR training (1st), compliance and ethical practices (2nd), risk management, waste control, and renewable energy generation (3rd), GRI standards (4th), GHG emissions, net-zero goals, and economic efficiency (5th), as well as water resources, biodiversity, and gender (6th).

To confirm these topics, GNTM analysis was conducted, beginning with an exploration of the network structure. The observed low density of connections in the network (24.21%) indicates diverse language usage in climate disclosures, reflecting the range of terms companies use to describe their climate-related actions, commitments, and impacts, supporting previous findings. Structural tests on the network confirmed the absence of regular, hierarchical, and random structures, suggesting coherent and logically organized documents. These tests also verified that aggregating disclosures preserved the integrity and semantic alignment of the content. Given the network's size, with 156,413 connections, a suitable data processing approach was needed. The Louvain community detection algorithm (Blondell et al., 2008) was employed for its efficiency in rapidly identifying important word communities by maximizing modularity and revealing coherent and significant communities.

Table 12 in the Appendix shows the key themes obtained from the network analysis. While minor differences exist between GNTM and LDA results, both methods highlight similar topics: CSR promotion, energy efficiency, carbon emissions, compliance with international standards, and gender diversity. Although these findings align, they remain broader than the TCFD's specific recommendations, raising concerns about companies' preparedness for climate-related risks. These results, consistent with distilBERT findings, suggest that significant progress is needed to achieve full alignment and maturity in climate risk reporting.

4.4. Determinants for TCFD Alignment

To identify the primary variables influencing TCFD alignment, the analysis was expanded through panel regressions[7]. The results reveal that specific linguistic and organizational characteristics, financial structures, and cultural traits are crucial for improving TCFD alignment. Short words, as measured by the AWL variable, are positively associated with

[7]The Fog and Flesch-Kincaid readability indices were remarkably similar across the companies and did not exhibit significant differences in the estimations. Only relevant findings are presented here.

alignment to the RISK, STRAT, and MET pillars. This finding aligns with Loughran and McDonald (2016), who emphasize the role of linguistic simplicity in fostering transparency and stakeholder trust, especially in the context of climate-related risks. Clear and concise communication ensures that the information is easily understood and actionable.

A greater quantity of words, as captured by the WC variable, negatively affects alignment with MET, but enhances GOV and STRAT alignment. This reflects the linguistic demands of each pillar: MET disclosures typically rely on specific, technical terms tied to standardized indicators, where brevity and precision are preferred. In contrast, GOV and STRAT benefit from more expansive narratives, where higher word counts contribute to clarity and contextual richness. In line with this result, lexical diversity, represented by the LEX variable, positively contributes to GOV and STRAT but negatively affects MET. Entropy (ENT), which captures the average information per word and is often used as a proxy for textual coherence, has a strong positive effect on MET and a negative influence on GOV and STRAT. This suggests that MET disclosures benefit from structured and concentrated language, where the repeated use of specific terms enhances clarity and comparability. By contrast, such structuring may be constraining for GOV and STRAT, which rely more on flexibility and elaboration. The result underscores how textual coherence can support standardized reporting, while potentially limiting the expressive range needed in more narrative-driven disclosures.

The role of the board in shaping TCFD alignment is also significant. A more diversified and independent board enhances alignment with MET and STRAT, reflecting the idea that a wide range of perspectives improves the depth and accuracy of climate metrics while fostering a strategy that is both forward-looking and independent of entrenched interests. The inclusion of women in boardrooms, as evidenced by the FEM variable, positively affects all pillars' coverage (GOV, MET, RISK, STRAT). This aligns with research by Liao et al. (2015), who argue that gender diversity strengthens board deliberations, fostering comprehensive and transparent climate disclosures. Women's involvement brings diversity of thought and inclusivity, which strengthens the board's ability to address climate change across governance, risk, metrics, and strategy. These findings underscore the importance of a diverse board in aligning with the TCFD framework, where varied viewpoints lead to more comprehensive and effective climate-related decision-making.

Table 5: Determinants of Climate Disclosure Alignment with TCFD Pillars: Panel EGLS Estimation Results.

	GOV	MET	RISK	STRAT
Lexicometrics				
AWL	-2.992 (-1.3620)	1.458** (1.9826)	3.60** (1.87)	3.12*** (3.28)
WC	1.630* (1.795)	-1.8932*** (-3.02)	-0.46 (-0.52)	2.56*** (5.68)
LEX	2.269* (1.923)	-1.42* (-1.51)	-1.18 (-0.74)	4.95*** (6.15)
ENT	-15.20*** (-2.075)	23.58*** (5.39)	2.96 (0.51)	-14.156*** (-4.95)
Board Characteristics				
PBD	-9.58 (-1.245)	1.92*** (4.21)	-1.71 (-0.34)	2.33*** (5.69)
IND	-1.24 (-0.89)	-1.08 (-1.21)	7.14 (0.06)	1.10* (1.61)
FEM	5.58*** (4.46)	2.83** (2.19)	5.30*** (8.69)	5.98*** (7.20)
Financial Information				
FF	9.10*** (3.31)	3.43 (1.11)	-3.18** (-2.18)	5.92*** (5.51)
STRATH	-0.174 (-1.394)	-0.204 (-0.81)	0.23* (1.50)	0.215*** (6.219)
ROA	0.004 (0.462)	-0.009 (-0.83)	0.008** (1.96)	0.014*** (3.48)
LEV	5.57*** (2.17)	-0.945 (-0.496)	2.45 (1.25)	2.71*** (3.31)
Cultural Influences				
PWD	2.20 (0.82)	-1.15 (-0.62)	-7.92 (-0.55)	-5.11*** (-2.73)
INDIV	3.81 (0.08)	8.83 (0.253)	4.86** (2.26)	4.29 (1.23)
MAS	-5.02 (-0.13)	9.23 (0.301)	-4.74*** (-2.78)	-5.20* (-1.71)
UAV	3.71 (0.73)	-1.27*** (-5.61)	4.62** (2.29)	1.51 (0.55)
LTO	-1.97 (-0.13)	1.31 (0.75)	-1.40** (-2.10)	6.13 (0.65)
INDUL	-1.59*** (-11.17)	-1.97*** (-3.401)	1.44 (0.25)	3.33*** (4.43)
Sustainability Performance				
ESG	0.024 (0.80)	0.04* (1.57)	0.01** (2.16)	0.07*** (11.53)
ETAX	0.048** (9.92)	0.052** (2.01)	0.152*** (8.18)	0.079*** (4.23)
Cst	64.57*** (3.54)	-41.542*** (-2.57)	23.79** (2.23)	-23.14** (-4.56)
R sq.	0.9373	0.9179	0.9755	0.9725
Adj. R sq.	0.8453	0.7977	0.9397	0.9321
F Stat.	10.195***	7.63***	27.22***	24.11***
nb. Obs	112	112	112	112

This table presents the estimation results of Equation 1 using a Panel EGLS model with cross-section fixed effects. All variables are expressed in logarithmic form. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The F-statistic supports the rejection of the null hypothesis that all individual-specific intercepts are jointly equal to zero. The Hausman test confirms that the fixed effects specification is appropriate. The Pesaran test showed no evidence of cross-sectional dependence in the residuals. For definitions of the variables used, see Table 2.

Financial factors also play a crucial role in achieving higher alignment with TCFD pillars. An increase in ownership diversity (higher FF) is associated with higher alignment in GOV and STRAT. This finding supports Bueno-García et al. (2022), who highlight that a lack of ownership diversity in a concentrated shareholder base often narrows the focus of corporate priorities, hindering detailed governance and strategy disclosures. On the other hand, major shareholders appear to drive better alignment with RISK and STRAT, exerting influence that helps focus attention on the long-term strategic implications of climate risks. Profitability (ROA) aligns with RISK and STRAT, reinforcing the idea that financial stability is a prerequisite for implementing ambitious climate strategies. Moreover, the control of debt levels (LEV) is important for GOV and STRAT, ensuring that sound financial management supports good governance practices and mitigates climate-related risks.

Cultural factors also contribute significantly to the alignment with TCFD pillars. Accepting unequal power distribution within the organization (PWD) negatively impacts STRAT, suggesting that such hierarchical structures limit the inclusivity and collaboration necessary for developing comprehensive and effective climate strategies. Cultural traits such as individualism (INDIV) positively impact MET, potentially reflecting that, in organizations with a stronger emphasis on individual initiative over group loyalty, climate metrics and targets disclosures are driven by the efforts of specific individuals or departments rather than a unified, organization-wide consensus. This suggests that the absence of collective alignment may result in disclosures that are less integrated across the organization. In terms of organizational culture, the MAS dimension, as defined by Hofstede and Minkov (2010), reflects a preference for achievement, assertiveness, and competition (masculinity) versus cooperation, care, and quality of life (femininity). The negative link between MAS and STRAT suggests that a stronger emphasis on masculine traits may hinder the development of a holistic and inclusive approach to strategy, which is better supported by feminine traits that prioritize collaboration, relationships, and long-term well-being. Finally, the capacity to manage uncertainty (UAV) is an important driver of MET, suggesting that organizations that embrace uncertainty are better positioned to create detailed and adaptive climate metrics. This finding aligns with broader cultural research that emphasizes the importance of flexibility and responsiveness in addressing climate challenges. The tolerance for norms (INDUL) reveals however differing attitudes towards STRAT, where greater flexibility and adaptability allow for long-term, sustainable climate strategies.

At last, the sustainability performance of firms plays a significant role in shaping the extent of their alignment with the TCFD pillars. ESG scores are positively associated with MET, RISK, and STRAT, with the strongest and most statistically significant effect observed for STRAT. This suggests that firms with stronger ESG score tend to place greater emphasis on disclosing forward-looking sustainability strategies, while also improving transparency around metrics and risk management. This result is further reinforced by the role of green revenue sources, as measured by the ETAX variable, which shows a consistently positive and statistically significant association with all four pillars. ETAX reflects the share of a firm's revenue derived from environmentally sustainable activities, and serves as a direct indicator of its operational commitment to the low-carbon transition. The broad and robust effect of ETAX suggests that firms generating substantial green revenues are more likely to engage in comprehensive climate-related disclosures, encompassing governance structures, risk management practices, performance metrics, and strategic planning. This finding aligns with Bhattacharya et al. (2021), who argue that sustainable practices not only reduce perceived corporate risk but also promote transparency and long-term accountability, thereby reinforcing alignment with frameworks such as the TCFD.

Importantly, the results presented in Table 6 show that the alignment to TCFD pillars significantly influences firm valuation, with stronger percentages associated with higher market-to-book ratios. The financial controls, including LEV and ROA, behave as expected, with LEV reflecting the negative impact of financial risk and ROA capturing the positive effect of profitability on valuation. These findings provide strong evidence for the relevance of our BERT alignment scores, demonstrating that they not only offer a reliable method for evaluating a firm's degree of compliance with TCFD recommendations, but also serve as significant explanatory variables for firm valuation.

Finally, although the empirical focus has been placed on the European energy sector, the broader design of the methodology allows for meaningful generalization. Sectors such as transport or agriculture, which are similarly exposed to climate-related pressures, may benefit from comparable analyses when sector-specific language and disclosure conventions are taken

Table 6: Impact of TCFD Disclosure Coverage on Market-Based Valuation: Panel EGLS Estimation.

	MB
GOV	4.56*** (4.180)
MET	4.29*** (2.54)
RISK	1.95* (1.51)
STRAT	4.06*** (4.19)
LEV	-0.47*** (-2.42)
ROA	0.09* (1.61)
Cst	0.65*** (6.03)
R sq.	0.9490
Adj. R sq.	0.9147
F Stat.	27.65***
nb. Obs	112

This table presents the estimation results of Equation 2 using a Panel EGLS model with cross-section fixed effects. All variables are expressed in logarithmic form. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The F-statistic supports the rejection of the null hypothesis that all individual-specific intercepts are jointly equal to zero. The Hausman test confirms the appropriateness of the fixed effects specification. The Pesaran test indicated no evidence of cross-sectional dependence in the residuals. For definitions of the variables, see Table 2.

into account. The framework also lends itself to application across different geographical contexts, provided that appropriate attention is given to regulatory environments and reporting cultures.

4.5. Robustness

To ensure the robustness of our findings for European energy companies, we complement the primary panel EGLS estimations with Quantile Regression at the median ($\tau = 0.5$) and Robust Least Squares (M estimation). This approach mitigates the influence of outliers and distributional effects while assessing the stability of results (Table 7 and Table 8). The consistent sign of coefficients across all models confirms the relationship between pillar coverage and the explanatory variables. Lower Pseudo R-squared (QReg) and Rw-Squared (RLS) values validate Panel EGLS as the primary method.

5. Managerial Implications

These results invite reflection on the role of language, structure, and interpretation in shaping climate-related financial disclosures. Disclosures are not merely passive compliance

Table 7: Robustness Checks for the Determinants of TCFD Disclosure Alignment

	Panel EGLS	Qreg	RLS	Panel EGLS	Qreg	RLS
	GOV			MET		
AWL	-2.992	0.46	2.23	1.848**	-1.26**	-0.027
WC	1.630*	2.33**	0.2899**	-1.8932***	0.21	-9035
LEX	2.269*	4.25**	0.2304	-1.42*	1.62	-2.18
ENT	-15.20***	-12.12*	-0.2384	1.45***	-5.2090	4.90*
PBD	-9.58	-2.40	1.65	1.92***	1.53*	1.33**
IND	-1.24	9.29**	1.27**	-1.08	5.85	3.28
FEM	5.58***	2.64***	1.75*	2.83**	1.84**	2.58**
FF	9.10****	0.06*	0.1029	3.43	-0.48	-0.175
STRATH	-0.174	-0.12*	-0.0590	-0.204	0.12	0.075
ROA	0.004	0.008	-0.0014	-0.009	0.013	-0.004
LEV	5.57***	0.46	1.3706**	-0.945	-2.79	-0.9941
PWD	2.20	-7.35*	-1.07	-1.15	1.41	1.08
INDIV	3.81	2.91	-9.96	8.83	-3.23***	-2.14
MAS	-5.02	-1.28	-5.83	9.23	2.46***	1.61
UAV	3.71	3.29	2.12	-1.27***	1.11	1.62
LTO	-1.97	1.06	1.02**	1.31	1.25	2.34
INDUL	-1.59***	-6.13**	-3.17***	-2.79***	-1.5804**	-4.31
ESG	0.024	0.0001	0.011	0.04*	0.047*	0.029
ETAX	0.048**	0.02*	0.035*	0.052**	0.015	0.021*
RSq./ Ps-RSq./ Rw-Sq.	0.9373	0.2760	0.3178	0.9179	0.2095	0.2325
	RISK			STRAT		
AWL	3.60**	0.304***	0.0413**	3.12***	0.8236*	0.0300
WC	-0.46	-0.023	-1.6059**	2.56***	1.2284**	2.6152**
LEX	-1.18	-0.379	-3.3914**	4.95***	2.8968*	5.1565***
ENT	2.96	2.204	5.1027	-14.156***	-4.9289***	-14.44*
PBD	-1.71	7.09	1.23	2.33***	1.53***	2.82*
IND	7.14	-2.20	2.65	1.10*	2.85*	1.12
FEM	5.30***	2.88***	2.21***	5.98***	1.52**	1.42***
FF	-3.18**	0.0432	0.0559	5.92***	-0.0665	-0.006
STRATH	0.23*	0.038*	0.0514	0.215***	0.059***	0.1120
ROA	0.008**	0.001**	0.0017**	0.014***	0.014**	0.0140*
LEV	2.45	1.67*	0.0019	1.80***	1.2081**	1.8568*
PWD	-7.92	6.91	-6.21*	-5.11***	-5.38	-2.67
INDIV	4.86**	9.15**	6.96**	4.29	1.89*	1.19**
MAS	-4.74***	-8.99	-7.06	-5.20*	-1.30**	-0.753
UAV	4.62	-1.08	0.0769	7.96	-1.95	-0.163
LTO	-1.40**	6.75	3.49	6.13	-3.66	0.266**
INDUL	1.44	-5.82	-2.98	3.33***	2.69**	0.306***
ESG	0.01**	0.004*	0.007**	0.07***	0.014**	0.018
ETAX	0.152***	0.08**	0.0075**	0.079**	0.006**	0.022*
RSq./ Ps-RSq./ Rw-Sq.	0.9755	0.2808	0.5104	0.9725	0.2836	0.3420

This table presents robustness checks for the estimation of Equation 1 using three methods: Panel EGLS with cross-section fixed effects, Quantile Regression at the median ($\tau = 0.5$), and Robust Least Squares. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Model fit is evaluated using R-squared (Panel EGLS), Pseudo R-squared (Qreg), and Rw-squared (RLS). Sparsity was not significant in Qreg estimations. No cross-sectional dependence was found in Panel EGLS residuals, and RLS residuals showed no signs of autocorrelation. Results appear in bold when significance is reached in at least two specifications.

Table 8: Robustness Checks for Valuation Effects of TCFD Disclosure.

	Panel EGLS	Qreg	RLS
	MB		
GOV	4.56***	0.2358*	0.004
MET	4.29***	0.0436**	0.51***
RISK	1.95*	0.028*	0.024*
STRAT	4.06***	0.03*	0.057***
LEV	-0.47***	-0.411***	-0.66***
ROA	0.09*	0.002*	0.002*
RSq./ Ps-RSq./ Rw-Sq..	0.9490	0.4077	0.3799

This table presents robustness checks for the estimation of Equation 2, which assesses the influence of TCFD pillar alignment on firm valuation. The estimations rely on three methods: Panel EGLS with cross-section fixed effects, Quantile Regression at the median ($\tau = 0.5$), and Robust Least Squares. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables are expressed in logarithmic form. Model validity is supported by the F-statistic and Hausman test results, which favour the fixed effects specification. No cross-sectional dependence was detected in the residuals.

tools; they are a space where firms signal, negotiate, and sometimes obscure their engagement with climate risk. These findings offer practical insights for accounting professionals seeking to interpret, evaluate, and improve the quality and relevance of corporate disclosures.

A first insight concerns the interplay between content breadth and discourse orientation. While some firms favour expansive documents that span a wide range of topics and exhibit high lexical variety, others adopt more concise and focused formats with targeted technical content. These are not stylistic variations but reporting strategies, often shaped by firm size, sectoral exposure, and internal resources. Yet, both strategies carry trade-offs. Reports with broader scope may dilute their message through redundancy or complexity, while narrowly crafted ones may fail to capture systemic linkages or emerging risks. For the accounting profession, which is increasingly involved in sustainability assurance (Simnett et al., 2009), this tension raises a familiar question: how to evaluate sufficiency and clarity in narrative reporting, particularly when no standard template applies. The persistent influence of readability, coherence, and vocabulary structure across both types of disclosures invites greater scrutiny of the linguistic assumptions embedded in emerging disclosure standards. Evaluating narrative performance should no longer be a rhetorical exercise but one informed by structured linguistic diagnostics.

The divergence observed between surface and semantic similarity to the TCFD framework further illustrates how disclosure evaluation depends on the lens applied. Surface-level assessments, based on keyword matching or template adherence, risk underestimating alignment where language diverges from standard formulations. Conversely, semantic similarity detect alignment that is conceptual rather than syntactic. This matters because it calls into question prevailing practices in sustainability assurance and audit, which often rely on highly formalized compliance matrices. If disclosures are to reflect genuine engagement with climate governance, then interpretive tools must evolve accordingly. BERT models offer one such path. However, their integration into assurance processes will require a clearer understanding of their boundaries, especially given that model outputs are shaped by training data and context-specific usage. For professional accountants, the challenge is twofold: to remain attentive to the possibilities opened by such models, while resisting their over-interpretation as definitive compliance scores.

At a thematic level, the findings point to an underlying fragmentation in how firms conceptualise their climate responsibilities. Despite a shared vocabulary around emissions, renewables, and CSR, the underlying narratives vary considerably. Standard-setters may hope that convergence will emerge through regulatory alignment, but the results suggest that firms continue to mobilise a wide and often inconsistent lexicon. This has implications for accounting professionals tasked with comparing disclosures across firms or sectors. Topic modeling and network analyses offer useful tools here : not as replacements for judgment, but as lenses to identify omissions, excesses, or the entrenchment of vague or recycled language. In a context where boilerplate language remains common, tools that reveal the structure and density of reported topics can help move the profession beyond form toward substance.

Perhaps most significantly, the regression results show that alignment with disclosure frameworks is not only a product of language, but also of governance, structure, and culture. Clear and concise language improves alignment, particularly where standardised metrics are expected. Yet linguistic traits alone are insufficient. Board diversity, ownership structure, profitability, and cultural traits all play meaningful roles. For preparers and reviewers of climate reports, this suggests that disclosure quality cannot be separated from the institutional conditions under which reporting occurs. This should temper expectations that external frameworks, however well-designed, can by themselves produce meaningful disclosures. Instead, internal capacity-building and structural governance reforms must accompany disclosure obligations if these are to reflect more than surface-level change.

Finally, the association between pillar-specific alignment scores and firm valuation highlights the material relevance of disclosure content. Climate narratives, when they align with strategic, governance, risk and metrics-related expectations, appear to serve a signalling function that markets recognize. This is not an argument for monetising disclosure per se, but it does suggest that the accounting profession must take narrative reporting seriously: not only as a means of compliance, but also as an increasingly central component of the firm's communication with capital markets. If climate risk is to be integrated into financial thinking, then narrative disclosures must be read with the same rigour and precision as financial statements.

6. Conclusion

This paper advances a rigorous, multi-level methodology to assess the alignment, structure, and informational value of climate-related financial disclosures in the European energy sector. Going beyond surface-level compliance, it offers a replicable approach that combines four analytical layers: readability and narrative structure via lexicometric indicators; alignment with the TCFD pillars using climate-trained BERT models; thematic development through LDA and GNTM; and the identification of structural, financial, and cultural drivers through panel regressions.

Three central findings emerge. First, alignment with the TCFD pillars is uneven across firms and varies significantly across the four dimensions. Our AI-based analysis indicates that strategy and metrics are more frequently addressed than governance or risk management, with overall alignment scores remaining modest but gradually improving over time. These gaps are not random: they correlate not only with firm-level characteristics such as size, but also with specific linguistic traits such as lexical diversity and entropy, which signal not just reporting effort but narrative intentionality. Readability matters, but it matters differently depending on the pillar.

Second, the maturity of disclosures, operationalised through thematic structuring, points to a fragmented reporting landscape. While key topics such as GHG emissions, CSR commitments, and risk mitigation recur across firms, topic models show low coherence and weak inter-topic connectivity. GNTM results in particular reveal a limited degree of narrative integration: most firms articulate separate concerns without embedding them into a strategic climate vision. This raises questions not about the presence of disclosures, but about their capacity to inform decisions and reflect embeddedness within organisational planning.

Third, alignment with the TCFD is not reducible to communication strategy. The regression results show that firm-level alignment is systematically explained by internal features, especially board gender diversity, ownership dispersion, leverage, and cultural orientation, rather than by environmental rhetoric alone. The inclusion of ESG scores and EU taxonomy-aligned green revenues in the models further supports this point: alignment reflects not only what firms say, but also how they perform and how they are structured and governed. This has direct implications for assurance practices and sustainability benchmarking: text analysis alone, if detached from firm fundamentals and sustainability performance, risks overlooking the true drivers of aligned climate disclosure.

Importantly, the analysis finds a significant and robust relationship between TCFD alignment and firm valuation, reinforcing the materiality of disclosure content. This result offers a clear message to accounting professionals: climate reporting is no longer a reputational artefact, but a signal recognised and priced by financial markets.

Taken together, these results advocate for a shift in how disclosures are assessed, assured, and interpreted. Rather than relying on superficial templates or checklist compliance, future efforts should integrate semantic and structural diagnostics with firm-level diagnostics. The tools developed in this paper are designed for precisely this purpose: they can support internal audits, guide strategic alignment, and inform regulatory oversight. For researchers, they open new avenues for comparative disclosure studies; for practitioners, they offer a pathway to more robust, credible climate communication.

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8. Appendix

Table 9: List of Companies, Abbreviations, Countries, and Sectors

Company	Abbr.	Country	Sector
Centrica plc	centrica	United Kingdom	Utilities (Gas, Electricity)
Électricité de France	edf	France	Utilities (Electricity)
EDP – Energias de Portugal	edp	Portugal	Utilities (Electricity, Renewables)
Enagás S.A.	enagas	Spain	Natural Gas Transmission
EnBW Energie Baden-Württemberg	enbw	Germany	Utilities (Electricity)
Enel S.p.A.	enel	Italy	Utilities (Electricity, Renewables)
Engie S.A.	engie	France	Multi-utilities (Gas, Electricity, Renewables)
Eni S.p.A.	eni	Italy	Oil and Gas Exploration and Production
E.ON SE	eon	Germany	Utilities (Electricity)
Equinor ASA	equinor	Norway	Oil and Gas Exploration and Production, Renewables
Fortum Oyj	fortum	Finland	Utilities (Electricity, Renewables)
Hera S.p.A.	hera	Italy	Waste Management and Utilities
Iberdrola S.A.	iberdrola	Spain	Utilities (Electricity, Renewables)
Neste Oyj	neste	Finland	Biofuels Production
Naturgy Energy Group S.A.	naturgy	Spain	Gas and Electricity Distribution
PKN Orlen S.A.	pkn	Poland	Oil Refining and Retail
Polska Grupa Energetyczna	polska	Poland	Utilities (Electricity)
Repsol S.A.	repsol	Spain	Oil and Gas Exploration and Production
RWE AG	rwe	Germany	Utilities (Electricity, Renewables)
Rubis SCA	rubis	France	Oil Storage and Distribution
Saras S.p.A.	saras	Italy	Oil Refining
Shell plc	shell	United Kingdom	Oil and Gas Exploration and Production, Renewables
Snam S.p.A.	snam	Italy	Natural Gas Transmission
SSE plc	sse	United Kingdom	Utilities (Electricity)
TotalEnergies SE	total	France	Oil and Gas Exploration and Production, Renewables
Tullow Oil plc	tullow	United Kingdom	Oil Exploration and Production
Veolia Environnement S.A.	veolia	France	Waste, Water and Energy Services
Verbund AG	verbund	Austria	Utilities (Electricity, Hydropower)

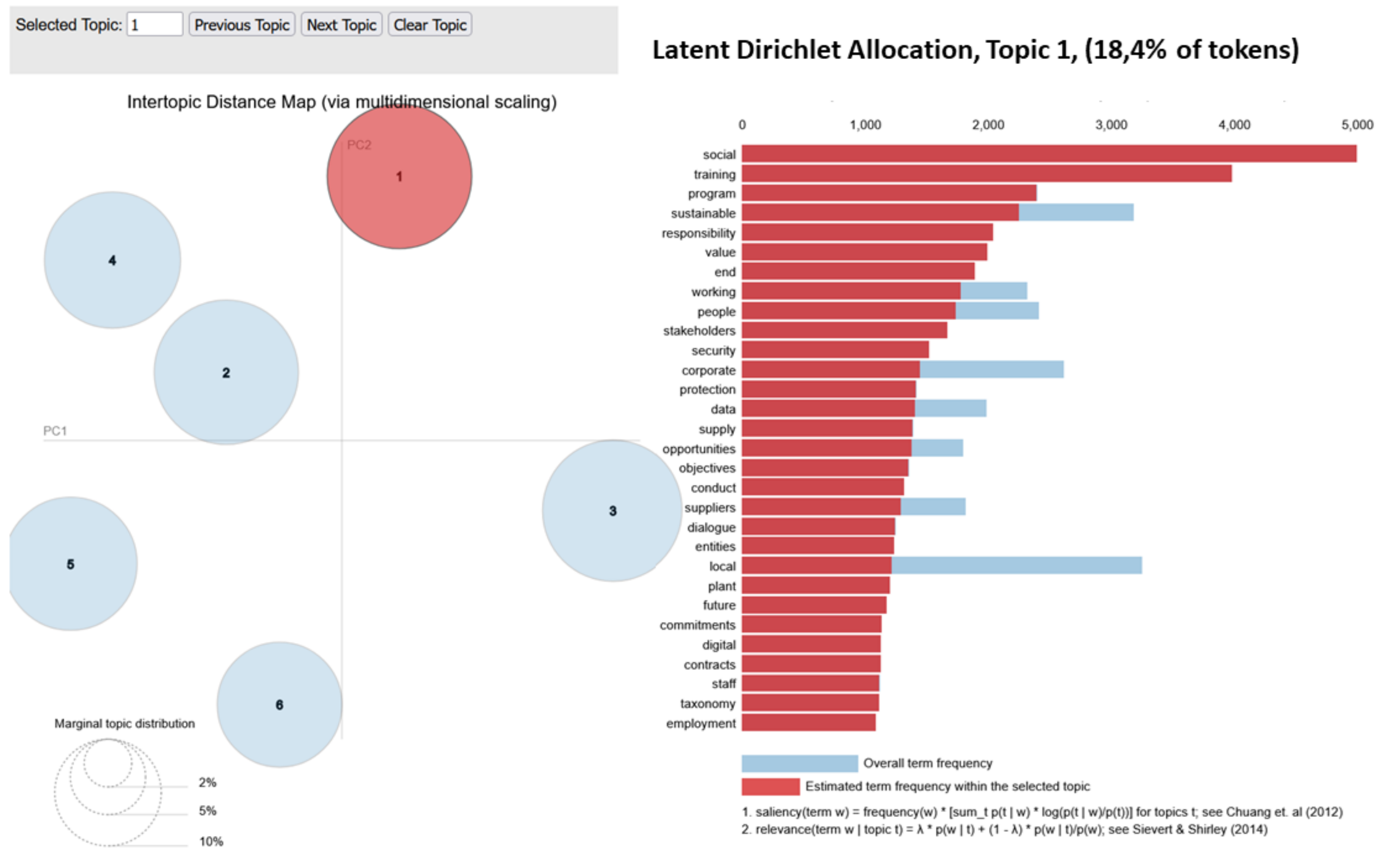
This table presents the companies included in the analysis, their abbreviations, countries of headquarters, and primary sector classification. The sector classification reflects the companies' main lines of business, acknowledging that some firms diversified their activities during the period 2020–2022. Company information was verified using multiple sources, including Refinitiv, Statista, Xerfi7000, and annual reports.

Table 10: Summary Statistics

Variable	Mean	Median	Max	Min	Std.Dev.	Skew.	Kurt.	Obs.
GOV	1.20	1.05	4.58	-0.60	1.19	0.86	3.23	112
MET	3.03	3.22	4.46	-0.87	1.16	-0.82	3.23	112
RISK	1.83	1.68	4.45	0.34	0.84	1.15	4.40	112
STRAT	3.60	3.87	4.53	-0.19	0.91	-1.77	6.66	112
AWL	2.15	2.15	2.30	1.77	0.07	-2.52	16.44	112
WC	10.31	10.54	11.98	6.01	1.09	-1.39	5.35	112
LEX	-1.59	-1.69	-0.33	-2.19	0.37	1.15	4.22	112
ENT	2.40	2.41	2.49	2.07	0.07	-1.98	8.81	112
Surf	23.85	24.06	43.81	5.56	8.60	-0.04	2.56	112
Sem	56.81	57.37	77.14	31.64	9.89	-0.54	2.95	112
PBD	46.23	48.00	69.00	19.00	11.54	-0.33	2.68	112
IND	0.57	1	1	0	0.50	-0.29	1.08	112
FEM	37.82	36.36	60.00	16.67	8.82	0.34	2.87	112
FF	3.99	4.29	4.60	-0.97	1.08	-3.60	16.42	112
STRATH	18.93	19.45	21.98	14.02	1.98	-0.59	2.46	112
ROA	4.82	3.94	22.90	-10.85	5.25	0.91	6.02	112
LEV	0.30	0.29	0.67	0.06	0.14	0.73	3.17	112
PWD	40.71	35.00	68	11	13.38	0.87	3.54	112
INDIV	72.93	76.00	79	47	7.93	-2.38	7.16	112
MAS	63.36	66.00	79	42	8.86	-1.58	4.68	112
UAV	71.04	75.00	99	35	19.46	-0.70	2.26	112
LTO	51.64	55.00	60	39	7.98	-0.41	1.67	112
INDUL	45.75	44.00	69	29	13.20	0.42	2.14	112
ESG	74.45	75.29	94.22	46.07	11.43	-0.28	2.45	112
ETAX	0.80	0.72	3.60	-2.21	1.51	0.05	2.32	112

This table presents the summary statistics for all variables used in the analysis. See Table 2 for definitions.

Figure 4: LDA, Intertopic distance map and associated bag of words.



This figure presents the output of the Latent Dirichlet Allocation (LDA) model applied to climate-related disclosures. The intertopic distance map below shows the relationships between the six extracted topics, with larger circles indicating more prevalent topics. The top bar chart displays the most representative terms for Topic 1, which covers 18.4% of the tokens. This visualization helps identify dominant thematic structures in climate narratives across firms. This analysis is based on the full set of climate-related disclosures issued by the European energy company studied in this paper over the 2020–2022 period.

Table 11: Climate Disclosures: Prevalent Trends and Concerns in 2022 (LDA Analysis)

Topic	Tokens	Meaning
1 (18.4%)	social, training, program, sustainable, responsibility, value, end, people, stakeholders, security, corporate, protection, data, supply, opportunities, objectives, conduct, suppliers, dialogue, entities, local, plant, future, commitments, digital, contracts, staff, taxonomy, employment	A sustainable corporate training program, rooted in social responsibility, ensures data security and local stakeholder engagement, aligning with future commitments and employment objectives.
2 (18,4%)	compliance, environmental, impact, rights, million, implementation, local, issues, risk, assessment, initiatives, process, rate, policy, code, processes, any, investment, set, implemented, practices, ethics, access, per, capital, impacts, principles, diversity, developed, criteria	Implementing local compliance policies and ethical practices is vital to assess and reduce environmental and social impact risks, ensuring rights and diversity.
3 (17,5%)	management, business, risk, report, waste, information, system, strategy, annual, committee, energy, power, sustainability, internal, plants, transition, activity, integrated, external, generation, action, plan, governance, renewable, treatment, chapter, plans, control, line, revenue	The annual business report emphasizes risk management, waste control, and renewable energy generation in an integrated sustainability strategy, aligned with revenue goals.
4 (16,5%)	years, gri, services, reporting, up, customers, products, particular, challenges, indicators, average, solutions, technical, period, requirements, agreement, used, executives, share, united, capacity, aligned, focus, grid, materials, standards, held, current, collective	Over the years, executives have focused on aligning products with GRI standards, addressing technical challenges, and meeting customer requirements.
5 (15,1%)	climate, emissions, energy, scope, gas, change, production, economic, ghg, targets, electricity, carbon, european, industrial, increase, target, sdg, below, net, network, carried, among, natural, public, co2, defined, objective, reduce, zero, due	European industrial production aims to reduce carbon emissions, aligning with SDG targets, through an increase in economic efficiency and a shift to net-zero emissions in the electricity network.
6 (13,7%)	water, measures, resources, board, managers, areas, biodiversity, proportion, countries, women, environnement, under, international, where, above, consumption, universal,five, registration, environment, french, organization, department, amount, around,topics, directors, prevention, metrics, several	Water resources, biodiversity measures, and women's representation on environmental boards are of global concern.

This table presents the six dominant topics extracted from climate-related disclosures using Latent Dirichlet Allocation (LDA) for the year 2022. The first column shows the topic number and its share of total tokens. The second column lists the most representative words per topic. The third column interprets the meaning of each topic, highlighting prevalent trends and disclosure concerns among European energy firms. This analysis is based on the full set of climate-related disclosures issued by the European energy company studied in this paper over the 2020–2022 period.

Table 12: Climate Disclosures: Trends and Concerns in 2022 (GNT Analysis)

Com.	Tokens	Meaning
1	management, climate, business, risk, report, system, environmental, sustainability, rights, change, information, impact, social, related, plan, local, process, data, customers, services, strategy, suppliers, annual, transition, environment, corporate, operations, solutions, biodiversity, protection, stakeholders, issues, monitoring, opportunities, internal, security, supply, assessment, available, processes, external, material, targets, action, systems, plans, resources	To promote environmental sustainability and social responsibility, management monitors and reports on business impact, engages with stakeholders, and collaborates with suppliers and customers to ensure resource availability and protect biodiversity in the face of climate change.
2	energy, water, emissions, gas, power, waste, plant, electricity, due, production, people, used, carbon, scope, products, renewable, market, plants, industrial, value, assets, end, natural, fuel, nuclear, increase, network, wind, hydrogen storage, co2, facilities, technology, generation, green, industry, treatment, capacity, consumption, materials, operation equipment, reduction, heat, direct, fuels, distribution	Increasing energy efficiency, reducing emissions, and shifting towards renewable energy sources are key strategies for lowering carbon emissions in the energy industry, with a focus on improving the value of assets, enhancing production, and investing in green technology and storage solutions for electricity and hydrogen.
3	gri, sustainable, international, compliance, global, policy, economic, national, code, reporting, european, eu, standards, framework, united, principles, activity, index, french, diversity, world, sector, requirements, investments, regulation, changes, department, regulatory, gender, skills, amount, paris, professional, initiative, accordance, according, conduct, standard, taxonomy, chief, regulations, associated, category, agreement, rules, legal, act	Global compliance with GRI and international standards is vital for sustainable business,encompassing economic principles, regulations, and gender diversity while aligning with legal standards and regulatory changes.
4	areas, measures, up, under, years, countries, operating, women, possible, period, initiatives, implementation, various, percentage, construction, relevant, located, different, men, place, make, several, improving, account, scenarios, taken, regions, take, costs, four, types, necessary, protected, aimed, old, operates, implement, appropriate, last, age, taking, adopted, expenditure, took, previous	Over the past four years, various measures and initiatives have been taken in different countries to improve gender diversity in construction areas. These efforts aim to reduce costs and create more inclusive working environments for both men and women.
5	million, training, investment, per, working, program, capital, average, share, conditions, around, decision, received, markets, hours, programmes, prior, awareness, decisions, online, days, adjusted, top, metric, groups, complaints, vulnerable, courses, sessions, worked, recommendations, making, force, raising, ebitda, grupa, programs, others, duration, ways, tons, dividend, remote, coe	Millions of dollars in investment were allocated for training programs, averaging per working hour. These initiatives aim to improve working conditions and raise awareness among employees, making informed decisions around capital allocation and online courses.
6	tax, ensure, evasion, achieve, meet, substantial, mitigate bribery, who, promoter, road, criteria, authorities, score, tolerance, significantly, zero, corruption, anti, screening, any, does, profit, harm, transport, do, identify, technical, dnsh, loss, public, debt, legislative, net, assess, fraud, needs, prevent, order form, income, far, decree, counteracting, private	To achieve substantial progress in counteracting tax evasion and bribery, authorities must implement anti-corruption measures with zero tolerance, ensuring legislative and technical criteria to prevent profit loss and harm.

This table presents the main concerns and disclosure trends extracted through Graph Neural Topic (GNT) modeling applied to climate-related disclosures. Each component (Com.) corresponds to a semantically distinct theme, derived from token frequency and contextual embedding patterns. The second column lists representative words (tokens) per component, and the third provides an interpretive summary. This analysis is based on the full set of climate-related disclosures issued by the European energy company studied in this paper over the 2020–2022 period.Results reveal a structured narrative landscape addressing environmental management, emissions, regulatory compliance, gender diversity, training, and anti-corruption measures.