Evaluating Climate-Risk Language in 10-K Filings: A ClimateBERT-Driven Study of Firm Valuation

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Dissertation written under the supervision of Julien Fouquau

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Abstract:

This thesis presents a transformer-based approach to quantify and price corporate climate-risk disclosures. By utilizing ClimateBERT, I classify Item 1A risk-factor text in S&P 500 10-K filings (2005–2024) to generate annual transition, physical, and general climate-risk scores for 8,001 firm-year observations. Fixed-effects regressions link these lagged scores to Tobin's Q, revealing a significant negative valuation effect for transition-risk language, especially in high-exposure sectors (Utilities; Transportation & Warehousing), while physical-risk impacts primarily arise within the same industries. By combining advanced NLP with rigorous panel econometrics, this study provides detailed, sector-sensitive metrics that illuminate how investors value different aspects of corporate climate-risk disclosure.

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Author: Anais Weghorst
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Resumo:

Esta tese apresenta uma abordagem baseada em transformadores para quantificar e precificar divulgações corporativas de riscos climáticos. Ao utilizar o ClimateBERT, classifico o texto da seção Item 1A Risk Factors dos relatórios 10-K das empresas do S&P 500 (2005–2024) para gerar pontuações anuais de risco climático de transição, físico e geral em 8001 observações ano-empresa. Regressões de efeitos fixos relacionam essas pontuações defasadas ao Q de Tobin, revelando um efeito negativo significativo de valoração para a linguagem relativa ao risco de transição, especialmente em setores de alta exposição (serviços públicos; transporte e armazenagem), enquanto os impactos do risco físico ocorrem, sobretudo, nas mesmas indústrias. Ao combinar PNL avançada com econometria de painel rigorosa, este estudo fornece métricas detalhadas e sensíveis ao setor que esclarecem como os investidores valorizam diferentes aspectos das divulgações de riscos climáticos corporativos.

Título da Dissertação: Avaliação da Linguagem de Risco Climático em Relatórios 10-K: Um Estudo Baseado no ClimateBERT sobre a Valoração das Empresas
Autora: Anais Weghorst
Palavras-chave: Risco Climático, PLN, ClimateBERT, 10-K, S&P 500, Valoração de Empresas

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1. Introduction

Climate change presents one of the most significant challenges to the global economy, as companies navigate both the physical impacts of a warming planet and the swift shift toward low-carbon business models. Physical climate risks, ranging from worsening storms and floods to ongoing issues like drought, jeopardize asset values, disrupt operations, and can lead to substantial remediation costs. At the same time, policy actions aimed at cutting greenhouse gas emissions, such as carbon pricing, regulatory mandates, and technology-forcing standards, introduce transition risks that may make existing capital stock outdated and alter competitive dynamics. In this context, investors, regulators, and other stakeholders have called for enhanced transparency regarding firm-level climate risks, resulting in standardized disclosure requirements under U.S. Regulation S-K Item 1A and evolving frameworks like the SEC's proposed climate-risk rule and the ISSB standards.

A rapidly growing body of literature documents that climate-related risks have measurable valuation effects. Early studies utilize carbon emissions and toxic-release data to link environmental performance with Tobin's Q and cost of capital (Al-Tuwaijri et al., 2004; Matsumura et al., 2014). More recent research employs text-analysis approaches to capture firm-specific exposures: Campbell et al. (2014) show that detailed 10-K risk narratives elicit negative stock reactions, Nagar & Schoenfeld (2024) demonstrate that weather-event language predicts returns around storms, and Li et al. (2024) find that non-proactive discussions of transition risks in earnings calls depress Tobin's Q. Against this backdrop, Vestrelli et al. (2024) report a "transparency premium" for climate-risk disclosures in Item 1A, highlighting that in some contexts, increased disclosure raises firm value.

This thesis builds on and extends these strands by creating a text-based measure of climate risk derived from ClimateBERT, a transformer model that has been further pretrained on climate-science corpora and fine-tuned to distinguish between transition, physical, and general climate content. I apply a two-stage classification pipeline to extract three firm-year scores from the Item 1A "Risk Factors" sections of 10-K filings and then relate each lagged score to market valuation as proxied by Tobin's Q. The analysis employs an unbalanced panel of 8,001 firm–year observations spanning 2005 through 2024 for S&P 500 constituents while controlling for size, asset intensity, leverage, liquidity, foreign sales, and capital expenditures, and includes firm and year fixed effects. I find that only transition-risk language carries a statistically significant negative association with Tobin's Q in the full sample, and that both transition and physical risk disclosures are penalized in "high-risk" sectors (Utilities; Transportation & Warehousing), whereas climate language has little valuation effect in "low-risk," knowledge-based industries (Information; Professional, Scientific & Technical Services).

The core findings are threefold. First, in the full sample, only transition-risk language shows a robust, negative association with Tobin's Q, suggesting that investors interpret explicit discussions of policy and technology uncertainties as a signal of genuine exposure. Second, sectoral analysis reveals that both transition and physical risk disclosures depress valuations in "high-risk" industries (Utilities and Transportation & Warehousing) whereas in "low-risk," knowledge-based sectors, the effects are muted or insignificant. Third, subsample and interaction tests around the COVID-19 pandemic confirm that extraordinary market volatility weakened the valuation linkage, underscoring the need to model structural breaks.

By integrating advanced NLP techniques with rigorous panel econometrics, this study contributes to the literature by providing a more detailed view of how various aspects of climate-risk language are priced and by underscoring the vital role of materiality and market context. The remainder of the thesis proceeds as follows. Chapter 2 reviews the theoretical channels through which climate risks can impact firm value and surveys empirical approaches to measuring textual climate risk. Chapter 3 elaborates on sample construction, ClimateBERT scoring methodology, and econometric specifications. Chapter 4 presents the primary regression results, including industry-specific analyses and robustness checks. Chapter 5 discusses the implications for investors, policymakers, and future research, and outlines the limitations of the study.

2. Literature Review

In this section, I first discuss how climate risk affects companies and their value. Next, I explore how climate risk has become more prevalent in risk disclosures, and finally, I derive my main hypothesis about the relationship between climate risk disclosure and market valuation.

2.1. How Does Climate Risk Affect Firm Value

In recent years, both theoretical models and empirical tests have shown that climate-related risks are systematically incorporated into asset prices and, therefore, into firm valuations. These risks arise from gradual shifts in temperature, sudden regulatory interventions, and direct physical events such as storms or floods. The existing literature can be organized into two main streams: the pricing of climate uncertainty/risk and the valuation effects of physical climate events. Additionally, some studies indicate that there is a climate-risk premium across asset classes.

2.2. Pricing of Climate-Related Uncertainty and Risk

Bansal et al. (2016) were among the first to embed stochastic temperature “tipping-point” disasters into a long-run risks (LRR) model with Epstein–Zin preferences. As global temperatures rise toward their 2 °C threshold, both the likelihood and severity of rare disasters increase, raising marginal utility in bad states and driving up the price of long-run temperature risk. Portfolios sorted on low-frequency temperature innovations earn a positive “temperature risk premium” that has nearly doubled, from roughly 0.13 percent to 0.40 percent per year, over the last eighty years. Almost all major US equity portfolios exhibit negative betas to these temperature shocks, implying that warming trends today predict lower consumption and lower asset values tomorrow.

At the firm level, Bolton and Kacperczyk (2021) extend this logic to carbon emissions themselves. Using the Trucost database’s scope 1 (direct on-site), scope 2 (purchased energy), and scope 3 (other indirect) CO_2 measures, firms are ranked by total emissions to form decile portfolios. Even after controlling for size, book-to-market, momentum, profitability, leverage, and industry effects, the highest-emission decile outperforms the lowest by several basis points per month. This “carbon premium” indicates that investors demand explicit compensation for bearing firms’ carbon-footprint risk.

Further supporting this view, Engle et al. (2020) construct a daily climate-news index from The Wall Street Journal and demonstrate that spikes in negative climate coverage disproportionately depress returns of high-emission and low-ESG firms, which is in line with investors repricing equity in response to adverse policy or news shocks.

2.2.1. Valuation Effects of Physical Climate Events

There is also growing literature on how actual weather and climate events, eg. floods, droughts or hurricanes transmit directly to firms’ operations and market values. Dell et al. (2014) survey panel-econometric studies linking temperature and precipitation anomalies to declines in agricultural output, health outcomes, energy consumption and GDP, underscoring that unanticipated weather shocks impose real economic costs that vary widely by region and sector.

At the micro level, Nagar and Schoenfeld (2024) introduce a text-based “weather exposure” score derived from frequency counts of storm- and climate-related language in 10-K risk disclosures. Their measure jumps demonstrably in the wake of major storms, predicts returns around future extreme-weather events, and loads on a distinct risk factor that earns an annualized premium of roughly 3.5%.

Yet the evidence on cash-flow impacts by climate risk is mixed. Addoum et al. (2020) find no systematic link between short-run temperature variation and US firms’ sales, productivity, or profitability, suggesting many companies have thus far hedged or adapted against current physical risks without yet internalizing their longer-term cost of capital.

2.2.2. Climate Risk Across Other Asset Classes

Other asset classes such as real estate or the housing market illustrates the capitalization of long-horizon climate risks. Bernstein et al. (2019) merge Zillow transaction data with highresolution sea-level-rise projections to examine coastal home prices. Using a rich hedonic specification that exploits micro-variation in elevation and inundation thresholds, they find that properties exposed to projected sea-level rise trade at discounts averaging 6.6% relative to comparable, unexposed homes. This discount is driven primarily by investor and second-home buyers, varies with local climate beliefs and has grown over time alongside scientific reports and media attention to rising seas.

Giglio et al. (2021) also provide a comprehensive review of climate finance across asset classes. They show that bonds issued by jurisdictions vulnerable to sea-level rise or drought carry higher credit spreads, while corporate green bonds issue at a modest "greenium" relative to conventional peers. They also document climate-risk pricing in commercial real estate, insurance-linked securities and commodity markets. Equities too respond to climate-news shocks: dynamic "hedge" portfolios that go long firms that rally on bad-news days and short those that fall deliver out-of-sample correlations of 20–30 percent with WSJ climate-news innovations.

But Giglio et al. (2021) also noted that in regards to different asset classes, particularly equity assets, literature still lacks a set of measures to systematically measure firms exposure to climate risk and conclude in their survey that there is "substantial scope for improvements of the measures of climate risk exposure" and that "increased disclosures by firms will provide new opportunities to measure firm's exposure to various types of climate risk".

Collectively, these studies demonstrate that both transition risks (embodied in temperature trends, carbon policies and environmental news) and physical risks (manifested in extreme weather and long-term climate shifts) are materially reflected in asset prices. Understanding how such risks are measured and priced provides the foundation for examining, in the following section, how firms communicate climate exposure through their public disclosures.

2.3. Disclosure of Climate Risk

In the United States, the regulatory foundation for firms' climate-risk disclosures rests on the SEC's 2005 risk-factor mandate (SEC, 2005) and its 2010 guidance explicitly calling for material climate risks, both physical and transition, to be reported in annual filings (SEC, 2010). Despite the mandatory nature of these requirements, managers retain discretion over whether to disclose climate risk at all and, if so, how extensively. Heinle and Smith (2017) model this choice as a signal of cash-flow variance: by releasing even imprecise information about future variability, a firm reduces investors' so-called variance-uncertainty premium under CARA preferences, thereby lowering its cost of capital, regardless of whether the disclosed signal reveals higher or lower risk. Extending this logic to environmental performance, Lyon and Maxwell (2011) show that in a "persuasion game" against activist auditors or NGOs, firms with middling environmental records may engage in strategic "greenwashing," disclosing just enough good news to avoid penalty but hiding downside. Crucially, credible third-party audits can tip the balance in favour of full, authentic disclosure by raising the expected cost of nondisclosure.

Voluntary disclosure regimes coexist with regulatory mandates, and a growing body of empirical work examines which stakeholders succeed in eliciting more informative climate reporting. Flammer et al. (2021) show that shareholder-led engagement can meaningfully enhance firms' voluntary climate-risk reporting and that investors reward this added transparency. Examining U.S. firms between 2010 and 2017, they exploit variation in the number of environmental proposals that large, long-term institutional investors submit at annual meetings. When these powerful investors file additional resolutions calling for detailed disclosure of emissions and climate-risk management, firms respond by improving their CDP climate-risk scores. Crucially, the authors find that this voluntary expansion of climate reporting is followed by higher valuations, measured as Tobin's Q, indicating that the market places a premium on the enhanced information. This study thus illustrates how targeted, credible shareholder pressure can complement mandatory requirements and yield tangible valuation benefits through greater climate-risk transparency. Ilhan et al. (2023) deepen this perspective by surveying 439 institutional investors and linking archival CDP and 10-K text-analytics evidence: investors with greater "power" (large asset owners, universal owners) and stronger environmental norms both demand and allocate more capital to firms with richer climate disclosures. Using regulatory shocks, France's Article 173 mandate, the Climate Action 100+ engagement, and the UK's carbon-reporting rule, they show that disclosure rises when investors can "influence" firms and that climate-minded investors subsequently "select" into those that disclose.

Beyond pressure tactics, the value relevance of voluntary carbon reporting has also been documented across developed and emerging markets. Jiang et al. (2021) examine S&P 500 and

BRIC firms, measuring both the propensity to respond to CDP surveys and the quality of responses (Leadership Index). They report that firms with more frequent and higher-quality carbon disclosures enjoy significantly higher Tobin's Q, especially in BRIC countries where baseline transparency is lower, and that robust reporting can mitigate the negative valuation effect of high emissions. In parallel, Matsumura et al. (2024) leverage SASB's sectoral materiality map to show that in industries deemed climate-material, firms that include climate-risk discussion in Item 1A of Form 10-K command a 50 bps lower cost of equity versus nondisclosers (versus a 23 bps difference in nonmaterial industries), implying that investors use industry-expected materiality as a credibility check when interpreting disclosures.

Finally, the audit function and financial-reporting quality can amplify the market's response to climate-risk narratives. Elliott et al. (2020) conduct a lab experiment showing that when firms credibly demonstrate higher overall reporting quality, via expanded audit commentary on key audit matters, investors' willingness to pay increases independently of their fundamental-value estimates, driven by both affective and cognitive perceptions of managerial cooperation. This finding underscores the potential for enhanced auditor engagement to elevate the perceived credibility and thus the value relevance of climate-risk disclosures embedded in financial reports.

Collectively, these theoretical and empirical advances highlight that climate-risk disclosure is shaped by a web of regulatory mandates, stakeholder pressures, strategic incentives, and third-party verifications. Understanding how and why managers choose to reveal or withhold climate risk information sets the stage for assessing the valuation consequences of that disclosure, to be addressed in Section 2.3.

2.4. Textual Analysis Frameworks for Climate Risk and Their Valuation Impacts

Recent research has increasingly depended on natural-language processing to quantify firms' climate-risk disclosures and examine their association with market outcomes. While earlier studies used simple keyword tallies, more sophisticated approaches, including network-based metrics and deep-learning classifiers, have produced nuanced measures of disclosure quality and extensiveness. This section reviews the main textual-analysis frameworks and their connections to firm valuation, setting the stage for my own model based on a transformer-based classification of 10-K risk factors.

2.4.1. Dictionary and Network-based Measures in 10-K Filings

Berkman et al. (2024) develop a firm-specific "ClimateRisk" score by combining the frequency of climate-related passages in Item 1A of 10-K filings with a relevance weight derived from expert-curated vocabularies. After standardizing by industry, their measure predicts both cross-sectional variation in Tobin's Q and time-series returns, confirming that more extensive mandated disclosures correlate with higher valuations. Vestrelli et al. (2024) propose the Semantic Brand Score (SBS), which treats each 10-K disclosure as a semantic network. Text gets analyzed by prevalence, the raw count of climate terms; diversity, the heterogeneity of words co-occurring with climate vocabulary; and connectivity, the centrality of climate nodes within the disclosure graph. Higher SBS values, signifying both breadth and depth of climate discussion, are associated with lower implied costs of capital, suggesting that investors reward firms for embedding climate risk more integrally into their risk narratives.

2.4.2. Transformer-based Classification of Voluntary and Regulatory Disclosures

Recent advances in natural-language processing have introduced transformer-based architectures, such as BERT and its domain-adapted variants, that leverage self-attention to model semantic relationships across entire documents. These models enable fine-grained classification of disclosure texts, capturing contextual nuances that simple keyword counts or network metrics miss.

Kölbel et al. (2022) fine-tune a pre-trained BERT model on firms' 10-K filings to categorize each sentence as relating to either transition risks (policy, technology, market shifts) or physical risks (extreme weather, asset damage). Aggregating these sentence-level classifications yields firm-year measures of disclosure intensity for each risk type, which the authors then link to changes in corporate CDS spreads across maturities. Their results demonstrate that transition-risk narratives and physical-risk narratives carry distinct credit-risk implications, highlighting the value of disentangling risk dimensions through transformer-based classification.

Building on this paradigm, Bingler et al., (2024) develop a ClimateBertCTI model to identify "cheap talk" in corporate climate disclosures. After further pre-training the base transformer on a large corpus of annual reports and climate-change literature, they fine-tune it to classify every paragraph in a firm's annual report across five dimensions: climate relevance, sentiment (risk versus opportunity), presence of a commitment, specificity of that commitment, and control categories. From these labels, they construct a Cheap Talk Index (CTI)—the proportion of paragraphs signaling commitments that lack specificity. Using panel regressions with firm, year-by-sector, and country fixed effects, the study shows that engagement by Climate Action 100+ is associated with significant reductions in CTI, whereas mere endorsement of TCFD recommendations corresponds to increases in cheap talk. Moreover, a higher CTI predicts greater subsequent growth in scope 1–2 emissions and an elevated probability of environmental controversies, underscoring that non-specific disclosures often signal weaker real-world climate performance and reputational risk.

2.4.3. Alternative Text-Sources: News and Earnings-Call Transcripts

Engle et al. (2020) construct a climate-news index by applying term frequency–inverse document frequency (tf–idf) weighting, which assigns higher weights to words that appear often in a given article yet infrequently across the broader corpus, to Wall Street Journal articles filtered through an IPCC-informed vocabulary. Innovations in this index predict both equity-return co-movements and the performance of dynamic hedge portfolios, highlighting how market-wide news flows serve as a priced signal of firms' climate-risk exposures.

Building on the idea that spoken disclosures convey valuable risk information, Sautner et al. (2021) turn to quarterly earnings-call transcripts to develop a firm-level climate-exposure measure. They begin with a small seed list of climate-related bigrams (e.g., "carbon tax," "renewable energy") and employ a machine-learning keyword-discovery algorithm to expand this list to context-specific bi- and trigrams. By classifying each transcript sentence into opportunity, regulatory, or physical climate themes and aggregating these counts into standardized exposure scores, they demonstrate that this soft-information metric commands a modest but statistically significant risk premium when examined using option-implied expected-return proxies. Moreover, they document that this premium is time-varying: rising during 2011–2014 alongside green innovation, state adaptation plans, and oil-price shocks, then receding post-2015. This shows how evolving economic and policy backdrops shape the pricing of distinct climate-risk dimensions.

Extending their framework to a global context, Sautner et al. (2023) apply the refined keyword-discovery method to over 10000 firms across 34 countries from 2002 through 2020. They validate their four exposure measures (overall, opportunity, regulatory, physical) through human audits, finding over 90 % precision in the top exposure decile, and demonstrate that the scores are robust to alternative seed lists and weighting schemes (tf–idf versus raw counts). Econometric tests link higher earnings-call exposure to notable real-economy outcomes, green job postings increase by 109 % and green patenting by 72 % per 1σ rise in exposure, and to financial market effects, including wider tail-risk costs in options markets and a positive, time-varying equity risk premium for an aggregate exposure factor. These findings confirm that executives' verbal climate narratives predict both firms' real-world green activities and their compensation for bearing climate-related risk.

Collectively, these studies demonstrate that textual measures of climate-risk communication, whether drawn from mandatory 10-Ks, voluntary TCFD reports, newspaper coverage, or earnings calls, carry significant valuation information. Network metrics capture the structural integration of climate terms; transformer models dissect thematic nuances; and news and spoken disclosures reveal dynamic pricing channels. Building on this foundation, my approach will apply a pre-trained, transformer-based classifier to Item 1A risk disclosures in 10-Ks, aiming to capture the subtleties of firms' mandated climate narratives and to test their association with market valuations.

2.5. Hypothesis Development

In response to growing evidence that climate-related uncertainties are systematically priced by investors (Bansal et al., 2016; Bolton & Kacperczyk, 2021), firms have come under increasing pressure from regulatory bodies, institutional investors, rating agencies and shareholder activists to disclose material climate risks in their annual reports. The U.S. Securities and Exchange Commission's 2010 guidance explicitly identified climate change as a risk factor warranting disclosure under Item 1A of Form 10-K, reinforcing firms' obligations to report potential regulatory costs, physical impacts, and transitional uncertainties associated with climate change (SEC, 2010). Concurrently, theoretical work by Lyon and Maxwell (2011) suggests that firms facing greater downside risk are compelled to disclose more extensively under threat of reputational and financial sanctions, while Campbell et al. (2014) empirically demonstrate that unusually extensive risk-factor disclosures in Form 10-K filings are met with negative abnormal returns, consistent with investors interpreting more extensive disclosures as conveying higher future risk. Complementing these insights, recent studies document that disclosures tied to weather-related events (such as floods, wildfires, droughts, and hurricanes) are followed by adverse market reactions (Griffin et al., 2023; Nagar & Schoenfeld, 2024), confirming that investors penalize firms for heightened physical risk exposures.

Building on this foundation and on Berkman et al. (2024) and Kölbel et al. (2022) use of Item 1A narratives as firm-specific risk proxies, I employ a fine-tuned ClimateBERT model to generate three mandatory-disclosure measures for each firm-year observation: an overall climate-risk score, a transition-risk score, and a physical-risk score. Following the empirical framework of Vestrelli et al. (2024), Tobin's Q is then regressed on this disclosure score and a comprehensive set of controls: size, R&D intensity, leverage, cash holdings, foreign exposure and capital expenditures. Because more extensive mandated disclosures, whether reflecting overall, transition, or physical climate-risk narratives, signal greater exposure to undiversifiable climate uncertainties (raising required returns), they are expected to depress market valuations.

H1. Increase climate-risk disclosure in Item 1A of the 10-K is negatively associated with firm market value.

To asses this hypothesis, the next chapter dives into the data used in my paper and the model used to get climate risk scores.

3. Data and Methodology

To test my hypothesis and build on the theoretical framework from Chapter 2, I developed an empirical strategy in three stages: assembling an unbalanced firm–year panel of current S&P 500 constituents, extracting and processing Item 1A disclosures, and estimating panel regressions that relate text-based risk measures to firm valuation.

3.1. Sample Construction

For my sample, I decided to use the current S&P500 constituents. My time window is from 2005 until 2025. In 2005, the SEC made risk disclosures mandatory in 10 Ks (SEC, 2005). Recognizing that some constituents were not publicly listed for the entire 2005–2025 window, this approach yields an unbalanced panel. From Compustat, I first retrieved the current S&P500 constituents and their GVKEYs. With the GVKEYs, I retrieved Compustat's annual fundamental data and the Central Index Key (CIK) and linked these identifiers to CRSP data by matching GVKEY to PERMCO. Monthly share prices and shares outstanding were obtained from CRSP, and, together with book-value data from Compustat, were used to compute Tobin's Q and the control variables for the panel regression in line with Vestrelli et al., (2024).

3.2. Text Data Retrieval and Preprocessing

For each S&P 500 firm for my time window, I retrieved the 10-K filings from the SEC's EDGAR database. Using the EDGAR Query API, I obtained the URLs of all 10-K documents for each CIK and year in the sample. With the URLs, I could then get the text of the 1A item for all 10-Ks using the Extractor API. The text was then pre-processed: I stripped unnecessary tags and headers and cleaned residual HTML artifacts to produce a standardized text corpus of risk-factor disclosures.

3.3. ClimateBERT

I implemented a two-stage text-classification pipeline based on ClimateBERT to obtain my text-based climate risk metrics.

BERT (Bidirectional Encoder Representations from Transformers) is a deep bidirectional Transformer model that generates contextualized token embeddings by conditioning on both left and right context through multiple self-attention layers; it was pretrained on massive corpora using masked-language and next-sentence prediction objectives, and its token embedding is typically used for downstream classification tasks. Input text is first tokenized into subword units (WordPieces), then passed through the BERT encoder to produce hidden states that capture rich linguistic and semantic relationships (Devlin et al., 2019).

ClimateBERT extends this paradigm to the climate-risk domain by further pretraining a BERT base model on climate-science and environmental text and then fine-tuning it on labeled sentences drawn from the TCFD guidelines and supplementary human annotation (Webersinke et al., 2022). In practice, the fine-tuning process begins with a training set of several thousand sentences, both climate-related and random non-climate examples, which is iteratively expanded by reviewing and relabeling "confusing" cases where class probabilities are close. For text classification, each sentence or paragraph is fed through the model to produce class probabilities (e.g., transition, physical, or general risk), and a threshold of eg. 0.80 is applied to assign binary labels, controlling for overall sentence volume when aggregating into firm-level risk scores. Webersinke et al. (2022) report that continuing pretraining of a DistilRoBERTa base model on the labelled TCFD corpus reduces the masked-language-model validation loss by approximately 46–48 percent relative to the non-adapted DistilRoBERTa baseline and yields error-rate reductions of up to 35.7 percent across downstream tasks such as text classification, sentiment analysis, and fact-checking. This demonstrates how ClimateBERT has great precision in detecting nuanced climate-risk language.

For the first stage of my pipeline, I employ the ClimateBERT model variant described by Bingler et al. (2024) to detect climate-related paragraphs. Unlike Bingler et al.'s ClimateBertCTI, which fine-tunes ClimateBERT for the Cheap Talk Index, I utilize only their paragraph-relevance classifier as provided. In their study, Bingler et al. fine-tune the ClimateBERT encoder by appending a two-class softmax head atop the [CLS] embedding and training on several thousand expert-annotated annual-report paragraphs labeled as climate-related or not. They report that this classifier achieves a weighted F1 of approximately 0.991 on held-out validation data, substantially outperforming keyword-based baselines and underscoring its ability to capture nuanced, context-dependent signals of climate-relevance. Table 1 shows some example paragraphs that have been analyzed using ClimateBERT.

In the second stage, I apply the Deng et al. (2022) ClimateBERT variant to classify individual sentences within the climate-related paragraphs into transition risk, physical risk, or general climate content. Deng et al. fine-tune their model on a corpus of 3,732 manually annotated earnings-call sentences (1,549 transition, 804 physical, 1,379 general), using an 80/20 train/validation split, WordPiece tokenization, and early stopping with patience of four epochs. Although I do not re-fine-tune this model, Deng et al.'s paper provides convergence curves showing that F1 exceeds 0.95 for both transition- vs.non-transition and physical-vs.non-physical classifications after approximately 500 update steps. They further report evaluation loss of 0.1627 and an F1 of 0.9738 (precision = 0.9740, recall = 0.9738) on the transition–physical binary task. Table 2 shows some example sentences that have been analyzed using ClimateBERT.

Table 1: Example Paragraphs with ClimateBERT Text Classification

Paragraphs	Classification	Predicted Score
We cannot be sure that existing environmental regulations will not be revised or that new regulations seeking to protect the environment will not be adopted or become applicable to us. Revised or additional regulations that result in increased compliance costs or additional operating restrictions, particularly if those costs are not fully recoverable from APS' customers, could have a material adverse effect on our financial position, results of operations or cash flows.	yes	0,9980
The semiconductor industry is characterized by vigorous protection, enforcement, and pursuit of intellectual property rights. From time to time, third parties have asserted and may in the future assert patent, copyright, trademark, and other intellectual property rights against technologies that are important to our business and manufacturing operations and have demanded and may in the future demand that we license their technology or refrain from using it.	no	0,9932
The market price of our common stock could be subject to significant fluctuations in response to factors such as the following, some of which are beyond our control: variations in our quarterly operating results; operating results that vary from the expectations of management, securities analysts and investors; changes in expectations as to our future financial performance, including financial estimates by securities analysts and investors; developments generally affecting industries in which we operate, particularly the energy distribution and energy generation industries; announcements by us or our competitors of significant contracts, acquisitions, joint marketing relationships, joint ventures or capital commitments; announcements by third parties of significant claims or proceedings against us; favorable or adverse regulatory or legislative developments; our dividend policy; future sale of equity or equity-linked securities; and general domestic and international economic conditions.	yes - but not included; predicted score too low	0,5098

Table 2: Example Sentences with ClimateBERT Text Classification

Sentences	Classification	Predicted Score
We have accrued liabilities for environmental clean-up sites, including sites for which governmental agencies have designated us as a potentially responsible party, where it is probable that a loss will be incurred and the cost or amount of loss can be reasonably estimated.	transition	0,9997
Conversely, as in certain past years, extreme warm weather conditions could increase Houston Electric's results of operations in a manner that would not likely be annually recurring.	physical	0,9999

3.4. Text-based Climate Risk Metrics

With the finetuned ClimateBERT models, I translated the text of the 1A items into three quantitative measures:

ClimateScore: I applied the ClimateBERT model fine-tuned by Bingler et al. (2024) for the downstream task of detecting climate-related paragraphs. The 1A items were split up into paragraphs, by splitting them whenever there is a text break. Each paragraph gets classified as either climate-related or not and a probability of that paragraph being part of that classification gets calculated. Consistent with Kölbel et al. (2022), I classified paragraphs with probability ≥ 0.80 as climate-related and computed an aggregate ClimateScore by dividing the number of sentences in those paragraphs by the total sentence count of the filing:

$$ClimateScore_{i,t} = \frac{\#\,\{sentences\ in\ climated\ related\ paragraphs\}}{TotalSentences_{i,t}}$$

TransitionRiskScore & PhysicalRiskScore: In the second stage, to distinguish between transition and physical risk, I used the Deng et al. (2022) fine-tuned version of ClimateBERT which detects if a sentence is transition or physical risk related. The 1A items were split into individual sentences using NLTK. Sentences which got classified as either transition or physical risk and got a probability ≥ 0.8 I counted as a transition / physical risk sentence. To get the Transition risk score and physical risk score I computed it the following way in line with Kölbel et al. (2022) :

$$TransitionRiskScore_{i,t} = \frac{\#\,\{transition\,risk\,sentences\}}{TotalSentences_{i,t}}$$

$$PhysicalRiskScore_{i,t} = \frac{\#\,\{physical\,risk\,sentences\}}{TotalSentences_{i,t}}$$

3.5. Dependent and Control Variables

In line with Vestrelli et al. (2024), I included a set of firm-level controls. Firm size was proxied by the natural logarithm of total assets, obtained from Compustat. Financial leverage was measured as the ratio of total debt to total assets, capturing capital-structure risk. R&D intensity, reflecting firms' innovation efforts, was computed as research and development expenses scaled by total assets. Cash holdings were defined as the ratio of cash and short-term investments to total assets, serving as a proxy for liquidity buffers. Capital-expenditure was measured by dividing capital expenditures by total assets, capturing firms' investment activity. All accounting data were retrieved from the Compustat annual fundamentals file using GVKEY identifiers and linked to CRSP via PERMCO codes. The dependent variable for each observation, Tobin's Q, is calculated as total assets minus book value of equity plus market value divided by the total assets.

Table 3: Description of Control Variables

Variable	Description
Size	Natural logarithm of company sales (SALES).
R&D	Ratio of R&D expenditure (XRD) to sales (SALES). If R&D is missing, then it is set to zero for the year t.
Leverage	Sum of long-term debt (DLLT) and debt in current liabilites (DLC) divided by book value of total assets (AT).
Cash	Cash and short-term investments (CHE) scaled by book value of total assets (AT).
Foreign	Foreing currency income/loss (FCA) divided by sales (SALE).
Capital Expenditure	Capital expenditure (CAPX) scaled by book value of total assets (AT).

3.6. Empirical Specification

With financial controls and climate-risk metrics assembled into a firm–year panel, I estimated three separate firm-fixed-effects regressions (one per risk measure) by pooled OLS:

$$Tobin's\ Q_{i,t} = \alpha + \beta_1 RiskMeasure_{i,t-1} + \upsilon X_{i,t-1} + \theta_{i-1} + \vartheta_t + \epsilon_{i,t-1} \qquad (1)$$

My dependent variable is Tobin's Q and my explanatory variable is the lagged RiskMeasure (ClimateScore, TransitionRiskScore or PhysicalRiskScore). Xi,t−1are the controls for size, leverage, R&D intensity, cash holdings, and capital expenditures. I selected OLS with fixed effects because it controls for unobserved, time-invariant heterogeneity, accommodates the unbalanced panel, and yields unbiased estimates under the assumption of strict exogeneity.

3.7. Summary Statistics

I assemble an unbalanced panel of 8,001 firm–year observations spanning 2005 through 2024, drawing exclusively on the set of companies that comprise the S&P 500 at the end of my sample period. By focusing on these large-cap constituents, I ensure that my analysis reflects the behaviors of the most widely held and economically significant U.S. firms, even as firms enter and exit the index over time.

Table 4 reports key summary statistics. Tobin’s Q, which proxies market valuation relative to replacement cost, averages 2.414 (SD = 1.973) and spans a wide range (0.138 to 23.563), reflecting substantial cross-sectional heterogeneity in firms’ growth and investment prospects. Firm size, measured as the natural logarithm of annual sales, has a mean of 5.353 (SD = 2.316). R&D intensity averages 0.052 (SD = 0.500), leverage (debt divided by assets) averages 0.291 (SD = 0.239), cash holdings (cash over assets) average 0.134 (SD = 0.146), foreign-exchange exposure (foreign currency gains or losses over sales) is effectively zero on average (SD = 0.008), and capital expenditures (CapEx over assets) average 0.037 (SD = 0.041).

Turning to my principal explanatory variables Climate Score, Transition Score, and Physical Score, all hand-coded from the Item 1A “Risk Factors” sections of firms’ annual 10-K filings, Climate Score exhibits the highest average intensity of discussion, followed by Transition Score, with Physical Score the lowest. This ordering is unsurprising: the broad “climate” category aggregates a wide array of environmental concerns, whereas transition-risk topics (policy uncertainty, carbon regulation, technology shifts) are necessarily a narrower subset, albeit still more salient than acute or chronic physical-risk events, which tend to be episodic and geographically concentrated. Moreover, firms typically emphasize transitional challenges, such as compliance costs and strategic repositioning, in their forward-looking disclosures more consistently than physical-risk exposures, which may be perceived as less predictable or material on an annual reporting cycle.

Table 4: Descriptive Statistics

Variable	Mean	St. Dev.	Min	Max
Tobin's Q	2,414	1,973	0,138	23,563
Size	9,010	1,447	0,000	13,319
R&D	0,052	0,500	0,000	37,347
Leverage	0,291	0,239	0,000	3,892
Cash	0,134	0,146	0,000	0,930
Foreign	0,000	0,008	-0,106	0,387
Capital Expenditure	0,037	0,041	0,000	0,606
Climate Score	0,140	0,164	0,000	0,837
Transition Score	0,047	0,069	0,000	0,473
Physical Score	0,018	0,021	0,000	0,237

4. Results

4.1. Climate Risk Measures Over Time

Figure 1 depicts the evolution of the three lagged disclosure scores, overall climate, transition risk, and physical risk, from 2005 through 2024, revealing a narrative of regulatory stimulus, gradual adoption, and recent acceleration in firms' mandated climate-risk reporting.

In the earliest years (2005–07), all three scores surge, reflecting the SEC's initial 2005 risk-factor mandate (SEC, 2005). The average overall climate-risk score jumps from 0.11 in 2005 to 0.145 in 2006 before settling into a plateau around 0.13–0.14 through 2009. A secondary, smaller uptick occurs in 2010, most pronounced for the transition-risk score (rising from 0.044 to 0.049), coinciding with the SEC's 2010 interpretive release formally calling out material climate risks under Item 1A of Form 10-K (SEC, 2010). This suggests that firms responded not only to the original mandate but also to the later clarification that both physical and transition risks warranted disclosure.

Over the following decade (2010–20), the overall score remains remarkably stable, oscillating narrowly between 0.128 and 0.141. Transition risk holds around 0.043–0.050, while physical risk climbs modestly from 0.016 to 0.018. These patterns indicate that, after the initial regulatory spurs, firms largely maintained their established climate narratives, updating them incrementally rather than overhauling the risk factors.

A pronounced inflection occurs after 2021. The overall climate score leaps from 0.130 in 2021 to 0.175 by 2024, its highest point in two decades. Transition risk rises from 0.042 to 0.065, and physical risk jumps from 0.018 to 0.024. This synchronized up-turn coincides with renewed regulatory momentum (notably the SEC's 2022 climate-disclosure proposal), the finalization of the ISSB standards, intensified investor activism around net-zero pledges, and the rising prominence of extreme-weather events in public discourse.

Throughout the entire sample, the ranking **overall > transition > physical** remains intact, indicating a hierarchical integration of climate topics in risk factors: firms first adopt broad climate-change terminology, then drill down into transition uncertainties, and finally elaborate on physical-risk specifics. The widening gap between overall and transition scores in the latest years, approaching 0.11 by 2024, suggests that while detailed transition policies remain important, broader climate framing continues to dominate corporate risk narratives. Meanwhile, the narrowing of the transition–physical gap, from ~0.034 in 2010 to ~0.041 in 2024, reflects a catching-up of physical-risk considerations as they gain parity with transition themes.

These dynamics underscore the sensitivity of textual-analysis metrics to discrete regulatory milestones. The early 2006 jump and the 2010 secondary rise both align with SEC actions, while the post-2021 acceleration reflects a confluence of policy, investor, and physical-event drivers. When entered into valuation regressions, this rich temporal variation will help disentangle whether markets respond more to incremental increases in general climate discourse or to shifts in the balance between transition and physical risk narratives.

Figure 1: Evolution of Climate Scores over the Years

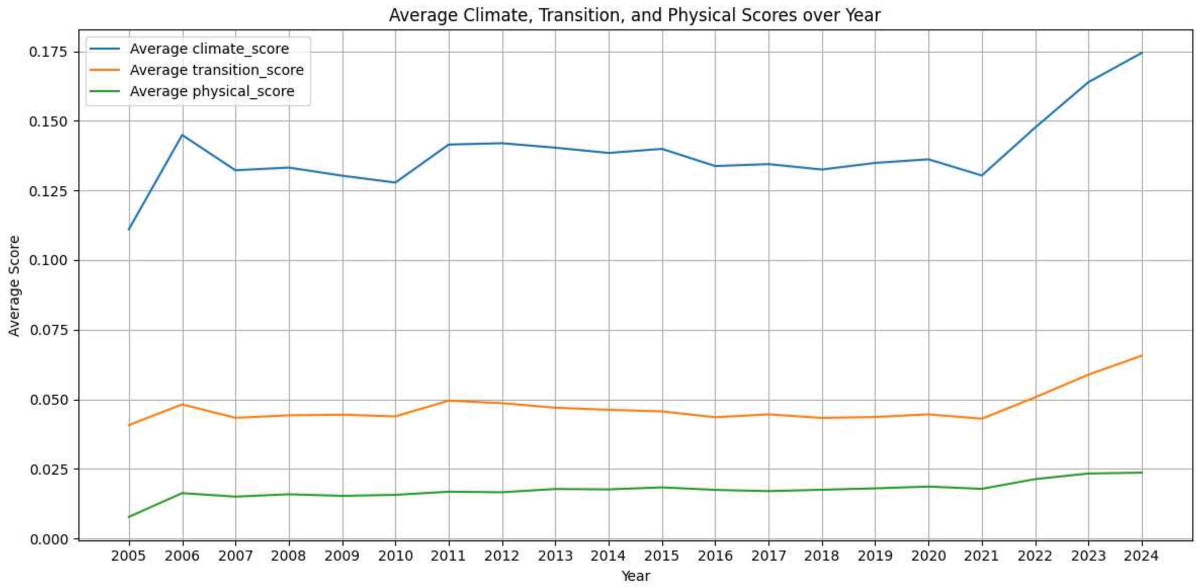
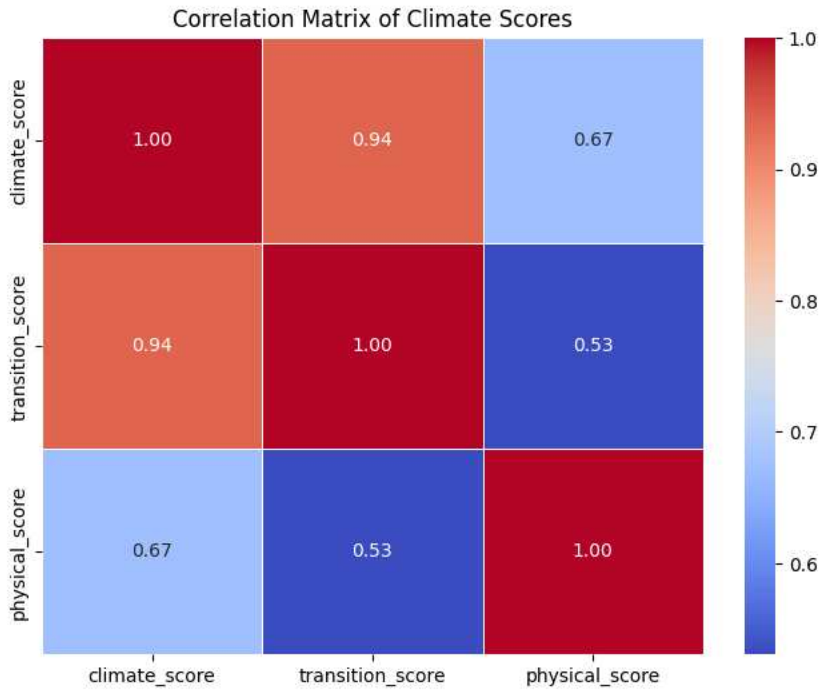


Figure 2 reports the pairwise Pearson correlations among my three ClimateBERT-derived risk scores across the full sample. The overall ClimateRisk score is almost perfectly collinear with TransitionRisk (r = 0.94), indicating that language related to policy, regulation, and technological change drives the aggregate climate-risk measure. Its correlation with PhysicalRisk is more moderate (r = 0.67), suggesting that discussion of chronic and acute climate impacts overlaps with but remains distinct from the broader score. Meanwhile, TransitionRisk and PhysicalRisk correlate at r = 0.53, reflecting a moderate degree of shared content. The extremely high correlation between ClimateRisk and TransitionRisk warns of multicollinearity if both measures were entered simultaneously, motivating separate regression specifications.

Figure 2: Pearson Correlations Among Risk Measures



To assess how these scores co-move within individual firms over time, I compute two complementary measures of firm-level association, summarized in Table 5. First, I calculate for each firm the Pearson correlation between its climate_score and transition_score series (and analogously for the other two pairs) and then report the distribution of those correlations. The median within-firm correlation between ClimateRisk and TransitionRisk is 0.83 (IQR: 0.64–0.93), whereas the medians for ClimateRisk–PhysicalRisk and TransitionRisk–PhysicalRisk are 0.70 (IQR: 0.34–0.86) and 0.39 (IQR: –0.06–0.71), respectively. Second, I demean each score by its firm-specific mean and compute pooled Pearson correlations on the pooled demeaned series; these "within-firm" correlations are 0.74 for ClimateRisk–TransitionRisk, 0.43 for ClimateRisk–PhysicalRisk, and 0.17 for TransitionRisk–PhysicalRisk. Both exercises confirm that transition- and broad climate-risk language move almost in lockstep within firms, while physical-risk language exhibits substantially more independent variation. These findings justify estimating each risk score in isolation in the regression models in chapter 4.3.

Table 5: Distribution of Within-Firm and pooled Within-Firm Correlations

Score Pair	Median (Q1-Q3)	Pooled Within-Firm
Climate - Transition	0.83 (0.64 - 0.93)	0.74
Climate - Physical	0.70 (0.34 - 0.86)	0.43
Transition - Physical	0.39 (-0.06 - 0.71)	0.17

4.2. Industry Results

Table 6 presents the distribution of firm-year observations across 18 two-digit NAICS industries in the 2005–2024 sample. Manufacturing dominates with 3,046 observations (38 %), followed by Finance & Insurance (1,178; 15 %), Information (658; 8 %), Real Estate Rental & Leasing (531; 7 %), Utilities (507; 6 %) and a range of other sectors each contributing below 5 % of the panel. This heterogeneity reflects both the differential population of public firms across sectors and the varying lengths of climate-risk narratives in Item 1A filings.

Table 6: Industry Overview in Sample

NAICS Industries	Observations
Manufacturing	3046
Finance and Insurance	1178
Information	658
Real Estate Rental and Leasing	531
Utilities	507
Retail Trade	335
Transportation and Warehousing	326
Professional, Scientific, and Technical Services	285
Mining	263
Wholesale Trade	208
Accommodation and Food Services	187
Administrative and Support and Waste Services	149
Health Care and Social Assistance	125
Construction	96
Nonclassifiable Establishment	55
Arts, Entertainment, and Recreation	30
Other Services (except Public Administration)	17
Agriculture, Forestry, Fishing and Hunting	5
Total	8001

4.2.1. High- and low-Climate Risk Industries – Deep Dive

To assess whether the valuation impact of climate-risk disclosures depends on the materiality of those risks, I follow Matsumura et al. (2024) in using the SASB Materiality Map to classify industries as material or nonmaterial for climate risk. An industry is deemed material if at least three of six climate issues (e.g., GHG emissions, energy management, physical-asset impacts) are flagged for that sector. Accordingly, the analysis focuses on two “high-risk” industries:

Utilities and Transportation & Warehousing; and two “low-risk” industries: Information and Professional, Scientific & Technical Services.

Utilities (NAICS 22; 507 observations) face pronounced transition risks (carbon regulation, renewable-portfolio standards) and acute physical risks (storm damage to generation assets, sea-level rise threats to infrastructure). Transportation & Warehousing (NAICS 48–49; 326 observations) similarly contend with fuel-efficiency mandates, electrification requirements, and extreme-weather disruptions to logistics networks. In contrast, Information (NAICS 51; 658 observations) and Professional, Scientific & Technical Services (NAICS 54; 285 observations) operate largely asset-light business models with minimal direct exposure to carbon-cost or facility-damage risks, making them natural comparators for determining whether any negative valuation association is concentrated in sectors where climate risks are truly material.

Looking at Figure 2-7, across the four industries, the year-by-year scatterplots reveal different disclosure trajectories that closely mirror each sector’s underlying climate-risk materiality.

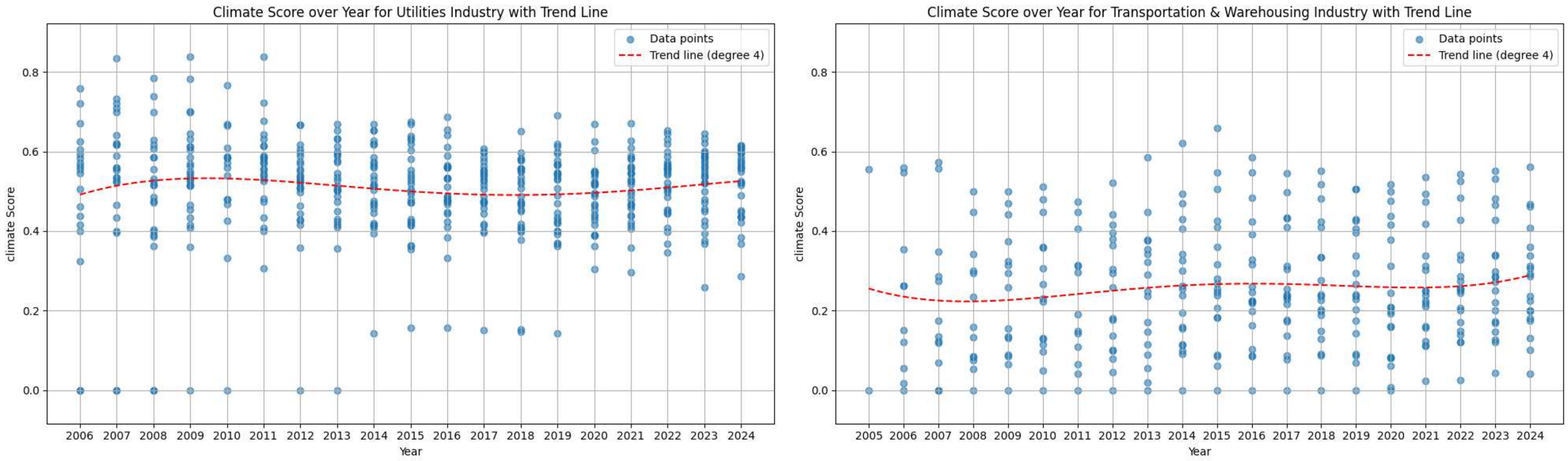
In the Utilities industry, overall climate-risk scores (Figure 2) surged in response to the SEC’s 2010 interpretive guidance, rising from cluster points near 0.45–0.60 in the late 2000s to peaks around 0.65, and then settled into a decade-long plateau around 0.50 before rebounding after 2021 to approach 0.60 by 2024. Transition-risk score (Figure 4) in Utilities followed an inverted-U shape, reaching roughly 0.18–0.20 in 2010, declining through the 2010s, and climbing again in the early 2020s, whereas physical-risk scores (Figure 6) remained minimal (below 0.01) until approximately 2015 and thereafter accelerated into the 0.05–0.14 range. These patterns suggest that power companies initially incorporated broad and policy-oriented climate language, only later deepening their disclosures of asset-level vulnerabilities as stakeholder pressure and extreme-weather events intensified.

Transportation & Warehousing firms exhibit a more gradual but nonetheless clear evolution in mandated climate narratives. Their overall climate-risk scores (Figure 2) rose steadily from about 0.22–0.30 in the mid-2000s to roughly 0.35 by 2024, reflecting incremental adoption of climate framing. Transition-risk scores (Figure 4) increased from near 0.07 to around 0.15, indicating continuous integration of fuel-policy and market-shift concerns, while physical-risk scores (Figure 6) climbed from virtually zero before 2010 to approximately 0.05 by the mid-2020s. Compared with Utilities, Transportation’s smoother upward trends and lower absolute levels imply a sector that has progressively, rather than abruptly, amplified its risk-factor narratives in line with evolving regulatory and operational demands.

By contrast, the Information and Professional, Scientific & Technical Services sectors, which are both classified as nonmaterial for climate risk, maintained flat, low-level disclosure profiles for most of the sample period. In Information, overall scores (Figure 3) remained below 0.03 until after 2020, rising only to 0.06 by 2024, while transition scores (Figure 5) declined from an initial 0.06–0.07 to near zero over the 2010s before a modest late-cycle uptick. Physical-risk scores (Figure 7) in this sector were nearly nonexistent throughout. Professional Services exhibited a modest inverted-U in overall climate scores (Figure 3), peaking around 0.04 in 2012 before retrenching to 0.02–0.03 and then rising to 0.06 by 2024, while transition and physical scores (Figure 5 & 7) only began to climb appreciably after 2015, and even then remained below 0.02. These subdued patterns confirm that, in industries where climate issues are deemed immaterial, mandated 10-K narratives have largely resisted regulatory and event-driven pressures until very recently.

Taken together, these unmodeled disclosure dynamics underscore two key insights: first, that regulatory milestones and real-world climate events have driven significant narrative intensification only in sectors with material exposures, and second, that within those sectors transition-risk languages lead disclosure evolution while physical-risk discussions emerge belatedly.

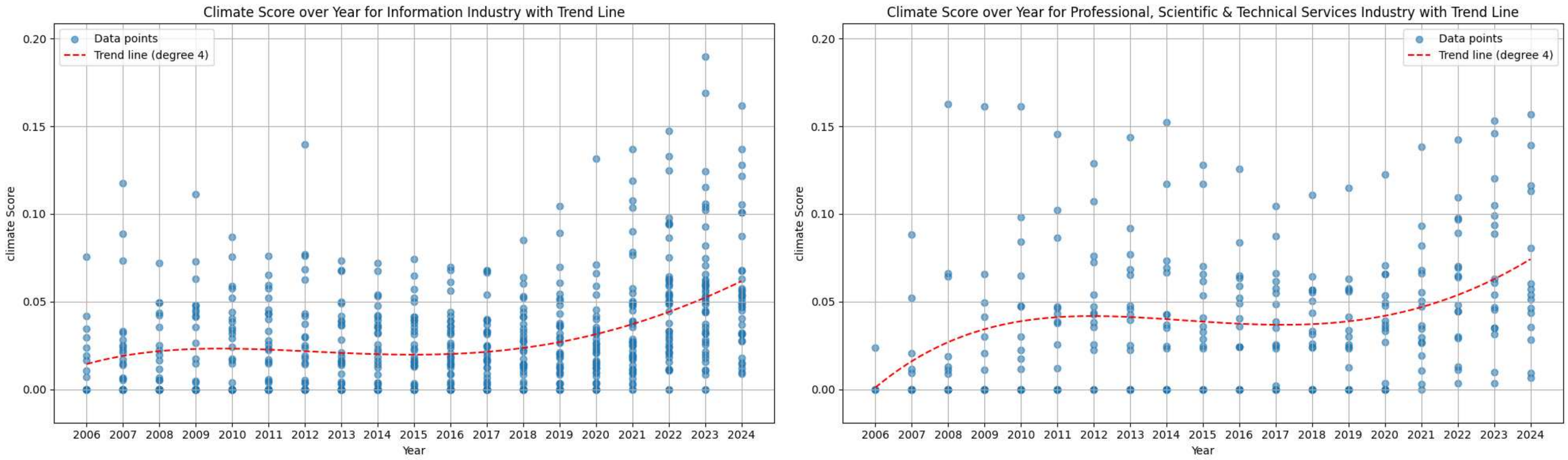
Figure 3: Climate Score Scatterplot for Utilities and Transportation & Warehousing



Climate Score over Year for Utilities Industry with Trend Line

Climate Score over Year for Transportation & Warehousing Industry with Trend Line

Figure 4: Climate Score Scatterplot for Information and Professional, Scientific & Technical Services



Climate Score over Year for Information Industry with Trend Line

Climate Score over Year for Professional, Scientific & Technical Services Industry with Trend Line

Figure 5: Transition Score Scatterplot for Utilities and Transportation & Warehousing

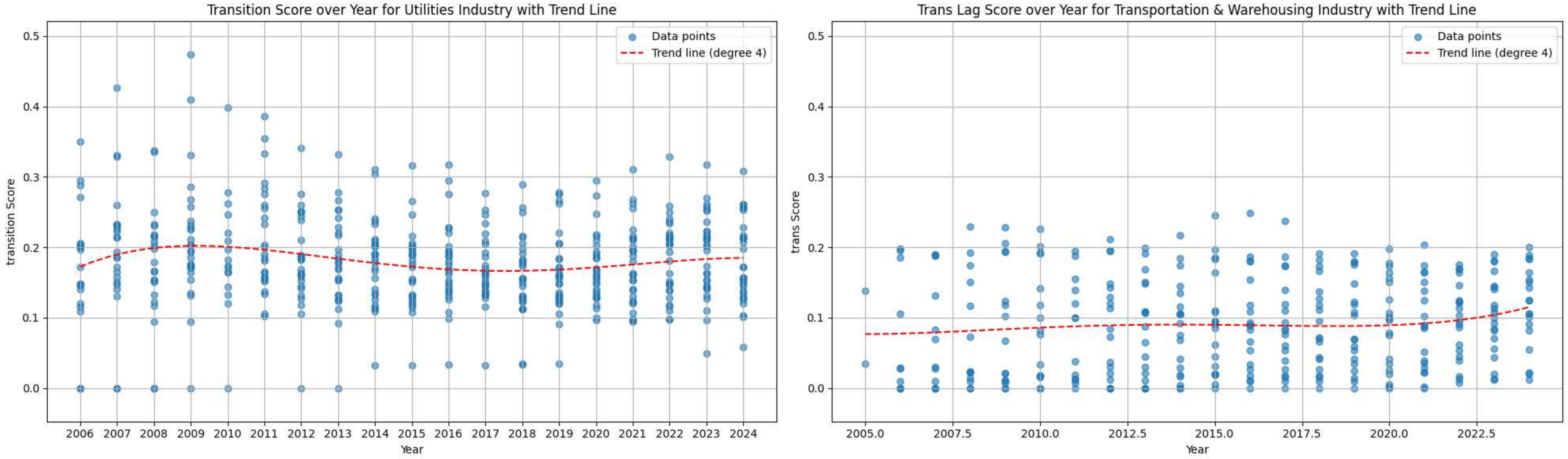


Figure 6: Transition Score Scatterplot for Information and Professional, Scientific & Technical Services

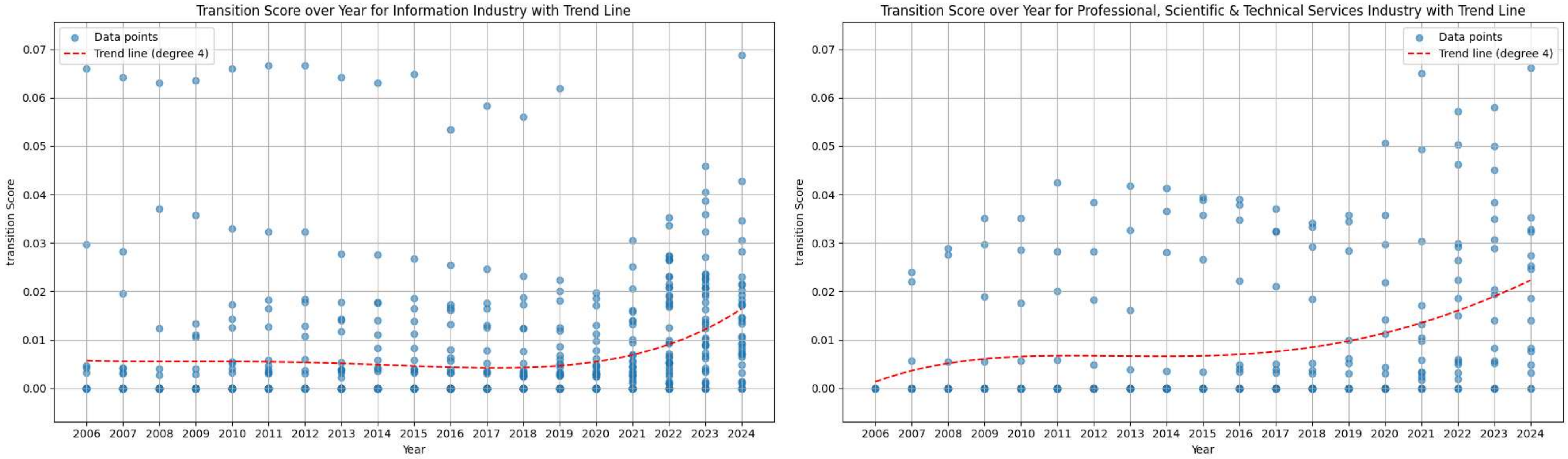


Figure 7: Physical Score Scatterplot for Utilities and Transportation & Warehousing

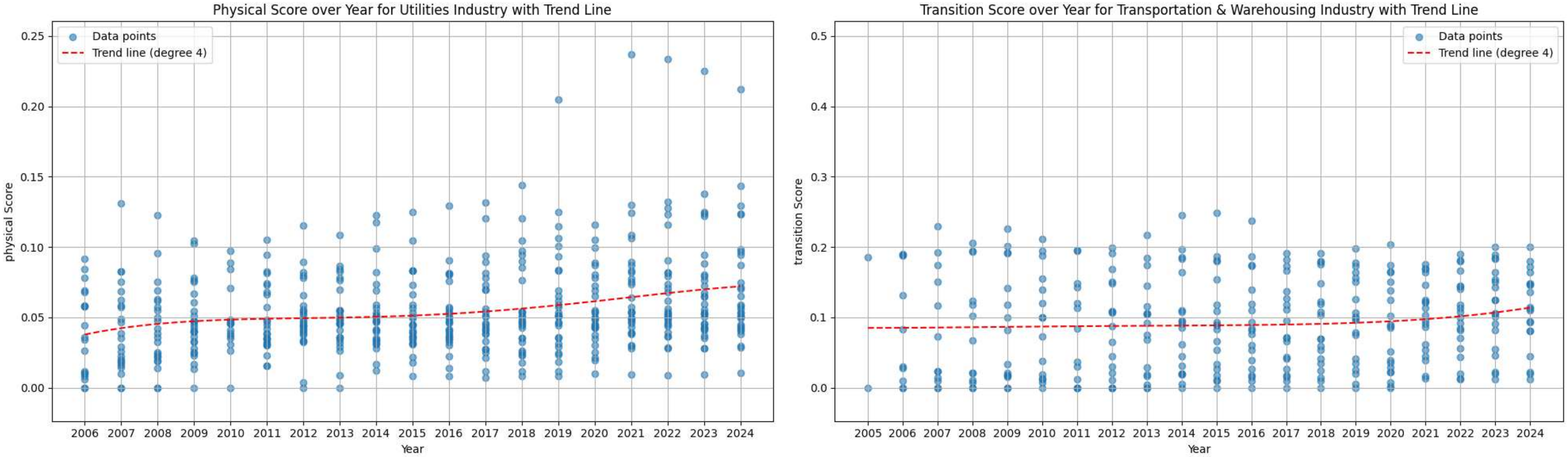
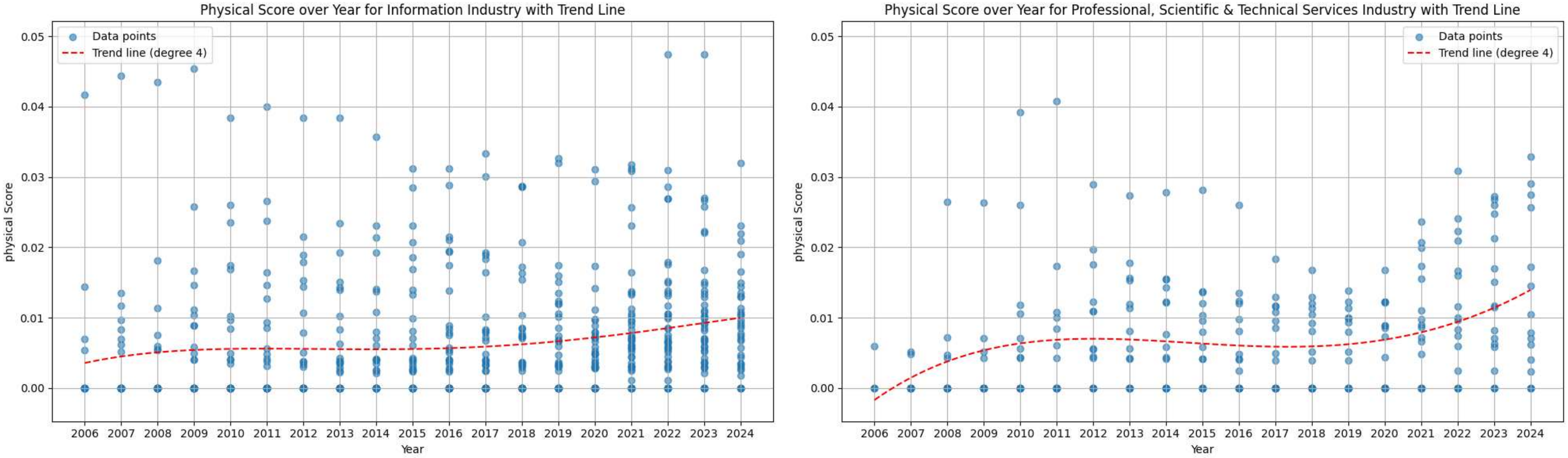


Figure 8: Physical Score Scatterplot for Information and Professional, Scientific & Technical Services



4.2.2. Industry-level Fixed-effect Analysis

In line with Li et al. (2024), who use industry fixed effects to reveal how text-based climate-exposure measures vary by sector, I estimate regressions of each risk metric on a full set of NAICS two-digit industry dummies, controlling for time fixed effects, and then plot the estimated coefficients against (with 95 % confidence intervals) a reference category of "Finance and Insurance" (Figure 8-10). The omitted category was chosen as a neutral benchmark due to its middling sample size (1,178 observations) and its more neutral exposure to either extreme weather or decarbonization mandates.

In Figure 8-10, across all three specifications, Utilities and Mining, Quarrying & Oil & Gas Extraction emerge as the most pronounced outliers, reflecting their substantial exposure to both physical climate hazards and policy-driven transition pressures.

When examining the overall climate-risk score (Figure 8), Utilities exhibit the largest positive coefficient, closely followed by Mining, with both industries registering values around 0.45 to 0.50 standard deviations above Finance & Insurance. Transportation & Warehousing, Other Services, Construction, and Agriculture & Forestry also display significantly elevated climate-risk discourse, although to a more modest degree (coefficients ranging from approximately 0.10 to 0.28). In contrast, sectors such as Professional & Technical Services, Information, and Health Care & Social Assistance report slightly lower climate-risk mention than the baseline, suggesting that industries characterized by largely indoor operations or limited direct exposure to climate hazards engage less frequently in climate-related narratives.

Turning to transition risk (Figure 9), the dispersion of industry effects is notably narrower. Utilities maintain the leading position, with a coefficient of approximately 0.19, and Mining again ranks second at around 0.17. Transportation & Warehousing and Other Services follow, but their confidence intervals approach zero, indicating only moderate differentiation from Finance & Insurance. Manufacturing, Construction, and Wholesale Trade register small positive deviations (roughly 0.03 to 0.05), whereas Information, Health Care & Social Assistance, and Professional & Technical Services cluster at or marginally below the baseline. This pattern underscores the concentration of transition-risk discourse in carbon-intensive and heavily regulated sectors, while service-oriented industries remain comparatively small.

Finally, the physical-risk score (Figure 10) reveals the least variation across industries. Only Utilities and Mining demonstrate statistically significant positive coefficients, approximately 0.04 and 0.03, respectively, highlighting their unique vulnerability to acute and chronic physical climate events. Other sectors, including Transportation, Retail Trade, Arts & Recreation, and Agriculture, display small positive point estimates but their confidence intervals overlap zero, implying that heightened physical-risk discussion is not widespread beyond the most exposed industries.

These results confirm that firms with substantial infrastructure footprints or high carbon intensity are consistently more likely to address physical and transition climate risks relative to financial-service firms, which serve as a de facto normative benchmark. Service-sector industries with limited direct exposure to climate hazards continue to under-discuss these risks, suggesting that industry characteristics play a pivotal role in shaping corporate climate-risk communication.

Figure 9: Industry Variations in Climate Risk Score

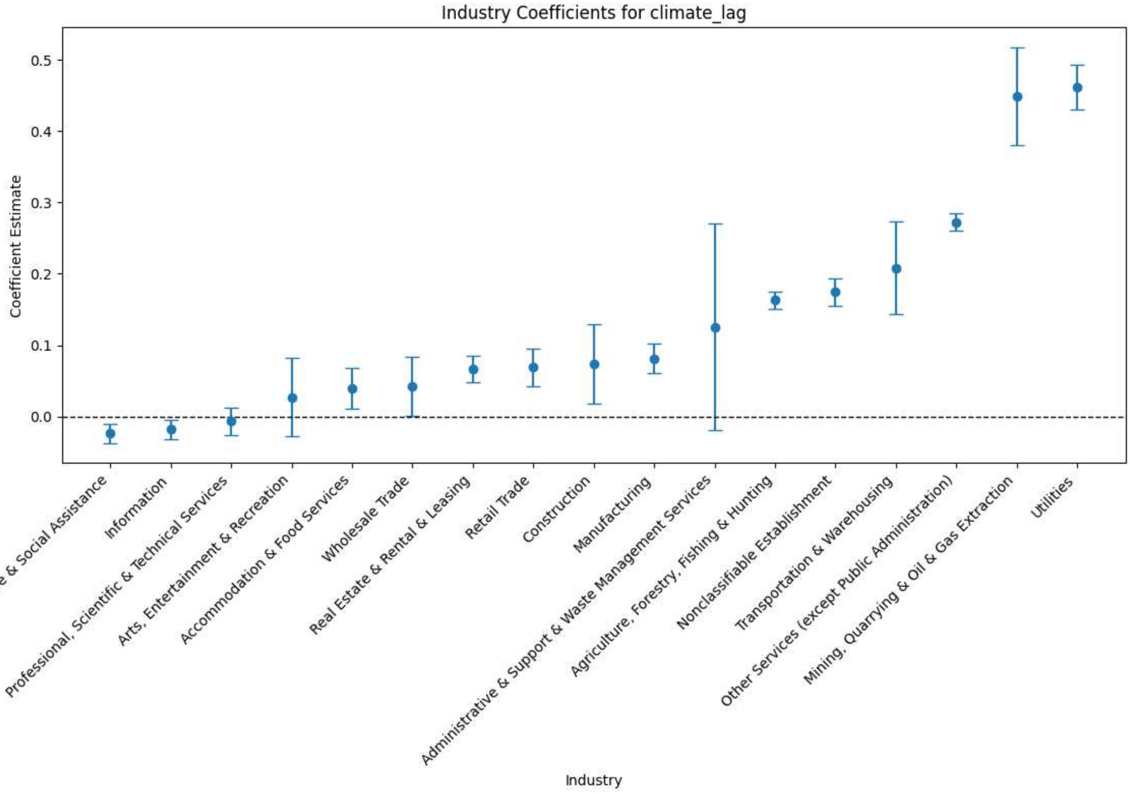


Figure 10: Industry Variation in Transition Risk Score

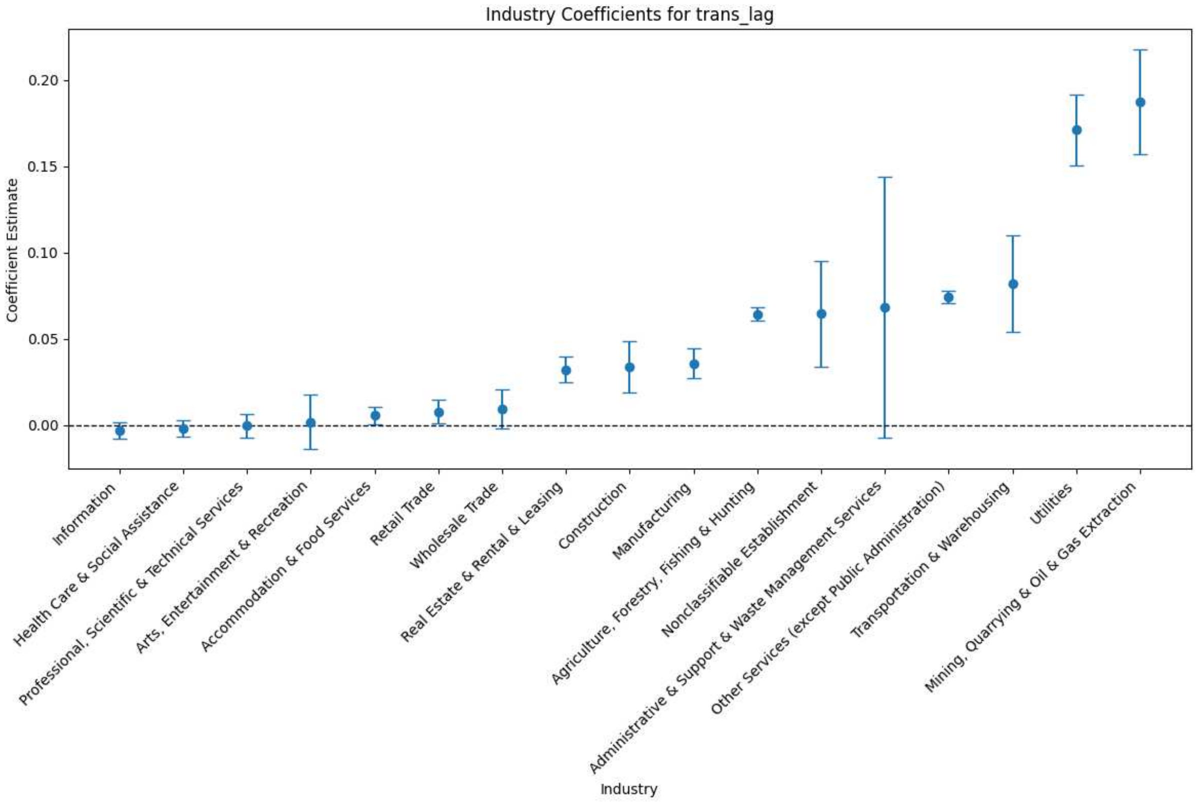
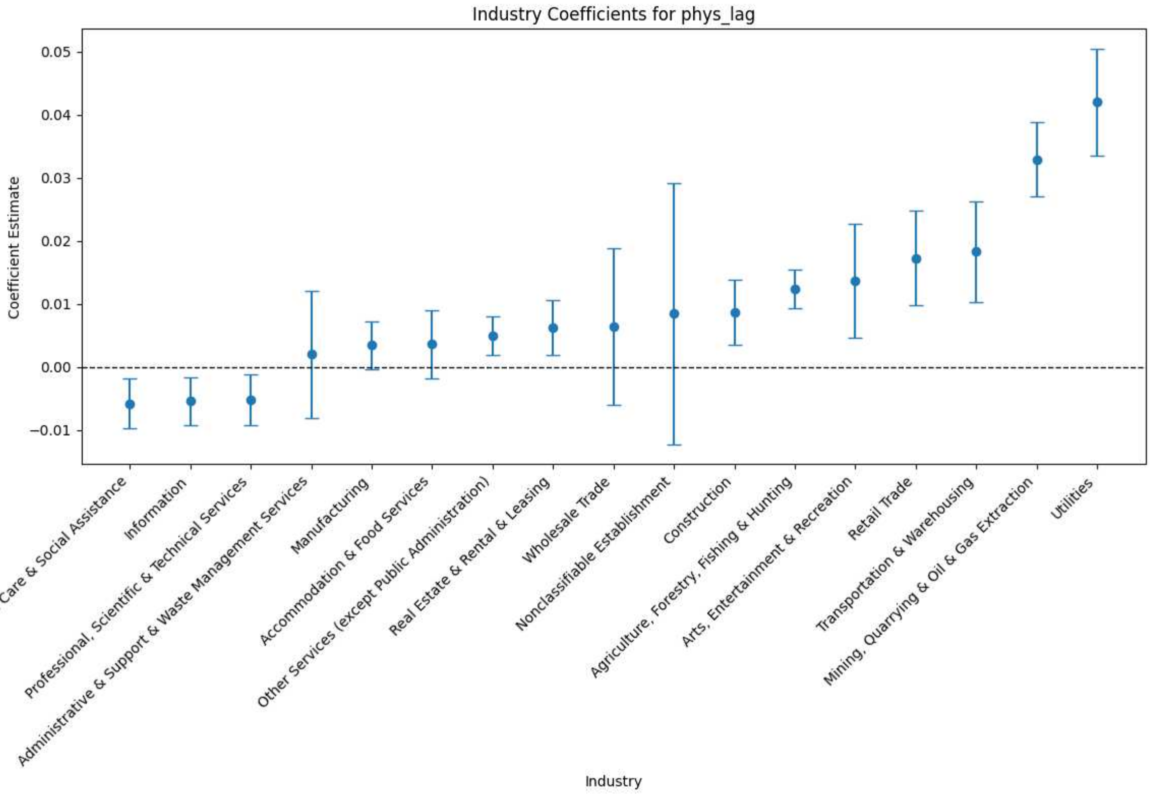


Figure 11: Industry Variation in Physical Risk Score



4.3. Impact of Climate Risk Disclosure on Firm Market Value

In Table 7, I investigate the impact of the 10K climate risk disclosures on Tobin's Q. I consider the different risks disclosed in the firms' reports. Each column in Table 7 displays the results for equation 1, with the variation being Climate Score (Model 1), Transition Risk Score (Model 2), and Physical Risk Score (Model 3), which each have been derived using ClimateBERT.

In the first specification (Model 1), the lagged overall ClimateRisk score enters with a coefficient of –0.247 (t = –0.84), indicating no statistically discernible effect on Tobin's Q. By contrast, when the TransitionRisk score is the sole risk regressor (Model 2), its lagged coefficient is –1.656 (t = –2.33, $p < 0.05$), implying that a one-unit increase in transition-risk language is associated with a 1.656-point decline in Tobin's Q. In the third specification (Model 3), the PhysicalRisk score likewise loads negatively (–1.765) but fails to reach significance (t = –1.30). Across all three models, the control variables behave as expected: larger firms and those with higher leverage, liquidity (cash ratio), and capital-expenditure intensity exhibit significantly higher Q, while greater asset intensity corresponds to lower valuation. The inclusion of industry × year fixed effects absorbs sectoral and temporal shocks, and the R-squared of approximately 0.03 aligns with prior firm-level studies of market valuation.

These findings suggest that investors penalize firms whose 10-K disclosures emphasize transition-related threats but do not systematically reward or punish broad climate-risk or physical-risk language. The significant negative coefficient on TransitionRisk stands in contrast to the "transparency premium" reported in Vestrelli et al. (2022), who document a positive effect of climate-risk disclosure on market value under ordinary attention conditions. Our result instead echoes their "attention trap" mechanism: when transition risk is prominent in firm filings, investors appear to infer heightened exposure to regulatory or market pressures, driving down valuations. The absence of a robust effect for physical-risk language may indicate that equity markets, at least over my sample period, place greater weight on firms' prospective policy and technology challenges than on chronic or acute climate events.

Table 7: Impact of Climate Risk Disclosure on Firm Market Value

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-0,2472		
	(-0,8411)		
Transition risk score (lag)		-1,6561**	
		(-2,3325)	
Physical risk score (lag)			-1,7653
			(-1,3028)
Size (lag)	0,0987***	0,0986***	0,0977***
	(2,7283)	(2,7266)	(2,7002)
R&D intensity (lag)	-0,2259***	-0,2258***	-0,2259***
	(-7,015)	(-7,014)	(-7,0143)
Leverage (lag)	1,6876***	1,6958***	1,6818***
	(12,681)	(12,749)	(12,626)
Cash ratio (lag)	1,0393***	1,0402***	1,0375***
	(4,7414)	(4,7468)	(4,733)
Foreign (lag)	0,3678	0,3849	0,3632
	(0,1763)	(0,1846)	(0,1741)
Capex ratio (lag)	4,6585***	4,6986***	4,6736***
	(6,6087)	(6,6743)	(6,6334)
Industry x Time FE	Yes	Yes	Yes
Observations	8000	8000	8000
N. of Groups	493	493	493
R2	0,0306	0,0312	0,0307
F-test	18,655	18,503	19,104

t-statistics are shown in parentheses

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

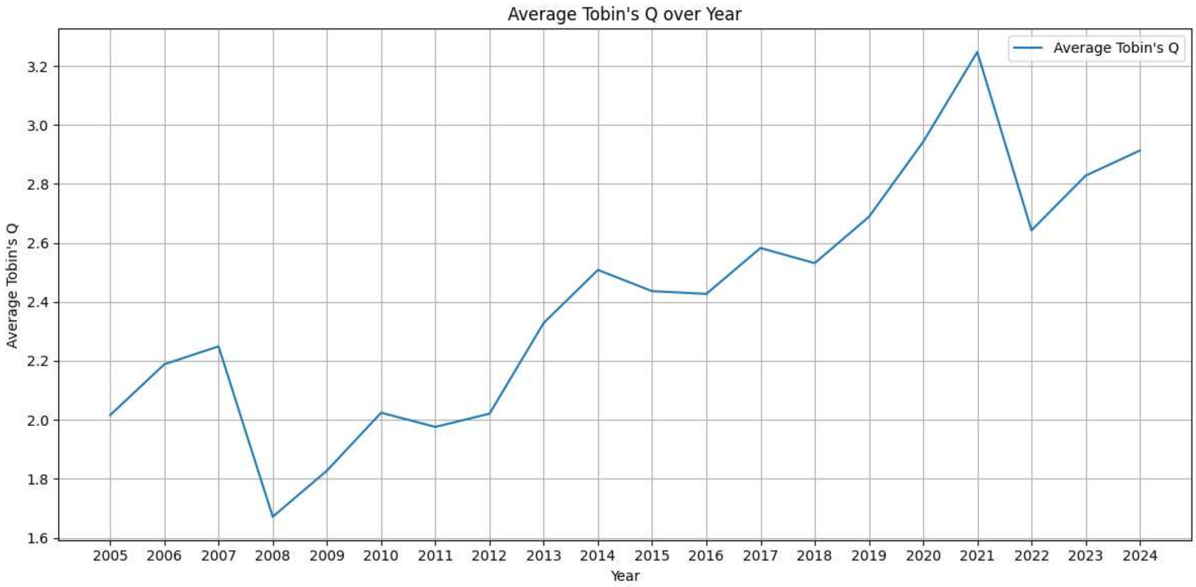
4.3.1. Firm Market Value Over Time

Figure 11 plots the cross-sectional mean of Tobin’s Q for our sample from 2005 through 2024. Several pronounced phases emerge. In the pre-crisis years of 2005–2007, average Q hovered steadily around 2.2. With the onset of the 2008 financial crisis, valuations collapsed to roughly 1.7, a decline of over 20 percent, before beginning a gradual recovery in 2009. By 2014, average Q had not only recouped pre-crisis levels but climbed to about 2.5, reflecting the combination of accommodative monetary policy, recovering corporate profits, and rebounding equity markets. From 2015 to 2016, valuations plateaued, after which they entered a sustained upward drift. This acceleration culminated in a peak of approximately 3.25 in 2020, coinciding with the early COVID-19 period and unprecedented liquidity injections by central banks.

In 2022, average Tobin's Q registered a sharp drop back to near 2.6, as monetary policy tightened, supply-chain frictions persisted, and geopolitical tensions rose. The subsequent two years saw a partial rebound, with Q rising to about 2.9 by 2024, suggesting that firms and markets began to adapt to the new interest-rate regime and lingering post-pandemic uncertainties.

These patterns show the importance of controlling for year-specific shocks when relating firm-level disclosures to market valuation. The dramatic swings in average Q, from crisis-driven troughs to liquidity-fuelled peaks, reflect aggregate forces that, if unaccounted for, could confound estimates of how climate-risk language influences equity prices. By including industry × year fixed effects in my regression models, I net out these common macroeconomic and market-wide fluctuations, thereby isolating the idiosyncratic link between each firm's climate-risk score and its Tobin's Q.

Figure 12: Average Tobin's Q Over the Years



4.3.2. Impact on Firm Market Value for Specific Industries

To assess whether the relationship between climate-risk disclosures and firm market valuation varies by sector, I also did the regression separately for four industry groups that differ substantially in their inherent climate exposure. I again focus on Utilities and Transportation & Warehousing, industries widely regarded as highly material in terms of both transition and physical climate risks, and compare them to two knowledge-based sectors, Information and Professional, Scientific & Technical Services, where climate impacts are typically less acute. Tables 10 through 13 report these industry-specific regressions, each including the same set of lagged control variables and industry × year fixed effects used in the aggregate analysis. Examining the sign, magnitude, and statistical significance of the ClimateRisk, TransitionRisk, and PhysicalRisk scores within each sector illuminates how investor sensitivity to climate disclosures depends critically on the underlying materiality of climate risks in a firm's operating environment.

Table 10 shows that, in the Utilities sector, all three ClimateBERT-derived scores carry a statistically significant negative valuation effect. In Model 1, a one-unit increase in the lagged broad ClimateRisk score is associated with a 0.126-point drop in Tobin's Q ($t = -1.96$, $p < 0.05$). When disaggregated, both TransitionRisk (-0.565, $t = -1.98$, $p < 0.05$) and PhysicalRisk (-0.409, $t = -2.38$, $p < 0.05$) likewise depress market value. These results imply that, for regulated utilities whose cash flows and asset bases are highly exposed to both policy shifts and extreme weather, any additional language around either transition or physical climate risks is interpreted by investors as a material warning signal.

In Transportation & Warehousing (Table 11), the broad ClimateRisk score itself is not significant, but both TransitionRisk (–3.959, t= –2.80, $p < 0.01$) and PhysicalRisk (–10.847, t= –3.42, $p < 0.01$) exert large and highly significant negative effects. This suggests that in an industry dependent on fuel, logistics networks, and infrastructure, investors react strongly to filings that emphasize either regulatory/technological disruptions or acute and chronic weather impacts, whereas more generic climate language alone carries no independent signal.

By contrast, in the Information sector (Table 12), none of the three risk measures reaches statistical significance at conventional levels, and the point estimates even flip sign in some specifications. Likewise, in Professional, Scientific & Technical Services (Table 13), only the TransitionRisk score is significant (–49.207, t = –3.17, $p < 0.01$), while broad ClimateRisk and PhysicalRisk remain muted. These findings are consistent with the lower financial materiality of climate exposures in knowledge-based and service industries: investors appear unconcerned by generic or physical-risk language in the absence of clear transition-risk implications.

Table 8: Impact of Climate Risk Disclosure on firm Market Value: Utilities

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-0,1256**		
	(-1,9623)		
Transition risk score (lag)		-0,5652**	
		(-1,9768)	
Physical risk score (lag)			-0,4088**
			(-2,3772)
Size (lag)	-0,0409	-0,0465	-0,0433
	(-1,1785)	(-1,3474)	(-1,2552)
Leverage (lag)	0,4233***	0,4591***	0,4366***
	(3,0454)	(3,3074)	(3,156)
Cash ratio (lag)	-0,1347	-0,2296	-0,0846
	(-0,3522)	(-0,596)	(-0,2212)
Foreign (lag)	-4,3238	-4,6594	-3,9912
	(-0,5964)	(-0,6429)	(-0,5514)
Capex ratio (lag)	-0,2626	-0,2335	-0,2799
	(-0,5902)	(-0,524)	(-0,6307)
Industry x Time FE	Yes	Yes	Yes
Observations	507	507	507
N. of Groups	31	31	31
R2	0,0351	0,0389	0,0352

t-statistics are shown in parentheses

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

Table 9: Impact of Climate Risk Disclosure on Firm Market Value: Transportation & Warehousing

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-0,293		
	(-0,4881)		
Transition risk score (lag)		-3,9587***	
		(-2,8043)	
Physical risk score (lag)			-10,847***
			(-3,4174)
Size (lag)	0,2754*	0,3192**	0,2952*
	(1,7321)	(2,061)	(1,9322)
R&D intensity (lag)	-3,1676	-3,6016	-3,2783
	(-0,9841)	(-1,134)	(-1,0406)
Leverage (lag)	-2,4098***	-2,0832***	-2,5519***
	(-4,7057)	(-4,0945)	(-5,2409)
Cash ratio (lag)	5,4006***	5,9289***	5,4376***
	(5,3932)	(6,0485)	(5,7443)
Foreing (lag)	23,249	26,803	23,427
	(1,3954)	(1,6315)	(1,4417)
Capex ratio (lag)	-2,7885*	-1,8625	-2,7671*
	(-1,7286)	(-1,148)	(-1,7609)
Industry x Time FE	Yes	Yes	Yes
Observations	326	326	326
N. of Groups	20	20	20
R2	0,2277	0,2482	0,258

t-statistics are shown in parentheses

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

Table 10: Impact of Climate Risk Disclosure on Firm Market Value: Information

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-4,2936		
	(-1,0916)		
Transition risk score (lag)		-4,8504	
		(-0,4103)	
Physical risk score (lag)			4,2987
			(0,3023)
Size (lag)	-0,2376	-0,1894	-0,1981
	(-1,2457)	(-0,9975)	(-1,053)
R&D intensity (lag)	-9,231***	-9,2307***	-9,1212***
	(-3,4395)	(-3,4261)	(-3,3963)
Leverage (lag)	2,3031***	2,3461***	2,3462***
	(3,6596)	(3,7212)	(3,7155)
Cash ratio (lag)	0,1044	0,1131	0,0849
	(0,1302)	(0,1404)	(0,1058)
Foreing (lag)	6,9693	5,4731	5,402
	(0,2512)	(0,1969)	(0,194)
Capex ratio (lag)	-0,733	-0,6843	-0,8165
	(-0,2394)	(-0,2232)	(-0,2647)
Industry x Time FE	Yes	Yes	Yes
Observations	658	658	658
N. of Groups	45	45	45
R2	0,0495	0,0478	0,0477

t-statistics are shown in parentheses

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

Table 11: Impact of Climate Risk Disclosure on Firm Market Value: Professional, Scientific & Technical Services

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-6,4981		
	(-1,141)		
Transition risk score (lag)		-49,207***	
		(-3,1712)	
Physical risk score (lag)			-24,83
			(-1,2093)
Size (lag)	-0,1269	-0,3305	-0,0798
	(-0,3109)	(-0,8126)	(-0,1956)
R&D intensity (lag)	5,4963	-2,2387	7,5512
	(0,4184)	(-0,17)	(0,574)
Leverage (lag)	11,015***	10,84***	11,194***
	(8,2535)	(8,7182)	(8,7389)
Cash ratio (lag)	4,4233***	4,4175***	4,1169**
	(2,6136)	(2,6565)	(2,4059)
Foreing (lag)	-14,799	-25,495	-10,597
	(-0,2505)	(-0,4384)	(-0,1791)
Capex ratio (lag)	25,154**	25,647**	25,792**
	(2,2997)	(2,3865)	(2,3533)
Industry x Time FE	Yes	Yes	Yes
Observations	285	285	285
N. of Groups	17	17	17
R2	0,2961	0,3205	0,2966

t-statistics are shown in parentheses

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

4.3.3. Impact on Firm Market Value Pre- and Post-COVID Period

To examine whether the COVID-19 shock altered the link between climate-risk language and firm valuation, I re-estimate the baseline specifications separately over two sub-samples, splitting the panel at the end of 2018. Table 8 presents results for the “pre-COVID” window (2004–2018), while Table 9 covers the “post-COVID” period (2019–2024). In both sets of regressions I retain the full suite of lagged control variables (size, R&D intensity, leverage, cash ratio, foreign sales share, CapEx ratio) and industry x year fixed effects.

In the pre-COVID sample (Table 8), the aggregate ClimateRisk score enters with a coefficient of –0.702 ($t = –2.43$, $p < 0.05$), indicating that firms whose 10-K disclosures contained more general climate-risk language experienced lower Tobin’s Q. By contrast, neither the TransitionRisk nor the PhysicalRisk score attains statistical significance in this period ($t = –0.91$ and –1.63, respectively). The control variables largely mirror their full-sample behavior: R&D intensity carries a negative and highly significant coefficient, while leverage, cash holdings, foreign sales share, and CapEx ratio each exhibit their expected positive associations with Tobin’s Q.

In the post-COVID window (Table 9), none of the three risk scores retains significance. The point estimates on ClimateRisk (–0.230), TransitionRisk (–0.178), and PhysicalRisk (–2.615) all lose statistical precision ($|t| < 1$), despite controls maintaining similar signs and magnitudes. The disappearance of the pre-pandemic ClimateRisk effect suggests that the extraordinary market volatility and liquidity interventions following early 2020 overwhelmed the valuation signal ordinarily conveyed by firms’ narrative disclosures. In other words, during periods of acute systemic stress, the equity market’s sensitivity to mandated climate-risk language appears substantially attenuated.

Taken together, these subsample results confirm that the negative association between broad climate-risk discourse and firm value is concentrated in “normal” market regimes, but that this relationship weakens considerably once exogenous shocks such as the COVID-19 pandemic introduce pervasive revaluation dynamics. Accordingly, future empirical work should account for such structural breaks—whether through rolling regressions, time-varying coefficient models, or interaction terms with crisis-period dummies—to avoid conflating transient market dislocations with the steady-state pricing of climate-risk disclosures.

Table 12: Impact of Climate Risk Disclosure on Firm Market Value (2004-2018)

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-0,7019**		
	(-2,4265)		
Transition risk score (lag)		-0,6695	
		(-0,9146)	
Physical risk score (lag)			-2,3745
			(-1,6285)
Size (lag)	-0,0098	-0,0109	-0,0097
	(-0,2443)	(-0,2704)	(-0,2407)
R&D intensity (lag)	-0,3402***	-0,3409***	-0,3404***
	(-13,194)	(-13,218)	(-13,2)
Leverage (lag)	0,495***	0,516***	0,503***
	(3,3714)	(3,5187)	(3,4259)
Cash ratio (lag)	0,9266***	0,9134***	0,917***
	(4,2331)	(4,1719)	(4,1888)
Foreing (lag)	4,1193*	4,0839*	4,0932*
	(1,9388)	(1,9211)	(1,9259)
Capex ratio (lag)	2,7277***	2,6926***	2,7207***
	(4,0504)	(3,9938)	(4,0358)
Industry x Time FE	Yes	Yes	Yes
Observations	5151	5151	5151
N. of Groups	458	458	458
R2	0,0462	0,0451	0,0455

t-statistics are shown in parentheses

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

Table 13: Impact of Climate Risk Disclosure on Firm Market Value (2019-2014)

Sample	Tobin's Q		
	Model 1	Model 2	Model 3
Climate risk score (lag)	-0,2296		
	(-0,3326)		
Transition risk score (lag)		-0,1778	
		(-0,1179)	
Physical risk score (lag)			-2,6154
			(-0,8348)
Size (lag)	-0,1192	-0,1199	-0,1215
	(-1,0644)	(-1,0702)	(-1,0848)
R&D intensity (lag)	0,3175*	0,3164*	0,3178*
	(1,8194)	(1,8134)	(1,8219)
Leverage (lag)	1,2058***	1,2073***	1,2118***
	(3,3434)	(3,3471)	(3,3611)
Cash ratio (lag)	1,4538***	1,4544***	1,4535***
	(3,0798)	(3,0796)	(3,0796)
Foreing (lag)	-4,7742	-4,7837	-4,7538
	(-1,526)	(-1,5291)	(-1,5197)
Capex ratio (lag)	3,6303*	3,6014*	3,6987**
	(1,9503)	(1,937)	(1,9862)
Industry x Time FE	Yes	Yes	Yes
Observations	2794	2794	2794
N. of Groups	489	489	489
R2	0,0157	0,0156	0,0159

t-statistics are shown in parentheses

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

5. Discussion and Limitations

This thesis provides new evidence that the valuation impact of mandated climate-risk disclosures in Form 10-K filings varies markedly by risk dimension and sectoral materiality. In the full sample, lagged transition-risk language is associated with a statistically significant decline in Tobin's Q, whereas neither an aggregate climate-risk score nor physical-risk language exerts a clear effect. When the analysis is restricted to "high-risk" industries—Utilities and Transportation & Warehousing—both transition and physical risk disclosures carry economically and statistically meaningful negative coefficients. In contrast, in "low-risk" sectors such as Information and Professional, Scientific & Technical Services, none of the risk measures reliably predicts valuation (with the lone exception of a large but isolated transition-risk coefficient in Professional Services). Taken together, these findings suggest that investors penalize firms for disclosing greater exposure to policy-driven uncertainties and weather-related threats only when those risks are inherently material to the underlying business model.

These results reinforce a growing body of work documenting a negative association between more extensive climate-risk disclosures and firm value. Campbell et al. (2014) show that unusually detailed risk-factor narratives in Form 10-K filings elicit negative abnormal returns, while Griffin et al. (2023) and Nagar & Schoenfeld (2024) find that text-based measures of weather-event exposure predict adverse stock reactions around wildfires and storms. More recently, Li et al. (2024) deploy a call-transcript measure of transition-risk language and report that non-proactive risk discussion depresses Tobin's Q, closely mirroring the negative transition-risk effect documented here in this thesis.

At the same time, however, there is credible evidence of a positive valuation premium for climate transparency under certain conditions. Vestrelli et al. (2024) report a "transparency premium" in 10-K disclosures, Flammer et al. (2021) and Jiang et al. (2021) show that voluntary CDP reporting and investor-led engagement are rewarded in equity markets, and Ilhan et al. (2023) demonstrate that powerful institutional owners allocate more capital to firms with richer climate disclosures. Together, these studies highlight that the market response to climate-risk disclosure depends critically on the setting, particularly the interplay between investor attention, perceived materiality, and the credibility of the information environment.

Several limitations of this study suggest avenues for further refinement. First, I rely exclusively on Item 1A of annual 10-Ks to measure climate-risk narratives, whereas other research incorporates alternative text sources—most notably earnings-call transcripts and voluntary sustainability reports—which may capture more timely or candid risk discussions. This single-source approach may also introduce noise or bias if boilerplate language or metaphorical references are misclassified; leveraging explainable-AI tools (e.g. SHAP or LIME) could help to unpack which phrases drive the ClimateBERT scores and guard against spurious correlations.

Second, the sample is confined to current S&P 500 constituents; extending the analysis to mid-cap, small-cap, or cross-listed firms, and to other geographies, would improve generalizability, statistical power, and insights into how different regulatory regimes shape the pricing of climate disclosures.

Third, although I cluster standard errors at the firm level, future work could employ multiway clustering or wild-cluster bootstrap methods to better account for residual dependence across firms and years and apply dimension-reduction techniques (such as principal component analysis) to ameliorate the multicollinearity between aggregate and transition-risk measures.

Fourth, the subsample analysis around the COVID-19 pandemic reveals that the negative valuation effect of climate-risk language is substantially attenuated in the post-2019 period. The extraordinary market volatility, unprecedented liquidity interventions, and sectoral repricing following early 2020 appear to have overwhelmed the steady-state informational content of 10-K disclosures. This finding underscores the necessity of modeling structural breaks—whether via rolling regressions, time-varying coefficient models, or interaction terms with crisis-period dummies—to avoid conflating transitory shocks with the underlying pricing of climate-risk narratives.

Finally, the observational panel design cannot fully establish causality: unobserved shifts in corporate strategy, investor composition, or concurrent ESG initiatives may confound the estimated associations. Instrumental-variable strategies, exploiting exogenous weather shocks, or event-study and difference-in-differences designs around regulatory announcements, would help isolate causal effects and deepen our understanding of when climate-risk transparency commands a premium or incurs a penalty in equity markets.

Future research can refine the policy and managerial implications of climate-risk disclosure in an era of accelerating regulatory and physical climate challenges by addressing these constraints through multi-source disclosure integration, expanded firm coverage, structural-break modeling, and cross-country comparisons.

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