MEASURING CLIMATE RISK FROM EARNINGS CALLS: PRICING, POLICY CREDIBILITY, AND THE CARBON PREMIUM PUZZLE

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February 27, 2026

Working Paper
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ABSTRACT

We study how climate-related risks enter asset prices by constructing firm-level measures of climate exposure from earnings call transcripts. We develop a semantic search framework – combining embedding-based retrieval and large language model classification – that extracts climate-relevant passages from over 51,500 transcripts of S&P 500 and STOXX 600 firms (2009–2025) and decomposes them into transition risks, physical risks, and opportunities, capturing forward-looking beliefs and information shocks. We validate these measures and then test whether investors reprice assets when new information about climate exposure arrives. Examining short-window abnormal returns around earnings calls that reveal unexpected shifts in climate risk perception, we find evidence of repricing – but only where policy environments make climate exposure credible. For European firms, transition risk attention predicts positive returns pre-Paris (+100 bps) but negative returns post-Paris (−50 bps), consistent with repricing once policy commitments become binding. No comparable reversal appears for US firms. These findings help explain why empirical studies have struggled to detect a carbon premium: the negative contemporaneous returns generated by ongoing repricing work against the positive expected returns that theory predicts in equilibrium, obscuring the premium in realized return data.

Keywords: Climate Risk Pricing, Paris Agreement, Repricing, Text as Data, Semantic Search, Earnings Calls, Green Innovation

JEL Codes: G12, G14, G32, Q54, C55, C81

I Introduction

How are climate-related risks reflected in asset prices? Theoretical models predict that assets exposed to climate transition costs carry a risk premium in equilibrium, but that during the transition toward this equilibrium, information shocks about climate exposure trigger discrete downward price adjustments on exposed assets (Pástor et al., 2021; Bansal et al., 2019). A growing empirical literature has sought to test these predictions, yet results remain contested. Studies using backward-looking measures such as carbon emissions or ESG scores find evidence of a carbon premium in some specifications but not others, with results sensitive to sample selection, time period, and regional scope (Bolton et al., 2022; Bolton and Kacperczyk, 2023). Meanwhile, portfolio-level analyses reveal that green assets have outperformed brown assets in recent years, but whether this reflects a risk premium, unanticipated repricing, or data-mining remains debated (Pástor et al., 2022; Giglio et al., 2021).

A core difficulty is that the standard measures used in this literature cannot isolate the firm-level information shocks that theory requires for identifying repricing: carbon emissions change slowly, ESG ratings are updated infrequently, and neither captures the forward-looking beliefs about climate exposure that are the theoretically relevant object for asset pricing. This measurement limitation raises the possibility that conflicting findings reflect not contradictory evidence about whether climate risks are priced, but differences in how, where, and when repricing occurs – differences that coarse measures cannot detect.

In this paper, we develop a text-based measurement framework that constructs high-frequency, firm-level measures of perceived climate risk exposure from corporate earnings call transcripts, and use these measures to provide new evidence on how and when climate risks are priced. Following the text-as-data tradition in economics (Gentzkow et al., 2019; Hassan et al., 2025; Sautner et al., 2023), we treat the share of a firm's earnings call devoted to climate-related topics as a proxy for the salience and perceived materiality of climate exposure to management. The key premise is that when a CFO devotes substantial time to discussing carbon pricing impacts, technology substitution threats, or clean energy opportunities in front of analysts, this reveals forward-looking beliefs about the firm's exposure, beliefs that are the theoretically relevant input for investor updating and asset repricing. Unlike static accounting metrics, these measures vary at the firm-quarter level, can be decomposed into

economically distinct channels, and capture perceived exposure as it evolves with the policy and technological environment.

Constructing such measures at scale requires overcoming a methodological constraint that has limited existing text-as-data approaches: the difficulty of reliably decomposing broad risk categories into their constituent economic channels while maintaining scalability across different taxonomies and time periods. Keyword-based methods have difficulty distinguishing different channels within transition risk or adapting as terminology evolves; supervised classifiers such as ClimateBERT (Webersinke et al., 2022) require costly retraining for each new application and cannot generalize across risk taxonomies; and while zero-shot LLM classifiers offer the flexibility to handle new categories without training data, applying them directly to corpora of millions of paragraphs remains prohibitively expensive, limiting their use to small-scale or pre-filtered samples. We address this by proposing a two-stage semantic search architecture. The first stage replaces keyword matching with semantic retrieval, identifying climate-relevant passages based on conceptual similarity to researcher-defined queries grounded in the Task Force on Climate-related Financial Disclosures (TCFD) taxonomy[1], processing millions of paragraphs in seconds without requiring labeled training data. The second stage applies an LLM classifier to the filtered subset, reduced by 99.4% from the original corpus, to distinguish between transition risks, physical risks, and opportunities with high precision. This modular design achieves substantially higher accuracy than existing approaches (F1-score 0.86 vs. 0.58 for ClimateBERT; precision 0.93 vs. 0.47) while remaining instantly adaptable to new risk categories through query specification rather than model retraining.

We organize climate exposure along the TCFD taxonomy into three dimensions—transition risks, physical risks, and climate-related opportunities—each reflecting distinct economic mechanisms with different asset pricing implications. Applying this framework to approximately 51,500 earnings call transcripts from S&P 500 and STOXX 600 firms over 2009–2025, we construct firm-quarter attention scores that capture how intensely each firm discusses specific climate channels relative to its sector peers.

Before using these measures in asset pricing tests, we establish that they capture eco-

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[1]The TCFD was formally disbanded in October 2023, with its monitoring responsibilities transferred to the IFRS Foundation. The taxonomy we employ is preserved in IFRS S2 (IFRS Foundation, 2023), which adopts the same classification of climate-related risks and opportunities. We retain the TCFD terminology throughout as it remains the standard reference in the academic literature.

nomically meaningful variation rather than measurement artifacts or disclosure conventions. The measures exhibit sparse, right-skewed distributions consistent with selective attention to material climate exposure: the median firm-quarter contains zero climate discussion, while the 95th percentile reaches 3.9% of earnings call content. Variance decompositions show that 88% of variation is firm-specific, with industry and time effects explaining only 9%, indicating the measures capture genuine heterogeneity across firms within the same sector rather than common trends. Cross-sectionally, attention concentrates in sectors with the highest carbon footprints and regulatory exposure: utilities, energy, and automobiles rank highest, consistent with economic priors. We further validate the measures against real economic outcomes: firms that emphasize climate-related opportunities file approximately 26% more green patents in the following year, and those discussing transition risks file roughly 12% more, conditional on industry-year fixed effects, existing innovative capacity, and lagged green patenting. Climate attention also amplifies the productivity of R&D spending in generating green patents, a pattern inconsistent with cheap talk. Together, this evidence establishes that our discourse-based measures reflect genuine forward-looking beliefs about climate exposure that translate into real corporate decisions.

The central empirical contribution tests whether investors reprice assets when firms reveal unexpected shifts in climate risk exposure, and whether policy credibility governs this dynamic. We construct climate attention shocks – the component of a firm's climate discussion not explained by fundamentals, sector trends, or its own recent history – and examine their association with short-window abnormal returns around earnings calls. Three findings emerge.

First, we document a sign reversal in the pricing of transition risk exposure for European firms around the Paris Agreement. Before Paris, transition risk attention shocks are associated with *positive* abnormal returns, with Q5–Q1 spreads reaching approximately +100 basis points, consistent with markets rewarding managerial awareness of transition dynamics in an environment where climate policy lacked credibility. After Paris, and the subsequent tightening of EU climate policy through ETS reforms, the European Green Deal, and binding sectoral regulations, the relationship inverts: high transition risk attention now predicts *negative* abnormal returns of approximately -50 basis points. This swing of roughly 150 basis points is consistent with the theoretical prediction in Pástor et al. (2021): once

4

policy commitments render transition costs credible, disclosing exposure to these costs reveals downside risk, triggering the contemporaneous price decline that simultaneously raises expected future returns on exposed firms. Importantly, the mechanism operates through perceived exposure revealed in discourse, not merely through accounting-based emissions. Markets penalize firms that *discuss* transition exposure, not simply those with high direct carbon intensity.

Second, this reversal does not appear for US firms. Both pre- and post-Paris spreads for transition risk are small and statistically insignificant, with no clear directional pattern. This regional asymmetry maps directly onto differences in policy credibility: the European policy environment, reinforced by binding regulatory instruments, made transition costs sufficiently certain for markets to price them, while greater US policy uncertainty, amplified by shifting federal administrations and the absence of comprehensive carbon pricing, left the information content of transition risk disclosure ambiguous. The contrast provides a within-sample placebo of sorts: the same measurement framework, applied to firms facing different policy environments, produces exactly the pattern that theory predicts.

Third, the pricing of climate-related opportunities attenuates over time. In Europe, opportunity attention predicts large positive returns pre-Paris but these effects diminish substantially in the post-Paris period, consistent with the progressive incorporation of climate growth prospects into equilibrium prices as these opportunities become widely anticipated. This attenuation is less pronounced for US firms, suggesting that European markets have incorporated climate opportunity information more quickly.

These results contribute to the climate finance literature in several ways. Where Pástor et al. (2022) show that recent green outperformance reflects unanticipated shifts in climate concerns rather than high expected returns, our event-study design identifies this repricing mechanism at the firm-quarter level: the negative post-Paris returns to transition risk disclosure in Europe are the contemporaneous price adjustments that, in equilibrium, generate a risk premium on exposed assets. The sign reversal locates the activation of this mechanism precisely at the point where policy credibility was established, providing sharper identification than studies relying on time-series variation in aggregate climate sentiment. Crucially, the negative contemporaneous returns generated by repricing work against the positive expected returns predicted in equilibrium, suggesting that much of the heterogeneity in the

empirical carbon premium literature may reflect the coexistence of these opposing forces in realized return data rather than contradictory evidence about whether climate risks are priced. The regional decomposition reinforces this interpretation: studies focused on US equities may find weak or absent premia not because markets ignore climate risk, but because US policy uncertainty prevents transition costs from becoming sufficiently credible for systematic repricing.

This paper makes three contributions. First, we provide direct firm-level evidence that investors reprice assets in the days following information shocks about firms' climate risk exposure – positive or negative – consistent with the repricing mechanism predicted by climate asset pricing theory. We further show that this dynamic is governed by policy credibility: repricing occurs only where binding policy commitments make transition costs credible. Second, we introduce a scalable semantic search framework for measuring nuanced concepts from unstructured text that achieves state-of-the-art accuracy without requiring labeled training data, offering a general-purpose tool for text-based economic measurement beyond the climate domain. Third, we construct and validate granular, high-frequency measures of perceived climate risk exposure that predict real economic outcomes, establishing that earnings call discourse reveals genuine forward-looking beliefs about climate exposure rather than performative disclosure.

The remainder of the paper proceeds as follows. Section II situates our work within the relevant literature. Section III describes the data. Section IV details the semantic search architecture and the two-stage classification pipeline. Section V establishes technical and economic validity of the measures. Section VI demonstrates that climate attention predicts green innovation and R&D investment. Section VII presents the asset pricing analysis. Section VIII concludes.

II   Related Literature

This paper connects three strands of literature: the theoretical and empirical debate on climate risk pricing, the measurement of firm-level climate risk exposure, and the broader text-as-data methodology in economics.

A. Climate Risk and Asset Pricing

A theoretical literature establishes the conditions under which climate-related risks should be reflected in asset prices. Pástor et al. (2021) develop a model in which assets exposed to environmental risks carry a premium in equilibrium, but in which the transition toward this equilibrium generates negative realized returns on brown assets as investors update beliefs about climate-related costs. Bansal et al. (2019) show that long-run climate risks affect asset valuations through their impact on expected consumption growth and its volatility. Giglio et al. (2021) survey the broader landscape, emphasizing the distinction between the repricing channel—discrete price adjustments when risk is first recognized—and the risk premium channel that operates in the new equilibrium. A key theoretical insight, central to our analysis, is that these channels have opposite implications for realized returns: repricing produces negative contemporaneous returns on exposed assets, while the equilibrium premium implies positive expected returns going forward.

Empirical tests of these predictions have produced contested results. Bolton et al. (2022) document a carbon premium in the cross-section of US stock returns, finding that firms with higher carbon emissions earn higher returns, consistent with compensation for transition risk. Bolton and Kacperczyk (2023) extend this analysis internationally and show that the carbon premium has risen over time with investor awareness and policy stringency. However, other studies find weak or absent carbon premia depending on the sample, time period, and risk measure employed. Pástor et al. (2022) argue that the recent outperformance of green relative to brown assets reflects unanticipated shifts in climate concerns—a repricing phenomenon—rather than a positive risk premium on green assets, cautioning against interpreting realized return differentials as equilibrium expected returns.

Evidence from corporate bond markets points to similar dynamics. de Jonge et al. (2025) document a positive and significant carbon premium in euro area corporate bonds, with a one standard deviation increase in Scope 1 and 2 emissions raising yield spreads by 26 basis points. Their decomposition into preference and risk channels reveals that the preference-driven component increased rapidly from 2020 to early 2022, and that firms receiving free EU ETS allowances face a substantially lower preference premium, highlighting the role of carbon pricing policy in shaping the cost of capital. Boermans et al. (2024) find that investors primarily reprice climate transition risk by rewarding green firms during periods of climate stress rather than penalizing brown firms, suggesting that the repricing channel

may operate asymmetrically across the greenness spectrum. Both studies find that climate risk pricing is substantially stronger in European than in US markets, a pattern consistent with the regional heterogeneity in policy credibility that we exploit in our empirical design.

Several factors contribute to these conflicting findings. First, most studies rely on backward-looking measures of climate exposure – primarily carbon emissions or ESG ratings – that change slowly and cannot isolate the firm-level information shocks that repricing theories require. Second, the literature has generally treated climate risk as a homogeneous category, pooling transition risks, physical risks, and opportunities despite their distinct economic mechanisms and potentially opposite asset pricing implications. Third, studies typically estimate average effects across time periods that span major policy shifts, obscuring the structural breaks that theory predicts when policy credibility changes. Our paper addresses each of these identification challenges: we construct forward-looking, high-frequency measures of perceived climate exposure that distinguish between risk dimensions, and we exploit the Paris Agreement as a natural experiment in policy credibility to identify the conditions under which repricing activates.

Regional heterogeneity in climate risk pricing has received growing attention. **?** show that option-implied tail risk for carbon-intensive firms is higher in countries with stricter climate policies. Bolton and Kacperczyk (2023) find that the carbon premium varies substantially across regions, with stronger effects in Europe than the United States. Our analysis contributes to this strand by providing a structural explanation for regional differences: the European sign reversal in transition risk pricing, contrasted with the absence of a comparable pattern in the US, suggests that policy credibility – not merely investor preferences –determines whether and when climate risks enter asset prices.

B. Measuring Firm-Level Climate Risk Exposure

A parallel literature has developed measures of firm-level climate risk exposure, predominantly from corporate disclosures. Sautner et al. (2023) construct firm-quarter climate risk scores from earnings call transcripts using keyword-based methods, distinguishing regulatory, physical, and opportunity exposures. Their work established earnings calls as a valuable source of high-frequency, firm-level climate risk information and demonstrated that textual climate exposure varies meaningfully across firms and over time. Hassan et al. (2019) develop a related framework for political risk, measuring firm-level exposure from the share

of earnings call text devoted to political topics.

These keyword-based measures have been productive but face inherent limitations. First, they rely on predetermined term lists that capture exact lexical matches, missing the diverse phrasings through which climate-related concepts are expressed in corporate discourse. A discussion of "stranded asset exposure from decarbonization mandates" is substantively identical to one about "write-downs on fossil fuel reserves due to net-zero legislation," but keyword methods may capture one and miss the other depending on which specific terms were pre-specified. Second, the rigidity of keyword lists makes it difficult to decompose broad risk categories into finer economic channels—distinguishing, for example, carbon pricing impacts from technology substitution threats within transition risk—because each decomposition requires crafting new term lists and validating them manually. Third, as climate-related terminology evolves rapidly with the policy and technological environment, static keyword lists risk becoming stale or incomplete.

An alternative strand uses backward-looking, accounting-based proxies. Carbon emissions data from providers such as MSCI or Trucost offer objective measures of firms' direct environmental footprint (Bolton et al., 2022; Bolton and Kacperczyk, 2023). ESG ratings from multiple providers aggregate diverse environmental criteria into composite scores. While valuable for measuring realized exposure, these proxies are updated infrequently, vary substantially across rating providers (Berg et al., 2022), and by construction cannot capture the forward-looking beliefs about climate exposure that drive investor updating and asset repricing. Emissions intensity measures what a firm currently emits; our measures capture what management perceives as material about the firm's future climate-related risks and opportunities.

Supervised machine learning classifiers represent a more recent approach. Domain-specific models such as ClimateBERT (Webersinke et al., 2022) achieve strong performance on climate content detection within their training domains. However, these models require expert-annotated training data, remain locked to their original classification tasks, and must be retrained to measure new constructs or adapt to evolving taxonomies. This limits their utility for studying emerging risks where categories are not yet well-defined or where researchers wish to iterate rapidly across different decompositions of exposure.

Our measurement framework addresses these limitations simultaneously. By replacing

keyword matching with semantic retrieval, we capture climate-related content based on conceptual similarity regardless of specific wording, inheriting the scalability of dictionary methods while achieving the contextual accuracy of supervised classifiers. The TCFD-grounded query structure enables systematic decomposition into granular channels—from broad transition risk down to carbon pricing mechanisms, stranded asset exposure, or technology substitution threats—without requiring separate training datasets for each. Relative to Sautner et al. (2023), our approach offers three specific advances: finer taxonomic granularity through the full TCFD hierarchy, robustness to terminological evolution through semantic rather than lexical matching, and the ability to decompose attention into economically distinct channels that can be separately validated and used in different empirical applications. These properties are not merely methodological refinements—they enable the empirical analysis in this paper, which requires distinguishing transition risk from opportunity attention and isolating firm-level information shocks that would be confounded in coarser measures.

C. Text-as-Data Methods in Economics

Our paper builds on a broader literature that treats text as economic data (Gentzkow et al., 2019; Hassan et al., 2025). This approach exploits the insight that language encodes information about beliefs, expectations, and perceived risks in real time as agents articulate their assessments through corporate disclosures, policy communications, and media coverage. Influential applications include Baker et al. (2016), who construct an economic policy uncertainty index from newspaper coverage; Hassan et al. (2019), who develop firm-level political risk measures from earnings calls; and Shapiro et al. (2022), who extract news sentiment to study macroeconomic effects. Related work has applied similar methods to central bank communication (Silva et al., 2025), social media (Cookson et al., 2023), and narrative-driven economic fluctuations (Shiller, 2020).

Methodologically, the literature has progressed from keyword-based approaches through supervised classifiers to dense text representations. Early applications relied on dictionaries or handcrafted rules (Baker et al., 2016; Hassan et al., 2019). The development of contextual embeddings from transformer models (Devlin et al., 2019), building on earlier distributed representations (Mikolov et al., 2013; Pennington et al., 2014), enabled richer text understanding but typically required supervised training for specific tasks. In economic applications, de Araujo et al. (2025) use embeddings from central bank communication to

forecast inflation, while Gu et al. (2024) apply embeddings of firm disclosures to predict post-announcement stock returns. Domain-specific models such as FinBERT (Huang et al., 2023) and ClimateBERT (Webersinke et al., 2022) demonstrate the potential of fine-tuned classifiers but remain constrained to their training domains.

More recently, large language models have offered zero-shot classification capabilities, allowing researchers to define categories through natural language prompts rather than labeled examples. While this flexibility is attractive, direct LLM classification of large corpora remains prohibitively expensive—processing our corpus of four million paragraphs would cost two orders of magnitude more without semantic pre-filtering—and produces non-deterministic results that complicate replication (**?**).

Our semantic retrieval approach occupies a distinct position in this methodological landscape. Drawing on advances in dense retrieval from information retrieval, particularly bi-encoder architectures (Reimers and Gurevych, 2019a) and approximate nearest-neighbor search (Karpukhin et al., 2020; Johnson et al., 2019), we define economic concepts through query sets and retrieve passages by embedding similarity. This combines the transparency and efficiency of keyword methods with the semantic sophistication of contextual embeddings, without requiring labeled data or model retraining. The optional second-stage LLM refinement layer exploits the 99.4% corpus reduction achieved by semantic filtering to make precise classification economically feasible—transforming LLMs from prohibitively expensive classifiers into practical precision instruments applied to pre-filtered subsets. This modular architecture allows researchers to choose their preferred point on the cost-accuracy frontier while maintaining scalability across different risk taxonomies and time periods.

III Data

A. Earnings Call Conference Transcripts

We obtain quarterly earnings call transcripts from FactSet for all firms included in the S&P 500 and STOXX 600 indices over the period 2010–2024. The dataset covers both prepared management remarks and question-and-answer sessions with financial analysts. Table 1 reports descriptive statistics. The final dataset contains 51,567 transcripts covering 1,486 unique firms, yielding approximately 4.4 million paragraphs. The S&P 500 sample

exhibits high stability (98.3% year-over-year retention), while the STOXX 600 sample shows more variation reflecting index rebalancing and data availability. Sample composition differences are addressed through firm fixed effects and region-specific analyses in empirical specifications. Appendix Table 10 reports the full yearly breakdown by region.

Table 1: Earnings Call Dataset

Note: Summary statistics for the earnings call transcript corpus. Transcripts are parsed into management discussion and Q&A sections and segmented into paragraphs. YoY retention rates show the percentage of firms appearing in consecutive years.

	EU (STOXX 600)	US (S&P 500)
Total Transcripts	21,827	29,740
Unique Firms	811	590
Total Paragraphs (millions)	1.8	2.6
Avg Words per Transcript	9,921	9,907
Avg Paragraphs per Transcript	82.4	86.7
Avg Years per Firm	8.0	12.6
YoY Firm Retention Rate	93.3%	98.3%

B. Financial Market and Accounting Data

Firm-level financial characteristics are obtained from Compustat (S&P Capital IQ), including firm size, book-to-market ratios, capital expenditures, R&D expenditures, cash holdings, and profitability measures. Variables are winsorized at the 1st and 99th percentiles and aligned to the earnings call timeline.

For U.S. firms, daily stock returns are from the CRSP Daily Stock File (accessed through WRDS), linked to Compustat via the CRSP/Compustat Merged Link Table (link types LC and LU). CRSP returns include delisting returns to avoid survivorship bias. For European firms, daily returns are constructed from Compustat Global Security Daily using adjusted prices: $P_{i,t}^{\text{adj}} = (P_{i,t}/\text{AJEXDI}_{i,t}) \times \text{TRFD}_{i,t}$, where AJEXDI adjusts for splits and TRFD incorporates dividends.

Cumulative abnormal returns (CARs) around earnings call dates are computed using the Fama-French five-factor model. For each firm-event, factor loadings are estimated over a 100-trading-day window ending 30 days before the event:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{\text{MKT}}(r_{m,t} - r_{f,t}) + \beta_i^{\text{SMB}}\text{SMB}_t + \beta_i^{\text{HML}}\text{HML}_t + \beta_i^{\text{RMW}}\text{RMW}_t + \beta_i^{\text{CMA}}\text{CMA}_t + \epsilon_{i,t},$$

$$(1)$$

requiring a minimum of 70 valid trading days. We examine event windows of $[0,0]$, $[-1,+1]$, $[0,+1]$, $[-1,+3]$, and $[-3,+5]$. U.S. and European daily factor returns are obtained from Kenneth French's data library.[2]

C. Carbon Emissions Data

Firm-level carbon emissions data are obtained from MSCI: annual Scope 1 and Scope 2 greenhouse gas emissions in metric tons of CO_2 equivalent, scaled by firm revenue to produce an emissions intensity measure. MSCI reports with a one-year publication lag; emissions are lagged accordingly in empirical specifications to ensure consistency with investors' information sets. We use the logarithm of emissions intensity in regression analysis.

D. Green Patent Data

We measure firm-level green innovation using patent data from Google Patents Public Datasets (accessed via BigQuery), focusing on patents classified under Cooperative Patent Classification codes for climate change mitigation technologies (Y02). Patents are linked to firms using fuzzy string matching between harmonized assignee names and company names in the earnings call dataset, then aggregated at the firm-year level by filing year. Firms without matched green patents in a given year are assigned zero.

IV   Method

This section describes the measurement pipeline that transforms raw earnings call transcripts into firm-quarter indicators of climate risk exposure. Figure 1 provides an overview. The architecture proceeds in four phases: corpus construction and semantic embedding (Phase I), theory-grounded retrieval using the TCFD taxonomy (Phase II), optional LLM refinement for maximum precision (Phase III), and aggregation into economic indicators (Phase IV). Each phase is described in turn.

Phase I: Data Infrastructure

We extract transcript text from each PDF and identify the two main sections of an earnings call: prepared management remarks and the question-and-answer session.[3] Call-level metadata—reporting date, fiscal quarter, firm name, and ticker—are harmonized using

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[2]Available at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.
[3]During this step, we also remove formatting noise and FactSet boilerplate statements.
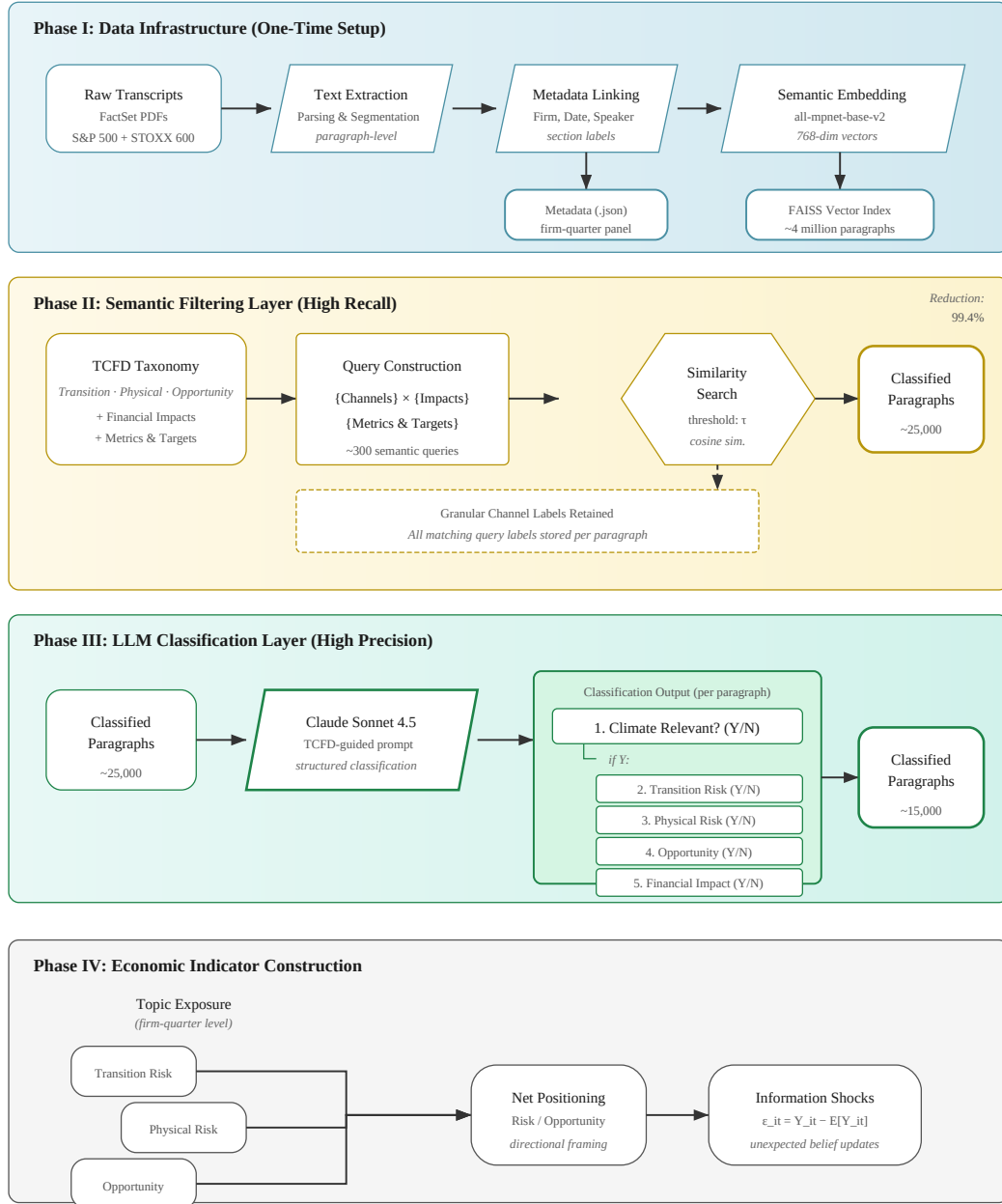
Figure 1: Semantic Measurement Pipeline

Figure 1: The pipeline converts raw earnings call transcripts into paragraph-level semantic representations, classifies climate-related risk and opportunity narratives, and aggregates them into firm-level economic indicators.

index-specific parsing rules that account for formatting differences between US and EU transcripts. Speaker turns are identified based on standardized cues, and each call is segmented into paragraphs, yielding a paragraph-level dataset in which each observation retains firm and call identifiers, temporal information, section labels (management or Q&A), and speaker metadata.[4]

Each paragraph is embedded into a dense vector representation using `all-mpnet-base-v2`, a general-purpose sentence transformer designed for semantic similarity tasks (Reimers and Gurevych, 2019b). Each paragraph p is mapped to a vector $\mathbf{x}_p \in \mathbb{R}^{768}$, L2-normalized so that inner products correspond to cosine similarity. Paragraphs conveying similar semantic content are mapped to nearby regions of the embedding space regardless of vocabulary or phrasing. The embedding step is deterministic and applied once to the full corpus.

The resulting embeddings are stored in a FAISS index for efficient approximate nearest-neighbor search (Johnson et al., 2019), enabling similarity queries over the full corpus of approximately four million paragraphs in sub-second time. Paragraph-level metadata are stored separately and linked to the index through stable keys, allowing flexible filtering and aggregation after retrieval.

A key advantage of this design is that embedding and indexing are performed only once. New topics can be analyzed by embedding a small set of query texts and querying the existing index, without reprocessing the corpus—contrasting sharply with supervised classifiers or LLM pipelines that require retraining or repeated full-corpus inference for each new construct.

Phase II: Semantic Search Layer

The next step is to identify climate-relevant content through semantic similarity search. Rather than relying on ad-hoc keyword selection, we ground query construction in the Task Force on Climate-related Financial Disclosures (TCFD) taxonomy, which provides a systematic framework for identifying the channels through which climate-related risks and opportunities may materially affect firms (Task Force on Climate-related Financial Disclosures, 2017).

The TCFD framework organizes climate-related business impacts into three categories: transition risks (policy, technology, market, and reputation changes), physical risks (acute

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[4]Speaker-level metadata are retained but not exploited in this paper.

and chronic climate impacts), and climate-related opportunities (resource efficiency, energy sources, products/services, markets, and resilience). Each category contains a hierarchical taxonomy extending from broad categories down to specific impact channels.

We construct queries using a bottom-up approach starting at the most granular level of the TCFD taxonomy. For each lowest-level risk or opportunity channel, we create multiple query variants that capture both the source of exposure and its potential business impacts, recognizing that firms may discuss climate factors either in terms of their underlying drivers or their anticipated effects on operations and financial performance. Table 2 illustrates this process with representative examples. Beyond risk and opportunity sources, we include queries based on the TCFD "Metrics & Targets" pillar to capture climate-related disclosures such as carbon footprints, emissions reduction targets, and exposed assets. In total, this yields approximately 340 distinct semantic queries across all TCFD categories.

Table 2: Query Construction Examples

TCFD Pillar	Risk/Opportunity Channel	Financial Impact	Example Queries
Transition Risk	Carbon pricing mechanisms	Increased costs	"carbon tax implementation", "emissions trading scheme costs", "carbon pricing regulatory compliance"
Transition Risk	Technology shifts	Capital expenditure	"renewable energy transition costs", "stranded fossil fuel assets", "clean technology investment requirements"
Physical Risk	Extreme weather events	Supply chain disruption	"flooding impact on operations", "hurricane supply chain disruption", "weather-related facility damage"
Physical Risk	Sea level rise	Asset impairment	"coastal facility flooding risk", "infrastructure climate adaptation", "sea level rise asset exposure"
Opportunity	Energy efficiency	Cost reduction	"energy efficiency cost savings", "operational efficiency improvements", "reduced energy consumption benefits"
Opportunity	Renewable energy	Revenue generation	"clean energy revenue opportunities", "renewable energy market growth", "green product demand increase"
Metrics & Targets	Emissions measurement	Risk management	"carbon footprint reporting", "scope 3 emissions tracking", "net zero commitment progress"

Each economic concept c is represented by a set of query texts $Q^c = \{q_1^c, \ldots, q_M^c\}$, embedded using the same sentence transformer that produced the paragraph embeddings. For every paragraph p with embedding $\mathbf{x}_p$, we compute its similarity to concept c as:

$$\text{sim}(p, c) = \max_{j \in \{1, \ldots, M\}} \mathbf{x}_p^T \mathbf{q}_j^c \tag{2}$$

The maximum operation ensures that a paragraph is considered relevant if it exhibits high similarity to any query in the concept's query set, capturing the diverse ways that economic concepts may be expressed. We apply this separately for each TCFD category, yielding distinct similarity scores for physical risks, transition risks, and climate opportunities for every paragraph in the corpus. The computation leverages the FAISS index to efficiently retrieve high-similarity paragraphs without exhaustive pairwise comparisons.

To convert continuous scores into binary classifications, we impose concept-specific thresholds τ^c: a paragraph is classified as relevant to concept c if $\text{sim}(p, c) > \tau^c$. We optimize thresholds through density-weighted validation that concentrates annotation effort in similarity score regions where threshold choice most affects classification performance. The validation protocol is detailed in Section V.

Phase III: LLM Classification Layer

The semantic search layer provides classified paragraphs suitable for many downstream analyses. However, semantic queries are intentionally permissive to maximize recall: a query designed to capture transition risks may also retrieve passages discussing related opportunities or neutral climate content. When applications require maximum precision in distinguishing between risk dimensions, we deploy a second-stage classification layer that refines the semantic search results.

This two-stage architecture confines computationally expensive LLM processing to the subset of paragraphs already identified as climate-relevant—a 99.4% reduction from the original corpus. We implement this layer using Claude Sonnet 4 via Anthropic's Batch API, which processes paragraphs in groups of 40 with structured prompts based on the TCFD taxonomy. Each paragraph receives six classifications: climate relevance, transition risk, physical risk, opportunity, financial impact channel, and impact direction. The structured prompt guides the model to distinguish between risks and opportunities that may be semantically similar but economically distinct.

The cost savings from semantic pre-filtering are substantial: processing the full corpus costs approximately $43 with the two-stage approach, compared to over $3,800 for direct LLM classification without filtering—a 100-fold reduction that makes systematic analysis of corporate climate discourse practical for standard research budgets. All subsequent empirical analyses employ the precision layer classifications, while robustness checks using semantic

17

search scores alone are provided in the appendix.

Phase IV: Economic Indicator Construction

The objective of our measurement framework is to construct firm-level indicators that capture the intensity of discussion around climate-related topics. We view an earnings call as a finite allocation of managerial attention across competing issues, and we use the distribution of textual content within the call to quantify this attention.

Let i index firms and t index quarters. Each earnings call is represented as a collection of paragraphs $\{(p_{it})_j\}_{j=1}^{P_{it}}$, where P_{it} denotes the total number of paragraphs in firm i's earnings call in quarter t. Let L_j denote the number of sentences in paragraph j, and $N_{it} = \sum_{j=1}^{P_{it}} L_j$ denote the total number of sentences in the call. The classification pipeline produces paragraph-level labels indicating relevance to specific climate-related categories and channels. We can construct indicators using either the semantic search classifications alone (Phase II) or the refined LLM classifications (Phase III), depending on their precision requirements.

For each of the three primary TCFD categories $c \in \{\text{Physical Risk, Transition Risk, Opportunity}\}$, we define $\mathcal{S}_{it}^c \subset \{(p_{it})_j\}$ as the subset of paragraphs classified as relevant to concept c. The primary exposure measure is the share of the conference call (measured in sentences) devoted to concept c:

$$\text{TopicExposure}_{it}^c = \frac{\sum_{j \in \mathcal{S}_{it}^c} L_j}{N_{it}} \tag{3}$$

This normalization yields a scale-free attention measure that is comparable across firms and time periods regardless of transcript length. The multi-label nature of our classification means that $\sum_c \text{TopicExposure}_{it}^c$ may exceed the total share of climate-relevant discussion, as paragraphs can contribute to multiple exposure measures simultaneously.

Beyond these aggregate measures, our framework enables construction of more granular exposure indicators for specific TCFD subchannels, such as carbon pricing mechanisms, climate litigation, or renewable energy opportunities. However, our downstream empirical analyses focus primarily on the three aggregate category measures, which provide sufficient granularity for most economic research applications while maintaining statistical power.

V Validation

This section establishes that our measures are both technically accurate and economically meaningful. We first evaluate classification performance against manually annotated data and established benchmarks (Subsection A). We then assess whether the resulting measures exhibit properties necessary for their use in applied empirical research: selective rather than boilerplate attention, predominantly firm-specific variation, and cross-sectional alignment with observable climate exposure (Subsections B–D).

A. Classification Performance

Converting continuous similarity scores to binary classifications requires concept-specific thresholds τ^c for each TCFD category. For standalone semantic search, we optimize thresholds to maximize F1-scores. For the first stage of our two-stage approach, we deliberately lower thresholds to maximize recall, since the LLM layer filters false positives. We validate threshold choices using density-weighted sampling, which divides similarity score space into 0.05-width bins and samples paragraphs proportional to population density. Manual annotation of sampled paragraphs enables computation of performance metrics weighted by bin density, ensuring reported accuracy reflects expected performance on the full corpus.

Table 3 reports results. Panel A compares our approach against ClimateBERT (Webersinke et al., 2022), a transformer model fine-tuned on climate-related financial disclosures and the current state-of-the-art for supervised climate content detection. Our two-stage method achieves substantially higher precision (0.93 vs. 0.47) while maintaining competitive recall (0.70 vs. 0.79), yielding a superior F1-score (0.86 vs. 0.58). Even our semantic search layer alone outperforms ClimateBERT in F1-score (0.61 vs. 0.58) despite requiring no domain-specific training data.

Panels B and C break down performance by TCFD category. The semantic search layer shows balanced performance across categories, with physical risk classification proving most challenging (recall 0.40), likely reflecting lower prevalence in the corpus. The LLM refinement layer delivers precision consistently above 0.90 across all categories while maintaining recall between 0.69 and 0.77, demonstrating the value of the two-stage architecture.

We also evaluate on the ClimateBERT detection dataset—the expert-labeled corpus on which ClimateBERT was trained. On this home-turf comparison, ClimateBERT achieves

precision of 0.98, recall of 0.98, and F1 of 0.98; our semantic search achieves 0.96, 0.85, and 0.90 respectively. Our approach delivers competitive results on a dataset specifically curated for the supervised model, without any domain-specific training.

Table 3: Classification Performance: Semantic Search and LLM Layers

Note: Classification performance for the two-stage measurement pipeline. Panel A benchmarks against ClimateBERT on our earnings call corpus. Panels B and C report category-level performance for the semantic search layer and the full two-stage method. Metrics are weighted by bin population density from stratified sampling validation.

Panel A: Benchmark Comparison (general climate)				
Method	Precision	Recall	F1	Threshold
Our Method (Two-stage)	0.93	0.70	0.86	——
Semantic Search Only	0.79	0.49	0.61	0.58
ClimateBERT	0.47	0.79	0.58	0.90

Panel B: Semantic Search Layer				
Category	Precision	Recall	Threshold	Sample Size
Physical Risk	0.78	0.40	0.58	400
Transition Risk	0.62	0.58	0.62	400
Opportunity	0.59	0.63	0.61	400
Climate (All)	0.79	0.56	0.58	400

Panel C: Two-stage Method (Semantic + LLM)				
Category	Precision	Recall	Threshold	Sample Size
Physical Risk	0.94	0.69	0.55	400
Transition Risk	0.90	0.74	0.59	400
Opportunity	0.93	0.77	0.59	400
Climate (All)	0.93	0.70	0.56	400

B. Distributional Properties

Table 4 reports summary statistics for the climate attention measures. The average firm devotes 0.60% of earnings call content to climate-related discussion, with substantial right-skew: the median is near zero while the 95th percentile reaches 3.87%. This pattern—many firms with minimal discussion and a tail of high-attention firms—is consistent across all climate dimensions. Physical risk discussion is rarest (mean 0.15%), while climate opportunities are discussed more frequently (mean 0.59%). The sparsity suggests that climate attention reflects selective engagement with material exposure rather than routine disclosure language.

Table 4: Descriptive Statistics for Climate-Related Semantic Measures

Note: Descriptive statistics for semantic climate indicators from earnings call transcripts (2009–2025). Values represent percentages of total sentences per call. Main categories in bold; subcategories indented. $N = 51{,}567$ earnings calls.

Variable	Mean	Std.Dev.	Min	P95	Max	% Zero
Physical Risk	0.15	0.80	0.00	0.83	23.24	92.7
Acute	0.07	0.51	0.00	0.00	18.28	95.9
Chronic	0.04	0.36	0.00	0.00	11.85	97.6
Transition Risk	0.14	0.86	0.00	0.52	30.78	94.3
Policy	0.04	0.45	0.00	0.00	30.78	98.0
Legal	0.00	0.07	0.00	0.00	5.08	99.7
Technology	0.03	0.33	0.00	0.00	12.64	98.1
Market	0.04	0.37	0.00	0.00	17.24	97.9
Reputation	0.00	0.11	0.00	0.00	11.47	99.8
Opportunity	0.59	2.05	0.00	3.64	37.81	80.6
Energy Source	0.27	1.20	0.00	1.54	31.19	88.4
Products & Services	0.13	0.69	0.00	0.88	26.65	91.7
Markets	0.06	0.48	0.00	0.00	18.68	96.3
Resource Efficiency	0.12	0.62	0.00	0.74	36.62	92.5
Resilience	0.17	1.01	0.00	0.76	28.25	93.3

Table 5 decomposes variation across time, industry, and firm dimensions. Year fixed effects explain 5% of variation in general climate attention, while industry fixed effects explain an additional 4%. The bulk of variation (88%) occurs at the firm level, indicating that climate attention is primarily a firm-specific characteristic rather than an industry or time phenomenon. Within-firm, firm fixed effects explain 53% of variance for general climate attention, implying roughly half reflects persistent firm characteristics while the other half varies over time. This concentration of variation at the firm level is essential for our empirical design: it ensures the measures capture meaningful heterogeneity across firms within the same industry that cannot be proxied by sector dummies.

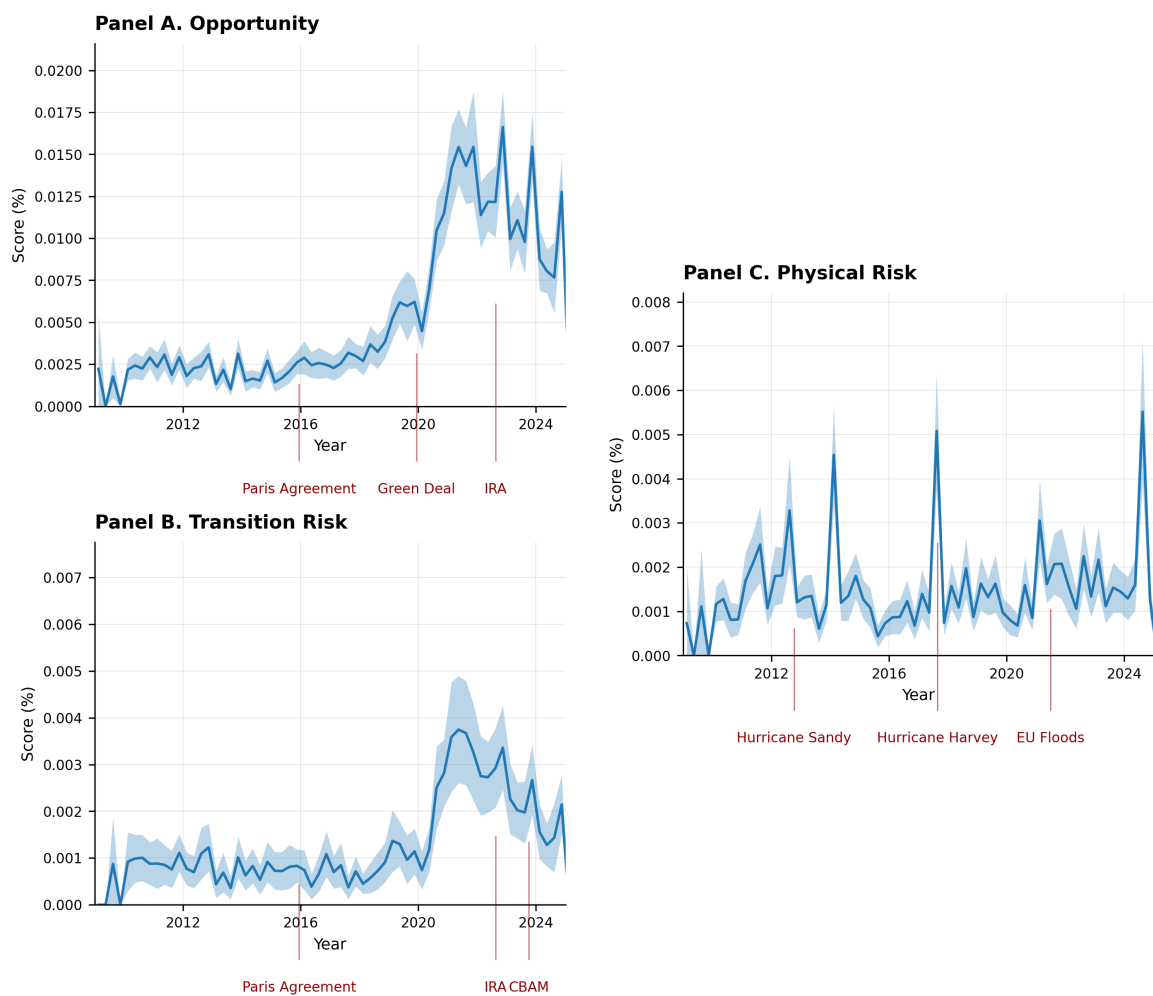**Figure 2: Evolution of Climate Risk Attention in Corporate Earnings Calls, 2009–2024.** Time series of climate-related attention across three dimensions from earnings call transcripts. All measures are expressed as percentages of total sentences. The sample includes S&P 500 and STOXX 600 firms. Vertical red lines indicate key climate policy milestones. Shaded areas represent 95% confidence intervals.

Table 5: Variance Decomposition of Climate-Related Semantic Measures

Note: Panel A reports incremental R^2 from regressions including year, industry, industry×year, country, and firm fixed effects. Panel B shows the share of within-firm variation explained by firm fixed effects.

			Panel A: Incremental R^2			
Variable	Year FE	Industry FE	Ind.×Year FE	Country FE	Firm-level	Sum
General	5.0%	3.9%	2.2%	0.6%	88.2%	100%
Regulation	0.9%	1.7%	2.0%	0.0%	95.4%	100%
Transition	5.2%	3.9%	2.3%	0.8%	87.7%	100%
Physical	0.6%	0.5%	3.7%	0.3%	94.8%	100%

	Panel B: Within-Firm Fraction of Variation		
Variable	Firm FE	Residual	Sum
General	53.1%	46.9%	100%
Regulation	34.2%	65.8%	100%
Transition	52.2%	47.8%	100%
Physical	20.2%	79.8%	100%

C. Cross-Sectional Validity

If the measures capture economically meaningful climate exposure, sectors with higher emissions or greater regulatory exposure should exhibit systematically higher climate attention. Table 6 reports sector-level averages for the three main TCFD dimensions. Utilities rank first in overall climate attention (2.09%), followed by Energy (1.11%) and Automobiles (0.95%)—sectors with substantial carbon footprints and direct exposure to transition policies. For transition risk specifically, Utilities and Energy again lead, consistent with their exposure to decarbonization pressures. Physical risk attention is highest in Automobiles (0.05%) and Insurance (0.04%), reflecting exposure to supply chain disruptions and weather-related claims respectively. Appendix Table **??** reports additional breakdowns by regulation and opportunity dimensions.

Table 6: Sector-Level Climate Attention

Note: Sector-level averages of climate-related semantic measures from earnings call transcripts, expressed as percentages of total sentences per call. Top ten sectors by mean exposure shown for each panel. Sample spans 2009–2025.

Panel A: Overall Climate Attention

Sector	Mean (%)	Std.Dev. (%)	P95 (%)	N Calls	N Firms
Utilities	2.09	4.36	10.77	1,155	32
Energy	1.11	2.93	7.01	1,097	25
Automobiles & Components	0.95	2.66	6.22	725	15
Real Estate Mgmt & Dev.	0.89	2.44	5.00	559	15
Media & Entertainment	0.82	2.39	5.48	833	22
Materials	0.73	2.60	4.85	2,877	67
Capital Goods	0.69	2.31	4.60	4,632	121
Semiconductors	0.63	2.16	4.40	1,008	22
Consumer Services	0.62	2.34	4.28	1,142	30

Panel B: Transition Risk

Sector	Mean (%)	Std.Dev. (%)	P95 (%)	N Calls	N Firms
Utilities	0.18	1.14	0.67	1,155	32
Energy	0.14	0.95	0.00	1,097	25
Real Estate Mgmt & Dev.	0.09	0.66	0.00	559	15
Materials	0.07	0.65	0.00	2,877	67
Food & Staples Retailing	0.06	0.55	0.00	1,034	25
Automobiles & Components	0.06	0.44	0.00	725	15
Consumer Services	0.05	0.52	0.00	1,142	30
Consumer Durables & Apparel	0.05	0.49	0.00	1,828	45

Panel C: Physical Risk

Sector	Mean (%)	Std.Dev. (%)	P95 (%)	N Calls	N Firms
Automobiles & Components	0.05	0.50	0.00	725	15
Insurance	0.04	0.33	0.00	4,315	103
Real Estate Mgmt & Dev.	0.03	0.39	0.00	559	15
Utilities	0.03	0.34	0.00	1,155	32
Consumer Services	0.03	0.26	0.00	1,142	30
Capital Goods	0.02	0.28	0.00	4,632	121
Materials	0.02	0.17	0.00	2,877	67

VI Climate Attention and Green Innovation

The preceding section established that our measures are technically accurate and exhibit sensible statistical properties. We now test whether they contain economically meaningful information about firms' actual strategic decisions. Specifically: does climate attention in earnings calls predict green innovation, or is it cheap talk?

This question matters both as validation and as a substantive finding. If firms that discuss climate opportunities and transition risks subsequently file more green patents and invest more in R&D—conditional on their existing innovative capacity—then the measures capture genuine forward-looking beliefs about climate positioning rather than performative disclosure. Establishing this is a prerequisite for the asset pricing analysis that follows, where

we ask whether markets price the same information.

We document three findings. First, opportunity and transition risk attention positively predict future green patenting, while physical risk attention does not. Second, climate attention amplifies the productivity of R&D spending in generating green patents: firms that both discuss climate opportunities or risks and invest heavily in R&D produce disproportionately more green patents than either factor alone would predict. Third, within-firm variation over time shows that elevated climate attention precedes increased R&D intensity, consistent with forward-looking investment commitments rather than ex-post rationalization.

A. Baseline Specification: Climate Attention and Green Patenting

Green innovation is measured using firm-level counts of green patent applications filed in year $t + 1$, with climate attention measured in year t. Since patent data are available only annually, we aggregate quarterly climate attention scores to firm-year measures by taking the mean across all earnings calls within each calendar year. The timing reflects that patenting is a lagged outcome of research activity initiated in response to strategic priorities revealed in corporate disclosures.

Because the dependent variable is a non-negative count with many zeros and a right-skewed distribution, we estimate the model using Poisson pseudo-maximum likelihood (PPML).[5]

A distinct challenge is distinguishing shifts in the <u>direction</u> of innovation toward green technologies from differences in firms' overall innovative capacity. More innovative firms produce more patents of all types, including green patents, and firms that patented green technologies in the past are more likely to do so again. To address this, all specifications control for both lagged green patenting (capturing persistence and path dependence) and patent stock, a perpetual-inventory measure of accumulated innovative capacity:

$$\text{PatentStock}_{i,t} = (1 - \delta)\,\text{PatentStock}_{i,t-1} + \text{TotalPatents}_{i,t},$$

where $\delta = 0.15$ is an annual depreciation rate following Hall (2007). Together, these controls allow us to ask whether climate attention predicts <u>additional</u> green innovation conditional on a firm's history of green patenting and its overall innovative capacity.

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[5]PPML provides consistent estimates under the weaker assumption that the conditional mean is correctly specified, without requiring that the data follow a true Poisson distribution (Silva and Tenreyro, 2006). This robustness is valuable given that patent counts typically exhibit overdispersion. PPML also handles zeros without requiring ad hoc transformations and avoids the retransformation problem of log-linearized OLS.

All specifications include industry-by-year fixed effects, so identification relies on within-industry-year variation: among firms in the same sector facing identical external conditions, do those emphasizing climate opportunities or risks innovate more in green technologies? This design addresses the concern that green patenting and climate attention could both respond to common industry-level drivers without one causing the other.

For each attention dimension $A_{i,t} \in \{\text{Opportunity}, \text{Transition Risk}, \text{Physical Risk}\}$, the baseline specification is:

$$E[\text{GreenPatents}_{i,t+1} \mid \mathcal{I}_{i,t}] = \exp\big(\beta A_{i,t} + \rho\,\text{GreenPatents}_{i,t} + \kappa\,\text{PatentStock}_{i,t} + \delta'\mathbf{X}_{i,t} + \gamma_{j\times t}\big),$$
(4)

where $\gamma_{j\times t}$ denotes industry-by-year fixed effects and $\mathbf{X}_{i,t}$ includes R&D intensity, capital expenditure intensity, cash holdings, headline return on equity, firm size (log total assets), and carbon emission intensity (log Scope 1–2 emissions per million USD revenue). Coefficients represent semi-elasticities: β on a standardized attention measure implies a $100 \times (e^{\beta} - 1)$ percent change in expected green patent counts. Standard errors are clustered at the firm level.

Table 7 reports baseline results. Opportunity attention enters with a coefficient of 0.23, implying that a one-standard-deviation increase is associated with approximately 26 percent more green patent applications in the following year. Transition risk attention is also positive and significant (0.11), corresponding to roughly 12 percent more green patents. Physical risk attention enters negatively (-0.29), consistent with physical risk operating as a contextual factor rather than a direct innovation driver.

Table 7: Climate Attention and Green Innovation: Baseline Results

Notes: Poisson pseudo-maximum likelihood estimates on an unbalanced firm-year panel (2009–2025). The dependent variable is the count of green patent applications filed in year $t+1$. Climate attention scores are standardized to have mean zero and unit variance. All specifications include industry-by-year fixed effects. Standard errors clustered at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Dependent variable	Green Patents$_{t+1}$			
	(1) Baseline	(2) Opportunity	(3) Transition	(4) Physical
Opportunity score (std.)		0.23***		
		(0.07)		
Transition risk score (std.)			0.11***	
			(0.03)	
Physical risk score (std.)				-0.29**
				(0.14)
Green Patents (1000s)	1.30**	1.30**	1.30**	1.30**
	(0.61)	(0.61)	(0.61)	(0.61)
Log Assets	0.38**	0.38**	0.38**	0.37**
	(0.16)	(0.16)	(0.16)	(0.16)
Scope 1–2 intensity (log)	-0.12	-0.12	-0.11	-0.11
	(0.11)	(0.11)	(0.11)	(0.11)
CAPEX / Assets	8.60***	8.60***	8.58***	8.54***
	(3.22)	(3.22)	(3.20)	(3.24)
Cash / Assets	-0.85	-0.85	-0.87	-0.96
	(0.87)	(0.87)	(0.88)	(0.91)
Cash / Assets (missing)	1.97*	1.97*	1.96*	1.94*
	(1.08)	(1.08)	(1.08)	(1.07)
Total Patents (1000s)	0.02	0.02	0.02	0.00
	(0.07)	(0.07)	(0.07)	(0.07)
R&D missing	-2.19***	-2.19***	-2.19***	-2.19***
	(0.25)	(0.25)	(0.24)	(0.25)
Headline ROE	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-0.42	-0.42	-0.47	-0.45
	(1.72)	(1.72)	(1.73)	(1.73)
Observations	9,859	9,859	9,859	9,859
Industry-year FE	Yes	Yes	Yes	Yes
Estimator	Poisson Pseudo-Maximum Likelihood			

B. R&D Expenditures and the Direction of Investment

The baseline results establish that climate attention predicts green patenting conditional on innovative capacity. But do firms that emphasize climate opportunities and risks actually allocate investment differently? If climate attention reflects cheap talk, the mapping from R&D to green patents should be similar across firms regardless of their climate discourse. If it signals genuine strategic reorientation, a given level of R&D spending should translate into more green innovation among firms that emphasize climate opportunities or transition

risks.

We test this by augmenting the baseline PPML specification with R&D intensity (standardized) and its interaction with climate attention:

$$E[\text{GreenPatents}_{i,t+1} \mid \mathcal{I}_{i,t}] = \exp\big(\beta_1 A_{i,t} + \beta_2 \text{R\&D}_{i,t} + \beta_3 A_{i,t} \times \text{R\&D}_{i,t} + \mathbf{Z}'_{i,t} + \gamma_{j \times t}\big),$$

where $\mathbf{Z}_{i,t}$ includes lagged green patenting, patent stock, and standard firm controls.

Table 8 reports results. The interaction between opportunity attention and R&D is positive and significant (0.18, s.e. 0.06), indicating that the marginal product of R&D spending in generating green patents is higher among firms emphasizing climate opportunities. The interaction with transition risk attention is even larger (0.50, s.e. 0.07). These estimates imply economically meaningful heterogeneity: among firms at the 75th percentile of opportunity attention, a one-standard-deviation increase in R&D is associated with roughly 65 percent more green patents, compared to 37 percent at the 25th percentile. This pattern is difficult to reconcile with cheap talk—if climate discourse were merely performative, the productivity of R&D in generating green innovation should not vary systematically with disclosure.

Table 9 addresses a complementary question: does climate attention predict changes in overall R&D intensity? Within-firm regressions show that opportunity and transition risk attention both positively predict subsequent R&D spending (coefficients of 0.03 and 0.02 respectively), while physical risk attention shows no association. Firms increase total R&D investment when they perceive climate-related opportunities or transition risks, reinforcing the interpretation that climate attention reflects substantive strategic shifts.

Taken together, the evidence points to a consistent conclusion: climate attention is associated with both the scale and direction of innovative investment. Firms discussing climate opportunities and transition risks spend more on R&D and convert that spending into green patents more efficiently. These results establish that our discourse-based measures capture genuine forward-looking beliefs about climate positioning—the foundation for the asset pricing analysis in the next section.

Table 8: Climate Attention, R&D Investment, and Green Innovation

Dependent variable	(1) Opportunity × R&D	(2) Transition Risk × R&D
	Green Patents$_{t+1}$	
Opportunity score (std.)	0.24***	
	(0.07)	
Transition risk score (std.)		0.12***
		(0.03)
R&D (std.)	0.32***	0.37***
	(0.11)	(0.10)
Opportunity × R&D	0.18***	
	(0.06)	
Transition risk × R&D		0.50***
		(0.07)
Lagged green patents	0.00***	0.00***
	(0.00)	(0.00)
Patent stock	-0.00	-0.00
	(0.00)	(0.00)
Log Assets	0.48***	0.48***
	(0.16)	(0.16)
CAPEX / Assets	6.43*	6.51*
	(3.80)	(3.81)
Scope 1–2 intensity (log)	-0.09	-0.08
	(0.09)	(0.10)
Headline ROE	-0.00	-0.00
	(0.00)	(0.00)
Intercept	-2.03	-2.09
	(1.65)	(1.65)
Observations	9,859	9,859
Industry-year FE	Yes	Yes
Estimator	Poisson Pseudo-Maximum Likelihood	

Notes: Poisson pseudo-maximum likelihood estimates. Standard errors clustered at the firm level in parentheses. Opportunity, transition risk, and R&D variables are standardized to mean zero and unit variance. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Within-Firm Effects of Climate Attention on R&D Investment

	(1) Opportunity	(2) Transition Risk	(3) Physical Risk
Dependent variable		R&D / Assets	
Opportunity score	0.03***		
	(0.01)		
Transition risk score		0.02**	
		(0.01)	
Physical risk score			-0.00
			(0.01)
Lagged green patents	0.00**	0.00**	0.00**
	(0.00)	(0.00)	(0.00)
Patent stock	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Log Assets	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Cash / Assets	-0.01**	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)
CAPEX / Assets	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)
Scope 1–2 intensity (log)	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Headline ROE	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Intercept	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)
Observations	9,084	9,084	9,084
Firm fixed effects	Yes	Yes	Yes
Estimator		Linear regression (within-firm)	

Notes: Linear fixed-effects regressions exploiting within-firm variation. All specifications include firm fixed effects. Standard errors clustered at the firm level. The dependent variable is R&D expenditures scaled by total assets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

VII   Climate Attention Shocks and Short-Window Returns

Having established that climate attention measures predict real corporate decisions, we now turn to the central question: does the information revealed in climate discourse enter asset prices, and if so, under what conditions?

This section tests whether unexpected climate attention—the component of a firm's climate discussion not explained by fundamentals, sector trends, or its own recent trajectory—predicts abnormal stock returns around earnings calls. We exploit the Paris Agreement as a natural experiment in policy credibility and document three findings: markets price climate attention asymmetrically across risk types; the sign of transition risk pricing reversed for European firms after Paris; and the magnitude of repricing responses attenuates over time

as climate risk becomes more fully incorporated into prices.

A. Hypotheses

We organize predictions around three themes: risk materiality, the dynamics of repricing, and cross-regional heterogeneity.

Standard asset pricing theory implies that risk shocks produce negative contemporaneous returns as prices adjust to reflect newly perceived exposure, while simultaneously raising expected future returns through a risk premium (Pástor et al., 2021; Bansal et al., 2019; Giglio et al., 2021). A precondition is that investors recognize climate exposures as material risks. The extent to which they do so likely depends on the credibility of climate policy: absent binding commitments, transition costs remain speculative; once policy becomes credible, these costs become sufficiently certain to warrant repricing. The Paris Agreement (December 2015) provides a sharp change in this credibility. Before Paris, discussing transition risks may have signaled managerial awareness, producing weakly positive or neutral market reactions. After Paris, and the subsequent tightening of EU policy instruments, the same disclosure reveals exposure to transition costs that markets now treat as material. We therefore predict that transition risk attention shocks produce negative abnormal returns in the post-Paris period, reflecting markets recognizing transition exposure as material, while producing zero or positive returns pre-Paris, when climate policy lacked the credibility needed for markets to interpret such disclosure as revealing genuine cost exposure. For opportunity attention, the prediction is unambiguous: firms signaling climate-related growth options disclose positive net present value prospects regardless of the policy regime. Physical risk attention is theoretically ambiguous, as discussing exposure to extreme weather could reveal vulnerability or demonstrate proactive risk management.

Second, the distinction between repricing and risk premia is central to interpreting climate-return relationships (Pástor et al., 2022; Giglio et al., 2021). When climate risk is first recognized as material, information shocks trigger discrete price adjustments. As risk becomes more fully incorporated into equilibrium prices, the marginal information content of climate disclosure declines: what was once news becomes expectation. We therefore expect the magnitude of abnormal returns associated with climate attention shocks to decline over time within the post-Paris period, as progressive incorporation shifts the dominant channel from repricing to risk premia.

Third, the speed and magnitude of repricing should vary with the local policy environment. European firms operate under a more credible and rapidly tightening regime, including the reformed EU ETS, the European Green Deal, and binding sectoral regulations, which should produce stronger initial repricing responses to transition risk attention shocks than those observed for US firms. However, if European markets have been repricing for longer, a greater share of transition risk may already be reflected in prices, and the differential may narrow over time. For US firms, greater policy uncertainty, amplified by shifting federal administrations and the absence of comprehensive carbon pricing, implies that transition risk disclosure carries more ambiguous information content.

B. Constructing Climate Attention Shocks

Identifying market responses requires isolating the *unexpected* component of climate attention. We construct attention shocks using a two-part hurdle model that reflects the data structure: most firm-quarters contain zero climate discussion, with a right-skewed distribution conditional on engagement.

The *extensive margin* models whether firm i discusses climate dimension d in quarter t:

$$P\Big(A_{i,t}^d > 0 \mid \mathcal{I}_{i,t-1}\Big) = \Phi\big(\alpha'\mathbf{X}_{i,t-1} + \gamma_{j\times t}\big), \tag{5}$$

where $\mathbf{X}_{i,t-1}$ includes lagged firm controls (assets, cash, capital expenditure, emission intensity, patent stock) and $\gamma_{j\times t}$ denotes sector-by-year fixed effects.

The *intensive margin* models attention depth conditional on engagement. On the subsample with $A_{i,t}^d > 0$:

$$E\Big[A_{i,t}^d \mid A_{i,t}^d > 0, \mathcal{I}_{i,t-1}\Big] = \Lambda\big(\beta'\mathbf{X}_{i,t-1} + \delta_{j\times t}\big), \tag{6}$$

estimated via quasi-maximum likelihood with a binomial family and logit link. Both stages include lagged attention $A_{i,t-1}^d$ to ensure shocks reflect new information rather than predictable persistence. Residuals are normalized by sector-year standard deviations for cross-sectional comparability.

C. Measuring Abnormal Returns

Cumulative abnormal returns (CARs) around earnings call dates are computed using the

Fama-French five-factor model estimated over a pre-event window (described in Section III). We examine windows of $[-1, +1]$, $[-1, +3]$, and $[-3, +5]$ trading days. Results are presented as Q5–Q1 spreads: the difference in average CARs between the highest and lowest shock quintiles.

D. Results

Figure 3 establishes the baseline relationship across the full sample (2010–2024), pooling regions and years. Three patterns emerge. Transition risk attention shocks predict negative abnormal returns: Q5–Q1 spreads are approximately -15 to -25 basis points, statistically significant at the $[-1, +3]$ and $[-3, +5]$ windows. Opportunity attention shocks predict positive abnormal returns of comparable magnitude, significant at shorter windows. Physical risk attention shows no consistent relationship with returns. Markets respond differentially to the three dimensions of climate discourse, treating transition exposure as a risk and climate-related growth prospects as value-relevant.

Figure 4 decomposes these estimates by policy regime (pre- versus post-Paris) and region (US versus Europe).

The bottom-left panel reveals the central finding. For European firms, transition risk attention shocks are associated with *positive* abnormal returns pre-Paris, with Q5–Q1 spreads reaching approximately $+100$ basis points at $[-3, +5]$. Post-Paris, the relationship inverts: high transition risk attention predicts *negative* abnormal returns of approximately -50 basis points. This swing of roughly 150 basis points is consistent with H1: before credible policy commitments, discussing transition risks signaled awareness that markets rewarded; after Paris made decarbonization binding, the same disclosure revealed material cost exposure, triggering downward price adjustments.

This reversal does not appear for US firms. Both pre- and post-Paris spreads are small and statistically insignificant, with no directional pattern, directly supporting H3a: the European policy environment made transition costs sufficiently credible for markets to price them, while US policy uncertainty left the information content ambiguous. The contrast provides a within-sample placebo: the same measurement framework, applied to firms facing different policy environments, produces exactly the pattern that theory predicts.

The opportunity panels reveal progressive price incorporation. In Europe, opportunity attention predicts large positive returns pre-Paris (approximately $+90$ basis points at $[-3, +5]$),
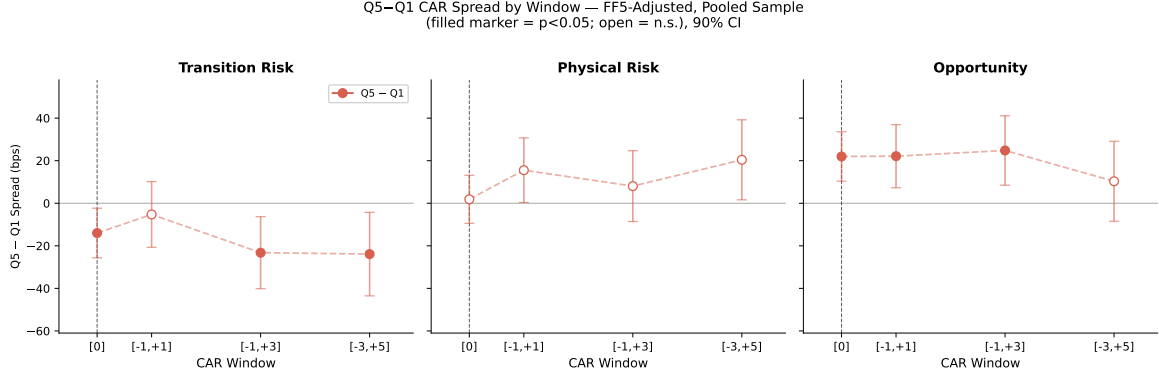
Figure 3: Q5–Q1 CAR Spreads by Climate Attention Dimension. Q5–Q1 spreads in cumulative abnormal returns (basis points) across four event windows for the full sample (2010–2024), pooling US and European firms. CARs computed using the Fama-French five-factor model. Filled markers indicate significance at $p < 0.05$; open markers indicate insignificance.

but these effects attenuate substantially post-Paris. This is suggestive of H2: as climate growth opportunities become widely anticipated, the marginal news content of earnings call discussion declines. The attenuation is less pronounced for US firms, consistent with European markets incorporating climate opportunity information more quickly.

Physical risk attention shows positive pre-Paris spreads for European firms that do not survive post-Paris, and no consistent pattern for US firms. Markets appear to lack well-developed frameworks for pricing physical hazard disclosure, or the information content of such discussion is genuinely ambiguous.

Table 13 reports corresponding regression estimates. The transition risk interaction with the post-Paris indicator is negative and significant; the opportunity interaction is negative, reflecting attenuation from a positive baseline. Appendix Table **??** confirms monotonic return patterns across quintiles.

E. Discussion

The results speak to two open questions in the climate finance literature.

The first concerns identification of the repricing mechanism. Pástor et al. (2022) show at the portfolio level that recent green outperformance reflects unanticipated shifts in climate concerns rather than high expected returns, but cannot pinpoint when or why repricing activates. Our event-study design identifies this mechanism at the firm-quarter level and locates its activation precisely at the point where policy credibility was established. The negative
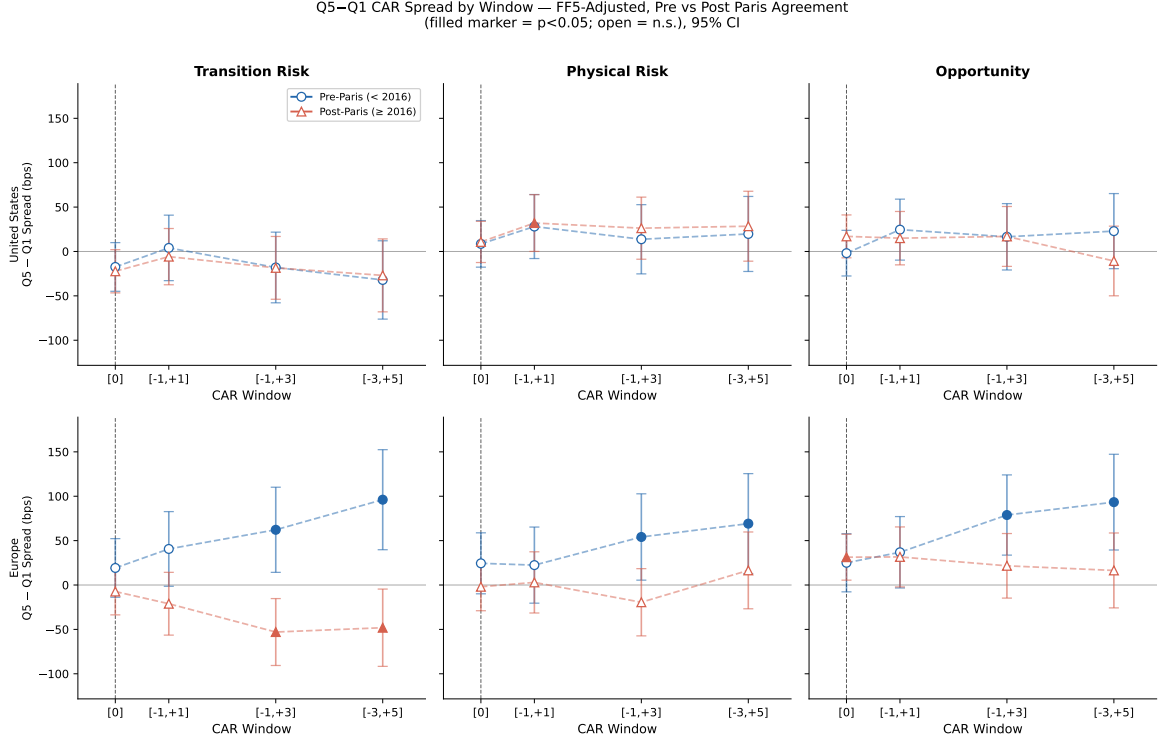
Figure 4: Q5–Q1 CAR Spreads by Region and Policy Regime. Q5–Q1 spreads
in cumulative abnormal returns (basis points) separately for pre-Paris (blue, before 2016)
and post-Paris (red, 2016 onward). Top row: United States. Bottom row: Europe. The
transition risk sign reversal for European firms (bottom left)—from +100 bps pre-Paris to
−50 bps post-Paris—is consistent with the Paris Agreement establishing sufficient policy
credibility for markets to price transition exposure as material risk.

post-Paris returns to transition risk disclosure in Europe are the contemporaneous price ad-
justments that, in equilibrium, generate a risk premium on exposed assets. Crucially, the
mechanism operates through perceived exposure revealed in discourse, not merely through
accounting-based emissions—markets penalize firms that *discuss* transition exposure, not
simply those with high direct carbon intensity.

The second concerns why existing studies have produced conflicting evidence on climate
risk pricing. Our regional decomposition suggests that much of the heterogeneity reflects
differences in policy environments rather than contradictory evidence about whether climate
risks are priced. Studies focused on US equities may find weak carbon premia not because
markets ignore climate risk, but because US policy uncertainty prevents transition costs from
becoming sufficiently credible for systematic repricing. The European evidence is consistent
with a market that has largely completed the initial repricing adjustment.

An important limitation is that our design identifies short-run price reactions, not long-

run value implications. The negative post-Paris returns are consistent with repricing, but firms penalized for transition risk disclosure may benefit from transparency in equilibrium if it reduces information asymmetry. Distinguishing repricing from the equilibrium risk premium requires longer horizons than our event windows permit. The attenuation of opportunity pricing post-Paris offers suggestive evidence that some dimensions are moving toward full incorporation, but formally testing whether transition risk repricing similarly attenuates within the post-Paris window would require finer temporal sub-splits, which we leave to future work.

VIII   Conclusion

This paper provides firm-level evidence on the conditions under which climate-related risks enter asset prices. We introduce a semantic search framework that combines embedding-based retrieval with large language model classification to extract climate-relevant passages from approximately 51,500 earnings call transcripts of S&P 500 and STOXX 600 firms over 2009–2025. The two-stage architecture achieves state-of-the-art classification accuracy (F1-score 0.86; precision 0.93) without labeled training data, while reducing computational costs by two orders of magnitude relative to direct LLM classification. By replacing rigid keyword dictionaries with flexible semantic queries and modular LLM refinement, the framework offers a general-purpose tool for text-based economic measurement: researchers can adapt it to new risk taxonomies – whether related to artificial intelligence, geopolitical tensions, or supply chain vulnerabilities – through query specification rather than model retraining.

Applied to climate risk, the framework produces high-frequency measures of perceived exposure that decompose corporate discourse into transition risks, physical risks, and opportunities. These measures capture forward-looking beliefs that static proxies such as carbon emissions or ESG ratings cannot isolate. We validate them against real outcomes: firms emphasizing climate opportunities file significantly more green patents and convert R&D spending into green innovation more efficiently, patterns inconsistent with cheap talk.

The central finding is that investors reprice assets in the days following information shocks about firms' climate risk exposure, but that this dynamic is governed by policy credibility. For European firms, transition risk attention shocks predict positive abnormal returns before the Paris Agreement but negative returns afterward—a swing of approximately

36

150 basis points consistent with the repricing mechanism that Pástor et al. (2021) characterize theoretically. Our event-study design identifies this mechanism at the firm-quarter level: once binding EU policy commitments made transition costs credible, disclosing exposure to these costs reveals downside risk, triggering contemporaneous price declines. No comparable reversal appears for US firms, where policy uncertainty leaves the information content of transition risk disclosure ambiguous.

This finding carries a broader implication for the climate finance literature. The negative contemporaneous returns generated by repricing work against the positive expected returns predicted in equilibrium, suggesting that conflicting empirical findings on the carbon premium may partly reflect the coexistence of these opposing forces in realized return data. Studies finding weak premia in US equities are consistent with our framework if US policy uncertainty prevents transition costs from becoming sufficiently credible for systematic repricing to begin. The attenuation of opportunity pricing over time further suggests that some dimensions of climate risk are progressively moving toward full price incorporation – a transition from the repricing channel to the equilibrium risk premium channel that theory predicts but that has been difficult to observe empirically.

Several limitations merit acknowledgment. Our design identifies short-run price reactions around earnings calls, not long-run value implications. Formally testing whether transition risk repricing attenuates within the post-Paris period, as convergence to equilibrium risk premia would imply, requires finer temporal decomposition than our current event windows permit. Our interpretation of the EU–US contrast relies on consistency with theoretical predictions rather than quasi-experimental identification in the strict sense. Finally, our measures capture the salience of climate topics in corporate discourse, which need not correspond one-to-one with the magnitude of underlying economic exposure.

As climate policy continues to evolve – for example with the implementation of the EU Carbon Border Adjustment Mechanism, the uncertain trajectory of US climate regulation, and emerging physical risk realizations – the framework developed here enables researchers to track how corporate climate perceptions and their market consequences shift in real time. The broader lesson is that the pricing of climate risk is not a static phenomenon to be estimated once, but a dynamic process whose speed and magnitude depend critically on the policy environment in which firms operate.

A   Data

Table 10: Earnings Call Dataset: Sample Composition by Year

Note: This table shows the temporal distribution of earnings call transcripts by year and region. The S&P 500 sample exhibits high stability with consistent firm participation, while the STOXX 600 sample shows more variation reflecting index rebalancing and data availability. Sample composition differences are addressed through firm fixed effects and region-specific analyses in empirical specifications.

Year	EU (STOXX600)		US (SP500)	
	Transcripts	Firms	Transcripts	Firms
2010	1,024	327	1,902	442
2011	1,135	368	2,012	448
2012	1,172	378	1,755	454
2013	1,229	387	1,829	464
2014	1,280	407	1,867	475
2015	1,449	558	1,736	477
2016	1,346	435	1,879	477
2017	1,362	438	1,908	489
2018	1,398	448	1,705	483
2019	1,541	518	1,907	488
2020	1,621	523	1,916	489
2021	1,036	532	1,937	491
2022	1,699	545	1,923	493
2023	1,728	557	1,941	496
2024	1,393	566	1,735	487
2025	1,414	567	1,788	491
Total / Unique	**21,827**	**811**	**29,740**	**590**

B Short-window returns

Table 11: Cumulative Abnormal Returns by Shock Type and Region (Pooled Sample)

Note: This table reports the coefficient on standardized attention shocks from regressions of CARs on shock quintile indicators, pooling across the full sample period (2010–2024). These estimates average over the pre/post Paris structural break and therefore understate regime-specific magnitudes. t-statistics in parentheses. Coefficients are in basis points. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	CAR[0]	CAR[-1,+1]	CAR[0,+1]	CAR[-1,+3]	CAR[-3,+5]	N
Panel A: Full Sample						
Transition Risk	-11.3	2.9	0.2	-12.9	-4.6	35,033
	(-1.61)	(0.31)	(0.02)	(-1.26)	(-0.40)	
Physical Risk	5.3	27.7***	23.2***	23.6**	47.6***	37,447
	(0.78)	(3.02)	(2.62)	(2.34)	(4.24)	
Opportunity	23.7***	29.6***	27.0***	31.5***	31.0***	38,921
	(3.36)	(3.30)	(3.09)	(3.20)	(2.79)	
Panel B: United States						
Transition Risk	-18.6*	-7.8	-10.3	-23.5*	-33.5**	18,393
	(-1.96)	(-0.62)	(-0.85)	(-1.68)	(-2.10)	
Physical Risk	10.8	43.7***	37.2***	36.8***	54.4***	19,805
	(1.21)	(3.50)	(3.07)	(2.70)	(3.61)	
Opportunity	14.6	26.6**	25.9**	30.1**	19.8	20,609
	(1.57)	(2.19)	(2.20)	(2.21)	(1.28)	
Panel C: Europe						
Transition Risk	-4.8	6.6	5.8	-6.3	24.2	16,640
	(-0.46)	(0.49)	(0.42)	(-0.42)	(1.42)	
Physical Risk	7.6	14.1	13.0	13.7	45.3***	17,642
	(0.72)	(1.05)	(1.01)	(0.92)	(2.72)	
Opportunity	34.0***	39.2***	35.7***	36.4**	50.0***	18,312
	(3.17)	(2.88)	(2.71)	(2.47)	(3.08)	

Table 13: Cumulative Abnormal Returns: Pre vs. Post Paris Agreement

Note: This table reports Q5–Q1 spreads in cumulative abnormal returns around earnings calls, separately for pre-Paris (2010–2015) and post-Paris (2016–2024) periods. CARs are computed using the Fama-French five-factor model. Quintiles are formed on climate attention shocks from the hurdle model. *t*-statistics in parentheses. Coefficients are in basis points. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	CAR[0]	CAR[-1,+1]	CAR[-1,+3]	CAR[-3,+5]
Panel A: Transition Risk				
Pre-Paris	18.2	21.4	58.7**	94.3***
	(1.12)	(1.24)	(2.31)	(2.89)
Post-Paris	-12.5	-35.2**	-48.1**	-52.6**
	(-0.89)	(-2.15)	(-2.34)	(-2.18)
Panel B: Physical Risk				
Pre-Paris	22.4	25.8	52.1*	74.2**
	(1.31)	(1.42)	(1.89)	(2.12)
Post-Paris	-4.2	2.3	-18.5	21.8
	(-0.28)	(0.14)	(-0.92)	(0.98)
Panel C: Opportunity				
Pre-Paris	24.1*	32.5**	78.4***	92.1***
	(1.72)	(2.18)	(3.42)	(3.15)
Post-Paris	18.6	22.4*	24.2	12.8
	(1.45)	(1.68)	(1.52)	(0.71)

Table 12: Firm Characteristics Across Attention Shock Quintiles

Note: This table reports mean firm characteristics across quintiles of climate attention shocks. Q1 contains firms with the most negative shocks (unexpectedly low attention); Q5 contains firms with the most positive shocks (unexpectedly high attention). The final column reports the Q5–Q1 difference with significance from a *t*-test. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Variable	Q1	Q2	Q3	Q4	Q5	Q5–Q1
Panel A: Transition Risk Shocks						
log(Total Assets)	10.27	9.89	9.54	9.17	9.35	-0.92***
Cash / Assets	0.08	0.11	0.13	0.16	0.16	0.08***
CapEx / Assets	0.05	0.04	0.04	0.03	0.04	-0.01***
log(Emission Intensity)	5.51	3.84	3.31	2.87	3.45	-2.05***
Patent Stock	1,256	1,673	1,061	1,105	970	-287
Panel B: Physical Risk Shocks						
log(Total Assets)	9.95	9.64	9.68	9.51	9.41	-0.55***
Cash / Assets	0.06	0.08	0.11	0.14	0.22	0.16***
CapEx / Assets	0.05	0.04	0.03	0.03	0.03	-0.02***
log(Emission Intensity)	5.17	3.90	3.42	3.03	3.25	-1.92***
Patent Stock	363	960	1,384	877	1,822	1,460***
Panel C: Opportunity Shocks						
log(Total Assets)	9.96	9.69	9.42	9.25	9.93	-0.03
Cash / Assets	0.09	0.11	0.14	0.18	0.10	0.00***
CapEx / Assets	0.04	0.04	0.04	0.03	0.04	0.00
log(Emission Intensity)	4.44	3.59	3.10	2.96	4.54	0.11***
Patent Stock	1,816	777	899	832	1,274	-542**

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