How do physical climate exposure and the quality of climate risk disclosure jointly affect market-perceived risk, as measured by idiosyncratic stock return volatility?

Maxime Cherix (maxime.cherix@unil.ch, https://github.com/maximecherix).

Abstract. This paper investigates how physical climate exposure and the quality of climate risk disclosure jointly affect market-perceived risk, measured by idiosyncratic stock return volatility. We construct a geographically grounded Physical Risk Score (PRS) using historical disaster data and a Disclosure Quality Score (DQS) derived from natural language processing of Form 10-K filings. By combining linear benchmarks with interpretable machine learning models, we document a robust nonlinear interaction. Markets penalize the opacity of low-quality disclosure with elevated volatility, while rewarding generic reporting with a "stability valley." High-quality disclosure acts as a revelation mechanism, significantly amplifying volatility; in this context, specific reporting resolves ambiguity but confirms risk, triggering a repricing effect. Conversely, for firms facing extreme physical exposure, high-quality disclosure appears to mitigate market uncertainty, thereby attenuating the associated volatility. These findings challenge the view that transparency is unconditionally stabilizing, suggesting instead that mandatory disclosure regimes may increase market turbulence by forcing exposed firms out of the safe harbor of boilerplate reporting.

1. Introduction.

Climate change has moved from an ethical or reputational issue to a material source of financial risk. The rising frequency and severity of extreme weather events disrupt production, supply chains, infrastructure, and labor, increasing uncertainty about firms' future cash flows. Physical climate risk has therefore become a central concern for financial markets, regulators, and risk managers.

At the same time, regulatory pressure on climate related disclosure has intensified. Firms are increasingly required to assess and report climate risks in their financial filings, especially in the Risk Factors section of Form 10 K. Yet disclosure quality remains highly uneven. Some firms provide detailed and firm specific information, while others rely on generic language, and disclosure volume does not necessarily imply disclosure quality.

Most of the climate finance literature studies whether climate risk affects asset prices, mainly through returns or risk premia. This paper instead examines how real physical exposure interacts with what firms choose to disclose. Specifically, we ask whether disclosure quality conditions how physical climate risk is reflected in markets.

We focus on stock return volatility rather than average returns. Volatility captures uncertainty and information asymmetry about future cash flows and is closely linked to the cost of capital, yet it remains relatively understudied in this literature.

This paper makes four contributions. We construct a Physical Risk Score based on historical disasters, develop a Disclosure Quality Score from Form 10 K texts using natural language processing, adopt an interaction centric framework to study how disclosure conditions the market impact of physical risk, and combine linear models with machine learning methods to uncover nonlinear and threshold effects.

2. Research Question and Literature.

2.1. Research Question.

This paper investigates how physical climate exposure and the quality of climate risk disclosure jointly affect firms' market-perceived risk. Formally, we ask:

> *How do physical climate exposure and the quality of climate risk disclosure jointly affect market-perceived risk, as measured by idiosyncratic stock return volatility?*

Market-perceived risk is captured through the idiosyncratic component of stock return volatility, isolating firm-specific uncertainty after controlling for common risk factors. Physical climate exposure is measured using a geographically grounded Physical Risk Score (PRS), while disclosure quality is proxied by a Disclosure Quality Score (DQS) derived from firms' legally binding climate disclosures in Form 10-K filings.

The central hypothesis of this paper is interaction-based. Physical climate exposure alone does not fully determine market risk; instead, its effect depends on how clearly and credibly firms communicate climate-related risks to investors. Specifically, we hypothesize that firms facing high physical climate

exposure but providing poor-quality disclosure experience elevated idiosyncratic volatility due to unre-
solved ambiguity and information asymmetry. Conversely, firms with high exposure and high-quality
disclosure may reduce ambiguity by clarifying risks, though such disclosure may also confirm adverse
information and lead to higher volatility if risks are revealed to be material. In this sense, disclosure
can act both as an ambiguity-reducing mechanism and as an information-revealing channel.

2.2. Climate Risk Pricing.
A growing body of literature examines whether climate risk is priced
in financial markets. Early contributions such as Bansal et al. [1] and Bolton and Kacperczyk. [3]
document that firms with higher carbon emissions or climate exposure earn different expected returns,
suggesting that climate risk commands a risk premium. Pankratz et al. [9] further show that extreme
weather events can negatively affect firm profitability and stock performance.

While this literature establishes the relevance of climate risk for asset prices, it primarily focuses
on returns, factor loadings, or valuation effects. Relatively little attention is paid to volatility as
an outcome variable, despite its direct interpretation as market uncertainty. Moreover, most studies
treat climate exposure as an unconditional firm characteristic, abstracting from the role of corporate
disclosure in shaping investor perceptions of climate risk.

2.3. Disclosure and Information Asymmetry.
A second strand of literature studies corporate dis-
closure and its impact on information asymmetry, risk, and asset prices. Classical theories emphasize
that higher-quality disclosure can reduce uncertainty and lower the cost of capital by improving in-
formation transparency. However, in the context of climate risk, disclosure incentives are complex.
Firms may strategically engage in selective disclosure or greenwashing, providing vague or boilerplate
statements that comply with regulatory requirements without conveying meaningful information.

Empirical work on climate-related disclosure documents substantial heterogeneity in disclosure
practices and mixed market responses. While some studies find that increased disclosure is associated
with lower risk and higher firm value through reductions in information asymmetry [7, 10], others
show that detailed disclosure can increase perceived risk or the cost of capital by revealing previously
unpriced transition or physical exposures [6, 3]. Importantly, much of this literature relies on linear
models and aggregate disclosure measures, which may fail to capture nonlinear interactions between
exposure and disclosure quality, including phenomena such as cheap talk or greenwashing [2, 11].

2.4. Machine Learning in Asset Pricing.
Recent advances in machine learning have introduced
flexible tools for modeling complex, nonlinear relationships in asset pricing. Studies such as Gu, Kelly,
and Xiu [5] demonstrate that machine learning models can outperform traditional linear specifica-
tions in predicting returns and risk. However, the use of machine learning raises concerns about
interpretability and economic meaning.

In response, a growing literature emphasizes interpretable machine learning techniques, such as
feature importance measures and SHAP values, which allow researchers to extract economically mean-
ingful insights from nonlinear models. In this paper, machine learning models are treated as function
approximators rather than black boxes, enabling the identification of interaction effects and nonlinear
thresholds in the relationship between climate risk, disclosure quality, and volatility.

3. Methodology.
This section describes the construction of the target variable, the physical cli-
mate exposure metric, the disclosure quality measure, and the financial controls used in the empirical
analysis. The methodology combines classical asset pricing techniques with natural language process-
ing and machine learning to isolate firm-level climate-related uncertainty.

3.1. Target Variable: Idiosyncratic Volatility.
To measure market-perceived firm-specific risk,
we construct an annual idiosyncratic volatility measure based on the Fama–French five-factor model
(FF5). The FF5 model is known to absorb a large share of cross-sectional return variation, meaning
that the remaining residual volatility more plausibly reflects firm-specific information shocks, including
climate-related uncertainty. More complex factor models or latent factor approaches could mechani-
cally reduce residual variance without improving economic interpretability. For each firm i and month
t, excess stock returns are modeled as

100 (3.1)
$$R_{i,t} - R_{f,t} = \alpha_i + \boldsymbol{\beta}_i^\top \mathbf{F}_t + \varepsilon_{i,t}.$$

101 where $R_{i,t}$ denotes the firm's return, $R_{f,t}$ the risk-free rate, and $\mathbf{F}_t = (MKT_t, SMB_t, HML_t, RMW_t, CMA_t)^\top$
102 the vector of Fama–French factors.
103 Under standard assumptions, the variance of excess returns admits the decomposition

104 (3.2)
$$\mathrm{Var}(R_{i,t}) = \boldsymbol{\beta}_i^\top \Sigma_F \boldsymbol{\beta}_i + \mathrm{Var}(\varepsilon_{i,t}),$$

105 where Σ_F is the covariance matrix of factor returns. The first term captures systematic (factor-driven)
106 risk, while the second term represents idiosyncratic risk.
107 For each firm-year, idiosyncratic volatility is computed as the standard deviation of monthly
108 residuals within the calendar year:

109 (3.3)
$$\sigma_{i,y}^{\mathrm{id}} = \sqrt{12} \cdot \sqrt{\frac{1}{T_y - 1} \sum_{t \in y} \varepsilon_{i,t}^2},$$

110 where T_y denotes the number of available monthly observations in year y. The factor $\sqrt{12}$ annualizes
111 the monthly volatility.
112 This construction isolates firm-specific uncertainty perceived by the market, net of common risk
113 factors. Unlike expected returns, idiosyncratic volatility captures uncertainty rather than average
114 outcomes and is directly linked to firms' cost of capital, investment decisions, and risk management
115 behavior.

116 **3.2. Physical Risk Score (PRS).** Physical climate exposure is measured using a Physical Risk
117 Score (PRS) constructed from historical disaster data.
118 We focus on major climate-related hazard categories, including floods, storms, droughts, wildfires,
119 and extreme temperature events. For each state s and disaster type h, we compute five raw indica-
120 tors: long-term frequency, long-term severity, recent frequency, recent severity, and a temporal trend
121 component.
122 To ensure comparability across hazard types, each indicator is standardized within disaster type:

123 (3.4)
$$Z_{s,h,k} = \frac{X_{s,h,k} - \mu_{h,k}}{\sigma_{h,k}},$$

124 where $X_{s,h,k}$ denotes indicator k for state s and hazard h, and $(\mu_{h,k}, \sigma_{h,k})$ are the mean and standard
125 deviation across states for that hazard.
126 We then construct a long-term exposure index and a recent exposure index at the state–hazard
127 level:

128 (3.5)
$$L_{s,h} = \frac{1}{2} \left(Z_{s,h}^{\mathrm{freq,LT}} + Z_{s,h}^{\mathrm{sev,LT}} \right),$$

129 (3.6)
$$R_{s,h} = \frac{1}{3} \left(Z_{s,h}^{\mathrm{freq,REC}} + Z_{s,h}^{\mathrm{sev,REC}} + Z_{s,h}^{\mathrm{trend}} \right).$$

130 Aggregating across hazards yields state-level exposure measures:

131 (3.7)
$$PRS_s = \frac{1}{2} \left(\frac{1}{H} \sum_h L_{s,h} + \frac{1}{H} \sum_h R_{s,h} \right),$$

132 where H denotes the number of hazard categories. Firms are mapped to states using headquarters
133 location, assigning each firm the PRS of its primary state of operation.
134 This construction captures both persistent climate risk and recent intensification, reflecting the
135 evolving nature of physical climate exposure.

3.3. Disclosure Quality Score (DQS). Disclosure quality is measured using firms' legally binding climate disclosures in Form 10-K filings. Specifically, we extract Item 1A (Risk Factors), which is the primary section where firms are required to discuss material risks, including climate-related ones.

The text is segmented into overlapping chunks of up to 512 tokens to match the input constraints of transformer-based language models. Each chunk is processed using ClimateBERT [12], a domain-specific language model fine-tuned on climate-related corpora.

For each chunk, we extract the following probabilities:
- p^{det}: probability that the text is climate-related,
- p^{spec}: probability that the disclosure is specific rather than boilerplate,
- p^{phys}, p^{trans}: probabilities that the content relates to physical or transition risk.

Disclosure volume alone is not informative: lengthy risk sections may contain no meaningful climate information, while concise disclosures may be highly specific. Accordingly, volume is not equated with quality.

Thus, we define a Disclosure Quality Score (DQS) that combines relevance, content quality, and risk signaling:

$$(3.8) \qquad \text{DQS}_{i,t} = \text{Relevance}_{i,t} \times \left(0.5 \cdot \text{Specificity}_{i,t} + 0.5 \cdot \text{RiskSignal}_{i,t}\right),$$

where relevance acts as a gate ensuring that only climate-related content contributes to the score.

The relevance component uses p^{det}. If the model detects the text is generic (non-climate), the multiplier is 0, forcing the entire DQS to 0. The specificity one uses p^{spec}. It rewards companies that use concrete language (e.g., "\$50M asset exposure") over vague "we monitor risks" statements. The Risk Signal represents the $\max(p^{\text{phys}}, p^{\text{trans}})$. It rewards the strength of the dominant risk signal. It does not penalize a firm that would mitigates physical risks while not mentioning transition risks, or vice versa.

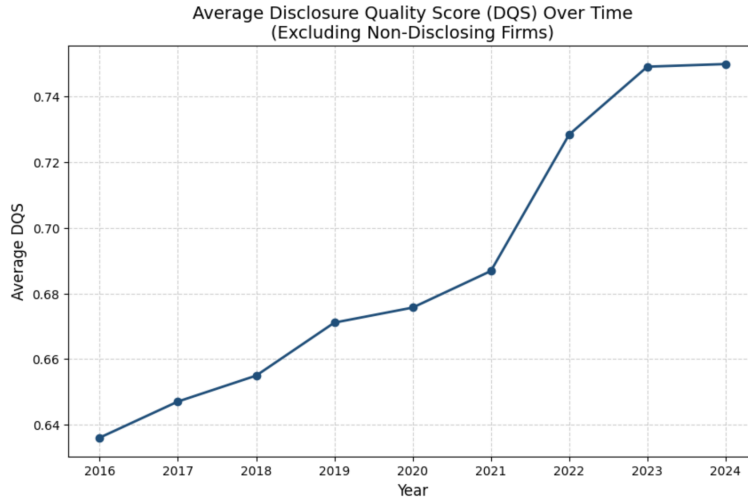Figure 1 shows the average DQS over the analysis period (excluding non-disclosing firms).

Figure 1.

4. Data Description. This section describes the data sources, sample construction, and key variables used in the empirical analysis. All datasets are publicly available or accessible through academic licenses, ensuring transparency and replicability.

4.1. Data Sources.

Stock Returns. Equity return data are obtained from the Center for Research in Security Prices (CRSP) database via Wharton Research Data Services (WRDS), accessed through HEC Lausanne. Monthly stock returns are used to estimate firm-level idiosyncratic volatility through a factor-based decomposition. CRSP provides a comprehensive and survivorship-bias-free coverage of U.S. publicly traded firms.

169   *Firm Fundamentals.* Accounting data used to construct financial control variables are sourced from
170   the COMPUSTAT North America database via WRDS, accessed through HEC Lausanne. These data
171   include balance sheet and income statement items required to compute leverage, profitability, liquidity,
172   growth, and valuation measures.
173   *Climate Risk Disclosure.* Textual data for climate disclosure analysis are drawn from Form 10-K
174   filings retrieved from the SEC EDGAR system. The filings are accessed through the University of
175   Notre Dame repository [8], which provides cleaned and raw versions of 10-K documents suitable for
176   large-scale natural language processing. The analysis focuses on the *Risk Factors* (Item 1A) section,
177   which is legally required and subject to regulatory scrutiny.
178   *Physical Climate Risk.* Data on natural disaster events are obtained from the Emergency Events
179   Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters [4].
180   The dataset covers the period 1900–2024 and provides detailed information on disaster type, location,
181   frequency, and severity. EM-DAT is widely used in the climate economics and disaster risk literature.

182   **4.2. Sample Construction.** The empirical universe consists of all US publicly traded firms with at
183   least 75% of revenues generated in the United States. This restriction, implemented via COMPUSTAT
184   data, ensures that physical climate risks measured at the U.S. state level are economically material to
185   firm operations and cash flows.
186   The sample period spans 2016–2024. Financial and climate variables are aggregated at the annual
187   firm-year level, yielding an unbalanced panel that reflects entry, exit, and reporting availability. Firm
188   headquarters locations are used to map companies to state-level physical climate risk measures. Figure
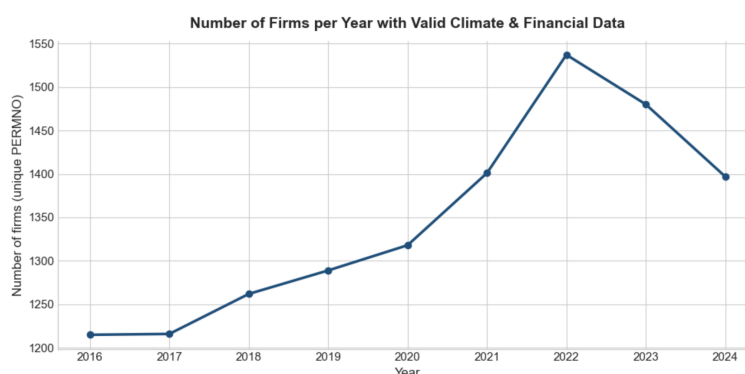189   2 displays the number of firms per year with valid climate and financial data.

Figure 2.

190   **4.3. Financial Control Variables.** To isolate the incremental effect of physical climate exposure
191   and disclosure quality on firm-level uncertainty, the analysis includes a set of standard financial controls
192   commonly associated with stock volatility.

- **Size** (log market capitalization): larger firms tend to exhibit lower idiosyncratic volatility due
  to diversification, scale, and greater analyst coverage.
- **Leverage** (total debt over total assets): higher leverage amplifies sensitivity to shocks and
  increases equity risk.
- **Profitability** (ROA, ROE): more profitable firms generally display more stable cash flows and
  lower uncertainty.
- **Liquidity** (cash over total assets): liquidity buffers reduce vulnerability to adverse shocks.
- **Growth** (asset growth): rapid expansion is associated with higher operational and financing
  uncertainty.
- **Valuation** (book-to-market ratio): captures differences between growth and value firms, which
  exhibit distinct volatility profiles.

204   These controls ensure that estimated climate-related effects are not confounded by well-established
205   financial determinants of idiosyncratic volatility.

5. Implementation. This section describes the end-to-end implementation of the empirical pipeline, emphasizing reproducibility, scalability, and methodological discipline. All steps were implemented in Python, following a modular architecture that separates data ingestion, feature engineering, modeling, and interpretation.

5.1. Pipeline Overview. The empirical workflow is organized into five sequential stages:

1. **Raw Data Ingestion.** Multiple raw datasets are imported independently: daily stock prices and returns, firm-level accounting data, natural disaster records, and regulatory filings. Each source is first cleaned and standardized within its own domain before any merging occurs, reducing the risk of compounding errors.

2. **Feature Engineering.** Two core explanatory variables are constructed:
   - The *Physical Risk Score (PRS)*, derived from historical disaster frequency, severity, and trends at the U.S. state level.
   - The *Disclosure Quality Score (DQS)*, extracted from Item 1A of 10-K filings using transformer-based natural language processing.

   Financial control variables are computed from firm fundamentals and aligned to the same annual frequency.

3. **Volatility Decomposition.** Firm-level idiosyncratic volatility is computed by estimating Fama–French five-factor regressions on monthly excess returns and extracting the variance of the residuals. This step transforms raw market data into a target variable that reflects firm-specific uncertainty rather than systematic risk.

4. **Model Training.** Machine learning models are trained to predict idiosyncratic volatility from PRS, DQS, their interaction, and financial controls. Hyperparameters are tuned using cross-validation on the training sample only.

5. **Validation and Interpretation.** Out-of-sample performance is evaluated on a holdout period. Model outputs are interpreted using coefficient analysis for linear models and feature importance and SHAP values for nonlinear models.

This modular structure allows each component of the analysis to be inspected, validated, and modified independently.

5.2. Modeling Strategy. The modeling strategy follows a progressive logic, moving from simple and interpretable models to more flexible nonlinear approaches.

ElasticNet Regression.. As a disciplined linear benchmark, we estimate an ElasticNet regression of future idiosyncratic volatility on physical risk exposure, disclosure quality, their interaction, and standard financial controls:

$$(5.1) \qquad y_{i,t+1} = \alpha + \beta_1 \, \mathrm{DQS}_{i,t} + \beta_2 \, \mathrm{PRS}_i + \beta_3 \left(\mathrm{DQS}_{i,t} \times \mathrm{PRS}_i \right) + \sum_k \gamma_k \, \mathrm{Control}_{k,i,t} + \varepsilon_{i,t},$$

where $y_{i,t+1}$ denotes the annualized idiosyncratic volatility of firm i in year $t+1$, extracted from the Fama–French five-factor model. All explanatory variables are standardized prior to estimation.

ElasticNet combines ℓ_1 (Lasso) and ℓ_2 (Ridge) regularization, allowing for simultaneous variable selection and shrinkage. This is particularly important in the present setting, where financial controls are correlated and climate-related variables may have weak but incremental explanatory power. By tuning the regularization strength and the Lasso–Ridge mixing parameter via cross-validation, ElasticNet provides a parsimonious and stable benchmark against which more flexible nonlinear models can be evaluated.

Random Forest Regressor.. Random Forests are employed to capture nonlinear effects and interaction structures that linear models may miss. In particular, they allow for threshold effects and heterogeneous responses of volatility to physical risk and disclosure quality. Feature importance measures provide a first-order assessment of variable relevance.

Gradient Boosting Regressor.. Gradient Boosting is used as a robustness check. By sequentially fitting weak learners to residuals, it often achieves higher predictive accuracy in structured tabular data. Consistency of results across ElasticNet, Random Forest, and Gradient Boosting strengthens confidence that the findings are not model-specific artifacts.

5.3. Data Splitting and Validation. To preserve temporal ordering and avoid look-ahead bias, a time-based split is adopted:

- **Training period:** 2016–2021
- **Test period:** 2022–2023

This approach mirrors a realistic forecasting exercise, in which models are trained on past information and evaluated on unseen future data. It enhances causal credibility by ensuring that disclosure quality and physical risk measures precede the volatility outcomes they aim to explain.

Within the training period, cross-validation is used exclusively for hyperparameter tuning. The test set is held out until final evaluation, providing an unbiased assessment of out-of-sample performance.

5.4. Computational Tools. The implementation relies on a modern open-source data science stack:

- **Python** for data processing and orchestration.
- **scikit-learn** for model estimation, regularization, and validation.
- **HuggingFace Transformers** for climate-specific natural language processing using pre-trained ClimateBERT models.
- **SHAP** for interpretable machine learning and visualization of marginal effects.

Together, these tools enable a transparent, reproducible, and scalable implementation that aligns with best practices in applied machine learning and empirical finance.

6. Results. This section presents the empirical findings of the study. We proceed from the linear benchmark to increasingly flexible machine learning models, highlighting how the interaction between physical climate exposure and disclosure quality consistently emerges as a key determinant of market-perceived risk.

6.1. ElasticNet Regression. Table 1 reports the results of the ElasticNet regression estimated on the sample of firms with climate-related disclosures. Several findings stand out.

Table 1

Elastic Net Regression Results (Test Set: 2022–2023)

Feature	Coefficient
Cash ratio	0.0345
PRS × DQS	0.0059
PRS	0.0042
Leverage	0.0027
Asset growth	0.0005
DQS	0.0000
ROE	0.0000
Book-to-market	0.0000
Equity ratio	−0.0176
ROA	−0.0444
Log market cap	−0.1085

Notes: The table reports standardized Elastic Net coefficients estimated on the test sample (2022–2023). The dependent variable is annualized idiosyncratic stock return volatility. All explanatory variables are standardized. The model includes an intercept (estimated at 0.3175). Performance metrics on the test set are $R^2 = 0.269$ and RMSE = 0.3246.

First, the Disclosure Quality Score (DQS) has a zero coefficient when considered in isolation. This suggests that disclosure quality, by itself, does not systematically reduce or increase idiosyncratic volatility. In other words, markets do not reward disclosure per se.

Second, the interaction term between physical exposure and disclosure quality, PRS × DQS, is positive and robust across regularization parameters. This suggests that climate disclosure becomes informative only when it is conditioned on real physical exposure.

Third, the financial control variables behave in line with theoretical expectations. Firm size (log market capitalization) is negatively associated with idiosyncratic volatility, reflecting diversification

and informational advantages. Higher leverage and asset growth are associated with increased volatility, while profitability measures tend to dampen firm-specific risk. These patterns lend credibility to the specification and suggest that the climate-related effects are not driven by omitted firm characteristics.

While the ElasticNet captures broad associations and enforces parsimony through regularization, its linear structure necessarily restricts interaction effects to a predefined form and cannot accommodate nonlinear thresholds or regime shifts in market responses. To relax these constraints, we next estimate a Random Forest Regressor.

6.2. Random Forest Regressor. Table 2 reports the Gini feature importance from the Random Forest Regressor. The out of sample R^2 increases from approximately 0.269 under ElasticNet to 0.359, representing a gain of roughly 33% in explanatory power relative to the linear benchmark. This performance leap provides strong evidence that the determinants of idiosyncratic volatility exhibit fundamentally nonlinear patterns and interaction effects that cannot be fully captured by linear specifications.

Table 2
Random Forest Gini Feature Importance

Feature	Importance
ROA	0.2778
log_mktcap	0.2293
ROE	0.1651
asset_growth	0.0820
book-to-market	0.0671
cash_ratio	0.0565
equity_ratio	0.0419
leverage	0.0240
DQS	0.0232
PRS×DQS	0.0215
PRS	0.0118

Notes: The table reports Gini feature importance, which reflects the relative frequency with which each variable is used to split nodes across trees. It captures predictive relevance but not the sign of the effect. Performance metrics on the test set are $R^2 = 0.3587$ and RMSE = 0.3040.

Consistent with financial theory, profitability measures emerge as the dominant predictors of volatility. Return on assets (ROA) is the most important feature, followed by firm size and return on equity, confirming that standard balance sheet fundamentals account for a large share of market perceived risk. At the same time, climate related variables contribute meaningful marginal predictive power beyond these traditional controls.

In contrast to the linear model, the Random Forest assigns non zero importance to the Disclosure Quality Score (DQS), with an importance weight of approximately 2.3%. This marks a sharp departure from the ElasticNet results, where DQS is entirely shrunk to zero. The Random Forest also treats disclosure and the interaction between disclosure and physical risk exposure as distinct and valuable signals. This suggests that disclosure quality also matters when evaluated jointly with underlying physical exposure rather than in isolation.

To further interpret the nonlinear mechanisms captured by the Random Forest, Figure 3 presents SHAP values along three complementary dimensions.

Panel (a) displays the SHAP summary plot, ranking features by their overall contribution to predicted idiosyncratic volatility. Consistent with prior results, traditional financial controls dominate the upper part of the distribution.

Panel (b) focuses on the marginal effect of disclosure quality on volatility. The dependence plot reveals a pronounced nonlinear pattern. At very low disclosure levels (DQS < 0.1), SHAP values are predominantly positive, indicating an uncertainty penalty for firms that provide little or no climate

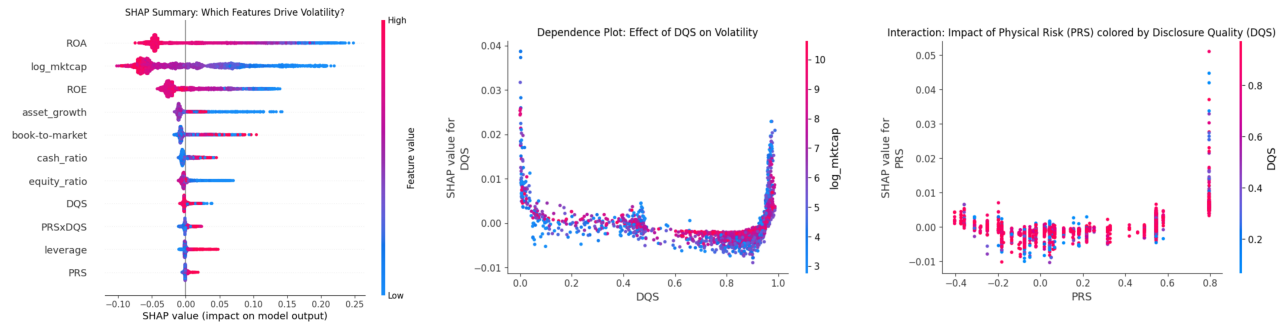**Figure 3.** *SHAP Values: Random Forest Regressor*

related information. As disclosure quality increases into an intermediate range (DQS ≈ 0.2–0.8), SHAP values cluster tightly around zero or become slightly negative, forming a stability valley in which moderate disclosure reduces information asymmetry without triggering adverse market reactions. At very high disclosure levels (DQS > 0.9), SHAP values rise sharply, producing a revelation shock. Extremely specific disclosure appears to act as negative confirmation of material risk, leading to higher predicted volatility.

Panel (c) examines the interaction between physical climate exposure (PRS) and disclosure quality (DQS). For firms with low to moderate physical exposure, SHAP values remain close to zero across the full range of disclosure quality, indicating that climate narratives have little impact when physical risk is immaterial. In contrast, a sharp spike in SHAP values emerges at high levels of physical exposure (PRS ≈ 0.8), signaling a strong increase in predicted idiosyncratic volatility. Importantly, the upper part of this spike is dominated by blue points, corresponding to low disclosure quality. This pattern indicates that, for highly exposed firms, omitting or downplaying physical climate risk amplifies market perceived uncertainty. In other words, when physical risk is severe, silence is interpreted negatively by the market and results in higher volatility. High disclosure quality does not eliminate volatility in this regime but appears to partially mitigate the uncertainty premium associated with extreme exposure. Overall, this interaction plot confirms that markets penalize opacity most strongly when physical climate risk is high, reinforcing the notion that disclosure and disclosure–risk interaction are distinct informational channels.

6.3. Gradient Boosting Regressor. The Gradient Boosting Regressor serves as a robustness check and further reinforces the nonlinear interaction patterns identified in the Random Forest analysis. Out-of-sample predictive performance remains strong and comparable to the Random Forest model, with a test-set R^2 of 0.330 and an RMSE of 0.311 (Table 3), indicating that the results are not driven by a specific tree-based architecture.

Feature importance rankings largely mirror those obtained under Random Forest, with firm fundamentals—particularly profitability (ROA) and size—remaining the dominant predictors of idiosyncratic volatility. Importantly, the interaction term between physical risk and disclosure quality (PRS × DQS) receives even greater relative importance under Gradient Boosting, ranking above standalone disclosure measures. This shift suggests that Gradient Boosting places more weight on localized nonlinear regions where disclosure quality meaningfully conditions the effect of physical risk exposure.

SHAP diagnostics (Figure 4) confirm and sharpen the interaction-centric interpretation. Overall, the Gradient Boosting results corroborate the central finding that markets respond nonlinearly to disclosure quality, and its combination with physical risk.

7. Conclusion. This paper provides a novel perspective on climate finance by demonstrating that the market pricing of physical climate risk is fundamentally conditional on corporate disclosure. By integrating a Physical Risk Score with a sophisticated NLP-based Disclosure Quality Score, we show that idiosyncratic volatility—a proxy for market uncertainty—responds nonlinearly to the interaction of these two forces.

Our results challenge the assumption of a simple linear relationship between disclosure and market stability. Instead, we identify two distinct mechanisms. First, independent of physical exposure, we

Table 3

Gradient Boosting Gini Feature Importance

Feature	Importance
ROA	0.4410
log_mktcap	0.1984
cash_ratio	0.0978
asset_growth	0.0579
book-to-market	0.0425
PRS×DQS	0.0394
DQS	0.0374
ROE	0.0316
equity_ratio	0.0275
leverage	0.0199
PRS	0.0066

Notes: The table reports Gini feature importance, which reflects the relative frequency with which each variable is used to split nodes across trees. It captures predictive relevance but not the sign of the effect. Performance metrics on the test set are $R^2 = 0.3300$ and RMSE = 0.3107.
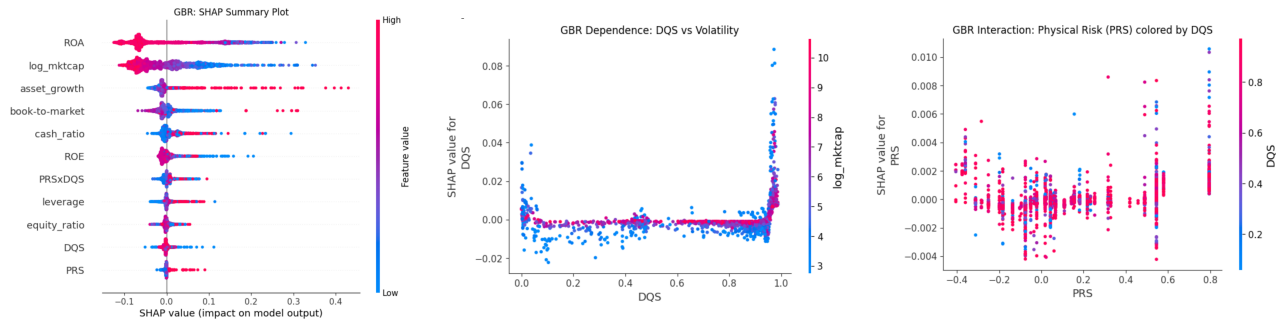

Figure 4. *SHAP Values: Random Forest Regressor*

document a non-linear volatility response to disclosure quality: markets penalize the opacity of very low disclosure (an "uncertainty penalty") and react sharply to the specific risks confirmed by very high disclosure (a "revelation shock"), while only intermediate levels of disclosure appear to offer a "stability valley" where volatility is minimized.

Second, when interacting with material physical exposure, this dynamic shifts. For highly exposed firms, the market prioritizes risk resolution over stability; high-quality disclosure in this context serves as a necessary, albeit volatility-inducing, correction mechanism. Collectively, these findings suggest that markets are efficient but nuanced: they do not blindly reward disclosure volume, but rather price the specific trade-off between the ambiguity of silence and the hard reality of revealed climate risks.

These insights have direct implications for policymakers and standard-setters. As mandatory climate disclosure regimes (such as the SEC's climate rule or the EU's CSRD) come into effect, regulators should not expect an immediate stabilization. Instead, they should anticipate that volatility will **persist** for opaque firms and **increase** for firms forced out of the safe harbor of generic reporting. This turbulence should not be viewed as a sign of market disorder, but rather as the necessary repricing of previously obscured risks. Furthermore, our findings suggest that to be effective, regulation must move beyond "comply-or-explain" frameworks toward mandates that penalize boilerplate language and reward specific, quantitative risk assessments.

While this study focuses on U.S. equity markets, the framework presented here opens several paths for future research. Extending this analysis to fixed-income markets could reveal whether credit spreads price this interaction similarly to equity volatility. Additionally, exploring how these dynamics play out in jurisdictions with different legal liability standards for disclosure could offer valuable cross-border comparisons. Ultimately, moving beyond the binary question of whether climate risk is priced to understanding *how* information quality conditions that pricing is essential for building a resilient

financial system in a warming world.

Declaration of Generative AI and Tool Usage. During the preparation of this work, the authors used generative AI technologies to enhance productivity and workflow efficiency. Specifically, ChatGPT 5.2 was utilized for brainstorming and the refinement of textual clarity, while Google Gemini 3 assisted with code completion and debugging during the implementation phase. Additionally, pre-trained natural language processing models (specifically ClimateBERT) were accessed via the HuggingFace platform.

We affirm that all methodological decisions, parameter selections, empirical interpretations, and validation procedures were conducted exclusively by the authors. These tools served solely as auxiliary aids and were not used as substitutes for scientific judgment or analytical rigor. The authors take full responsibility for the content of this work.

REFERENCES

[1] R. Bansal, D. Kiku, and M. Ochoa, *Climate change and growth risks*, Working Paper 23009, National Bureau of Economic Research, 2016, https://doi.org/10.3386/w23009.

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

[3] P. Bolton and M. Kacperczyk, *Do investors care about carbon risk?*, Journal of Financial Economics, 142 (2021), pp. 517–549, https://doi.org/10.1016/j.jfineco.2021.05.008.

[4] Centre for Research on the Epidemiology of Disasters, *Emergency events database (EM-DAT)*. UCLouvain, Brussels, Belgium, 2024, https://www.emdat.be.

[5] S. Gu, B. Kelly, and D. Xiu, *Empirical asset pricing via machine learning*, The Review of Financial Studies, 33 (2020), pp. 2223–2273, https://doi.org/10.1093/rfs/hhaa009.

[6] E. Ilhan, Z. Sautner, and G. Vilkov, *Carbon tail risk*, The Review of Financial Studies, 34 (2021), pp. 1540–1571, https://doi.org/10.1093/rfs/hhaa071.

[7] E. M. Matsumura, R. Prakash, and S. C. Vera-Muñoz, *Firm-value effects of carbon emissions and carbon disclosures*, The Accounting Review, 89 (2014), pp. 695–724, https://doi.org/10.2308/accr-50692.

[8] B. McDonald, *Software repository for accounting and finance (SRAF)*. University of Notre Dame, 2024, https://sraf.nd.edu.

[9] N. Pankratz, R. Bauer, and J. Derwall, *Climate change, firm performance, and investor surprises*, Management Science, 69 (2023), pp. 6794–6818, https://doi.org/10.1287/mnsc.2023.4685.

[10] M. Plumlee, D. Brown, R. M. Hayes, and R. S. Marshall, *Voluntary environmental disclosure quality and firm value: Further evidence*, Journal of Accounting and Public Policy, 34 (2015), pp. 336–361, https://doi.org/10.1016/j.jaccpubpol.2015.04.001.

[11] Z. Sautner, L. van Lent, G. Vilkov, and R. Zhang, *Firm-level climate change exposure*, The Journal of Finance, 78 (2023), pp. 1449–1498, https://doi.org/10.1111/jofi.13219.

[12] N. Webersinke, M. Kraus, J. A. Bingler, and M. Leippold, *ClimateBERT: A pretrained language model for climate-related text*, arXiv preprint arXiv:2110.12010, (2021), https://doi.org/10.48550/arXiv.2110.12010.