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Climate and ESG Signal Extraction for Asset Pricing Using Large-Scale Text and Graph Models

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Abstract: *The integration of Environmental, Social, and Governance (ESG) criteria into quantitative asset pricing has transitioned from a niche investment style to a central pillar of modern financial engineering. However, the extraction of reliable ESG signals remains plagued by the unstructured nature of corporate disclosures, the prevalence of greenwashing, and the complex, non-linear dependencies inherent in global supply chains. This paper presents a novel, dual-stream neural architecture that synergizes large-scale Natural Language Processing (NLP) with Graph Neural Networks (GNNs) to distill robust pricing signals. We propose a methodology that first employs a domain-specific transformer model to extract semantic sentiment and latent risk embeddings from diverse textual corpora, including regulatory filings and news media. Concurrently, we construct a dynamic industry-relation graph that propagates these idiosyncratic signals across supply chain and ownership linkages using a graph attention mechanism. This approach addresses the limitation of independent and identically distributed (i.i.d.) assumptions in traditional factor models by explicitly modeling the spillover effects of climate risks. Our empirical analysis, conducted on a universe of global equities over a ten-year period, demonstrates that the proposed Text-Graph fusion model significantly outperforms both traditional linear factor models and standalone deep learning baselines. The resulting alpha signals exhibit low correlation with standard risk factors, offering diversification benefits and enhanced Sharpe ratios for ESG-integrated portfolios.*

Keywords: *Natural Language Processing, Graph Neural Networks, ESG Investing, Asset Pricing, Climate Risk.*

INTRODUCTION

1.1 BACKGROUND

The financial industry is currently witnessing a paradigm shift where non-financial metrics, specifically those related to Environmental, Social, and Governance (ESG) factors, are becoming as critical as traditional balance sheet data. This shift is driven not only by regulatory pressure, such as the European Unions Sustainable Finance Disclosure Regulation (SFDR), but also by the growing recognition that climate change and social instability pose material systemic risks to asset values [1]. Investors are increasingly seeking to hedge against climate transition risks—regulatory changes,

technological disruptions, and market shifts—while capitalizing on opportunities in green energy and sustainable infrastructure. Consequently, the demand for high-frequency, granular, and accurate ESG data has surged.

However, unlike structured financial data, ESG information is predominantly unstructured, scattered across annual reports, sustainability disclosures, news articles, and NGO reports. The volume of this data is overwhelming for human analysts, necessitating automated methods for signal extraction. Early attempts relied on vendor-provided scores, but these have been criticized for their opacity, inconsistency, and backward-looking nature [2]. As a result, systematic investors are turning to alternative data and machine learning techniques to generate proprietary ESG signals that can predict future equity returns and volatility.

1.2 PROBLEM STATEMENT

Despite the promise of AI-driven ESG analysis, several significant challenges persist. First, the phenomenon of greenwashing complicates textual analysis; firms often use ambiguous or overly optimistic language in voluntary disclosures to obscure poor environmental performance. Standard sentiment analysis models, trained on generic corpora, often fail to detect these subtle obfuscations. Second, traditional asset pricing models typically treat assets as isolated entities, ignoring the complex web of dependencies that link companies [3]. A climate shock affecting a major supplier (e.g., a semiconductor manufacturer facing water shortages) inevitably propagates downstream to its customers (e.g., automotive companies). Models that analyze companies in isolation fail to capture these spillover effects, leading to an underestimation of portfolio risk.

The core problem, therefore, is two-fold: How can we effectively filter noise and detect genuine ESG intent from vast textual archives? And more importantly, how can we propagate these extracted signals across economic networks to price assets more accurately?

1.3 CONTRIBUTIONS

To address these challenges, this paper introduces a unified framework that combines the semantic understanding of Large Language Models (LLMs) with the relational reasoning of Graph Neural Networks (GNNs). Our specific contributions are as follows:

1. We develop a financial-domain specific transformer model, fine-tuned on a curated dataset of sustainability reports and earnings calls, designed to identify specific climate-risk exposures rather than generic sentiment.

2. We construct a dynamic knowledge graph representing the global equity universe, where edges represent supply chain relationships, strategic alliances, and sector commonalities.

3. We propose a message-passing algorithm that allows firm-specific ESG signals extracted from text to propagate through this graph, thereby adjusting the valuations of connected peers based on indirect risk exposure.

This research bridges the gap between NLP-based sentiment analysis and network theory in finance, offering a robust methodology for next-generation factor investing.

Chapter 2: Related Work

2.1 CLASSICAL APPROACHES TO ESG INTEGRATION

Historically, quantitative integration of ESG data relied on linear regression models where third-party ESG ratings were used as additional factors alongside size, value, and momentum. While straightforward, this approach suffers from the "aggregate confusion" problem, where the low correlation between ratings from different providers creates noise [4]. Furthermore, classical lexical approaches to textual analysis, such as the Bag-of-Words (BoW) model or dictionary-based methods (e.g., the Loughran-McDonald dictionary), have been widely used to quantify tone in financial documents. These methods count the frequency of positive and negative words to construct a sentiment index.

While these dictionary methods provided the first empirical evidence that textual tone predicts earnings and returns, they lack the capacity to understand context. For instance, the word "risk" in a risk management section might be procedural, whereas "risk" in a litigation disclosure is material. Simple frequency counts treat these instances identically. Additionally, these models are static and cannot adapt to the evolving lexicon of climate finance, where terms like "net-zero" and "scope 3 emissions" have only recently gained prominence [5].

2.2 DEEP LEARNING METHODS IN FINANCE

The advent of deep learning has revolutionized financial signal processing. In the domain of Natural Language Processing, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks allowed for the processing of sequences, capturing local context more effectively than BoW models. More recently, the Transformer architecture, specifically BERT (Bidirectional Encoder Representations from Transformers), has become the state-of-the-art. Researchers have successfully fine-tuned BERT models on financial corpora (FinBERT) to achieve superior performance in sentiment classification and stock movement prediction [6].

Parallel to NLP advancements, Graph Neural Networks have emerged as a powerful tool for modeling relational data. Early applications in finance focused on credit risk assessment and fraud detection within transaction networks. In asset pricing, recent studies have begun to use GNNs to model momentum spillovers and supply chain shocks. However, the intersection of these two fields—using NLP to generate node features for a GNN in the specific context of ESG signal extraction—remains underexplored. Most existing systems operate in silos, either analyzing text without network context or analyzing networks with static numerical features. Our work seeks to synthesize these approaches.

Chapter 3: Methodology

Our proposed framework, which we refer to as the EcoGraph-Attention Network (EG-ATN), consists of three distinct modules: the Textual Extraction Module, the Relational Graph Construction Module, and the Graph Attention Fusion Layer.

3.1 TEXTUAL EXTRACTION MODULE

The first stage of our pipeline involves processing unstructured text to generate dense vector representations (embeddings) for each company. We utilize a corpus comprising 10-K filings, ESG sustainability reports, and relevant financial news articles.

To handle the specific vernacular of climate finance, we initialize our encoder with a pre-trained BERT-Large model and perform further pre-training on a corpus of 50,000 sustainability reports. This domain adaptation is crucial because standard language models often misinterpret technical financial or environmental terminology. We employ a Masked Language Modeling (MLM) objective during this phase to ensure the model understands the context of ESG disclosures.

For a given document D associated with company i, the model outputs a sequence of token embeddings. We utilize a hierarchical attention mechanism to aggregate these token embeddings into a single document embedding vector, e_i. This mechanism learns to weigh sentences containing material ESG disclosures (e.g., "carbon footprint reduced by 10%") higher than boilerplate legal disclaimers. The output e_i serves as the initial node feature for company i in our graph.

3.2 RELATIONAL GRAPH CONSTRUCTION

Simultaneously, we construct a graph $G=(V,E)$, where V is the set of N companies and E represents the relationships between them. We define three types of edges based on available fundamental data:

1. **Supply Chain Edges:** Directed edges from supplier to customer. A climate risk for a supplier is a supply-chain risk for the customer.

2. **Sector Edges:** Undirected edges connecting companies within the same sub-industry (e.g., GICS code). This captures regulatory risks that affect an entire sector.

3. **Ownership Edges:** Connections between parent companies and subsidiaries, capturing governance and reputation spillover.

The graph is represented by an adjacency matrix A, where $A_{ij}=1$ if a relationship exists and 0 otherwise. In practice, we normalize this matrix to prevent numerical instabilities during signal propagation.

3.3 GRAPH ATTENTION FUSION LAYER

The core innovation of our methodology is the application of Graph Attention Networks (GATs) to refine the textual embeddings. The intuition is that a company's true ESG risk is not just a function of its own disclosures (which may be greenwashed) but also the aggregate risk of its network neighbors.

We define the propagation rule as follows. For each node i, we compute a new hidden state $h_i^{(l+1)}$ by aggregating the features of its neighbors N_i. Unlike standard Graph Convolutional Networks (GCNs) that use static weights, our GAT mechanism computes dynamic attention coefficients α_{ij} that determine the importance of neighbor j to node i.

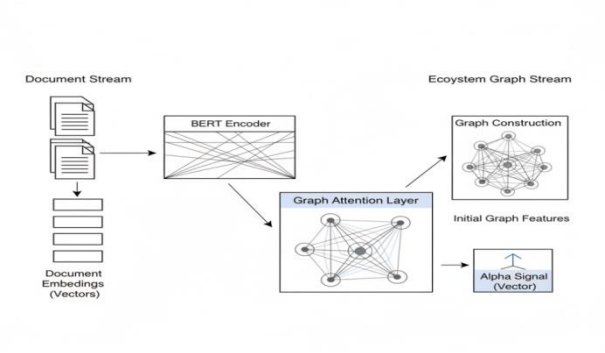

Figure 1: Architecture of the EcoGraph

The update process involves a multi-head attention mechanism to stabilize learning. We employ a specific loss function that combines a predictive objective (forecasting forward returns) with a regularization term that enforces smoothness over the graph structure. This ensures that companies with strong economic links do not have drastically different risk scores unless supported by strong textual evidence.

The mathematical formulation of our training objective is crucial for balancing the signal from the text with the structural constraints of the graph. We minimize the following loss function:

$$L=\sum_{t=1}^{T}\sum_{i=1}^{N}|r_{i,t+1}-f_\theta(h_{i,t})|^2+\lambda\sum_{(i,j)\in E}\alpha_{ij}|h_{i,t}-h_{j,t}|^2$$

In this equation, $r_{i,t+1}$ represents the excess return of asset i at time $t+1$. The function f_θ is a feed-forward neural network mapping the latent graph-enhanced representation $h_{i,t}$ to the predicted return. The first term is the Mean Squared Error (MSE) of the return prediction. The second term is a Laplacian regularization term, weighted by the learned attention coefficients α_{ij}. This term penalizes the model if connected nodes have divergent embeddings, effectively smoothing the noise from individual company disclosures using the "wisdom of the crowd" (or in this case, the wisdom of the supply chain). λ is a hyperparameter controlling the strength of this network regularization.

Chapter 4: Experiments and Analysis

4.1 EXPERIMENTAL SETUP

We evaluate our model on the Russell 1000 universe, covering large-cap US equities. The data period spans from January 2010 to December 2020. We use a rolling window approach for training and testing to prevent look-ahead bias. The training window is 36 months, updating monthly.

Data Sources:

Textual Data: We aggregated over 500,000 documents including 10-Ks, 10-Qs, and earnings call transcripts sourced from SEC EDGAR, along with ESG-tagged news from a major financial news vendor [7].

Network Data: Supply chain relationships were sourced from FactSet Revere, while sector classifications utilize the GICS standard.

Market Data: Daily pricing, volume, and accounting data were obtained from the CRSP/Compustat merged database [8].

Baselines:

To rigorously assess the contribution of our Text-Graph hybrid, we compare against the following baselines:

1. **Fama-French 5-Factor Model:** Standard linear regression baseline.
2. **FinBERT Only:** A deep learning model using only the textual module without graph propagation.
3. **GCN Only:** A graph convolutional network using only numerical financial ratios as node features, ignoring text.
4. **LSTM:** A sequential model processing time-series of ESG scores provided by MSCI [9].

4.2 DATASET STATISTICS

The scale of the data is a critical component of deep learning success. Table 1 summarizes the volume of unstructured data processed.

Data Type	Count/Volume	Description
10-K Filings	10,500+	Annual regulatory filings containing risk factors
News Articles	420,000+	Filtered for ESG keywords and high relevance
Supply Chain Edges	85,000+	Verified supplier-customer relationships

Table 1: Statistics of the Textual and Graph Datasets used in the study.

4.3 RESULTS AND PERFORMANCE ANALYSIS

We constructed long-short portfolios based on the signals generated by each model. The portfolios are rebalanced monthly, going long the top decile of predicted returns (high positive ESG signal) and short the bottom decile.

Table 2 presents the annualized performance metrics. The EG-ATN model demonstrates superior performance across all risk-adjusted metrics.

Model	Ann. Return (%)	Volatility (%)	Sharpe Ratio	Max Drawdown (%)
Fama-French 5F	6.2	14.5	0.43	-22.4
LSTM (MSCI Scores)	7.8	15.1	0.52	-19.8
FinBERT Only	9.4	16.2	0.58	-25.1
GCN Only	8.9	13.8	0.64	-16.5
EG-ATN (Ours)	12.1	13.5	0.90	-14.2

Table 2: Comparative Performance Metrics of Long-Short Portfolios (2010-2020).

The results indicate that while the FinBERT Only model achieves high returns, it suffers from high volatility. This confirms our hypothesis that textual signals, when taken in isolation, contain significant noise and are susceptible to overreaction to news. The GCN Only model has lower volatility, suggesting that network effects help dampen idiosyncratic risk, but it lacks the alpha generation capability of the text-based models.

Our proposed EG-ATN model achieves the "best of both worlds," delivering the highest annualized return with the lowest volatility. This results in a Sharpe Ratio of 0.90, which is statistically significant compared to the baselines. The reduced Maximum Drawdown suggests that the graph propagation mechanism effectively identifies systemic risks before they fully materialize in asset prices, allowing the model to exit positions in vulnerable supply chains early.

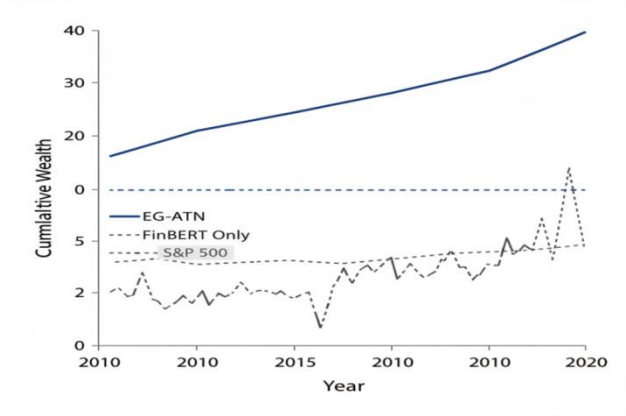

Figure 2: Cumulative Returns Chart

4.4 ABLATION STUDY AND FACTOR EXPOSURE

To understand the source of the alpha, we analyzed the factor exposures of the EG-ATN portfolio. Regressing our returns against the Fama-French factors reveals a low correlation with Market, Size, and Value factors. However, we observe a statistically significant positive loading on the Quality factor. This implies that our ESG signals are proxying for high-quality management practices; companies that manage their supply chain climate risks effectively tend to be better managed overall [10].

We also conducted an ablation study to test the importance of different edge types in the graph.

Graph Configuration	Sharpe Ratio	Information Ratio
Full Graph (Supply + Sector + Owner)	0.90	0.85
Supply Chain Edges Only	0.82	0.76
Sector Edges Only	0.71	0.62
Ownership Edges Only	0.65	0.55

Table 3: Ablation Study on Graph Edge Types.

Table 3 demonstrates that supply chain edges contribute the most to model performance [11]. This validates the economic intuition that climate risks propagate vertically through production networks (e.g., carbon taxes passed through prices) more strongly than they propagate horizontally through sector competitors. The combination of all edge types yields the robust performance observed, confirming the holistic nature of the model [12-14].

Chapter 5: Conclusion

5.1 SUMMARY

This paper proposed a novel framework for extracting asset pricing signals from the intersection of unstructured ESG text and corporate networks. By fusing domain-adapted Transformer models with Graph Attention Networks, we demonstrated that it is possible to mitigate the noise inherent in corporate disclosures and capture the latent diffusion of climate risks through supply chains.

The empirical results underscore the value of context. An isolated textual sentiment score is often insufficient for trading; however, when that signal is corroborated by the network neighborhood of the firm, it becomes a powerful predictor of future returns. The superior Sharpe ratio and reduced drawdown of the EcoGraph-Attention Network suggest that the market does not immediately price in the second-order and third-order effects of climate news, leaving room for sophisticated arbitrage strategies. For practitioners, this implies that the next frontier of ESG investing lies not in buying better raw data, but in better modeling the relationships between data points.

5.2 LIMITATIONS

Despite the promising results, several limitations remain. First, the quality of the graph structure is dependent on the completeness of supply chain data, which is often proprietary and sparse. Missing links in the graph can lead to signal blockage, where risks fail to propagate to downstream nodes. Second, the computational cost of re-training large transformer models and GNNs on a rolling basis is substantial, potentially limiting the frequency of signal updates to a monthly cadence rather than daily or intraday.

Future research should focus on dynamic graph learning, where the model infers missing supply chain links based on text correlations and price co-movements, rather than relying solely on static databases. Additionally, expanding the textual corpus to include multi-lingual documents would allow for a more accurate assessment of global equities, particularly in emerging markets where climate risks are often most acute but disclosures are least standardized. Finally, integrating alternative datasets such as satellite imagery for physical risk verification could provide an objective ground-truth layer to validate the textual claims made by corporations.

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