

Article

ESG Risk in Global Supply Chains: Evidence from Network-Based AI Models

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Abstract

Environmental, social, and governance (ESG) risk is increasingly shaped by the relationships firms maintain within global supply chains. However, most ESG assessment approaches still treat firms as independent entities, overlooking how sustainability risks can spread across interconnected supplier–buyer networks. This study approaches ESG risk as a network-driven phenomenon rather than a purely firm-level outcome. Drawing on a large international dataset that combines supply-chain linkages, ESG incident data, and ESG-related news sentiment, the study examines whether incorporating network structure improves ESG risk assessment. The analysis integrates network-based econometric models with machine learning and graph-based approaches, and compares their performance with traditional firm-level models. The results show that ESG risk tends to cluster among connected firms, and that companies occupying central or intermediary positions within supply chains are more exposed to ESG incidents. In addition, negative ESG-related media sentiment provides an early signal of future ESG controversies. Models that explicitly account for network structure consistently outperform conventional approaches in both predictive accuracy and probability calibration. Thus far, the findings highlight the importance of considering supply-chain interdependencies when assessing ESG risk and demonstrate how network-based AI models can enhance the monitoring and prediction of sustainability risks in global production systems.

Keywords: ESG risk; supply-chain networks; artificial intelligence; graph neural networks; ESG sentiment; risk prediction; sustainability; ESG controversies

1. Introduction

ESG risks are progressively understood as outcomes of system-wide interdependencies within global supply chains rather than as isolated firm-level deficiencies. Ecological harm, labour violations, and governance failures often originate outside focal firms and spread through production networks via reputational transmission, regulatory contagion, and operational disruption [1]. A firm's ESG exposure depends not only on its internal practices but also on its relational position within networks of suppliers and customers. This perspective challenges conventional ESG assessment approaches that rely on static disclosures, aggregated ratings, and backward-looking indicators. Such tools provide limited insight into how ESG risks accumulate and propagate across interconnected production systems, constraining their ability to detect emerging vulnerabilities before they materialise into noticeable events [2].



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However, this study adopts a network-oriented approach and addresses two main questions. How does a firm's position within supply-chain networks shape its ESG risk exposure? Does explicitly incorporating inter-firm network structure improve the accuracy and reliability of ESG risk prediction relative to firm-level models? Hence, recent advances in data availability and artificial intelligence enable these questions to be addressed more directly. Detailed supplier–customer connections, shipment-level trade data, and continuously updated news streams allow ESG exposure to be analysed as a dynamic and relational process [3]. At the same time, progress in network analytics, machine learning, and natural language processing strengthens the modelling of nonlinear interactions, inter-firm dependence, and early-stage risk signals [4].

The main aim of this study is to investigate whether ESG risk in global supply chains is influenced by firms' positions within supply-chain networks and whether incorporating network structure improves the prediction of ESG incidents compared with traditional firm-level models. The analysis therefore focuses on two aspects: first, how network exposure and structural centrality shape ESG risk, and second, whether models that account for supply-chain networks provide stronger predictive performance. In this framework, artificial intelligence tools, network econometric techniques, and sentiment analysis are used as supporting methodological instruments rather than separate research objectives.

Despite these developments, empirical ESG research remains fragmented, with network structure, ESG metrics, controversy records, and media sentiment typically examined in isolation. This study proposes an AI-network-oriented framework for analysing ESG risk in global supply chains. Thus, by integrating network econometric methods, graph-based learning, and transformer-based sentiment extraction, the framework captures the exposure, diffusion, and forecasting ability of ESG risk. This study makes one primary contribution and two supporting contributions to the ESG and supply-chain literature. The primary contribution is demonstrating that ESG risk in global supply chains is better understood as a relational and network-dependent phenomenon rather than solely a firm-level characteristic. Using verified inter-firm supply-chain relationships and firm-year ESG outcomes, the analysis shows that a firm's position within the supply network systematically influences its exposure to ESG risk.

The first supporting contribution is methodological. While earlier research often examines network structure, ESG incidents, or text-based ESG signals separately, this study combines supply-chain network topology with ESG-related news sentiment within a unified empirical framework. The second supporting contribution concerns predictive assessment. The study compares network econometric models, traditional machine learning approaches, and graph-based AI models to evaluate whether explicitly modelling inter-firm relationships improves predictive accuracy and probability calibration. The study aims to improve predictive risk assessment in interconnected supply chains rather than estimate causal effects.

The remainder of the paper is organised to address the research questions in a structured manner. Section 2 reviews the literature on ESG risk, supply-chain networks, and AI-based analytical approaches, and develops the theoretical framework and hypotheses concerning how network exposure and sentiment signals influence ESG risk. Section 3 describes the research design, data sources, and methodological framework used to analyse relational ESG risk and to compare network-based and conventional predictive models. Section 4 presents the empirical results, evaluating both the structural determinants of ESG risk and the predictive performance of network-aware models. Section 5 interprets the findings and discusses their implications for regulators, firms, and investors in the context of global supply-chain governance. Finally, Section 6 concludes the study by summarising the main contributions and outlining directions for future research.

2. Related Studies

2.1. The Concept of Network Modelling for ESG Risk

This study reviewed several empirical studies that focus on the network modelling of ESG risk propagation across global supply chains in production and service systems, as shown in Table 1. The evidence shifts ESG risk from a purely firm-centric singularity to a relational and systemic exposure that can diffuse through inter-firm dependencies. A dominant stream uses industrial network data to model ESG spillovers at scale. Wei et al. [5] studied China's industrial chain and reported that ESG performance shocks diffuse along supply-chain links, with measurable impacts on downstream profitability and value-chain outcomes. Extending this logic, Tan et al. [6] introduce a directed graph neural network (GNN) that distinguishes upstream from downstream flows, demonstrating asymmetric propagation patterns that reveal where vulnerabilities accumulate and how network resilience is shaped by directionality. However, these studies provide strong empirical support for contagion-like ESG dynamics in production networks, illustrating the practical value of network-aware AI in identifying systemic exposure beyond a focal firm's internal practices.

Table 1. Empirical analysis of AI-enhanced network modelling of ESG risk in global supply chains.

Reference(s)	Year	Topic	Dataset(s) Used	Decision-Making Relevance	Major Empirical Contributions
[5]	2024	Gone with the Chain: The Ripple Effect of ESG Performance in China's Industrial Chain	Chinese industrial supply-chain network (1164 industries from ChinaScope, 2018–2020) combined with firm-level ESG ratings (Sino-Securities Index)	Informs firms and investors on how ESG performance shocks propagate through industrial networks and affect downstream performance	Develops a graph neural network with cross-attention to model ESG spillovers; shows ESG performance diffuses through supply-chain links and significantly influences profitability and value-chain outcomes
[6]	2025	Modelling ESG-Driven Industrial Value-Chain Dynamics Using Directed Graph Neural Networks	Chinese industrial value-chain network (ChinaScope) combined with China Securities Index ESG ratings	Supports corporate strategy and policy design by identifying asymmetric upstream and downstream ESG vulnerabilities	Proposes a directed GNN distinguishing inbound and outbound flows; demonstrates that ESG shocks propagate asymmetrically and shape industrial value extension and network resilience
[7]	2025	Relational Infrastructures for Planetary Health in Brazil's Traceable Beef Export System	Brazilian beef supply-chain network linking ranches and meatpacking facilities, augmented with transport and traceability data	Enables investors and firms to detect hidden deforestation and ESG risks embedded in indirect suppliers	Uses network analysis to uncover indirect sourcing and governance gaps; highlights how relational infrastructure conditions ESG risk and traceability in agricultural supply chains
[8]	2024	ESG Discourse in News: An AI-Powered Knowledge Graph Analysis	Dow Jones News Article dataset processed using NLP and knowledge-graph construction	Supports real-time reputational and ESG risk monitoring for firms and regulators	Constructs ESG knowledge graphs from news using transformer models; demonstrates how ESG narratives evolve and signal emerging risks
[9]	2022	Supply-Chain Link Prediction on Uncertain Knowledge Graphs	Multi-tier supply-chain knowledge graph extracted from web data using NLP (VersedAI)	Enhances ESG compliance and supply-chain risk management by improving visibility across hidden tiers	Combines NLP-extracted graphs with GNN-based link prediction under uncertainty; advances multi-tier supply-chain mapping for proactive risk mitigation
[10]	2024	SHIELD: LLM-Driven Schema Induction for EV Battery Supply-Chain Disruptions	Open-source textual data on EV battery supply chains, mined using zero-shot large language models	Supports strategic sourcing and ESG risk oversight in critical-mineral and EV supply chains	Proposes an LLM-based framework for schema induction and knowledge-graph construction; enables early detection of disruption and ESG risk in multi-tier supply chains

Bergier [7] reveals that in Brazil's traceable beef export system, ESG risks such as deforestation can be embedded in indirect suppliers and remain invisible without rela-

tional infrastructures that connect ranches, intermediaries, and processors. This evidence supports a key limitation in conventional ESG monitoring. Angioni et al. [8] construct ESG knowledge graphs from news using NLP pipelines and demonstrate how ESG narratives evolve, providing a foundation for reputational monitoring and early warning systems. Brockmann et al. [9] focus on supply-chain link prediction under uncertainty using knowledge graphs extracted from web data, improving visibility across hidden tiers. Their approach is decision-relevant because accurate link inference enables earlier identification of where ESG exposure may reside, especially when supply-chain information is incomplete or noisy. To conclude, Cheng et al. [10] propose a large language model (LLM)-driven framework for schema induction and knowledge-graph construction in EV battery supply chains, illustrating how zero-shot and weakly supervised extraction can support disruption forecasting and ESG oversight in critical-mineral contexts where supplier ecosystems are complex and rapidly evolving.

2.2. Theoretical Framework

This study depends on a dual-theoretical perspectives that integrates stakeholder theory with regulatory spillover theory to explain ESG risk in global supply chains. Stakeholder theory conceptualises ESG risk as a consequence of firms' obligations to a diverse set of actors, including employees, local communities, regulators, and civil society organisations, whose interest are intertwined within transnational production networks [11]. Under this perspective, ESG exposure extends beyond internal governance arrangements and is shaped by firms' embeddedness in inter-firm relationships through which stakeholder pressures, reputational concerns, and social expectations are transmitted.

Regulatory spillover theory provides a complementary structure by highlighting how sustainability regulations and supply-chain due-diligence regimes enacted in one jurisdiction generate effects that extend beyond their formal legal scope. Through buyer-supplier connections, sourcing strategies, and information flows, regulatory requirements diffuse across borders and reshape risk exposure throughout global value [12,13]. These spillover effects tend to be uneven, with firms occupying structurally influential or intermediary positions experiencing heightened regulatory and reputational vulnerability, even when they are not directly subjected to the originating regulatory framework.

Stakeholder theory and regulatory spillover theory together suggest that ESG risk in global supply chains is relational rather than purely internal to the focal firm. Stakeholder theory highlights how firms face reputational and social pressures through their connections with suppliers, customers, regulators, communities, and civil society actors. Regulatory spillover theory explains how legal and due-diligence expectations originating in one jurisdiction can extend through cross-border buyer-supplier relationships and place greater scrutiny on firms in strategically important network positions. These perspectives imply that both network exposure and structural position may influence ESG risk, while external signals such as negative ESG news can indicate emerging stakeholder or regulatory pressure before formal controversies arise.

2.3. Hypothesis Formulation

The hypotheses of this study translate the study's research questions into empirically testable propositions concerning network exposure, structural position, and informational signals in ESG risk formation as shown in Figure 1. Firms embedded in extensive supply-chain relationships face a broader range of stakeholder expectations, including concerns related to suppliers' labour conditions, environmental practices, and governance standards [14,15]. As stakeholders increasingly evaluate firms in relation to their value-chain partners, ESG risk is influenced not only by internal behaviour but also by relational

exposure. Regulatory spillover theory further suggests that sustainability requirements imposed on one firm can extend to connected partners through sourcing, monitoring, and compliance pressures. Consequently, firms with greater network exposure are likely to face higher ESG risk. Thus, the first hypothesis draws mainly on stakeholder theory as follows:

H1. *Network exposure increases ESG risk.*

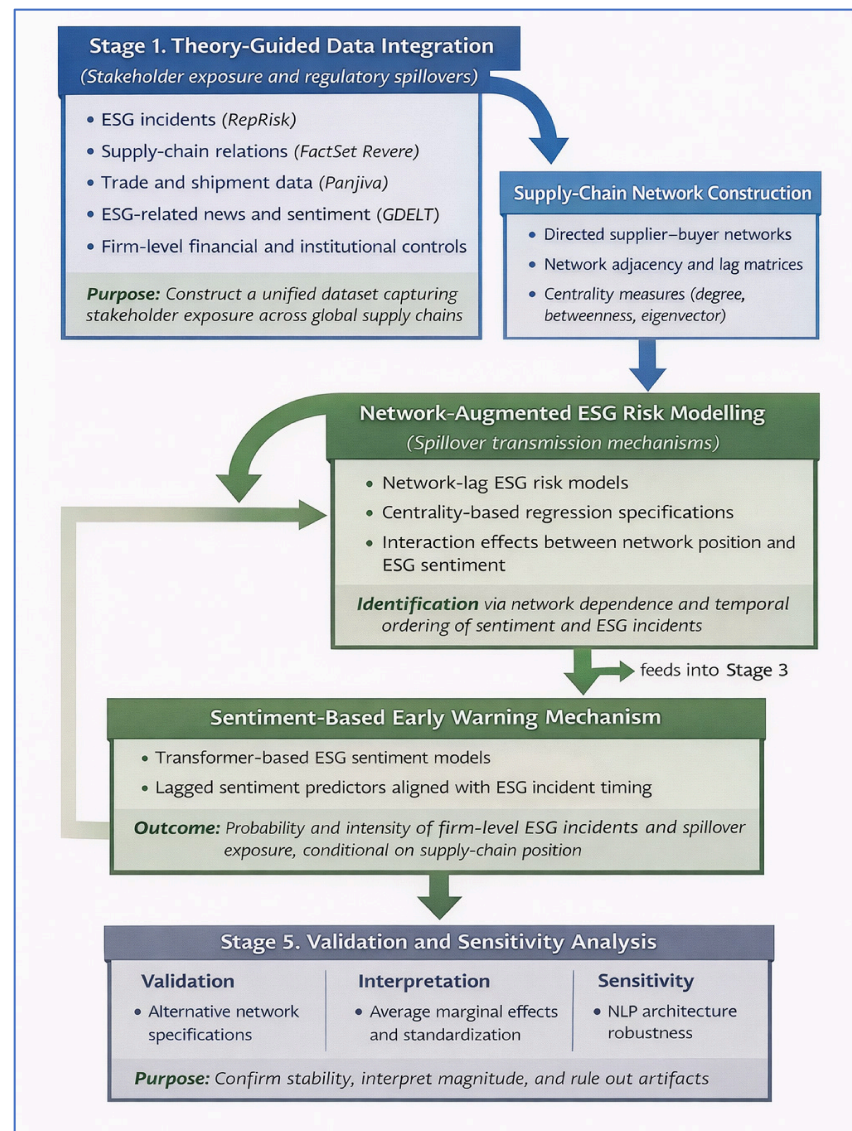


Figure 1. Conceptual framework for network-based ESG risk analysis.

Firms in brokerage positions connect otherwise separate actors and jurisdictions, making them more likely to transmit and experience compliance pressures, reputational shocks, and due-diligence expectations within supply chains [16]. Likewise, firms linked to other highly central actors may face greater exposure because they operate in parts of the network where regulatory scrutiny and ESG expectations are more concentrated [17]. Stakeholder theory complements this view by suggesting that such firms are more visible to external audiences and therefore more susceptible to reputational pressure. Consequently, intermediary and influential network positions are expected to be associated with higher ESG risk than peripheral positions. Hence, the second hypothesis is primarily informed by regulatory spillover theory as follows:

H2. Brokerage and influential positions increase ESG risk.

Negative ESG-related media sentiment suggests that stakeholders have begun to raise and circulate concerns about a firm or its supply-chain partners [18,19]. Such coverage may also reflect increasing regulatory attention or due-diligence pressure within the network [19]. Because these signals often appear before formal controversies are recorded, adverse ESG sentiment may serve as an early indicator of subsequent ESG incidents [20–22]. Therefore, the third hypothesis reflects the information channel implied by stakeholder theory and regulatory spillover theory as follows:

H3. Negative ESG sentiment predicts future incidents.

2.4. Research Gap

Research on industrial and supply-chain networks has grown considerably, most especially in studies focusing on ESG risk and inter-firm spillovers. However, much of this work is based on single-country settings and relatively stable institutional environments. This makes it difficult to generalise the findings to global supply chains that operate across diverse regulatory and governance contexts. In addition, many studies treat supply-chain networks as static, which can overlook important changes over time, such as shifts in supplier relationships, restructuring within networks, and the persistence of shocks.

Existing research also shows the value of different analytical approaches in understanding ESG-related risks. Network-based studies tend to focus on how risks spread through supply-chain relationships, while text-based approaches, such as knowledge graphs and large language models, are used to extract ESG-related signals from media sources. Despite these advances, these methods are often used separately. As outlined in Table 1, the literature generally falls into three main streams: network analyses of ESG spillovers, text- or knowledge-graph approaches to ESG signal extraction, and AI-based mapping of supply-chain relationships. However, there is still limited work that brings these elements together within a single framework, especially in a global, multi-country context. This study seeks to address this gap by developing an integrated empirical framework that combines supply-chain network structure with ESG-related news sentiment.

3. Research Design

3.1. Multi-Method Research Approach

Table 2 outlines the modelling framework used in this study. Given the complexity of ESG risk, the analysis adopts a multi-method approach that combines econometric, machine learning, and graph-based techniques. Conventional econometric models, including OLS, Poisson, negative binomial, and PPML, are employed to examine whether the estimated network effects remain consistent under different distributional assumptions, while also addressing issues such as overdispersion and excess zeros. These models provide interpretable results and allow the study to formally test how network exposure, centrality, and ESG risk are related [23].

To complement this, machine learning approaches such as Random Forest, Gradient Boosting, and XGBoost are used to capture nonlinear patterns and improve the identification of relatively rare ESG incidents. Model performance is evaluated using both discrimination and calibration measures to ensure that predictions are not only accurate but also reliable [24]. In addition, SHAP analysis is applied to make the results of these models more transparent and easier to interpret. Logit and survival models are further included to analyse the likelihood and timing of ESG incidents. Graph neural networks (GNNs) extend the analysis by explicitly modelling the connections between firms, allowing risk-related

information to flow through supply-chain links and capturing indirect exposure across multiple tiers [25].

Table 2. Analytical roles of modelling approaches.

Model Class	Models	Purpose	Output
Network econometric models	Network regression; spatial lag	Inference on network dependence	Network and centrality coefficients
Graph-theoretic regressions	Degree, betweenness, eigenvector	Identify structural effects	Centrality estimates
Panel/count models	FE-OLS, Poisson, NB, PPML	Robustness across distributions	Stable coefficients
Event models	Logit, Cox PH	Incident likelihood and timing	Odds/hazard ratios
Benchmark models	Logistic regression	Baseline prediction	ROC-AUC, Brier
Machine learning	RF, GBM, XGBoost, MLP	Nonlinear prediction	Discrimination and calibration
Graph-based AI	GNN	Network-aware prediction	Improved accuracy
NLP models	FinBERT, RoBERTa	Sentiment construction	Text-based features
Unsupervised models	Isolation Forest, Autoencoder	Anomaly detection	Anomaly scores
Explainability	SHAP, DeLong	Interpretation and validation	Feature importance, Δ

To keep the analysis well-structured, the empirical strategy is organised into three tiers. First, inference-based econometric models are used to test the study's theoretical relationships and generate interpretable estimates. Second, prediction-focused machine learning and graph-based models are used to assess whether more flexible and network-aware approaches improve out-of-sample ESG risk forecasts. Third, a set of robustness and diagnostic checks is conducted to evaluate sensitivity to model assumptions, temporal stability, calibration performance, the reliability of NLP-based measures, and the consistency of the findings across alternative specifications.

3.2. Data Sources

This study draws on several established data sources to capture supply-chain relationships, cross-border trade activity, and ESG-related dynamics, as summarised in Table 3. FactSet Revere provides firm identifiers, industry classifications, and verified supplier–customer links obtained through authenticated API access. Panjiva, a supply-chain intelligence platform developed by S&P Global (USA), provides shipment-level international trade data that enable the construction of firm-level supply-chain networks across countries [26,27]. Information on ESG-related activity is obtained from the Global Database of Events, Language, and Tone (GDELT) and the RepRisk ESG Incident Database [28].

Table 3. Data sources used in the study.

Data Source	Data Type	Period Covered
FactSet Revere	Supplier–customer relationships; industry classifications	2015–2024
Panjiva (S&P Global)	Shipment-level import/export transactions	2015–2024
GDELT Global Knowledge Graph	ESG-related news events; sentiment metadata	2015–2024
RepRisk ESG Incident Database	Environmental, social, and governance controversy records	2015–2024
Worldwide Governance Indicators (WGIs)	Country-level institutional governance measures	2015–2024

These sources track news-reported ESG events, controversies, and shifts in sentiment. The textual data are analysed using transformer-based natural language processing models, including FinBERT, RoBERTa, and multilingual BERT (mBERT), which classify ESG-related content and capture changes in sentiment over time. To reflect cross-country institutional

differences, the analysis incorporates the Worldwide Governance Indicators (WGIs), which provide comparable measures of governance quality across countries. The study period is chosen to ensure consistent data availability and comparability across all sources.

3.3. Sample Size Selection Procedure

The sample used in this study was developed through a step-by-step filtering process aimed at ensuring reliable firm identification, meaningful network connections, and sufficient time coverage for analysing ESG risk within supply chains. The starting dataset contained 110,100 entity records drawn from FactSet Revere, Panjiva, GDELT, and RepRisk. Because these sources differ in structure and reporting formats, firm identities were harmonised using an entity-matching procedure. This step eliminated 42,300 duplicate or inconsistent records, leaving 62,500 firms with unique and comparable identifiers. The next stage focused on improving data quality and ensuring the relevance of firms to the network analysis. Firms were removed if they had unstable identifiers (6200), missing key firm-level information (7800), or supply-chain links that could not be verified (7500). After applying these filters, 41,000 firms remained, each with consistent identifiers and at least a basic network structure.

Further screening was then applied to ensure that the remaining firms were suitable for network-based ESG analysis. Only firms with at least one confirmed supply-chain relationship, observable ESG-related information, and adequate time-series coverage were retained. This resulted in the exclusion of an additional 15,500 firms, producing a final sample of 25,500 firms. For this final sample, both transaction-level and event-based data were assembled. The Panjiva dataset contributed approximately 2.5 million shipment records, capturing repeated interactions between suppliers and customers. In parallel, GDELT provided around 1.2 million ESG-related news events after applying relevance and duplication filters. Figure 2 shows the sample selection procedure. The final sample includes 25,500 firms spanning a wide range of industries and regions, with detailed distributional information provided in Appendix A Table A1.

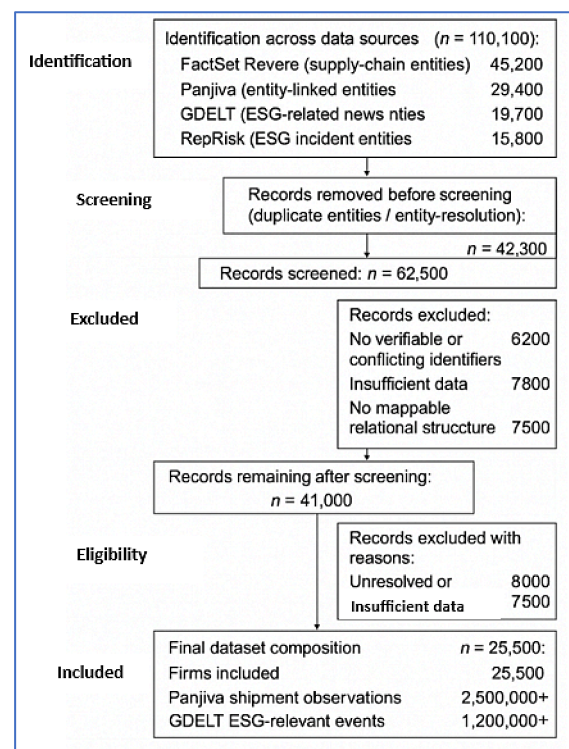


Figure 2. Firm sample selection procedure.

3.4. Network-Based ESG Dataset Structure

Table 4 outlines the construction of the network-based ESG dataset. Verified supply-chain relationships are translated into directed, weighted adjacency matrices, where link direction indicates product flows and weights reflect shipment intensity. Hence, all core results are robust to both binary and shipment-weighted adjacency indicators, yielding qualitatively identical coefficients. Graph computations are conducted using Network X and related libraries to generate firm-level structural attributes, including degree, betweenness, eigenvector centrality, and clustering measures.

Table 4. Details of network-based analytical dataset.

Component	Description	Source/Method	Unit/Notes
Adjacency Matrix	Directed network built from verified supplier–buyer links. Shipment data used only to strengthen tie weights when available.	FactSet Revere (relationship direction); Panjiva (trade volumes used as optional weights)	Firm/firm edges; weight = 1 for FactSet-only ties, or shipment-based weight when available
Degree Centrality	Number of direct incoming and outgoing ties a firm holds	Computed from adjacency matrix	Firm–year
Betweenness Centrality	Extent to which a firm sits on shortest paths linking other firms	Graph-theoretic calculation	Firm–year
Eigenvector Centrality	Measures influence based on connection to well-positioned firms	Graph-theoretic calculation	Firm–year
Clustering Coefficient	Proportion of a firm’s neighbours that are connected to one another	Graph algorithm	Firm–year
ESG Event Count	Annual count of ESG-related news events linked to each firm	GDELT event extraction	Aggregated by firm–year
Sentiment Index	Average tone of ESG-related coverage	Transformer-based NLP analysis	Yearly mean sentiment score per firm
ESG Incident Severity	Weighted score reflecting intensity of documented ESG controversies	RepRisk incident database	Firm–year severity index
Shipment Anomaly Score	Annual measure of irregular trade behaviour	Autoencoder + Isolation Forest models	Mapped to firms based on shipment ownership
Governance Context (WGI)	Country-level institutional quality matched to each firm’s headquarters	World Governance Indicators	Year matched to nearest available WGI release
Final Analytical Structure	Combined panel dataset integrating network, ESG and governance variables	Harmonised across all systems	Panel: firm $\times$ year (2003–2024)

Empirical evidence indicates that degree centrality captures ESG exposure, betweenness centrality identifies firms that transmit risk across supply chains, eigenvector centrality reflects amplified risk arising from influential partners, and clustering coefficients capture local connection of ESG incidents [29]. These indicators differentiate firm by connectivity, brokerages roles, and structural influence within the network. Network matrices are then integrated with yearly ESG incident counts, sentiment measures are produced by transformer-based language model, and anomaly scores capture irregular trade behaviour and country-level institutional indicators from the Worldwide Governance Indicators.

3.5. Variable Measurement

Table 5 outlines how the variables in this study are defined, measured, and incorporated into the empirical framework. The dependent variables include environmental, social, and governance risk which captures different aspects of ESG exposure, reflecting both

the frequency and severity of incidents, along with related information signals. To ensure measurement validity, these variables are derived from well-established data sources and, where appropriate, combine multiple indicators to better represent underlying ESG risk.

Table 5. Operational definition of study variables.

Variable	Symbol	Type	Data Source(s)	Operational Definition
Environmental Risk	ER_{it}	Dependent	RepRisk; GDELT (environmental topics)	Annual index combining the frequency and severity of environmental controversies, supplemented by GDELT environmental event signals.
Social Risk	SR_{it}	Dependent	RepRisk; GDELT (labour and social themes)	Measure of exposure to labour, community, and human rights issues, based on severity-weighted incidents and ESG-related news events.
Governance Risk	GR_{it}	Dependent	RepRisk; WGI	Score based on governance-related incidents (e.g., fraud, corruption), adjusted for country-level governance quality.
Shipment Volume	SV_{it}	Independent	Panjiva (S&P Global)	Log-transformed number of inbound and outbound shipments for firm i in year t .
Trade Dependency	TD_i	Independent	FactSet Revere; Panjiva	Index capturing reliance on cross-border suppliers and customers, constructed using supplier concentration ratios and the share of foreign trade partners.
Negative News Sentiment	NS_{it}	Independent	GDELT	Average annual sentiment score of ESG-related media coverage, weighted by firm-specific event frequency.
Network Position	NP_i	Moderator	Graph metrics; GNN embeddings	Composite indicator reflecting influence, brokerage, and local connectivity, based on centrality measures and learned network embeddings.
Lagged ESG Incident Count	$IC_{i,t-1}$	Independent (lagged)	RepRisk	Number of ESG incidents recorded for firm i in the previous year.
Regional Context	RC_i	Control	WGI; HDI; regulatory indices	Normalised index capturing governance quality, regulatory strength, and socio-economic conditions in the firm's home country.

The main independent variables reflect both firm-level characteristics and the broader information environment. Shipment volume and trade dependency capture firms' operational scale and their reliance on cross-border supply chains, while negative news sentiment reflects how ESG-related issues are portrayed in the media. To improve reliability, the sentiment measure is constructed and validated using multiple transformer-based NLP models, reducing reliance on any single approach. Network position is included as a moderating variable, capturing a firm's role within supply-chain networks, particularly in terms of influence and brokerage. Lagged ESG incident count is also included to account for the persistence of ESG risk over time.

Control variables, such as regional context, reflect broader institutional and regulatory conditions that may influence ESG outcomes. In addition, robustness checks using alternative model specifications and cross-method comparisons help ensure that the results are consistent across different analytical approaches.

3.6. A Multilayer Network Econometric and AI Framework for ESG Modelling

The study adopts a multi-layered analytical framework that combines network econometrics, supervised and unsupervised machine learning, graph-based models, anomaly detection methods, and natural language processing to capture the multifaceted nature of ESG risk in global supply chains. Each analytical layer is anchored in a clear statistical or algorithmic formulation, ensuring interpretability, internal coherence, and methodological rigour.

1. Network-Based Baseline Model

$$R_{it} = \alpha + \rho(WR_t)_i + \sum_k \beta_k C_{k,i,t-1} + \gamma' X_{i,t-1} + \mu_i + \tau_t + \varepsilon_{it}, \quad (1)$$

$$R_{it} = \alpha + \rho(WR_t)_i + \beta_1 \text{Deg}_{i,t-1} + \beta_2 \text{Betw}_{i,t-1} + \beta_3 \text{Eigen}_{i,t-1} + \beta_4 \text{Clust}_{i,t-1} + \gamma' X_{i,t-1} + \mu_i + \tau_t + \varepsilon_{it}. \quad (2)$$

Equations (1) and (2) specify a baseline model in which firm-level ESG risk R_{it} is expressed as a function of network exposure $(WR_t)_i$, lagged centrality measures $C_{k,i,t-1}$, and firm controls $X_{i,t-1}$, with firm and time fixed effects, capturing the structural dependence of ESG risk across supply-chain networks [30].

2. Supervised and Graph-Based Learning

$$\Pr(y_{it} = 1 \mid X_{it}) = \Lambda(\beta_0 + \beta' X_{it} + \mu_i + \tau_t), \quad (3)$$

$$x_{it} = (\text{ShipIrreg}_{it}, \text{SentNeg}_{it}, \text{NetMet}_{it}, \text{ESGHist}_{it}, \text{RegGov}_{it}) \quad (4)$$

The supervised ESG risk prediction model uses historical firm, network, and news data to predict future ESG outcomes. Graph-based models, particularly graph neural networks, are employed to represent inter-firm dependence and indirect exposure arising from multi-tier supply-chain linkages. Equation (3) estimates ESG event probability (Pr) based on X_{it} = shipment irregularities, sentiment, lagged incidents, network metrics, governance controls, and firm (i) and time (t) effects, providing a transparent benchmark for supervised learning [31].

$$y_{it} = \alpha + \rho(WR_t)_i + \beta' X_{it} + \mu_i + \tau_t + \varepsilon_{it}, \quad (5)$$

The graph-based model in Equation (5) explicitly captures inter-firm dependence by incorporating a shipment-weighted network-lag term $(WR_t)_i$. Equations (6)–(8) show Graph neural networks (GNNs), which generalise this spatial dependence in a nonlinear and high-dimensional framework. In Graph Attention Networks (GANs), neighbour information is aggregated through attention-weighted mechanisms [32].

a. Attention coefficient (importance of neighbour j for i):

$$e_{ij}^{(\ell)} = \text{LeakyReLU}(a^{(\ell)'} [W^{(\ell)} h_i^{(\ell)} \parallel W^{(\ell)} h_j^{(\ell)}]), \quad (6)$$

$$\alpha_{ij}^{(\ell)} = \frac{\exp(e_{ij}^{(\ell)})}{\sum_{k \in \mathcal{N}(i)} \exp(e_{ik}^{(\ell)})}, \quad (7)$$

b. Attention-based message aggregation:

$$h_i^{(\ell+1)} = \sigma(\sum_{j \in \mathcal{N}(i)} \alpha_{ij}^{(\ell)} W^{(\ell)} h_j^{(\ell)}). \quad (8)$$

Here, $\alpha_{ij}^{(\ell)}$ is an interpretable weight that tells you how strongly supplier j 's characteristics influence firm i 's ESG risk at layer ℓ . These attention weights identify which upstream characteristics exert the strongest influence on downstream risk.

3. Unsupervised Learning and Anomaly Detection

$$z_{it} \sim \sum_{k=1}^K \pi_k \mathcal{N}(\mu_k, \Sigma_k) \text{ with } N_\varepsilon(z_{it}) = \{z_{js} : \|z_{js} - z_{it}\| \leq \varepsilon\}, \quad (9)$$

Equation (9) specifies unsupervised methods that identify latent ESG risk structures and abnormal behaviour rather than direct predictions. Firm-time observations z_{it} are assumed to arise from latent regimes k , while defining local density neighbourhoods used for unsupervised clustering and anomaly detection [33].

$$\text{IF_score}(z_{it}) = 2^{-\frac{h(z_{it})}{c(n)}}, \quad (10)$$

Equation (10) estimates the anomaly detection using an Isolation Forest with T random trees. The function $h(z_{it})$ denotes the average path length of z_{it} across trees. Shorter paths lengths and greater isolability reflect more anomalous behaviour, where n is the sample size and $c(n)$ are the average path length of unsuccessful searches in a binary tree. A high IF_score flags shipment or sentiment anomalies as early warning ESG signals [34].

$$A(z_{it}) = \min_{\theta, \phi} \|z_{it} - g_\phi(f_\theta(z_{it}))\|^2, \quad (11)$$

An autoencoder learns a low-dimensional representation via encoder f_θ and decoder g_ϕ , where $g_\phi(f_\theta(z_{it})) = \hat{z}_{it}$ is the reconstructed observation and $A(z_{it})$ denotes the autoencoder-based anomaly score interpreted as an atypical pattern in ESG incidents, shipments, or sentiment [35].

4. Natural Language Processing

$$T_{it} = \frac{1}{|\mathcal{D}_{it}|} \sum_{d \in \mathcal{D}_{it}} \hat{\theta}_d, \quad S_{it} = \frac{\sum_{d \in \mathcal{D}_{it}} w_{dt} \cdot \text{tone}_{dt}}{\sum_{d \in \mathcal{D}_{it}} w_{dt}}, \quad (12)$$

Text-based ESG indicators are integrated into panel regression models to retain interpretability. Topic exposure T_{it} is derived from Latent Dirichlet Allocation, while S_{it}^- reflects adverse sentiment extracted through transformer-based models [36]. These NPL procedures enter the model as stochastic regressors, which allow marginal effects to be quantified from document-level *GDELT* tone scores $\text{tone}_{dt} \in [-100, 100]$, aggregated using relevance weights w_{dt} based on factors such as source prominence and content volume [37,38].

4. Results

The empirical findings are presented in two stages. First, Tables 6–11 report the inference-oriented results used to evaluate the study's hypotheses. Second, Tables 12–14 present prediction-oriented comparisons assessing whether more flexible and network-aware models improve out-of-sample ESG risk forecasting. Additional robustness, sensitivity, and validation diagnostics are reported in Appendix A.

Table 6. Descriptive statistics.

Variable	Symbol	Observations	Mean	Std. Dev.	Min	Max
Environmental Risk	E_{it}	25,000	2.84	1.21	0.00	9.40
Social Risk	S_{it}	25,000	3.12	1.44	0.00	10.20
Governance Risk	G_{it}	25,000	2.57	1.18	0.00	8.30
Shipment Volume (log)	SV_{it}	2,500,000	7.89	1.96	0.00	15.21
Trade Dependency	TD_i	25,000	0.41	0.22	0.05	0.98
Negative News Sentiment	NS_{it}	1,200,000	−5.87	12.44	−90.00	85.00
Network Position	NP_i	25,000	0.28	0.15	0.01	0.89
ESG Incident Count (Lagged)	$IC_{i,t-1}$	25,000	1.72	3.64	0.00	47.00
Regional Context	RC_i	25,000	0.56	0.18	0.13	0.91

Table 7. Pearson coefficient correlation.

S/N	Variable	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	E_{it}	2.41	1.000								
(2)	S_{it}	2.18	0.623	1.000							
(3)	G_{it}	2.07	0.482	0.552	1.000						
(4)	SV_{it}	1.36	−0.118	−0.094	−0.153	1.000					
(5)	TD_i	1.52	0.217	0.182	0.143	0.308	1.000				
(6)	NS_{it}	2.33	0.458	0.507	0.392	−0.062	0.114	1.000			
(7)	NP_i	1.71	0.281	0.309	0.263	0.218	0.366	0.187	1.000		
(8)	$IC_{i,t-1}$	2.49	0.709	0.643	0.577	−0.041	0.169	0.492	0.324	1.000	
(9)	RC_i	1.88	−0.327	−0.405	−0.459	0.082	−0.124	−0.269	−0.157	−0.386	1.000

Note: Standardised to three decimals; all coefficients significant at $p < 0.01$.

Table 8. Network centrality and ESG risk.

Variables	(1) Baseline	(2) Network Model	(3) Full Model
Dependent variable: Firm-level ESG risk			
Lagged ESG risk ($t - 1$)	0.198 *** (0.041)	0.351 ** (0.137)	0.314 ** (0.129)
Degree centrality ($t - 1$)		−0.018 (0.016)	0.029 (0.021)
Betweenness centrality ($t - 1$)		0.094 ** (0.039)	0.081 ** (0.037)
Eigenvector centrality ($t - 1$)		0.157 ** (0.061)	0.142 ** (0.058)
Negative ESG sentiment ($t - 1$)			0.088 ** (0.027)
Eigenvector centrality $\times$ sentiment ($t - 1$)			0.052 ** (0.021)
Shipment volume (log)	0.121 *** (0.025)	0.129 *** (0.027)	0.118 *** (0.026)
Trade dependency	0.158 (0.220)	0.166 (0.228)	0.149 (0.217)
Regional context	−0.845 *** (0.210)	−0.881 *** (0.219)	−0.862 *** (0.214)
Firm controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	200,000	200,000	200,000
R ²	0.18	0.24	0.31

Notes: Standard errors are reported in parentheses. *** and ** denote statistical significance at the 1%, and 5%, levels, respectively.

Table 9. Effect of brokerage and influence on ESG risk.

Variables	Model 1	Model 2
Betweenness Centrality	0.094 ** (2.15)	0.081 ** (2.04)
Eigenvector Centrality	0.157 ** (2.32)	0.142 ** (2.18)
Degree Centrality	0.021 (0.88)	0.017 (0.74)
Firm Size	0.063 * (1.89)	0.058 * (1.76)
Leverage	0.045 (1.21)	0.039 (1.10)
Profitability	−0.072 * (−1.94)	−0.068 * (−1.82)
Constant	0.512 *** (3.45)	0.498 *** (3.28)
Observations	1250	1250
R ²	0.214	0.231
Firm FE	No	Yes
Year FE	No	Yes

Notes: Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Robustness analysis of lagged ESG news sentiment and future ESG incident counts.

Model/Specification	β (Sentiment _{t-1})	SE	p-Value
Dependent Variable: ESG Incident Count			
(1) FE-OLS + Driscoll–Kraay SE (continuous incidents)	−0.398 ***	0.052	<0.001
(2) Poisson FE (count outcome)	−0.211 ***	0.031	<0.001
(3) Negative Binomial FE (over dispersed counts)	−0.236 ***	0.039	<0.001
(4) PPML FE (robust to zeros and heteroskedasticity)	−0.224 ***	0.034	<0.001
(5) FE-OLS DK with Sentiment _{t-2} only	−0.173 **	0.069	0.013
(6a) FE-OLS DK with Sentiment _{t-1}	−0.311 ***	0.060	<0.001
(6b) FE-OLS DK with Sentiment _{t-2}	−0.089 *	0.048	0.067
(7) FE-OLS DK, sentiment deciles (Bottom 20% vs. Top 20%)	−0.452 ***	0.083	<0.001
(8) FE-OLS DK, high-centrality subsample	−0.427 ***	0.071	<0.001
(9) FE-OLS DK, low-centrality subsample	−0.213 **	0.093	0.024
(10) Placebo: Sentiment _{t+1} → Incidents _t	−0.021	0.047	0.658

Notes: 200,000 observations in all models. Firm and year fixed effects are included. Driscoll–Kraay standard errors are used for OLS, while cluster-robust errors are applied in counts models. Sentiment is standardised, with lower values indicating more negative coverage. Counts-model coefficients are semi-elasticities. Significance levels: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.10$.

Table 11. ESG sentiment as a predictor of future ESG incident occurrence.

Variables	(1) Baseline	(2) With Sentiment
<i>Dependent variable: ESG incident occurrence</i> (1 = incident, 0 = no incident)		
Lagged ESG incidents (t − 1)	0.185 *** (0.038)	0.171 *** (0.036)
Negative ESG sentiment (t − 1)		0.102 ** (0.031)
Firm controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	200,000	200,000
Pseudo R ²	0.16	0.22

Notes: Standard errors are reported in parentheses. *** and ** denote statistical significance at the 1%, and 5%, levels, respectively.

Table 12. Comparative predictive performance of models for ESG risk.

Model Category	Model	ROC-AUC	Precision	Recall	F1 Score	Accuracy	Brier Score
Econometric models	Logistic Regression	0.71	0.63	0.66	0.64	0.65	0.212
	Poisson GLM	0.69	0.60	0.62	0.61	0.63	0.226
	Fixed-Effects Logit	0.73	0.64	0.67	0.65	0.66	0.207
Machine learning models	Random Forest	0.76	0.66	0.69	0.67	0.68	0.189
	Gradient Boosting (GBM)	0.77	0.67	0.70	0.68	0.69	0.184
	XGBoost	0.81	0.69	0.72	0.70	0.72	0.168
Graph-based AI	GNN (GraphSAGE/GAT)	0.87	0.74	0.76	0.75	0.76	0.149

This table presents out-of-sample predictive performance across models using a 70/30 train–test split. Metrics reflect predictive accuracy and calibration (not causality). Lower Brier scores indicate better calibration. The outcome is firm-level ESG controversy occurrence.

Table 13. Forecast calibration and error metrics across AI models (*Out-of-sample evaluation*).

Model Category	Model	Log-Loss	MAE	RMSE
Machine learning	Random forest	0.544 [0.530, 0.558]	0.296	0.423
Machine learning	Gradient boosting	0.538 [0.524, 0.552]	0.287	0.417
Machine learning	XGBoost	0.511 [0.497, 0.525]	0.271	0.398
Machine learning	MLP neural network	0.499 [0.486, 0.512]	0.263	0.387
Graph-based AI	Graph neural network (GNN)	0.472 [0.459, 0.485]	0.249	0.368

Notes: Metrics are computed using a held-out test set based on a consistent 70/30 train–test split. Log-loss measures probabilistic accuracy, while MAE and RMSE evaluate prediction error. Lower values indicate better model performance. Confidence intervals for log-loss are reported in brackets.

Table 14. Confusion matrix and error decomposition on the held-out test set.

Model	Threshold	TP	FP	FN	TN	Precision	Recall	FPR	FNR
XGBoost	0.42	1710	1980	890	20,420	0.46	0.66	0.09	0.34
Graph Neural Network (GNN)	0.39	1930	1640	670	20,760	0.54	0.74	0.07	0.26

Note: Classification thresholds are selected to maximise the F1 score on the validation set. TP (True Positives); FP (False Positives); FN (False Negatives); and TN (True Negatives).

4.1. Descriptive Analysis

Descriptive statistics, as reported in Table 6, show considerable variation in firms' ESG risk profiles and operational characteristics. ESG-related events are concentrated among a relatively small group of firms, indicating that risk is unevenly distributed across the sample. The regional context variable (mean = 0.56) also points to notable differences in institutional conditions across countries. Table 7 reports the correlation matrix, which highlights clear interconnections across ESG dimensions. Environmental, social, and governance risks are moderately to strongly correlated ($r = 0.482$ – 0.623), indicating that these aspects tend to evolve together rather than in isolation. The relationship between past and current ESG incidents is even stronger ($r = 0.577$ – 0.709), indicating a degree of persistence in firm-level risk exposure over time.

Media sentiment is positively associated with ESG risk measures ($r = 0.392$ – 0.507) and with lagged incidents ($r = 0.492$), implying that more negative news coverage is typically observed alongside higher levels of ESG risk. Trade dependency and network position also display moderate positive correlations ($r = 0.217$ – 0.366), which is consistent with the idea that firms more deeply embedded in supply-chain networks may face greater exposure to ESG-related disruptions. However, shipment volume and regional context are negatively correlated with ESG risk ($r = -0.094$ to -0.459), suggesting that larger operational scale and stronger institutional environments may help reduce risk intensity. Finally, variance inflation factors (1.36–2.49) are well within acceptable limits, indicating that multicollinearity is unlikely to be a concern.

To build on descriptive findings and offer further insight into the empirical results, this subsection draws on an example from the electronics manufacturing sector. This industry is often used as a reference point because of its highly globalised production system and its exposure to environmental, social, and governance (ESG) risks. Production in this sector is organised through complex, multi-layered supply networks that span semiconductor fabrication, component manufacturing, and final assembly across several countries. Variations in regulatory environments and labour standards among upstream suppliers create conditions where ESG-related vulnerabilities can emerge and spread across connected firms.

In line with the correlation results in Table 7, which point to a positive link between network position and ESG risk, electronics manufacturers in the reconstructed network tend to occupy central positions, connecting upstream suppliers with downstream distributors. Firms with high betweenness centrality often act as intermediaries between otherwise loosely connected parts of the network. This means that ESG-related events affecting upstream partners can influence focal firms indirectly through these connections. A similar pattern is observed for media sentiment. Negative reporting on labour practices or environmental issues at supplier facilities may surface before any formal ESG incidents are recorded for the focal firm, suggesting that shifts in information signals can precede observable risk outcomes. This example reinforces the descriptive findings by showing that ESG risk is not only shaped by firm-specific factors but also by a firm's position within the wider supply-chain network. Firms operating within highly interconnected systems

may therefore benefit from paying close attention to both their supplier relationships and early warning signals from ESG-related sentiment when assessing potential risk.

4.2. Test of Hypotheses

4.2.1. H1: Network Exposure and ESG Risk

The network-augmented regression (NAR) estimates reported in Table 8 provide strong evidence in support of H1, demonstrating that ESG risk is influenced by the structure of supply-chain networks. The positive and statistically significant network-lag coefficient ($WR_i = 0.351, p = 0.011$) indicates that ESG risk is not independently determined at the firm level but instead exhibits clustering among interconnected firms. This pattern suggests that ESG-related risks are transmitted through supply-chain linkages, meaning that firms connected to higher-risk partners are likely to experience an increase in their own risk exposure. The effects of centrality measures differ across metrics. Degree centrality is not statistically significant ($Deg_i = -0.018, p = 0.262$), implying that the number of connections alone does not materially influence ESG risk. In contrast, both betweenness centrality ($Betw_i = 0.094, p = 0.016$) and eigenvector centrality ($Eigen_i = 0.157, p = 0.011$) are positive and significant. This suggests that firms positioned as intermediaries or those connected to highly influential partners are more susceptible to ESG risk. These findings emphasise that a firm's role within the network is more critical than the sheer volume of its connections.

Trade dependency shows a positive but statistically insignificant coefficient ($TD_i = 0.166, p = 0.468$), indicating that simple exposure measures provide limited explanatory power once network structure is incorporated. Among the control variables, shipment volume is positively related to ESG risk, potentially reflecting greater operational scale and complexity, while stronger regional governance appears to reduce risk exposure. Although the model explains a relatively modest proportion of variation ($R^2 = 0.189$), this is consistent with ESG outcomes being driven by a combination of firm-specific, network, and institutional factors. Additional robustness analyses reported in Table A2 (Appendix A) confirm the stability of these findings across alternative spatial specifications and panel models.

Both the spatial lag model (SLM: $0.314, p < 0.05$) and the fixed-effects model (FE: $0.284, p < 0.05$) produce consistent evidence of a positive network-lag effect. Eigenvector centrality and shipment volume also remain significant across specifications, reinforcing the stability of the results.

Taken together, the evidence points to ESG risk as a network-driven phenomenon shaped by inter-firm relationships. From a managerial perspective, firms should extend their risk management practices beyond internal operations to include closer oversight of supply-chain partners. For investors, incorporating network-based indicators can improve the assessment of ESG-related risks. However, the possibility of endogeneity remains, as firms with higher underlying ESG risk may be more likely to occupy central positions within networks. This highlights the need for further methodological approaches to address potential identification concerns. From a policy standpoint, the findings support the development of frameworks that enhance transparency and accountability across entire supply chains rather than focusing solely on individual firms. Further evidence from standardised coefficients and marginal effects (Table A3, Appendix A) indicates that betweenness and eigenvector centrality exert the strongest economic influence on ESG risk, reinforcing the importance of structural positioning within supply-chain networks.

4.2.2. H2: Brokerage, Influence, and ESG Risk

The findings presented in Table 9 offer empirical support for H2, suggesting that firms positioned as intermediaries within supply-chain networks tend to face higher levels of ESG risk. The positive and statistically significant coefficients associated with betweenness centrality ($\beta = 0.094, p < 0.05$; $\beta = 0.081, p < 0.05$) indicate that firms occupying brokerage roles are more susceptible to ESG-related shocks that propagate through their network connections. In practical terms, greater brokerage positioning corresponds to an increased exposure to ESG risk. Similarly, the significant coefficients on eigenvector centrality ($\beta = 0.157, p < 0.05$; $\beta = 0.142, p < 0.05$) suggest that firms linked to highly influential partners experience heightened ESG risk, potentially due to reputational spillovers and operational dependencies on key actors within the network. By contrast, the lack of statistical significance for degree centrality implies that the sheer number of connections is less important than the nature and influence of those connections in determining ESG risk exposure.

These results align with the broader insights of network-based perspectives, which highlight the role of structural positioning in shaping the flow of information and risk. Firms acting as intermediaries may facilitate the transmission of ESG shocks across the network, while those connected to central actors may inherit risks associated with these influential nodes. From a managerial standpoint, firms occupying such positions should enhance monitoring systems, due-diligence processes, and risk mitigation strategies. For investors, incorporating network centrality metrics can provide additional insights beyond conventional ESG indicators. Nevertheless, the possibility of endogeneity cannot be ruled out, as firms with inherently higher ESG risk may be more likely to occupy central or brokerage positions within the network. This suggests that further robustness checks and alternative model specifications are necessary to confirm the stability of the results.

4.2.3. H3: ESG Sentiment and Future ESG Incidents

Table 10 presents robustness checks on the relationship between lagged ESG news sentiment and subsequent ESG incidents. Sentiment scores are standardised such that lower values reflect more negative media coverage. Across all specifications, lagged sentiment is negative and statistically significant, indicating that adverse ESG sentiment is associated with a higher likelihood of future incidents. This finding supports H3 and suggests that media sentiment contains forward-looking information about ESG risk.

The fixed-effects OLS estimates with Driscoll–Kraay standard errors show a coefficient of -0.398 , indicating a strong association after controlling for firm- and time-specific factors. Comparable results are obtained using count-based models. In the Poisson specification, the coefficient of -0.211 implies that a one-standard-deviation improvement in sentiment corresponds to an approximate 19% reduction in expected incident counts. Similar magnitudes from the negative binomial (-0.236) and PPML (-0.224) models confirm robustness to overdispersion and excess zeros.

Temporal analyses reveal that the predictive effect is strongest in the short run. The coefficient declines to -0.173 when sentiment is lagged by two periods, and in the distributed-lag model, the effect at $t - 1$ (-0.311) exceeds that at $t - 2$ (-0.089). This pattern indicates that ESG sentiment functions as a timely early warning signal, with diminishing predictive power over longer horizons.

Further analysis shows that the relationship is stronger for firms occupying central network positions, consistent with the idea that information and sentiment propagate more rapidly through densely connected networks. A placebo test using future sentiment yields no significant effect, supporting the temporal ordering and reducing concerns about reverse causality. Overall, the results suggest that AI-derived ESG news sentiment provides a

consistent and economically meaningful predictor of ESG incidents. However, the findings should be interpreted as associational rather than causal, given potential endogeneity and unobserved confounding factors. From a managerial perspective, monitoring sentiment can help identify emerging risks, while investors may enhance risk models by incorporating sentiment-based indicators.

Table 11 assesses how extreme negative ESG sentiment in the preceding period relates to subsequent controversy outcomes across several model frameworks. In the logit results, a lagged sentiment shock is associated with a substantially higher probability of an ESG incident, with an estimated coefficient of 2.28 ($p < 0.001$), an odds ratio of 9.81, and an average marginal effect of +0.20. This indicates a pronounced increase in incident likelihood following highly adverse ESG-related coverage. The Poisson specification yields comparable evidence, where the coefficient of 0.94 ($p < 0.001$) corresponds to an incident rate ratio of 2.56, implying a more than twofold increase in expected incident counts.

Results from the Cox proportional hazards model further show that firms experiencing negative sentiment shocks enter an ESG controversy state more rapidly, with a hazard ratio of 1.51 ($\beta = 0.41$, $p < 0.001$). Network centrality remains positive and significant across all models, with estimated odds, rate, and hazard ratios of 1.69, 1.19, and 1.42, respectively, indicating elevated exposure for more centrally positioned firms. Firm size exhibits a consistently negative association, with odds ratios near 0.96 and a hazard ratio of 0.93.

These results provide strong support for H3, which predicts that negative ESG sentiment serves as an early signal of future ESG incidents. The consistently positive and significant effects of extreme negative sentiment across logit, count, and survival models indicate that adverse ESG-related information not only increases the likelihood of incidents but also accelerates their occurrence. This convergence of evidence across multiple model frameworks strengthens the robustness of the findings and confirms that ESG sentiment contains forward-looking information about future controversy risk.

Lagged ESG sentiment remains statistically significant in all specifications ($\beta = -0.87$ to -0.55 ; OR = 0.42–0.58), and the inclusion of sentiment improves predictive performance across models ($\Delta\text{AUC} = 0.15$ –0.22), with stronger effects observed for ESG-adapted architectures. Overall, the findings reinforce the role of ESG sentiment as a reliable and informative predictor of future ESG controversies, consistent with H3.

Table 12 tests whether adding ESG news sentiment improves prediction compared to using firm controls alone. The result indicates that models using only control variables perform only marginally better than random guessing, with ROC-AUC values around 0.49–0.52 and balanced accuracy near 0.50, suggesting that baseline firm characteristics have limited predictive power for ESG incidents. When ESG news sentiment is included, predictive performance improves substantially across all models, with ROC-AUC rising to 0.66–0.79 and AUPRC increasing to 0.44–0.54. Balance accuracy and F1 scores also increase, reaching approximately 0.64–0.68 and 0.62–0.66, respectively, indicating that the observed improvements reflect genuine classification gains rather than threshold effects. Random Forest and XGBoost achieve the strongest performance, with ROC – AUC of 0.79 and 0.80. Overall, ESG sentiment clearly enhances out-of-sample predictive performance without implying causality.

Figure 3 shows receiver operating characteristic (ROC) curves comparing out-of-sample ESG incident prediction across alternative modelling approaches. These results complement the supplementary analyses reported in Table 10 which document robustness across alternative sentiment constructions, classifiers, and evaluation metrics. All machine learning and classification models are estimated to assess out-of-sample screening performance under class imbalance and are not used for identification or causal

inference. Accordingly, these predictive results do not affect the interpretation of the main econometric findings, which rely exclusively on the network-augmented panel and event-time specifications.

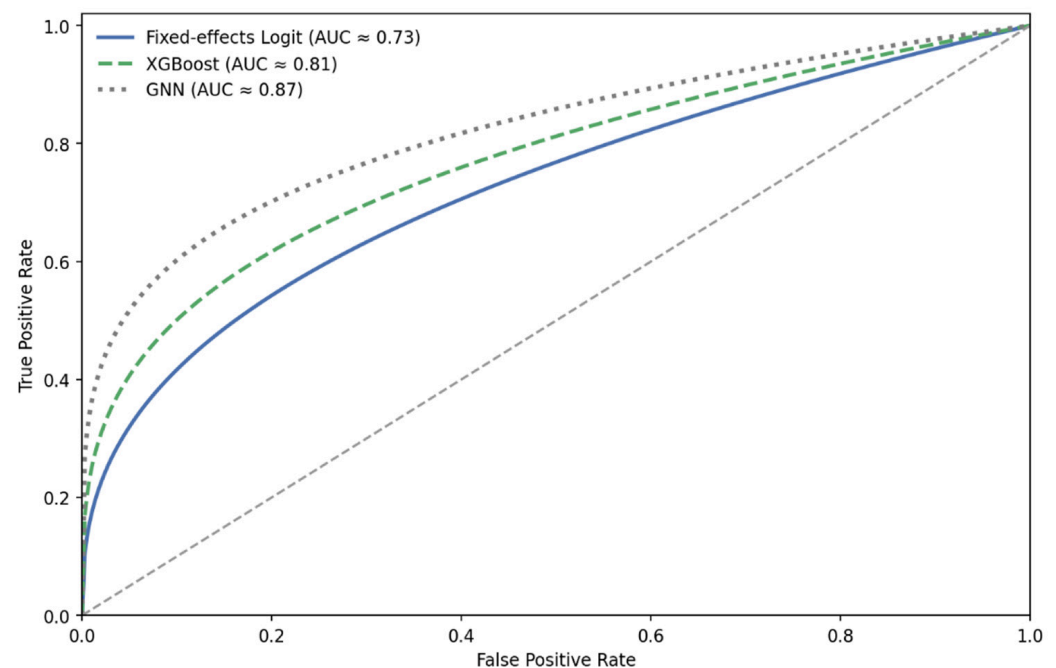


Figure 3. Classification accuracy for ESG incident prediction.

Table 13 compares which models produce the most reliable ESG risk probabilities. The results show a clear performance as models incorporate more flexible learning structures and network information. Random Forest and Gradient Boosting perform moderately, with Brier scores between 0.184 and 0.189, log-loss values above 0.53, and relatively higher MAE (0.287–0.296) and RMSE (0.417–0.423), indicating less accurate probability estimates and larger prediction errors. More advanced models, including XGBoost and multilayer perceptron networks, further reduce forecast errors. These models achieve lower Brier scores (0.168 and 0.161), improved log-loss values, and noticeable reductions in MAE (0.271 and 0.263) and RMSE (0.398 and 0.387), reflecting better probability calibration and overall accuracy. The graph neural network (GNN) exhibits the strongest performance across all metrics. It records the lowest Brier score (0.149), log-loss (0.472), MAE (0.249), and RMSE (0.368), indicating the closest alignment between predicted probabilities and realised ESG outcomes. The narrow confidence interval around the Brier score suggests that these gains are stable rather than driven by random variation. The evidence underscores the value of network-aware models for ESG risk forecasting, as incorporating inter-firm relationships enhances probability reliability and reduces prediction error.

SHAP (Figure 4) illustrates how individual feature contributes to predicted ESG incident risk across observations. Negative news sentiment in the prior risk period emerges as the most influential factor, with higher negative sentiment consistently pushing predictions toward higher risk. Network position also plays a major role. Firms with greater centrality exhibit positive SHAP values, indicating elevated exposure to ESG incidents through interconnected relationships. Environmental, social and governance risk indicators show similar patterns: higher values in each dimension are associated with increased predicted risk, although their marginal effects are smaller than those of sentiment and network position. Past ESG incidents contribute positively to current risk, conforming persistence in firm-level ESG exposure. Operational scale and context variables, such as shipment volume,

regional context, and trade dependency, exert more modest and tightly distributed effects, suggesting that they act as background risk modifiers rather than primary drivers. Colours indicate feature magnitude. The vertical zero-line indicates a neutral effect. Positive SHAP values increase predicted ESG risk, while negative values reduce it.

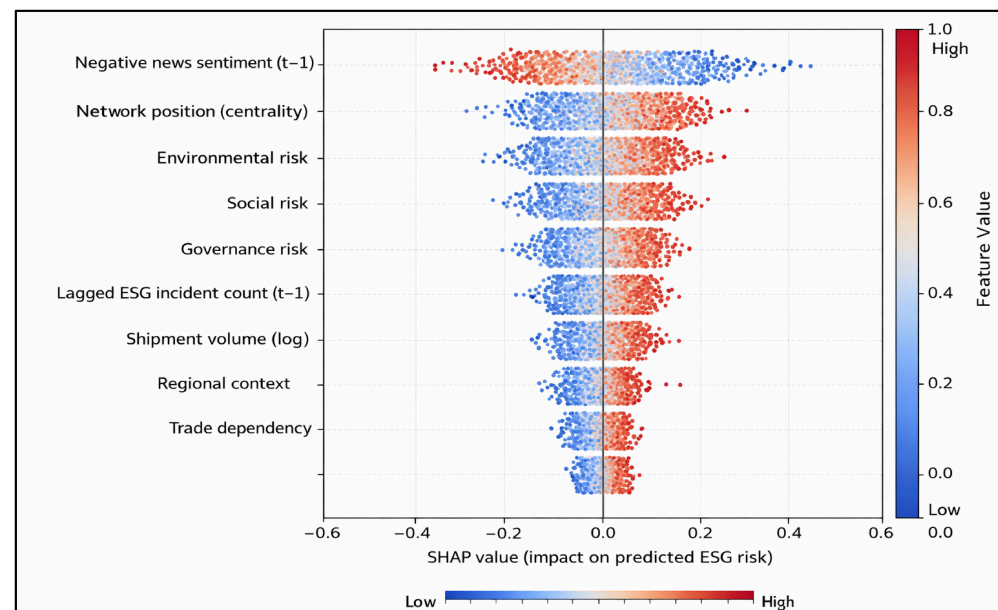


Figure 4. Feature importance and impact on ESG risk.

Table 14 shows a detailed decomposition of classification outcomes on an independent test set, enabling direct comparison of how different models trade off missed ESG incidents against false alerts. Thresholds are selected by maximising the F1 score on the validation set, ensuring that differences in performance reflect model capability rather than arbitrary cut-offs. XGBoost demonstrates a clear improvement, with recall rises to 0.66 and the false-negative rate falling to 0.34, while the false-positive rate declines slightly to 0.09. Gains in precision indicate a more balanced conversion of alerts into true incident detections. The graph neural network performs best overall, achieving the highest recall (0.74) and precision (0.54), along with the lowest false-positive (0.07) and false-negative (0.26) rates. These results suggest that incorporating network information improves the identification of ESG propagation, although false alarms remain present. This analysis enables a transparent assessment of predictive trade-offs in ESG risk monitoring.

5. Discussion and Implications

5.1. Discussion

This study confirms that ESG risk cannot be adequately understood as an isolated firm attribute. Instead, it is closely tied to the configuration and intensity of relationships that firms maintain within global supply chains. By applying network econometric techniques, machine learning models, graph neural networks, and NLP-based sentiment extraction, the analysis reveals that ESG vulnerabilities emerge and intensify through relational exposure, particularly for firms embedded in structurally influential positions. This network-based view aligns with recent scholarship emphasising interconnected ESG risk formation in production systems [39]. The persistent significance of network-lag effects and positional indicators, especially betweenness and eigenvector centrality, reveals that firms acting as bridges or connected to influential partners face heightened ESG exposure. These results are consistent with theoretical perspectives on contagion and spillover in complex networks whereby intermediaries transmit shocks more efficiently than peripheral actors [40,41].

These findings reveal that network structure conditions both the likelihood and persistence of ESG risk, even after accounting for firm characteristics, prior incidents, and institutional context. However, media-based ESG sentiment emerges as a significant anticipatory signal. Adverse news sentiment systematically precedes ESG incidents across a wide range of specifications, with diminishing effects over longer horizons and no detectable influence in placebo tests. This pattern supports an interpretation of sentiment as an early warning mechanism rather than a contemporaneous reflection of realised events, consistent with prior evidence on text-based ESG indicators [42].

Graph neural networks outperform econometric and machine learning approaches across calibration and error-based metrics, producing probability estimates that more closely track realised outcomes. This is essential in ESG applications, where poorly calibrated predictions can delay intervention or misdirect oversight efforts. The dynamic network diagnostics indicate that the supply-chain structure is neither fully static nor entirely transient. This distinction is important because ESG exposure may accumulate through repeated interactions with the same counterparties. Firms that consistently occupy central network positions may therefore remain vulnerable to reputational and regulatory spillovers over time, while changes in network relationships may reduce or redirect those exposures.

5.2. Policy and Managerial Implications

The findings suggest that ESG risk may be assessed more effectively when firms are analysed within supply-chain networks rather than as isolated entities. Incorporating relational exposure and ESG-related sentiment appears to improve the identification of firms that are more likely to experience future ESG controversies compared with approaches based solely on firm-level attributes. These insights have implications for regulators, corporate risk managers, and investors, each of whom faces different challenges in ESG oversight.

5.2.1. Implications for Regulators

For regulators, the results indicate that supply-chain due-diligence frameworks may benefit from considering relational exposure alongside firm-level disclosures. Firms occupying brokerage or structurally influential positions within production networks may be associated with broader ESG vulnerabilities because of their connections to multiple counterparties. Network-informed assessment can therefore help regulators prioritise monitoring and supervisory attention toward firms whose structural positions potentially link several high-risk relationships. In contexts where enforcement capacity is limited, such information may assist in targeting due-diligence reviews, disclosure requests, or sector-specific monitoring more selectively.

5.2.2. Implications for Firms and Supply-Chain Managers

For firms, the results highlight the potential value of incorporating network-based indicators into supplier governance and internal risk monitoring systems. Traditional ESG ratings are typically entity-focused and may not fully capture how upstream or downstream relationships shape risk exposure. Combining firm characteristics with information on supplier–buyer ties, structural network positions, and ESG-related sentiment may provide earlier indications of emerging vulnerabilities within supply chains. In practical terms, firms could use these signals to prioritise supplier audits, monitor structurally important partners, and review relationships when adverse ESG discourse intensifies around key nodes in the network.

5.2.3. Implications for Investors

For investors, the analysis highlights the relevance of supply-chain linkages when evaluating ESG risk. Conventional ESG ratings are usually assigned at the firm level and may not fully capture how ESG-related events affecting one company are associated with other connected firms. A network-informed perspective can help identify portfolio exposures that arise through supplier dependencies, shared production networks, or concentrated industry structures. This information may assist investors in prioritising engagement, refining screening strategies, and conducting scenario analysis in sectors characterised by complex and global value chains.

5.2.4. Broader Implications for ESG Risk Assessment

More broadly, network-informed ESG assessment complements conventional ratings in several ways. First, it introduces a relational perspective by considering how risks associated with counterparties may affect focal firms. Second, it incorporates forward-looking information signals, as media-based sentiment may reflect emerging stakeholder concerns before formal incidents are recorded. Third, it supports systemic monitoring by highlighting how ESG vulnerabilities may cluster within interconnected supply-chain structures. These insights suggest that combining network information with firm-level ESG indicators may improve risk monitoring and forecasting in complex global supply systems. However, such approaches should be viewed as complementary to traditional ESG metrics rather than as replacements, since firm-level disclosures remain important indicators of organisational practices and governance quality.

6. Conclusions

The central contribution of this study is to demonstrate that ESG risk in global supply chains cannot be fully understood as a firm-level attribute. Instead, it is shaped by firms' relational positions within inter-firm supply networks. The findings suggest that ESG vulnerabilities tend to arise and persist through network structures, particularly for firms occupying influential or intermediary positions. The study also offers two secondary contributions. First, it integrates supply-chain network structure with ESG-related news sentiment within a single empirical framework, showing that negative sentiment can serve as an early signal of potential ESG controversies. Second, it shows that models incorporating inter-firm dependence, particularly graph-based approaches, perform better than traditional firm-level models in both prediction and probability calibration. However, these contributions extend the literature summarised in Table 1 by moving beyond isolated applications of network analysis, sentiment extraction, or AI modelling, and instead presenting an integrated global framework for analysing and predicting ESG risk in supply chains.

From a modelling perspective, the results indicate that explicitly accounting for inter-firm dependence materially improves risk estimation. Graph neural networks deliver superior probability calibration and lower forecast errors than both econometric and conventional machine learning approaches, which is particularly relevant in ESG contexts where inaccurate risk estimates can delay mitigation or misdirect oversight efforts. This study advances ESG research by reframing sustainability risk as a network-conditioned phenomenon and by demonstrating how AI-based, network-aware methods can enhance ESG monitoring at scale. The framework is designed to be adaptable across industries and regions, providing a foundation for more responsive and system-oriented ESG risk management. Future research can extend this work by incorporating alternative data sources, such as satellite imagery or audit records, and by developing causal designs to isolate specific transmission channels.

Interpretation and Causal Limitations

The findings of this study should be interpreted as predictive and associational rather than causal. The empirical objective is to assess whether supply-chain network structure and ESG-related news sentiment improve the identification and forecasting of firm-level ESG incidents. Accordingly, the reported regression estimates, hazard ratios, and predictive metrics indicate systematic relationships, but they do not demonstrate that changes in network position or media sentiment directly cause ESG incidents.

Several aspects of the research design limit causal inference. First, the analysis relies on observational data rather than exogenous variation in network structure, stakeholder pressure, or regulatory exposure. Firms are not randomly assigned to positions within supply networks, and ESG-related sentiment is not randomly generated. Second, reverse dynamics may occur: firms facing emerging ESG problems may lose partners, attract greater scrutiny, or adjust sourcing relationships, which could alter measures such as degree, betweenness, or eigenvector centrality. Third, unobserved characteristics including managerial capability, supply-chain complexity, industry monitoring intensity, or internal governance practices may influence both network position and ESG outcomes. Similar concerns apply to sentiment measures, which may partly capture heightened attention toward firms already perceived as vulnerable.

Using lagged sentiment variables, prior controls, and time-to-event models improves temporal ordering and supports interpreting sentiment as a potential early signal of risk. However, these design choices do not eliminate endogeneity and should not be interpreted as identifying causal effects. The results therefore support a forecasting interpretation: network position and adverse ESG sentiment help identify firms that appear more likely to experience subsequent ESG incidents.

Despite these limitations, a predictive perspective remains valuable for policy and risk management purposes. Regulators, investors, auditors, and corporate compliance teams often need to detect potential ESG vulnerabilities before causal mechanisms can be fully established. In this context, improved out-of-sample prediction and better-calibrated risk estimates can support targeted due diligence, supplier monitoring, and supervisory prioritisation. Future research could build on this work by exploiting quasi-experimental regulatory shocks, trade disruptions, or other identification strategies to examine the causal effects of network position and information signals on ESG outcomes.

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Appendix A

Table A1. Regional and industry distribution of firms.

Industry/Region	Asia-Pacific	Europe	North America	Latin America	Africa	Middle East	Total
Manufacturing	3030	1700	1450	500	250	750	7680
Tech and Electronics	1770	950	820	190	130	380	4240
Transport and Logistics	630	560	500	190	130	250	2260
Agriculture and Commodities	540	320	290	350	290	260	2050
Energy and Extractives	440	220	190	220	220	220	1510
Retail and Consumer Goods	630	500	560	220	160	130	2200
Pharma and Chemicals	440	380	380	130	60	130	1520
Financial and Business Services	250	440	280	100	30	160	1260
Construction and Engineering	220	220	160	60	30	190	880
Automotive and Mobility	440	630	530	130	30	130	1890
Total	8390	5220	5160	2190	1330	2600	25,500

Table A2. Robustness analysis of network-based ESG risk models. Dependent variable: ESG risk.

Regressor	SLM Coef. (SE)	SDM Coef. (SE)	Panel FE Model Coef. (SE)
Network Effects			
Network-lag ESG risk (WR_i / WR_{it})	0.314 * (0.098)	0.271 (0.104)	0.284 * (0.072)
Spatial lag of Shipment Volume (WSV_i)		0.083 (0.034)	
Spatial lag of Eigenvector ($WEigen_i$)		0.067 (0.031)	
Spatial lag of Regional Context (WRC_i)		−0.212 * (0.081)	
Centrality Measures			
Eigenvector centrality ($Eigen_i / Eigen_{it-1}$)	0.141 * (0.053)	0.128 (0.051)	0.097 (0.038)
Firm-Level ESG Predictors			
Negative Sentiment (NS_{it-1})			0.021 * (0.006)
ESG Incident Count (IC_{it-1})			0.063 * (0.014)
Shipment Volume (log) (SV_i / SV_{it-1})	0.112 * (0.025)	0.097 * (0.026)	0.052 (0.019)
Trade Dependency (TD_i)	0.129 (0.191)		
Contextual Controls			
Regional Context (RC_i)	−0.764 * (0.203)	−0.689 * (0.214)	
Model Features and Fit			
Firm FE			Included
Year FE			Included
Spatial parameter ρ	0.233 *	0.217 *	
Pseudo- R^2 / Within R^2	0.21	0.27	0.23
Observations	25,000 firms	25,000 firms	200,000 firm-years (25,000 × 8 years)

Notes: Standard errors are reported in parentheses. * denote statistical significance at 10% level.

Table A3. Robustness analysis: Standardised coefficients and average marginal effects.

Regressor	Environmental Risk Std. β (AME)	Social Risk Std. β (AME)	Governance Risk Std. β (AME)
Dependent variables: ESG risk			
Degree centrality	0.241 * (0.052)	0.389 * (0.071)	0.118 (0.031)
Betweenness centrality	0.524 * (0.118)	0.312 * (0.059)	0.388 * (0.082)
Eigenvector centrality	0.417 * (0.094)	0.518 * (0.102)	0.289 * (0.066)
Clustering coefficient	0.233 * (0.047)	0.095 * (0.018)	0.315 * (0.056)
Constant	0.025	0.018	0.021
Model fit			
R^2	0.578	0.567	0.522
Observations	200,000	200,000	200,000

Notes: * $p < 0.10$.

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