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Firmographica: Knowledge Graph and AI-based Framework for Short-Selling Risk Assessment

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Abstract

This study investigates how corporate ownership structures affect short selling in publicly traded banking firms by integrating knowledge graph methodologies with regression analysis. By combining graph-based centrality metrics with traditional indicators like firm size and ownership concentration, we systematically identify and rank the factors that influence short-selling activity. Our results indicate that firm size, the degree of ownership concentration, and PageRank centrality are consistently significant predictors of both the level and intensity of short-selling positions. Additionally, insider trading activity is shown to be a critical determinant of short-selling volatility, suggesting that internal market behaviors provide unique predictive value beyond standard financial metrics. The findings underscore the broader potential for graph analytics and machine learning approaches to enhance financial risk modeling and market surveillance. By providing a richer, network-driven perspective, this research contributes to a better understanding of market dynamics, supports the development of more robust governance frameworks, and informs both regulatory policy and investment strategies aimed at promoting transparency and stability in the financial sector.

Keywords: Knowledge Graph, Short Selling, Network Analysis, Regression, Ownership Structure, Corporate Governance

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1. Introduction

In financial markets, corporate ownership structures are integral to governance, market stability, and investor confidence. Complex networks involving shell entities, crossholdings, trusts, and other opaque ownership arrangements can obscure financial realities, complicating regulatory transparency and accountability. Short selling, a trading strategy that profits from a company's declining share price, serves as a crucial market mechanism for exposing inefficiencies, overvaluations, and governance weaknesses that might otherwise remain hidden from investors.

Agency theory [1] suggests that ownership patterns influence the alignment of interests between shareholders and managers, directly affecting governance effectiveness and firm risk profiles. When ownership structures obscure accountability or exacerbate conflicts of interest, they create vulnerabilities that attract short sellers. Recent high-profile market events highlight the urgency of systematically analyzing hidden ownership relationships for early risk detection. For instance, in December 2022, Hindenburg Research's report on the Adani Group revealed fraudulent practices involving offshore shell entities, leading to a market capitalization loss exceeding $104 billion, approximately 40% of the group's total value [2]. Similarly, Elon Musk's acquisition of Twitter, which involved opaque ownership structures and undisclosed financial backers, raised significant regulatory and governance concerns [3]. These cases demonstrate how concealed ownership complexities can undermine investor confidence and amplify short-selling pressure.

Short sellers often target firms with governance weaknesses linked to their ownership. Dispersed ownership limits oversight, while poor governance can misalign managerial incentives with shareholder interests. In contrast, high insider ownership or concentrated control can discourage short selling by signaling managerial confidence or limiting share availability. Understanding these dynamics requires accurate identification of patterns in ownership structures, insider trading, and market behavior. Automating ownership assessment through graph-based network analysis and machine learning can improve transparency, helping investors and regulators detect governance issues before they lead to market disruptions.

To systematically analyze ownership structures and their impact on short-selling activity, we introduce Firmographica, a framework that integrates knowledge graph and machine learning. By constructing a directed graph that captures ownership relations among selected NASDAQ-traded companies in the banking sector, we extract key structural features such as graph centrality measures and the Herfindahl-Hirschman Index (HHI) to quantify ownership concentration and influence. Complementing these network-based insights with insider trading data, largest shareholder stakes, and firm size into a regression framework, we seek to uncover their meaningful correlations with short-selling positions.

The remainder of this paper is structured as follows. Section 2 reviews the related literature on short selling and data-driven assessment of ownership structures; Section 3 details our methodology for knowledge graph construction, network analysis, and regression modeling; Section 4 presents the empirical results and discusses their implications. Finally, Section 5 concludes with key takeaways and directions for future research.

2. Related Literature

The role of ownership structures in corporate governance and stability has been extensively examined in finance research. [4] analyzed global variations in ownership concentration, emphasizing its influence on shareholder protections and governance mechanisms. [5] further demonstrated how concentrated ownership affects corporate decision-making and control in East Asian firms, underscoring the importance of ownership networks in assessing governance risks and market stability.

Short selling is often associated with market efficiency, as it facilitates price discovery and exposes overvalued firms. Firms with weak governance and agency conflicts are more likely to attract short sellers [6], who can further exacerbate volatility [7] and future negative returns [8]. The following ownership dimensions can be significant drivers of short-selling activity:

- Ownership concentration is typically associated with stronger oversight by controlling shareholders [9], reducing agency conflicts and detracting short sellers due to lower free float [4]. Conversely, firms with dispersed or weakly connected ownership structures are more vulnerable to short interest due to managerial opportunism and governance inefficiencies [10].
- High insider ownership often aligns managerial incentives with shareholder interests, mitigating agency conflicts [1]. Consequently, firms with significant insider ownership tend to have fewer short sales due to reduced governance risks [11]. However, entrenched insiders may resist transparency, potentially increasing agency risks if oversight mechanisms are weak.
- High institutional ownership can both deter and attract short sellers. On the one hand, institutional investors act as monitors of corporate governance, reducing agency conflicts

[12]. On the other hand, their participation in the securities lending markets facilitates short selling [13]. High institutional scrutiny may further expose governance weaknesses, making such firms attractive to short sellers.

Graph-based network analysis is instrumental for uncovering complex ownership structures and their impact on financial risk. [14] applied network analysis methods to measure systemic financial risk. However, traditional network analysis often centers on descriptive metrics and structural features, providing limited predictive power. [15] demonstrated how graph analysis and machine learning can help reveal hidden beneficial ownership structures. Using this integrated approach, we can also assess how ownership patterns expose firms to short-selling pressures.

Insider trading activity is an important signal about managerial confidence and firm stability. [16] demonstrated that insider trades can influence future stock performance, while [17] found that insider transactions reflect expectations about the firm fundamentals. Thus, incorporating insider trading data into the ownership analysis can enhance short-selling prediction.

Market concentration measures, such as the HHI, also provide valuable insights into ownership dominance and competitive dynamics. [18] explored HHI to evaluate market power, while [19] analyzed its effectiveness for competitive assessment in the banking sector. By integrating HHI into the graph network analysis, we can quantify ownership concentration and gauge its impact on short selling.

3. Methodology

Our methodology focuses on the banking sector, which is characterized by heightened sensitivity to economic fluctuations, interest rate changes, regulatory shifts, and potential financial manipulations, contributing to its volatility. To investigate the relationship between corporate ownership structures and short-selling risk, we employed a structured, multistep approach. This includes data acquisition and pre-processing, construction of a directed ownership knowledge graph, and selection of structural and financial features for regression analysis. The details of each step are outlined below.

3.1. Data Acquisition and Processing

To choose specific companies for our analysis, we used the FINRA API, which provides bimonthly short interest change reports. We randomly selected a mix of 216 small, medium, and large-cap banking firms covering the reporting period between January 1, 2024 and October 31, 2024. For each company, we also obtained Form 13-D and 13-G filings through the SEC API, which also provides granular ownership details, including major shareholder disclosures, insider ownership percentages, and institutional stakes. We also collected insider trading data from the SEC API for the selected companies over the same time period of 10 months.

Once the raw data was collected, it underwent a series of pre-processing steps to ensure accuracy and consistency before integration into the knowledge graph. This process involved data cleaning to remove duplicates, correct inconsistencies in ownership percentages, standardize and disambiguate entity names. Ownership relationships were verified by cross-referencing SEC filings and institutional ownership data to identify discrepancies. Entity resolution was performed using the London Stock Exchange Group (LSEG) Data & Analytics API to link records referring to the same entity via LSEG PermID. Finally, normalization and standardization were applied using the Anthropic Claude Sonnet 3.5 Large Language Model to address missing values, inconsistencies, and formatting variations across data sources.

3.2. Ownership Knowledge Graph Construction

We used the Neo4j graph database [20] to structure the cleaned ownership data into a directed knowledge graph. The graph consists of three entity node types: Company, Owner

(Company), and Owner (Person). Each node is enriched with firmographic attributes, including company jurisdiction, linked entity PermID, and disambiguated company name, ensuring data consistency and standardization.

Edges represent ownership relationships and are weighted by percentage ownership, providing a quantitative measure of control. A directed edge from node A to node B with weight x signifies that A holds x% of B's shares, with weights constrained to the range [0,100]. Figure 1 illustrates the graph's node and relationship structures.

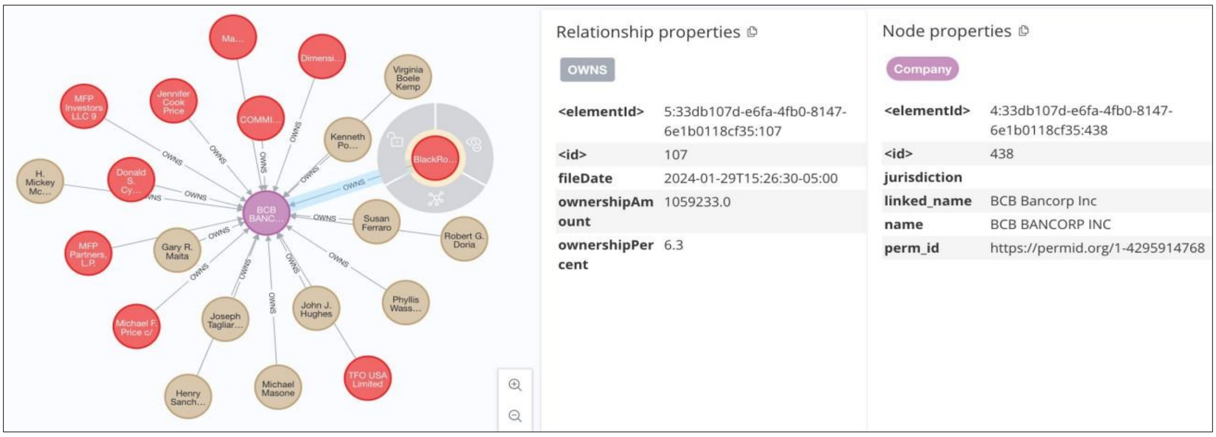


Figure 1. Sample Company Node and Relationship View in Neo4j

This structured knowledge graph facilitates visualization and analytics, enabling the computation of graph centrality measures and ownership concentration and dispersion.

3.3 Feature Selection

To model short-selling positions and risks, we identified and analyzed the following structural and financial dimensions of a firm's exposure. Together, these features provide a comprehensive framework for understanding the factors influencing short-selling activity.

3.3.1 Ownership Structure Metrics

Analyzing a company's ownership structure provides valuable insights into its susceptibility to short-selling activities. In this context, we focus on the following features:

- **Number of Trusts:** Trusts often serve as vehicles for estate planning and tax optimization, potentially leading to increased opacity in ownership. A higher number of trusts within a company's ownership structure can complicate investors' assessments of the firm's governance and financial health, thereby influencing short-selling behavior [21].
- **Largest Shareholder's Ownership Stake** reflects ownership concentration. A dominant shareholder may deter short sellers due to perceived stability and potential insider support for the stock. Conversely, a lower concentration might indicate dispersed ownership, possibly attracting short-selling due to perceived vulnerabilities [22].
- **Ratio of Largest to Second-Largest Stakes** further informs the distribution of ownership. A high ratio suggests a significant disparity between the two largest shareholders, which can either deter or attract short sellers, depending on perceptions of the dominant shareholder's influence and intentions.

By incorporating these ownership structure metrics into a regression analysis, our objective is to capture and quantify their effects on short-selling behavior.

3.3.2 HHI

The HHI is a widely used measure of market concentration that quantifies the degree of ownership consolidation within a given set of entities. Originally developed in the context of antitrust regulation and competition economics [23, 24]. HHI is particularly useful for assessing the dominance of a few large players in a market. In the context of our ownership knowledge graph, where nodes represent public companies and their corporate and individual owners, and directed edges capture ownership relationships weighted by their percentage stake, HHI serves as a measure of ownership concentration of a company:

$$HHI_c = \sum_{i=1}^{N} \omega_{i,c}^2 \tag{1}$$

where $\omega_{i,c}$ represents the percentage of Owner node i in Company node c, and N is the total number of owners with stakes in company c. The HHI value can range from 0, indicating a highly fragmented ownership, to 10,000 if there is a single owner.

In the context of short selling, high HHI can reduce the free float and make borrowing shares more difficult, potentially discouraging short sellers. But concentrated ownership can also increase volatility if one large shareholder's actions significantly move the market, masking governance issues that attract short sellers in the first place. Conversely, dispersed ownership can weaken oversight due to governance vulnerabilities, but also increase share availability and liquidity, which may entice short sellers.

3.3.3 Graph Network Centrality

In our directed ownership graph, edges are weighted by ownership percentages, enabling us to capture how stakes propagate across multiple tiers of investors. Although we initially considered eigenvector centrality [25], it can disproportionately boost the standing of "sink" nodes making it less suited for a directed graph. By contrast, PageRank [26] employs both normalization and a damping factor d to prevent rank from accumulating in "sink" nodes and provides a more balanced measure of ownership influence in a directed network.

$$PR(i) = (1-d) + d \sum_{j \in N(i)} \frac{PR(j)A_{ji}}{\sum_{k \in N(j)} A_{jk}}, \tag{2}$$

where A_{ji} represents the ownership weight from node j to node i, and $N(i)$ is the set of upstream neighbors of node i.

In our analysis, weighted PageRank centrality complements traditional concentration measures like the HHI by providing additional insights into short-selling risks. High PageRank scores indicate firms owned by multiple influential stakeholders, making them subject to greater scrutiny and potential coordinated short-selling pressure. Likewise, owners with high PageRank exert significant influence across their holdings, amplifying the impact of their strategic decisions on market liquidity and stability. Conversely, entities with low PageRank scores may be more exposed to idiosyncratic risks due to their limited network influence [27]. These attributes make PageRank a valuable measure for capturing the dynamics of influence in a directed and diversified ownership network, and it is therefore prioritized in our final short-selling risk models.

3.3.4 Insider Trading Activity

Insider trading – transactions by executives, directors, and significant shareholders – provides insights into market sentiment and a company's financial health. Insider purchases often indicate confidence in the firm's prospects, while insider sales may suggest concerns or liquidity needs [28]. In the context of short-interest modeling, a high volume of insider selling, particularly when aggregated over time, may serve as an early warning signal of potential stock declines, triggering increased short-selling activity. Conversely, substantial insider purchases may discourage short sellers, as insider confidence can reduce perceived downside risk.

To incorporate this into our regression model, we normalize insider trading data, collected from the SEC API, by the number of shares outstanding to ensure comparability across companies, and aggregate these normalized values over the span of 10 months from January to October 2024 for each company:

$$I_c = \sum_{t=1}^{T} \frac{S_{c,t}}{O_c}, \tag{3}$$

where I_c is the aggregated normalized insider trading activity for company c, $S_{c,t}$ represents the net shares traded by insiders (purchases minus sales) at time t, and O_c is the total number of shares outstanding for company c.

By integrating normalized insider trading activity into our regression model, we capture an additional layer of market sentiment that complements structural ownership measures like the HHI and graph centrality metrics.

3.3.5 Volatility, Capitalization, and Total Assets

Finally, we obtained volatility, market capitalization, and total assets on the balance sheet for each company from the Yahoo Finance API. Volatility, also known as the beta (β), captures a stock's sensitivity to market fluctuations. Higher beta stocks exhibit greater price swings, attracting short sellers due to higher potential returns from price declines. In contrast, lower beta stocks tend to be more stable and less attractive for short-selling [29].

Market capitalization and total assets serve as proxies for firm size and financial stability. Larger firms with high market capitalization and substantial total assets generally experience lower short-interest risk due to greater liquidity and investor confidence. In contrast, smaller firms are more susceptible to volatility and short-selling pressures [30]. To enhance the interpretability and mitigate the effects of extreme values, we apply a log transformation to both market capitalization and total assets.

By integrating these financial indicators alongside ownership structure metrics (HHI and centrality measures) and insider trading activity, we construct a comprehensive framework to predict short-selling positions and their volatility.

4. Results

4.1 Correlation Analysis

We examined bivariate relationships between ownership concentration, graph centrality, financial metrics, and short-selling positions using Pearson and Spearman correlation analyses. The heat maps in Figure 2 summarise these results.

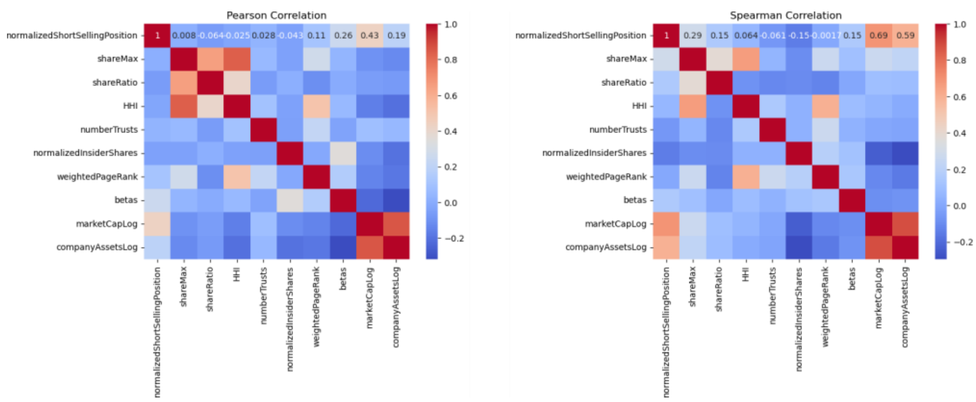


Figure 2. Pearson and Spearman Correlation Heatmaps of Features

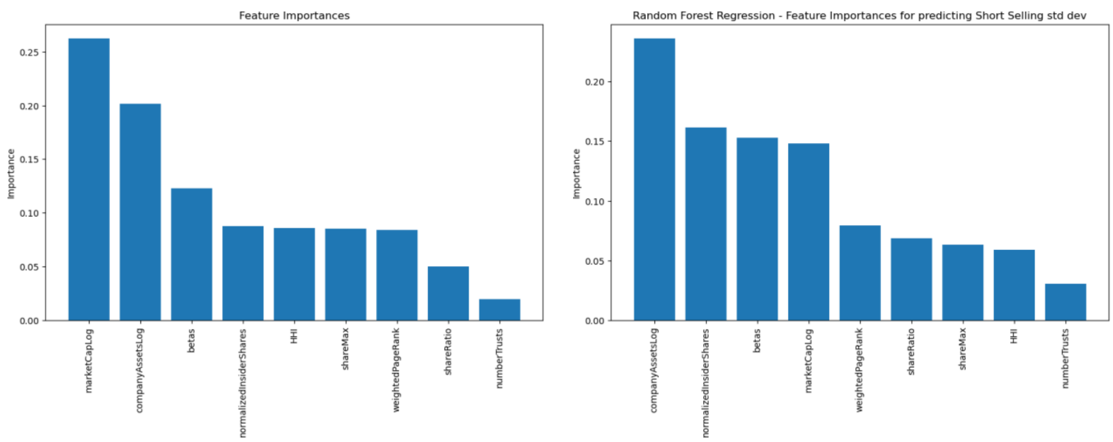
The normalized short-selling position shows varying degrees of correlation with the explored features. Notably, the largest shareholder's ownership stake (shareMax) displays a moderate positive Spearman correlation (0.29) with short-selling positions, suggesting that a higher concentration of shares in a single holder could influence the shares available for short-selling. The ratio of the largest to the second largest ownership stakes (shareRatio) also has a weak positive correlation (0.15), indicating that variations in ownership distribution might affect short-selling activity.

Meanwhile, other ownership concentration metrics, such as the HHI and PageRank scores, reveal a minimal direct correlation with short-selling positions when considered independently. However, correlation analysis does not fully capture the interplay among multiple factors, which underscores the need for regression analysis to explain multivariate relationships and their influence on short selling.

4.2 Regression Analysis

To model prediction of average short-selling positions using ownership, network, and firmographic features, we tried Random Forest (RFR), Support Vector (SVR), and a Neural Network (NNR) regressions. RFR delivered the best overall performance, achieving a mean squared error (MSE) of 1.57, compared to 2.49 for SVR and 2.53 for NNR. This likely reflects RFR's ability to handle non-linear relationships and capture complex feature interactions via its ensemble of decision trees.

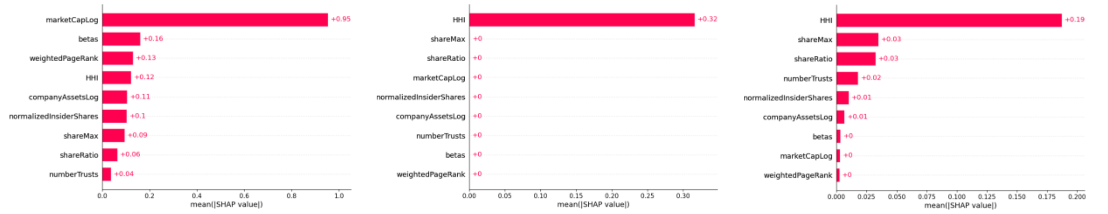
Figure 3a shows the RFR's feature importances, where market cap (marketCapLog) and total assets on the balance sheet (companyAssetsLog) emerge as the most influential predictors. This suggests that larger firms tend to have more predictable short-selling positions. The largest shareholder's stake (shareMax), HHI, and PageRank score, which reflect ownership concentration and network centrality, show moderately high importance, although they are less dominant than liquidity-related metrics.



(a) Short-Selling Position Prediction (b) Short-Selling Volatility Prediction

Figure 3. Feature Importance in RFR

To examine how each model weighs individual predictors, we computed SHapley Additive Explanation (SHAP) values [31]. As depicted in Figure 4, HHI is the most influential predictor in both SVR and NNR, while PageRank score and HHI exhibit relatively higher importance in RFR. This confirms that ownership concentration and network centrality strongly influence short-selling positions. Market cap remains an influential factor across all models, although with lesser importance in SVR and NNR.

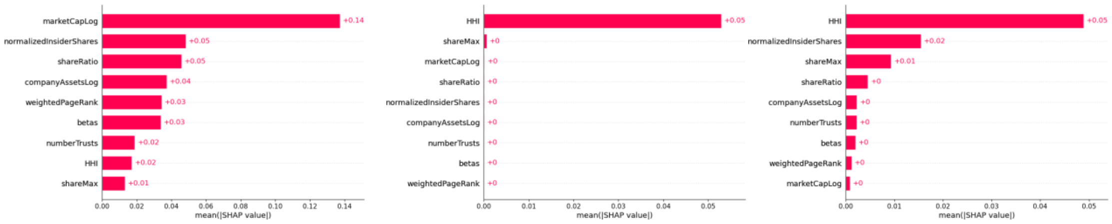


(a) RFR (b) SVR (c) NNR

Figure 4. SHAP values for models predicting short-selling positions

To explore short-selling position volatility (standard deviation), we applied the same three regression models. All three regressors achieved substantially lower MSE values (0.11 for RFR, 0.6 for both SVR and NNR), indicating that fluctuations in short-selling positions are easier to predict than average levels. Figure 3b shows the second highest feature importance for insider trading. Further, according to the SHAP plots in Figure 5, market cap, followed by normalizedInsiderShares and shareRatio, have the highest importance in RFR, while HHI is still dominant in both SVR and NNR. This pattern suggests that insider trading may exert a stronger effect on the volatility of short positions than on their average levels.

The SHAP analysis for short-selling volatility (Figure 5) highlights a shift in feature importance. Insider trading activity (normalizedInsiderShares) emerges as a more significant predictor of volatility than the average short-selling position. HHI continues to play a crucial role, particularly in SVR and NNR models, further underscoring the importance of ownership concentration in influencing short-selling dynamics.



(a) RFR (b) SVR (c) NNR

Figure 5. SHAP values for models predicting short-selling position volatility

5. Conclusion

This paper introduced a knowledge graph- and machine learning-based framework to analyze the impact of corporate ownership structures on short-selling activity. By constructing a knowledge graph enriched with firmographic attributes, we effectively captured ownership relationships and stakes, enabling network analysis and regression modeling. Our findings identified ownership concentration (measured by HHI), network centrality (captured by PageRank), insider trading activity, and firm size as significant predictors of short selling, with their relative importance varying across outcomes such as short-selling position averages and volatility.

The comparative SHAP analyses emphasized the value of employing diverse machine learning models to uncover the multifaceted factors influencing short-selling behavior. This methodological diversity enhances predictive insights and strengthens the framework's applicability. For practitioners, incorporating network-level ownership data into routine risk assessments can improve the detection of governance vulnerabilities and support more informed lending and investment decisions. Regulators can leverage Firmographica for enhanced market surveillance, uncovering hidden ownership concentrations that may signal systemic risks.

Future research could extend this framework to other industries with complex ownership networks, such as sectors with significant cross-border operations or heightened regulatory scrutiny, offering a broader perspective on short-selling risk drivers. Incorporating temporal analyses and real-time market indicators could further refine predictive accuracy. Additionally, integrating alternative data sources, such as social media sentiment or news coverage, could enrich the knowledge graph, broadening its predictive capabilities and practical applications.

By advancing the integration of knowledge graph analytics and machine learning in financial contexts, this research contributes to fostering market transparency, improving governance oversight, and bolstering investor confidence. Ultimately, it highlights the transformative potential of graph-based approaches in enhancing financial risk assessment for both practitioners and policymakers.

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Authors' Contribution Statement
The authors contributed equally to all steps of the preparation of the article.

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