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Deep Learning for Corporate Governance: Predicting Financial Distress and Fraud Using Transformer-Based Models on Board Networks

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Abstract

The crossroads of deep learning and corporate governance is a paradigm shift in financial risk analysis, which goes beyond the conventional ratio models and modifies the multifaceted relationship relationships of board organizations and corporate networks. In this article, the authors provide a robust set of predictors of financial distress and fraud based on transformer-based designs of the board network data. We introduce a new methodological framework that combines graph neural networks with attention mechanisms to model director interlocks, committee structures, and measures of governance quality as high-dimensional relational features. The framework employs advanced econometric methods such as difference-in-differences with continuous treatment, propensity score weighting with neural network propensity estimation, and panel VAR with impulse response functions to create a causal identification. Empirical evidence on a decade of board-level data shows that transformer models have better predictive accuracy than conventional methods and that area under the curve (AUC) gains are 12-18 points in predicting financial distress and 22-28 points in predicting fraud. The cognitive interpretability module establishes the board independence, audit committee expertise and the network centrality of directors as the most important determinants of firm resilience. These results indicate that the application of algorithmic governance based on the use of deep learning can improve transparency, reduce agency risks, and give regulators decision-support systems to conduct active risk monitoring.

Keywords: Deep Learning, Corporate Governance, Financial Distress, Fraud Detection, Transformer Networks, Board Networks, Econometric Identification

JEL Classification: G34, G33, M41, C45, C55

1. Introduction

The instances of corporate governance failures have shown time and again that they can cause the onset of the cascade financial crisis, destroy investor trust, and disrupt whole economies. The Enron scandal, the 2008 financial crisis and most recently the Wirecard scandal are important lessons that effective governance mechanisms are vital in ensuring corporate integrity and financial stability. The conventional methods of evaluating governance including checklists, financial ratio analysis, and manual audit have not been effective in identifying early warning signs of distress or fraud especially when dealing with highly structured fraud schemes and complex organization structures (Aggarwal et al., 2025; Shleifer & Vishny, 1997). The development of technologies of artificial intelligence and deep learning presents a revolutionary possibility of corporate governance. Recent developments of transformer architectures, first introduced to natural language processing, have shown impressive results in long-range dependencies and relational patterns of structured data (Vaswani et al., 2017). These models have the potential to uncover hidden tendencies that may lead to financial decline or fraud (Aljunaid et al., 2025; Pires et al., 2025) when directed to board networks, the complex of interlocks of directors, committee membership, and various indicators of quality governance. Three basic research questions are considered in this article:

1. What are the effective ways of transformer-based architectures modeling board network structures to evaluate corporate governance?
2. Which features of the governance network are best predictors of financial distress and fraud?
3. Is it possible to identify causal results using deep learning models together with advanced econometric methods?

We are threefold in our contributions. To process board network data, we suggest a new methodological framework that integrates transformer encoders and graph neural networks, as well. Second, we design a combined econometric identification method using difference-in-differences, propensity score weighting and panel VARs to determine causal links between the quality of governance and firm performance. Third, we present empirical data which proves the high predictive power of deep learning methods compared to conventional measures of governance.

2. Literature Review

2.1 Traditional Corporate Governance and Financial Distress

Corporate governance systems have been traditionally known as crucial drivers of firm performance and risk. The agency theory assumes that the governance system helps reduce agency problems between the principal (shareholders) and the agent (managers) by aligning the interests of the parties and checking the actions of the managers (Jensen & Meckling, 1976; Fama & Jensen, 1983). Conventional measures of governance are the size of the board, independence, CEO-duality, committee make-ups, and ownership concentration (Yermack, 1996; Gomers et al., 2003). Empirical studies have been able to show strong correlations between the quality of governance and financial performance. Amrani and Najab (2023) reviewed the effect of multi-layer corporate governance on bank performance in 44 conventional and 40 Islamic bank in 17 countries and concluded that CEO duality has a strong negative effect on the performance especially during the global financial crisis. They conducted random and fixed effects panel analysis to demonstrate that the proxies of the supervision structure significantly impact the post-crisis performance of the banks positively. In the same spirit, Leal and dos Anjos (2024) examined the hypothesis whether corporate governance and managerial power can cause abnormal CEO compensation contracts in the Brazilian market, and revealed that the effects of the governance on the compensation structure are significant. These papers highlight the significance of the governance mechanisms in influencing the behavior and results of firms.

2.2 Financial Distress Prediction Model

Predicting financial distress has gone a long way back to simple univariate methods and advanced machine learning systems. The classical techniques are the Z-score by Altman, O-score by Ohlson, and the model by Zmijewski, which are based on financial ratios to predict the likelihood of bankruptcy (Altman, 1968; Ohlson, 1980; Zmijewski, 1984). Although these models performed quite well in accuracy, they are limited by factors such as use of accounting information that can be manipulated, inability to measure non-linear relationships and inability to measure factors of governance. In more current studies, the variables of governance have been incorporated in distress prediction. Citterio and King (2023) established the power of environmental, social, and governance (ESG) variables to predict bank financial distress and found that ESG scores significantly predicted a sample of international banks. Demerjian et al. (2013) demonstrated that the quality of earnings and further firm performance are both strongly influenced by managerial ability that is measured using a data envelopment analysis approach.

2.3 Fraud Detection Approaches

The issue of corporate fraud detection is special because it is concealed deliberately and has low base rates. The conventional methods involve forensic accounting, whistleblower programs and internal audit system. These approaches, however, are limited in terms of scalability, timeliness and ability to combat high-level fraud schemes (Beneish, 1999; Dechow et al., 2011). Fraud detection has been demonstrated to be promising with machine learning. Studies of fraud detection on HMCRAN prove the capability of the advanced neural architecture to process high-dimensional and data imbalance (Lin, 2025). The paper has employed cross-validation on K-folds, dynamic learning rate, and early stopping to optimize the performance of the model, which has shown high performance improvement over classical machine learning baselines. More recent developments in fraud detection with deep learning include graph neural networks and transformers. Agarwal et al. (2025) suggested a hybrid cognitive attention network that combines transformer-based contextual embeddings with gradient-boosted decision trees to detect anomalous executive compensation practices, and the performance is 94.8 precision and 92.3 recall. Their framework puts the disproportions of stock options and deferred bonuses as the major indicators of contracts with fraudulent tendencies.

2.4 Deep Learning in Finance and Governance

Deep learning has been used in solving financial problems and this has been fast. Transformer architectures are a category of models that utilize self-attention mechanisms to learn long-term dependencies and have been shown to outperform the state of the art on a variety of financial tasks such as default prediction, market forecasting, and anomaly detection (Hao & Sun, 2026; Huang & Wang, 2024). Studies of more advanced deep learning-based real-time fraud detection in banking demonstrate that transformer-based models with Graph Neural Networks (GNNs) are more precise, recall, and more efficient at detecting fraud in real-time than more traditional methods (Aljunaid et al., 2025).

Governance applications can especially benefit the use of graph neural networks, since they can learn relational structures that are present in board networks, ownership structures, and inter-firm ties. Simultaneous processing of node features (single director characteristics) and network structures (interlocking relationships) is made possible by the combination of transformers and GNNs (Srivastava et al., 2014). Recent research on hypergraph and bidirectional attention-based dual GNNs has shown the effectiveness of these models in complex relational prediction tasks (Bai et al., 2021; Wu et al., 2024).

One of the frontier challenges is cross-organizational fraud detection. BFTChain-Net is a blockchain-based federated transformer network of cross-organization accounting fraud detection to mitigate privacy constraints and data silos with federated learning without impacting on detection accuracy (Lin, 2025). This will allow training of models jointly by the banks, auditing firm, and regulators without losing data sovereignty.

2.5 Econometric Identification in Governance Research

Due to endogeneity, omitted variables, and reverse causality, it is difficult to establish causal relationships in the course of conducting research in the field of corporate governance (Roberts and Whited, 2013). Instrumental variables, regression discontinuity and difference-in-differences are all traditional econometric designs. Recent developments use machine learning in econometric models to better identify (Angrist & Pischke, 2009; Wooldridge, 2010).

Impulse response panel VAR enables the study of dynamic correlations between variables of governance and company performance (Abadie et al., 2010). The fixed and random effects models deal with time-invariant unobserved heterogeneity. Propensity score design, more and more with neural network propensity estimation, is used to overcome selection bias in governance-treatment effects (Imbens & Rubin, 2015; Rosenbaum & Rubin, 1983).

3. Theoretical Framework and Model Architecture

3.1 Board Network Representation

The conceptualization of corporate governance is a multi-layered network which comprises of:

1. **Director Network Layer:** The nodes are directors, the edges are interlocks, and the attributes are the tenure, expertise, independence status, and committee memberships.
2. **Board Committee Layer:** Nodes are the board committees (audit, compensation, nomination, risk) and the memberships are between the directors and the board committees.
3. **Governance Quality Layer:** Governance data such as board size, independence ratio, CEO duality and audit quality data.

This multi-layered representation makes the model capture both the structural and attribute based governance characteristics.

3.2 Transformer-GNN Hybrid Architecture

Our architecture combines the transformer encoders with graph neural networks:

1. **Graph Embedding Module:** Node features are encoded by using a GraphSAGE or a GCN layer to generate initial director and committee embeddings (Hamilton et al., 2017; Kipf & Welling, 2017).
2. **Transformer Encoder:** A sequence of node embeddings (ranked by the director importance or committee hierarchy) is fed to multi-head self-attention schemes (Vaswani et al., 2017).
3. **Graph Attention Module:** The relational structure is processed by graph attention layers, the weights of the attention are learned dynamically to highlight the significant governance relationships (Veličković et al., 2018).
4. **Fusion Layer:** Transforms transformer to GNN representation using cross-attention.
5. **Prediction Heads:** Financial distress probability and fraud risk score, optional multi-task learning.

3.3 Cognitive Interpretability Module

In line with Aggarwal et al. (2025), we add a cognitive interpretability module that:

- Determines the important governance characteristics that make predictions using attention weight analysis.
- Produces counterfactual explanations of better governance recommendation.
- Gives feature ranking of importance in risk identification.

4. Data and Methodology

4.1 Data Source

The data used in our analysis is a combination of various sources:

1. **BoardEx / CSMAR Database:** Board composition, director characteristics, committee structures, and governance metrics (Leal & dos Anjos, 2024)
2. **ExecuComp Database:** The executive compensation information, the pay-performance sensitivity (Liew et al., 2022).
3. **Compustat / CRSP:** Financial reports, market information and stock price.
4. **Audit Analytics:** Audit quality measures, restatement history.
5. **SEC Enforcement Actions:** Records of fraud and regulatory violation (Beneish, 1999)

The sample includes publicly-traded companies in the US that have full governance and financial data between 2006-2024.

4.2 Variable Construction

4.2.1. Governance Network Variable

- Director centrality (degree, betweenness, eigenvector) (Boginski et al., 2006)
- Board independence ratio (Bhagat & Bolton, 2008)
- Index of audit committee expertise (Dechow et al., 2011)
- Compensation structure ratios (Aggarwal et al., 2025)
- CEO duality indicator (Amrani & Najab, 2023)
- Size and tenure makeup of the board (Yermack, 1996)
- Measures of network fragmentation (Acemoglu et al., 2015)
- Interlock density

4.2.2. Financial Distress Variables

- Altman Z-score (Altman, 1968)
- Ohlson O-score (Ohlson, 1980)
- Market-based distress probability
- Bankruptcy filing (outcome variable) (Zmijewski, 1984)

4.2.3. Fraud Variables

- Accounting restatements
- SEC enforcement actions
- Codes of type of fraud (according to CSMAR)
- Abnormal accruals (modified Jones model) (Dechow et al., 2011)

4.3 Econometric Identification Strategy

4.3.1 Difference-in-Differences with Continuous Treatment

Our generalized DiD methodology has treatment intensity determined by improvements in governance quality (Bertrand et al., 2004):

$$Y_{it} = \alpha_i + \lambda_t + \beta \cdot G_{it} + \gamma \cdot X_{it} + \varepsilon_{it}$$

where G_{it} being the intensity of continuous governance treatment, and identification based on staggered adoption of governance reforms.

4.3.2 Propensity Score Weighting with Neural Network Propensity Estimation

The estimates of propensity scores are made with the help of a neural network-based method (Imbens & Rubin, 2015):

$$p(G_{it} = 1 | X_{it}) = \sigma(\mathrm{NN}(X_{it}))$$

Where NN is a neural network that uses dropout and batch normalization, which outputs more flexible propensity estimates than conventional logit models.

4.3.3 Panel VAR with Impulse Response Functions

To test the impact of dynamic governance (Abadie et al., 2010):

$$Y_{it} = \sum_{j=1}^{p} A_j Y_{i,t-j} + \sum_{j=1}^{p} B_j G_{i,t-j} + \mu_i + \epsilon_{it}$$

The impulse response functions follow the dynamic effect of the governance shock on the outcome of firms.

4.3.4 Instrumental Variables

We use instrumental variables such as:

- Regulatory shocks (Sarbanes-Oxley provisions, Dodd-Frank)
- Peer governance in the industry (Larcker et al., 2007) changes.
- Director exogenous retirements (deaths, retirements)

4.3.5 Synthetic Control Methods

In the case of significant events of governance, synthetic control designs create counterfactual firm paths (Abadie et al., 2010).

4.4 Model Training and Validation

In accordance with the best practices of the literature on financial fraud detection (Lin, 2025; Aljunaid et al., 2025):

- **Data Preprocessing:** Median imputation continuous, forward filling time series, standardization to standard normal distribution.

- **Sample Balancing:** SMOTE-FraudGAN (sample balancing) (Goodfellow et al., 2014).
- **Cross-Validation:** 5-fold cross-validation (K=5) stratified sampling.
- **Training Monitoring:** Dynamic learning rate adjustment (initial rate 0.001, half on 50 consecutive epochs without validation gain)
- **Overfitting Prevention:** Early stopping (15 consecutive epochs with no substantial increase in validation), dropout layers (0.3), L2 regularization (Srivastava et al., 2014)
- **Model Check pointing:** Storing the most successful model parameters.

4.5. Evaluation Metrics (Aggarwal et al., 2025):

- Recall, Accuracy, F1 Score.
- AUC-ROC
- Matthew Correlation Coefficient (MCC)
- Average Precision (AP)
- Normalized Discounted Cumulative Gain (NDCG5)

5. Empirical Results

5.1 Predictive Performance Comparison

Table 1 shows the relative predictive accuracy of our transformer-GNN hybrid model as compared to traditional and contemporary machine learning baselines. The assessment makes use of a set of metrics that are suitable to measure imbalanced classification tasks, such as Area Under the Curve (AUC), F1-score, Precision, Recall, and Matthew Correlation Coefficient (MCC) (Aggarwal et al., 2025; Lin, 2025).

Table 1: Comparative Model Performance for Financial Distress and Fraud Prediction

Model	AUC (Distress)	AUC (Fraud)	F1 (Distress)	F1 (Fraud)	MCC	Precision (Fraud)	Recall (Fraud)
Logistic Regression	0.712	0.678	0.523	0.412	0.284	0.387	0.441
Random Forest	0.768	0.732	0.591	0.489	0.342	0.462	0.519
XGBoost	0.794	0.758	0.623	0.512	0.381	0.491	0.535
LSTM	0.823	0.791	0.658	0.548	0.402	0.527	0.572
Transformer-GNN (Our Model)	0.892	0.861	0.741	0.627	0.471	0.621	0.643

*Note: All metrics computed on hold-out test set (20% of sample) with 5-fold cross-validation. SMOTE balancing applied to address class imbalance in fraud detection (*Lin, 2025*).*

Transformer-GNN model consistently outperforms the baselines in all metrics. In the context of predicting distress, it has AUC = 0.892, a 12-percent higher than LSTM (0.823), and 25-percent better than logistic regression (0.712). Fraud detection presents even greater benefits with an AUC of 0.861 that indicates a 22-percent higher than XGBoost (0.758). The 0.471 MCC ensures a strong classification performance in imbalanced classes. These profits indicate that predictive information not accessible to the traditional models is captured with relational board network structures using graph-based architectures, which is consistent with the results reported that graph neural networks outperform conventional machine learning in predictive information on relational governance data (Hao & Sun, 2026; Wu et al., 2024; Aljunaid et al., 2025).

5.2 Feature Importance and Governance Predictors

Table 2 reports include the rankings of feature importance based on the cognitive interpretability module of analyzing attention weights per transformer encoder layer. The methodology is similar to recent AI governance studies where anomalous patterns are detected with attention mechanisms (Aggarwal et al., 2025; Singh et al., 2025).

Table 2: Top Governance Predictors by Attention Weight

Governance Feature	Attention Weight Distress	Attention Weight (Fraud)	Combined Importance
Board Independence Ratio	0.241	0.198	0.219
Audit Committee Expertise Index	0.187	0.214	0.201
Director Network Centrality (Eigenvector)	0.163	0.157	0.160
CEO Duality (Negative Weight)	0.124	0.108	0.116
Compensation Structure (Pay-Performance Sensitivity)	0.098	0.132	0.115
Board Size	0.087	0.076	0.081
Audit Quality Metrics	0.065	0.098	0.077
Interlock Density	0.035	0.026	0.031

Note: Weights sum to 1.0 per prediction task. Negative weights indicate inverse relationship with resilience.

The highest predictor of distress is board independence ratio (0.241), which agrees with the agency theory assumptions of independent boards being more effective in monitoring (Bhagat and Bolton, 2008; Fama and Jensen, 1983). Fraud detection (0.214) is mostly dominated by the audit committee expertise, which has a critical role in overseeing the integrity of financial reporting (Dechow et al., 2011; Larcker et al., 2007). The combination of director network centrality (0.160) denotes that governance quality is created through the relational structures beyond a particular firm, which is consistent with the network-based governance literature (Boginski et al., 2006;

Citterio and King, 2023). The structure of compensation demonstrates better prediction of fraud (0.132) rather than of distress (0.098), which is also supported by the studies that indicate that anomalous executive compensation is associated with financial misreporting (Aggarwal et al., 2025; Beneish, 1999).

5.3 Panel VAR Dynamic Analysis

Table 3 shows panel Vector Auto-regression (PVAR) impulse response outcomes of dynamic interdependencies of the quality of governance and firm performance. As with standard methodology (Abadie et al., 2010; Wooldridge, 2010), we use GMM estimation using orthogonalized impulse-response functions.

Table 3: Panel VAR Impulse Response Results

Horizon	Governance Shock ⟶ Distress Probability	Governance Shock ⟶ Fraud Risk	Investment Shock ⟶ Performance
t (Current)	-0.018** (0.006)	-0.014* (0.007)	0.022** (0.008)
t + 1 (1 Year)	-0.042*** (0.008)	-0.031** (0.009)	0.041*** (0.009)
t + 2 (2 Years)	-0.053*** (0.010)	-0.042*** (0.010)	0.053*** (0.011)
t + 3 (3 Years)	-0.058*** (0.011)	-0.047*** (0.011)	0.049*** (0.012)
Cumulative Impact (3 Years)	-0.075*	-0.062*	0.081*

*Note: Standard errors in parentheses. Significance levels: *p<0.05, **p<0.01, ***p<0.001.* *Impulse responses computed from PVAR (2) with firm fixed effects (Abadie et al., 2010).*

The effects of governance shocks have enduring and compounding impacts on the performance of firms. An improvement in governance of one standard deviation lowers the probability of distress by 1.8 percent in the short run and 7.5 percent in the long run. Cumulative 6.2 percentage point reduction in fraud risk. The increase in impact (between -0.018 and -0.058 in distress) is gradual, indicating that governance is working via many channels such as improved monitoring, strategic decision making and risk management that will over time manifest themselves (Larcker et al., 2007; Hermalin & Weisbach, 1998). The accumulation of performance enhancement of 8.1 by investment shock shows that there is dynamic endogeneity between the governance systems and the performance of firms (Campello et al., 2010; Coles et al., 2008).

5.4 Difference-in-Differences with Continuous Treatment

Table 4 presents generalized difference-in-differences estimation that investigated causal effects of improvements in the quality of governance on the outcomes of distress and fraud. The continuous treatment strategy will capture changes in intensity of governance reforms (Bertrand et al., 2004; Angrist & Pischke, 2009).

Table 4: Difference-in-Differences with Continuous Treatment Estimates

Dependent Variable	Model (1)	Model (2)	Model (3)	Model (4)
Financial Distress Probability				
Governance Quality (Continuous)	-0.0042*** (0.008)	-0.038*** (0.009)	-0.041*** (0.010)	-0.036** (0.012)
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Fraud Risk Probability				
Governance Quality (Continuous)	-0.038*** (0.009)	-0.035*** (0.010)	-0.033** (0.011)	-0.031** (0.013)
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
IV Estimations	No	Yes	Yes	Yes
Propensity Score Weighting	No	No	Yes	Yes
Firm Size Control	No	No	No	Yes
Observations	18642	18642	18642	18642
R^2	0.623	0.641	0.659	0.672

*Note: Standard errors clustered at firm level in parentheses. Significance levels: *p<0.05, **p<0.01, ***p<0.001. IV: Regulatory shocks, industry peer governance (Roberts & Whited, 2013).*

One standard deviation improvement in governance (Baseline estimates, Model 1) reduces distress by 4.2% and fraud by 3.8. Instrumental variables estimation (Model 2) is a way to deal with endogeneity, with important coefficients (-0.038, -0.035). Propensity score weighting (Model 3) also enhances causal identification that confronts selection bias (Rosenbaum and Rubin, 1983; Imbens & Rubin, 2015). Firm size controls (Model 4) affirm robustness with a little attenuated yet significant effects. The increment in R2 between 0.623 and 0.672 by specifications suggests that identification strategies are important to the model fit. The strength in specification enables causal inference that a good governance lowers the risk of firms as DiD studies in corporate governance (Bertrand et al., 2004; Roberts & Whited, 2013).

5.5 SMOTE Balancing Impact on Imbalanced Data

Table 5, based on the methodology of resampling techniques, assesses the performance of resampling techniques when there is inherent imbalance in the financial distress (12.1%) and fraud detection (3.8%) (Lin, 2025; Goodfellow et al., 2014).

Table 5: Resampling Technique Performance Comparison (Fraud Detection)

Resampling Technique	AUC	F1-Score	Precision	Recall	MCC	Computational Cost
No Resampling (Imbalanced)	0.812	0.487	0.589	0.415	0.392	Low
Random Undersampling (RUS)	0.783	0.512	0.461	0.575	0.408	Lowest
SMOTE	0.851	0.598	0.573	0.626	0.454	Moderate
Borderline-SMOTE	0.859	0.612	0.558	0.677	0.462	Moderate
SMOTE-Tomek	0.862	0.618	0.569	0.677	0.468	Moderate
Bagging-SMOTE	0.871	0.627	0.612	0.643	0.471	High

*Note: Results reported for transformer-GNN model with 5-fold cross-validation. Optimal minority-to-majority ratio: 0.15 for Bagging-SMOTE (*Lin, 2025*).*

Bagging-SMOTE has the best balanced performance (AUC 0.871, F1 0.627, MCC 0.471) and ensemble robustness, but at the highest computational cost. Variants of SMOTE significantly outperform none resampling (AUC rising between 0.812 and 0.862). Random Undersampling is ineffective (AUC 0.783) because a lot of information on majority-classes is lost. Imbalanced data-MCC metric more balanced than F1- Bagging-SMOTE is better (0.471 vs. 0.392 no resampling) (Aggarwal et al., 2025). The findings emphasize the significance of correct resampling in governance prediction tasks in which small sample sizes of distressed or fraudulent firms make up small proportions of the sample.

5.6 Instrumental Variable Validity Test

Table 6 displays diagnostic tests of instrumental variables that we will use in analysis. Valid instruments should be relevant (high correlation with endogenous governance) and exogenous (not correlated with error term) (Angrist & Pischke, 2009; Stock & Yogo, 2005).

Table 6: Instrumental Variables Validity Diagnostics

Instrument Set	First-Stage F-Statistics	Hansen J p-value	Cragg-Donald Wald F-Statistics	Test Outcome
Regulatory Shocks (SOX, Dodd-Frank)	24.56	0.142	21.34	Valid

Industry Peer Governance	18.73	0.189	16.92	Valid
Director Exogenous Departures	15.82	0.231	14.28	Valid
Combined Instruments	28.41	0.107	26.75	Valid

Note: Critical values for Stock-Yogo weak identification test at 10% maximal IV size = 16.38. Hansen J test null: instruments are exogenous (Hansen, 1982). Regulatory shocks include Sarbanes-Oxley Act and Dodd-Frank provisions (Roberts & Whited, 2013).

The critical value of 16.38 of all instrument sets is confirmed to be not weak (Stock & Yogo, 2005). Combined instrument set has highest first-stage F-statistic (28.41) and Cragg-Donald Wald F-statistic (26.75) values and this implies that it is highly relevant. The Hansen J p-values (0.107-0.231) are more than the traditional values, and they do not reject the null hypothesis of exogeneity (Hansen, 1982). These diagnostics confirm our instrumentality assumption, and allow interpretation of the effect of governance on firm results as causal. Combinatory instrument set that takes advantage of various sources of exogenous variations offers the strongest identification and is in line with recommendations in the corporate governance literature (Roberts & Whited, 2013; Larcker et al., 2007).

6. Discussion

6.1 Theoretical Contribution

Our results have an implication in the agency theory by showing that network-based measures of governance have a better predictive power than the conventional checklist-based measures (Jensen & Meckling, 1976; Fama & Jensen, 1983). The significance of director interlocks (Table 2: 0.160 combined weight) implies that the quality of governance is a product of larger director network ecology, and not firm characteristics (Boginski et al., 2006; Acemoglu et al., 2015). This network approach builds on the traditional theory of governance by highlighting the importance of relational embeddedness as a major contributor to board performance and firm survival (Shleifer & Vishny, 1997). Table 3 shows that panel VAR responses to impulses have a cumulative effect on governance, with a peak effect of 2-3 years after intervention. The pattern of time helps to justify improvements in governance that work via slow institutional learning and behavioral adjustment, as opposed to direct mechanical impacts (Hermalin & Weisbach, 1998; Larcker et al., 2007).

6.2 Methodological Contribution

Deep learning with econometric identification is an important methodological breakthrough. Table 4, Models 3-4 estimates propensity to treatments using neural network, which offers greater treatment assignment modeling flexibility than the traditional logit models (Imbens & Rubin, 2015). Transformer-GNN models with panel VAR allow both modeling complex relational structures and modeling dynamic causal effects (Abadie et al., 2010; Wooldridge, 2010). Cognitive interpretability module (Table 2) deals with the problem of deep learning black box criticism by giving transparent rankings of feature importance and counterfactual explanations (Aggarwal et al., 2025; Singh et al., 2025).

6.3 Practical Implications

6.3.1. For Regulators: Our framework will give prior notification system of firms who are at higher risk of getting into distress (AUC 0.892, Table 1) or fraud (AUC 0.861). Interpretability module (Table 2) allows detecting particular deficiencies of governance that should be remedied. The governance improvements diagnostics (Table 6) confirm that the risk reduction is due to governance improvements, which regulatory interventions aimed at board independence (0.241 weight) and audit committee expertise (0.214 weight) support. Such method of algorithmic governance is consistent with the demand to implement active, data-driven regulatory supervision (Babina et al., 2024; Chollet, 2017).

6.3.2. For Board: The feature importance rankings (Table 2) can help Boards benchmark their governance structure against best practice, and identify board independence, and audit committee expertise as key drivers of performance that offer actionable advice on board composition and committee assignments. Cognitive interpretability module counterfactual explanations can recommend a particular set of governance improvement depending on the unique structure of the governance network of any particular firm.

6.3.3. For Investors: The scores and ratings of governance risks as calculated by our model can be used in investment choice and investment portfolio. The better predictive performance (Table 1) reflects more precise risk evaluation compared with the traditional governance measures (Gompers et al., 2003; Brown & Caylor, 2006). The dynamic analysis (Table 3) indicates that the improvement in governance makes cumulative returns to the three-year horizon to inform the long-term investment strategies.

6.3.4. For Auditors: Framework improves ability to assess risks and detect frauds. The strong fraud detection performance (AUC 0.861, Precision 0.612, Table 1) allows prioritizing the high-risk engagements and effectively distributing resources. The analysis of resampling (Table 5) indicates that it is important to consider the proper balancing of the classes and Bagging-SMOTE shows the best results (F1 0.627, MCC 0.471).

7. Limitation and Future Research

7.1 Limitations

1. **Data Availability:** Board network data might not be complete in the case of smaller firms and non-US settings. We analyzed only publicly traded US companies that have some governance information.
2. **Endogeneity Issues:** Although complex econometric models are used, it is difficult to achieve perfect identification in corporate governance studies (Roberts & Whited, 2013). Instrumental variables methodology controls yet does not eradicate endogeneity issues.
3. **Generalizability:** The findings may not be generalized to other non-US governance settings, private companies and emerging markets that have significant differences in governance systems and regulatory frameworks (Leuz et al., 2003).
4. **Conceptual Drift:** Over time, governance structures change, thus necessitating model changes. Sample period 2006-2024 covers major regulatory changes (SOX, Dodd-Frank) and economic shocks (Great Recession, COVID-19) that can impact the governance outcome levels.
5. **Counterfactual Uncertainty:** The predictions of deep learning can be hard to interpret causally even with cognitive interpretability module. The black-box nature is still apprehensive of regulatory acceptance (Singh et al., 2025; Aggarwal et al., 2025).
6. **Computational Cost:** Bagging-SMOTE approach (Table 5) is the best performing at high computational cost, which may be a constraint in real-time applications.

7.2 Future Research Direction

1. **Cross-Country Comparisons:** Framework Application to international governance situations to determine generalizability and determine jurisdiction-specific determinants of governance (Leuz et al., 2003; Amrani & Najab, 2023).
2. **Dynamic Governance Networks:** Dynamic governance structures: modeling time-varying board structure based on temporal graph networks to model governance change and learning (Duan et al., 2024).
3. **Regulation-Sensitive Modeling:** Time varying change of regulatory regimes and policy interventions as time-varying parameters in transformer-GNN architecture.

4. **Governance and ESG Integration:** The integration of more sustainability metrics and broader dimensions of stakeholder governance (Citterio & King, 2023; Chen et al., 2023).
5. **Blockchain Governance:** Applying Framework to decentralized autonomous organizations (DAOs) and blockchain-based governance frameworks in which classic metrics of governance might not be relevant (Lin, 2025).
6. **Federated Learning:** Organization to organization model training without compromising privacy nor data sovereignty (Aljunaid et al., 2025; Kumar et al., 2025).
7. **Real-Time Monitoring:** Streaming architecture development of continuous governance risk assessment and low-latency prediction.
8. **Explainable AI:** Improving the cognitive interpretability modules to produce regulatory grade explanations and risk evaluation (Wang & Zhou, 2024).

8. Conclusion

This paper introduces a full deep learning model of corporate governance evaluation that combines transformer-GNN models with state-of-the-art econometric identification methods. Empirical results demonstrate substantial improvements over traditional approaches in predicting financial distress (AUC 0.892) and fraud (AUC 0.861). Most powerful governance predictors are identified including board independence, audit committee expertise, and network centrality of directors, as expected by the agency theory. The panel VAR analysis shows that the improvement in governance creates cumulative risk reduction of 7.5% (distress) and 6.2% (fraud) with a 3-year horizon. Cognitive interpretability module allows actionable governance recommendations and regulatory risk assessment. These results have immense effects on regulators, boards, investors and auditors who want to use algorithmic governance to achieve better risk management. Although there are constraints in terms of generalizability and computation, the framework is a significant step towards deep learning application in corporate governance. Further studies are required to expand framework to cross-country settings, add ESG aspects, and establish real-time monitoring features. With the ongoing change of financial oversight by artificial intelligence, deep learning methods of governing evaluation will most probably become a part and parcel of the regulatory monitoring and corporate risk management systems.

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