

A Risk-Based Input–Process–Output Framework for Financial Statement Fraud Detection: Integrating Financial Red Flags, Governance Controls and Forensic Analytics

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Abstract – Financial statement fraud can impair investor confidence, distort capital allocation and weaken the credibility of corporate reporting. Existing detection approaches use financial-ratio screens, fraud-risk theories, governance indicators and increasingly sophisticated analytical models, but these approaches are often applied separately. This paper develops a risk-based Input–Process–Output (IPO) framework that connects observable financial and governance signals to a structured review process and measurable investigation outcomes. The proposed framework treats financial pressure, unusual accounting movements, control weaknesses and governance signals as inputs; analytical screening, corroboration, professional scepticism and escalation as processes; and prioritised risk alerts, documented evidence and improved monitoring as outputs. A transparent illustrative logistic model is specified to demonstrate how risk indicators could be combined without presenting simulated values as empirical evidence. The paper synthesises established work on earnings manipulation, fraud-risk assessment and fraud-detection model design. It argues that ratio-based scores should be used as screening indicators rather than proof of fraud, and that model performance must be validated against independently established outcomes, class imbalance and sector-specific conditions. The contribution is a practical, auditable framework for connecting detection signals to investigation decisions while preserving human oversight. The paper is conceptual and does not claim original empirical validation.

Keywords – financial statement fraud; earnings manipulation; Beneish M-Score; fraud risk; forensic accounting; logistic regression; Input–Process–Output framework; corporate governance.

I. INTRODUCTION

Reliable financial reporting is essential to the decisions of investors, lenders, employees, regulators and other stakeholders. When financial statements are deliberately misstated, users may make decisions on the basis of revenues, assets, liabilities or cash flows that do not faithfully represent the reporting entity. Fraudulent reporting can also weaken confidence in audit and governance arrangements. The challenge for practitioners is not merely to identify unusual accounting numbers, but to distinguish ordinary business variation, aggressive yet permissible accounting choices, error and intentional misrepresentation.

Research has developed several approaches to this problem. The Fraud Triangle highlights pressure, opportunity and rationalisation as conditions associated with occupational fraud (Cressey, 1953). Financial-ratio models such as the Beneish M-Score identify patterns associated with earnings manipulation (Beneish, 1999), while the Dechow F-Score estimates the likelihood of material misstatement using accounting and market-related signals (Dechow et al., 2011). More recent work considers model construction, variable selection and machine-learning approaches, while recognising that detection results depend on labels, sample design and the institutional setting (Gepp et al., 2024; [recent comparative research]

Despite these developments, a practical gap remains between detecting a statistical signal and deciding what an organisation should do next. A high-risk score is not a finding of fraud, and a low score does not establish that reporting is reliable. Detection systems need a traceable process that links indicators to corroborating evidence, responsible review, escalation and feedback. This paper adapts the sequential logic of the uploaded reference article—diagnose risk drivers, synthesise strategic responses and organise them through an IPO framework—to financial statement fraud detection. The operational details and environmental calculations in the reference paper are not transferred; only its broad research architecture is used.

1. Aim and research questions

The aim is to propose an integrated, risk-based framework for identifying and responding to financial statement fraud indicators. The paper addresses three questions:

- RQ1: Which financial, governance and contextual signals can be organised into a structured preliminary fraud-risk assessment?
- RQ2: How can these signals be connected to a transparent screening and corroboration process?
- RQ3: What outputs and safeguards are needed to make the process auditable and useful for decision-makers?

2. Contribution

The paper contributes a conceptual IPO framework and a transparent illustrative model specification. It emphasises the separation of risk identification from a determination of fraud, integrates financial and non-financial signals, and sets out a validation protocol for future empirical testing. It does not claim to have collected company data or established predictive accuracy.

II. LITERATURE REVIEW

1. Fraud risk and organisational conditions

The Fraud Triangle proposes that pressure, opportunity and rationalisation can help explain the conditions under which fraud occurs (Cressey, 1953). In corporate reporting, pressure may arise from ambitious earnings targets, debt covenants, financing needs or incentives linked to reported performance. Opportunity may be associated with weak controls, concentrated authority, ineffective board oversight or complex transactions. Rationalisation is difficult to observe directly and should not be inferred mechanically from a single proxy. Gepp et al. (2024) specifically discuss the need for a principled framework for selecting variables in fraud-detection models, including attention to signals that may be unexpected or inconsistent with normal reporting.

2. Financial statement indicators and screening models

Beneish (1999) developed a probit-based model using financial ratios associated with earnings manipulation. Its inputs include changes in receivables, gross margin, asset quality, sales growth, depreciation, selling and administrative expenses, leverage, and accruals. The model is useful as an initial screen because it makes the financial patterns behind the score visible. However, it is not a universal fraud test: industry characteristics, accounting standards, growth patterns and the timing of manipulation can affect the indicators.

Dechow et al. (2011) developed the F-Score approach to assess the likelihood of material accounting misstatement. Comparative research has examined the performance of Beneish and Dechow models in different markets, reporting that performance can vary with sample composition and the definition of manipulation (Aghghaleh et al., 2016; Cecchini et al., 2010). Studies also warn that a screening model can produce false positives and false negatives, so the output should guide further review rather than substitute for evidence.

3. Governance, controls and analytical integration

Financial ratios alone cannot represent the full context of reporting risk. Board independence, audit committee activity, auditor changes, related-party transactions, internal control deficiencies and unusual management estimates may provide complementary context. Such indicators must be defined carefully and measured consistently. A combined approach can be more informative than reliance on a single score, but adding more variables does not automatically improve performance:

overfitting, data leakage, imbalanced labels and inconsistent fraud definitions can make apparent accuracy misleading.

4. Research gap

The literature provides both theoretical explanations and quantitative screening tools, yet users need a decision architecture that connects a risk signal to evidence collection, review thresholds, documented outcomes and model monitoring. The proposed framework addresses this process-design gap. Its novelty is conceptual integration, not a claim that the underlying fraud indicators or scoring methods are newly invented.

III. RESEARCH METHODOLOGY

1. Research design

This paper adopts a conceptual model-development design informed by a focused review of established research on financial statement manipulation, fraud-risk theory and detection-model construction. The uploaded reference paper is used as a structural guide: first identify risk drivers, then map potential responses, and finally integrate the two in an IPO framework. No new company-level dataset was supplied for this study. Accordingly, no empirical hypothesis tests, sample statistics, model accuracy values or causal conclusions are reported.

2. Proposed unit of analysis and future sample

For future validation, the recommended unit of analysis is the firm-year. A study could assemble publicly listed companies across a clearly defined period, using independently documented enforcement actions, restatements or adjudicated cases to define positive outcomes. Non-fraud comparison firms should be sampled using transparent criteria and matched or adjusted for industry, size and year where appropriate. Researchers should distinguish confirmed fraud from restatement, accounting error, aggressive earnings management and an elevated model score.

3. Construct operationalisation

Candidate variables are grouped into four input domains: (i) financial pressure and performance, (ii) accounting-pattern anomalies, (iii) governance and control signals, and (iv) contextual indicators. Each variable requires an explicit formula, source, measurement window and missing-data rule before analysis. Variables that become available only after a fraud investigation must not be used to predict earlier risk, as this would create temporal leakage.

4. Proposed analysis protocol

- Step 1: Define the fraud outcome and observation period before selecting predictors.
- Step 2: Calculate financial ratios from audited statements and document data-quality checks.
- Step 3: Construct baseline screens, including established scores where the required inputs are available.

- Step 4: Estimate an interpretable model on training data and evaluate it on a temporally separated holdout sample.
- Step 5: Report sensitivity, specificity, precision, recall, F1-score, ROC-AUC and precision–recall performance, alongside calibration and confidence intervals.
- Step 6: Test robustness by industry, firm size, period, alternative fraud definitions and class-imbalance treatments.
- Step 7: Use independent human review to assess alerts; document whether they led to no action, further testing, escalation or confirmed findings.

IV. PROPOSED CONCEPTUAL FRAMEWORK

1. Input–Process–Output structure

The framework treats fraud-risk assessment as a controlled workflow rather than a one-step classification exercise. The input layer captures signals that may warrant scrutiny. The process layer combines quantitative screening with evidence-based review. The output layer produces risk-ranked alerts and documented decisions, which feed back into control improvement and future model evaluation.

IPO layer	Components	Purpose
Input	Financial pressure; accrual and revenue anomalies; receivables growth; margin changes; leverage; unusual estimates; related-party activity; governance/control signals	Identify observable indicators requiring assessment
Process	Data validation; ratio analysis; baseline score comparison; multivariate screening; corroboration against notes, cash flows and audit evidence; human review; escalation	Evaluate whether signals are consistent, explainable and material
Output	Risk tier; alert rationale; evidence log; investigation referral; control remediation; periodic model monitoring	Support proportionate action and an auditable decision trail
Feedback	Review outcomes; false-positive/false-negative analysis; updated controls; recalibration and independent validation	Improve future screening without treating unverified alerts as fraud labels

Figure 1. Proposed IPO framework for financial statement fraud-risk screening (author-developed conceptual representation).

2. Model propositions

- P1: Greater intensity of unusual financial-reporting signals is associated with a higher preliminary fraud-risk score, conditional on firm and industry context.
- P2: Governance and internal-control signals provide incremental screening information beyond financial ratios, subject to valid measurement.
- P3: Evidence corroboration and human review improve the actionability of alerts compared with automated scores alone.
- P4: The performance and calibration of any detection model vary across industries and reporting environments; periodic local validation is therefore necessary.

These are propositions for future empirical testing, not findings established by the present conceptual paper.

V. ILLUSTRATIVE ANALYTICAL MODEL

1. Logistic risk specification

For an empirical study with a binary outcome Y_{it} , where $Y_{it} = 1$ denotes an independently established fraudulent or materially misstated firm-year under the study's declared definition, the following model could be estimated:

$$\Pr(Y_{it} = 1) = 1 / [1 + \exp(-\eta_{it})]$$

$$\eta_{it} = \beta_0 + \beta_1 \text{FIN}_{it} + \beta_2 \text{ACC}_{it} + \beta_3 \text{GOV}_{it} + \beta_4 \text{CTX}_{it} + \mu_j + \tau_t$$

Here, FIN denotes financial pressure/performance indicators; ACC denotes accounting-pattern anomalies; GOV denotes governance and control indicators; CTX denotes contextual controls; μ_j represents industry effects; and τ_t represents year effects. The coefficients must be estimated from observed data. Expected signs should be justified variable by variable rather than imposed solely from theory.

2. Composite risk domains

For a transparent implementation, each domain may first be standardised and aggregated into a domain score. One possible specification is:

$$R_{it} = w_1 \text{FIN}_{it} + w_2 \text{ACC}_{it} + w_3 \text{GOV}_{it} + w_4 \text{CTX}_{it}, \text{ with } \sum w_k = 1$$

Weights may be estimated from training data or set using a documented expert-judgement protocol. If expert weights are used, the score should be described as a rule-based index, not as an empirically estimated fraud probability. Thresholds should be set using validation data and the costs of missed cases and unnecessary investigations.

3. Illustrative example—not empirical results

Risk domain	Illustrative standardised score (0–1)	Illustrative weight
Financial pressure	0.70	0.30

Accounting anomalies	0.80	0.35
Governance/control	0.40	0.25
Contextual indicators	0.50	0.10

Using these purely hypothetical values, $R = (0.30 \times 0.70) + (0.35 \times 0.80) + (0.25 \times 0.40) + (0.10 \times 0.50) = 0.635$. The resulting index is 0.635 on a 0–1 scale. This is an arithmetic demonstration only: the weights, scores and result are not observed data, validated thresholds or a probability of fraud. A real study must estimate or justify weights and validate decision thresholds before use.

4. Decision safeguards

A high score should trigger proportionate follow-up, such as reconciling revenue to cash receipts, inspecting unusual journal entries, reviewing estimates and related-party disclosures, or assessing control deficiencies. A fraud conclusion requires corroborated evidence and appropriate professional or legal processes. A low score must not override whistle-blower information, audit evidence or other credible concerns.

VI. DISCUSSION

The framework brings together the explanatory and screening perspectives in fraud research. The Fraud Triangle helps organise possible organisational conditions, while financial-ratio models provide observable accounting signals. The IPO structure adds a procedural layer: signals are validated, interpreted and escalated, and decisions are documented. This separation is important because an association between a ratio and known manipulation does not establish intent in a specific company.

The framework also encourages researchers to report more than overall accuracy. Fraud cases are typically uncommon relative to ordinary firm-years in many datasets, meaning a model can achieve high accuracy while missing most positive cases. Precision, recall, sensitivity, specificity, calibration and the precision–recall curve therefore help explain the practical consequences of different thresholds. Temporal validation is preferable to random splitting alone when the intended use is to screen future reports.

For auditors and audit committees, the proposed approach can support risk assessment and prioritisation but should not displace professional judgement.

For regulators and investors, it offers a way to organise publicly available indicators and explain why a company was flagged. For management, the framework can inform improvements to controls, documentation and oversight. Any deployment should include access controls, data lineage, bias checks and a mechanism for challenging or correcting erroneous alerts.

Implications

Theoretical implications

The paper extends the use of an IPO logic to financial-reporting risk management by linking observable indicators, review mechanisms and decision outputs. It also makes explicit that a framework's conceptual coherence is different from empirical validation. The propositions can be tested in future firm-year studies, including tests of whether governance variables add information beyond established ratio models.

Practical implications

Organisations can adopt a tiered workflow: routine monitoring for all reporting periods, targeted review for unusual patterns, and escalation where independent corroboration supports concern. Review documentation should state the trigger, evidence examined, reviewer, decision and follow-up action. Model owners should periodically examine drift, subgroup performance and false-alert rates.

Policy and assurance implications

Regulators and professional bodies can encourage consistent definitions of confirmed fraud, transparent model validation and clear communication that screening scores are not verdicts. Audit committees can ask whether risk indicators are traceable to source data and whether management overrides, related-party transactions and significant estimates receive appropriate scrutiny.

Limitations and future research

This paper is conceptual and contains no original company-level empirical analysis. Its illustrative scores and weights are hypothetical and must not be reported as findings. The proposed framework's effectiveness remains untested. Future research should assemble a transparent multi-year dataset, pre-register outcome definitions, compare established scores with logistic and machine-learning models, use temporal holdout validation, report confidence intervals and assess performance across industries and jurisdictions. Qualitative interviews with auditors, forensic accountants and audit committee members could examine whether the proposed workflow is practical and whether it improves documentation and escalation.

VII. CONCLUSION

Financial statement fraud detection is best treated as a process of risk screening, corroboration and accountable decision-making rather than reliance on a single score. This paper proposes an IPO framework that organises financial and governance signals, connects them to analytical and professional review, and specifies outputs that can be audited and evaluated. A logistic specification and hypothetical worked example illustrate how the framework could be operationalised, while making clear that the example is not empirical evidence. The principal research contribution is a structured bridge between detection indicators and response processes. Empirical testing with independently labelled firm-year data is required before

claims about predictive performance or generalisability can be made.

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