

Project management: Leonhard J. Lösse, M.Sc.

Challenging Local Interpretability of Financial Reporting Fraud Predictions

Based on accounting fraud detection models, model-agnostic approaches will be applied. An increase in predictions' interpretability provides the basis for more efficient and risk-oriented audits and enforcements.

Motivation

Serious direct and indirect (financial) damages result from erroneous financial reporting – especially from intended fraud cases (Rezaee 2005). Various stakeholders are affected, i.a. investors, auditors and enforcement (Persons 1995). Due to limited resources and risk-oriented approaches, there is an essential need for effective and efficient risk assessment of financial reporting.

Background

Relative misclassification costs vary for the type of prediction error as well as for different groups of stakeholders. Most approaches include false-positive-rates being too high for practical implementation (Beneish 2021):

1. Train models with lower false-positive-rates or
2. increase transparency of predictions to make high false-positive-rates handleable.

Research Questions

RQ: To what extent can model-agnostic approaches offer additional locally interpretable results of financial reporting fraud predictions?

RQa: Does the performance of prediction models vary for different types of fraud?

RQb: Can model-agnostic approaches locally identify accounts affected by manipulations?...

Setting & Data

Especially based on detection model by Bao et al. 2020:

- detection of accounting fraud, proxied by AAERs
- raw financial data of publicly listed US firms

Use of raw financial data offers possibility to analyse predictions according to their actual type of fraud and features triggering these fraud predictions.

Approach – Individual Conditional Expectation (ICE)

Enables to visualize interactions between variables, which are obscured by PDP showing one line for each instance representing predictions for different values of a variable (Goldstein et al. 2015).

Group misstatements by affected accounts. The types of misstatements and features are not equal. The type can represent a single used variable, e.g. inventory, or match to multiple variables, e.g. „misstated liabilities“ corresponds to current liabilities and long-term debt. Misstated revenues or e.g. accounts receivable seem to be predominant vs. few cases of misstated liabilities or payables. Expectations (here exemplarily focussing on misstated revenues vs. others):

- Non-misstated observations should be characterized throughout by low levels of fraud-probabilities
- Misstated observations should have generally higher probabilities of misstatements
- Misstated revenues should stand out by indicating that probabilities of misstatements increase with higher revenues
- In contrast, misstatements other than revenues (e.g. affecting liabilities) should not be triggered by the revenue feature

Approach – Local Interpretable Model-agnostic Explanations (LIME)

Using perturbed input data and corresponding predictions to estimate ‚new‘ local surrogate models (Ribeiro et al. 2016). Analyse individual predictions according to their classification:

True Positives:

- Which are the contributing variables for each observation's prediction?
- Do the contributing variables match with the actual misstated account categories?

False Positives:

- Which variables contribute to false positive predictions? (e.g. do revenues trigger more false positives compared to other accounts?)

False Negatives:

- Do prediction models miss a certain type of fraud?

Contributions

Theoretical

- Evaluation of model-agnostic explanations
- Challenging operating principles of accounting fraud detection models and identify patterns for further improvements of accounting fraud detection models

Practical

- Identify indicators or actually misstated accounts which provide transparency for domain experts' plausibility checks, thus, enable efficient resource allocation for further investigations
- Support the use of machine learning approaches by increasing trust through higher levels of transparency and comprehensibility

Literature Cited

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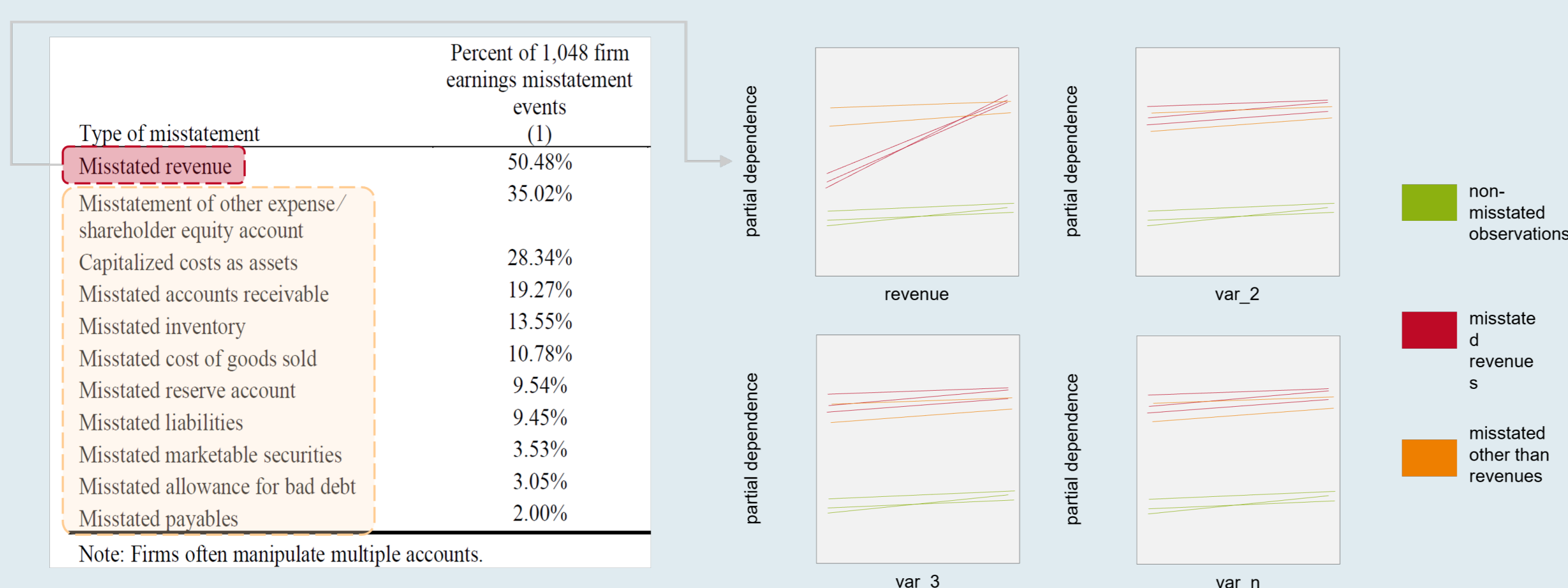


Figure 1: Draft of expected Individual Conditional Expectations exemplary for misstated revenues and their potential drivers