SESSION 2: AUDITING, ACCOUNTING AND EARNINGS MANAGEMENT

ASSESSING EARNINGS MANAGEMENT: A COMPARATIVE STUDY

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OPEN ACCESS

How to cite: Toudas, K., Boufounou, P., & Tsogka, D. (2023). Assessing earnings management: A comparative study. In E. Karger & A. Kostyuk (Eds.), *Corporate governance: An interdisciplinary outlook* (pp. 30–32). Virtus Interpress. https://doi.org/10.22495/cgaiop6

Received: 13.10.2022
Accepted: 21.10.2022
Keywords: Earnings Management, Creative Accounting, Corporate Governance
JEL Classification: M41, M42, O16
DOI: 10.22495/cgaiop6

Abstract

Earnings management, defined by Schipper (1989) as the purposeful intervention by management in the earnings determination process, usually to satisfy its own objectives, is one of the most important issues in modern corporate governance literature. Earnings management is one of the most commonly used methods of creative accounting, defined as "the exploitation of weaknesses in various accounting rules and laws, or even their violation, in order for a company to present financial statements to its advantage" (Baralexis, 2004). Data mining techniques used for detecting fraudulent financial statements include decision trees (Ngai et al., 2011; Sharma & Panigrahi, 2013), neural networks (Chen et al., 2009; Kirkos et al., 2007), the naïve-bayes classifier (Phua et al., 2010), the Bayesian belief networks (Heckerman, 1997; Pearl, 1988; Kotsiantis et al., 2006), the support vector machines (Cortes & Vapnik, 1995; Cecchini et al., 2010), the logistic regression models (Hosmer & Lemeshow, 2000), the classifier ensembles (Perols, 2008), the genetic algorithms (Hoogs et al., 2007, Javadian Kootanaee et al., 2021), the k-nearest neighbor classifier (Sorkun & Toraman, 2017; Moepya et al., 2014; Abdelmoula, 2015). Amongst the logistic regression methods,

the most commonly used for earnings management detection, are the Spathis' Z-score model (Spathis, 2002) and the Beneish M-score model (Beneish, 1999). The purpose of this study was to provide a critical evaluation of these two techniques. Two models were applied to data from listed companies in the Athens Stock Exchange in 2018 (the last year before the covid pandemic). Although both methods demonstrated that the earnings management probabilities are low, their estimates for individual companies do not always agree. Given the importance of estimating the existence of earnings management for analysts, investors, and supervisory authorities assessing corporate governance, it would be appropriate to extend this study by comparing these findings to those estimated using alternative methods.

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