



A neural network approach to measure real activities manipulation



Jesper Haga, Jimi Siekkinen, Dennis Sundvik*

Hanken School of Economics, P.O. Box 287, Handelsplanaden 2, 65101 Vasa, Finland

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ABSTRACT

A growing body of literature is examining the concept of real activities manipulation in various contexts. In these studies, the researcher typically models abnormal real activities and draws inferences based on the output measures. Thus, the results of the studies hinge critically on the underlying models. We contribute by examining alternative approaches to measure three varieties of real activities manipulation. Neural network models based on a self-organizing map and a multilayer perceptron are used in variation to a frequently used linear approach. The purpose of the study is to examine whether the neural network models outperform linear-based models in the detection of real activities manipulation. According to the results, the multilayer perceptron models are remarkably strong while the traditional linear models are underachievers. These results are specifically evident when common comprehensive measures are used.

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1. Introduction

There is vast literature in accounting that focuses on managers' incentives and actions to manage earnings. Prior studies have identified a wide variety of settings where managers hypothetically manage earnings due to an underlying incentive (see Healy and Wahlen (1999) for a literature review). Until recently, most of this research has focused on accrual-based earnings management. However, a growing body of the accounting literature is now turning to the concept of real activities manipulation (i.e. real earnings management). For instance, the survey study by Graham, Harvey, and Rajgopal (2005) pointed out that financial executives are willing to manipulate real activities in order to meet certain targets although the activity potentially reduces firm value. Roychowdhury (2006) then set the stage for empirical studies by estimating abnormal real activities with a linear regression approach. This study extends the literature by examining a neural network-based approach to measure real activities manipulation.

In his seminal paper, Roychowdhury (2006) discussed the management of operational activities and developed measures of sales manipulation, overproduction, and reduced discretionary expenditures. Based on these measures, firms were found to rely on real activities manipulation to avoid losses. Furthermore, a number of studies have employed the same measures in detecting real activities management. To name a few, Cohen, Dey, and Lys (2008) documented a significant increase in real earnings management

after the passage of the Sarbanes–Oxley Act in 2002 while there was a simultaneous decrease in accrual-based earnings management. Likewise, in an environment where investor protection is weaker, Kuo, Ning, and Song (2014) investigated the Chinese split share structure reform and found firms to have shifted to less detectable and under-scrutinized real activities manipulation when the use of discretionary accruals was constrained. Zang (2012) has also provided evidence consistent with managers managing real activities and accruals interchangeably. Furthermore, Cohen and Zarowin (2010) found that seasoned equity offering firms engaged in real activities manipulation and that subsequent operating underperformance could be linked with the real consequences of operational decisions to manage earnings. Recently, Kim and Park (2014) found a significantly positive relation between clients' opportunistic operating decisions and the likelihood of auditor resignation, except in the case of overproduction. Other evidence of real earnings management as a risk-increasing factor has been provided by Ge and Kim (2014) from the perspective of credit rating agencies and bondholders.

Despite the growing interest in recent research, only a limited number of studies have suggested detection model variations. For example, Gunny (2010) modified the original Roychowdhury (2006) models slightly and presented measures of abnormal R&D, abnormal SG&A, abnormal gains on asset sales, and abnormal production costs. These measures have, however, rarely been used in subsequent research. A number of studies¹ have additionally begun to use comprehensive or aggregate measures to capture the total

* Corresponding author. Tel.: +358 40 3521761.

E-mail addresses: jesper.haga@hanken.fi (J. Haga), jimi.siekkinen@hanken.fi (J. Siekkinen), dennis.sundvik@hanken.fi (D. Sundvik).

¹ Cohen et al. (2008), Cohen & Zarowin (2010), Zang (2012), Kim and Park (2014), Ge and Kim (2014) and Kuo et al. (2014).

effects of real activities manipulation by combining the original variables in different ways. These combinations could be interpreted as a simple method to reach stronger results. Given the growing body of research on the subject it is furthermore surprising that no empirical research has been devoted to the study of alternative measures in any larger extent. By observing the vast literature in measuring accrual-based earnings management, it becomes evident that less effort has been put on developing the estimation techniques of real activities manipulation. This study fills this gap in the literature by proposing an alternative way to proxy for real activities manipulation by applying various types of neural networks in the measurement phase.

Other researchers within the field of accounting have also used the neural network technique due to the appealing advantages when compared to traditional methods. For instance, Höglund (2012) assessed whether models based on neural networks outperform linear and piecewise linear-based models in estimating discretionary accruals as a proxy for accrual-based earnings management. He found that models based on neural networks generally outperform the detection ability of the linear regression models. In an earlier preliminary study, Tsai and Chiou (2009) developed neural network and decision trees models to predict the level of accrual earnings management. Recently, Höglund (2015) also developed and assessed the performance of a local regression-based discretionary accrual estimation model based on self-organizing maps and found such a model to outperform commonly used cross-sectional models. Furthermore, financial studies (Vellido, Lisboa, & Vaughan, 1999; Paliwal & Kumar, 2009) provide literature reviews) have successfully applied neural networks. However, to our knowledge, no study has used artificial neural networks to model real activities manipulation.

The purpose of this study is to examine whether alternatives to a linear approach in the form of neural network-based models could be used to detect real activities manipulation. We include traditional linear regression models in the study, in addition to neural network models based on a self-organizing map and a multilayer perceptron. By so doing, we contribute to the literature on the detection of real activities manipulation. We document that the multilayer perceptron models outperform the original linear approach, especially regarding comprehensive measures. Hence, we recommend researchers to be cautious when drawing inferences from comprehensive measures of real activities manipulation with linear regression models. Additionally, we suggest that researchers apply the individual measures presented by Roychowdhury (2006) when the linear regression approach is used.

Section 2 of this study presents the different traditional approaches for measuring real activities manipulation and the possibilities of applying neural networks. The research methodology and design is presented in Section 3. Section 4 provides the results of the study and discusses them. Ultimately, Section 5 concludes the study.

2. Measures of real activities manipulation

In line with Healy and Wahlen (1999), earnings management is the result of managers using judgment in their financial reporting due to an underlying incentive. Financial reports can for instance be altered in order to influence contractual outcomes that are based on reported accounting figures. This managerial intervention can occur not only via accounting procedures, but also through operational decisions. Managers may have a battery of methods available, ranging from acceleration of sales to reduction in research and development and maintenance expenditures.

Roychowdhury (2006:337) defined real activities manipulations as “departures from normal operational practices, motivated by managers’ desire to mislead at least some stakeholders into

believing certain financial reporting goals have been met in the normal course of operations”. Roychowdhury (2006) continued by noting that real activities manipulation occurs when managers engage in activities such as giving price discounts and cutting discretionary expenditures more extensively than normal given the economic circumstance. Real activities manipulation is significantly different than accrual-based earnings management since managing operational activities have direct effects on cash flow and can be negative for future firm value.

2.1. Detecting real activities manipulation

There is no perfect way to measure real activities manipulation. Studies in this area have therefore used models to estimate the phenomena. The problem in using estimation models is that earnings management, and more specifically real earnings management, is not directly measurable, not even ex-post. The study of Roychowdhury (2006) can be seen as the most influential study when it comes to the development of real activities manipulation proxies. He measured real activities manipulation as the abnormal levels of cash flow from operations, discretionary expenses, and production costs. Subsequent studies using the same metrics (Cohen & Zarowin, 2010; Cohen et al., 2008; Zang, 2012) provide further evidence that these measures capture real activities manipulation. The abnormal levels are obtained by comparing estimates generated by linear models with the actual levels of cash flow from operations, discretionary expenses, and production costs. In prior studies the sample mean or median is expected to be zero under the null hypothesis of no real activities manipulation. Hence, findings of differences between normal and actual levels indicate real earnings management.

For the first measure, Roychowdhury (2006) expresses normal cash flow from operations (CFO) as a linear function of sales and change in sales in the current period. The model is estimated by running the following cross-sectional regression for each industry and year:

$$\frac{CFO_t}{A_{t-1}} = \alpha_0 + \alpha_1 \left(\frac{1}{A_{t-1}} \right) + \beta_1 \left(\frac{S_t}{A_{t-1}} \right) + \beta_2 \left(\frac{\Delta S_t}{A_{t-1}} \right) + \varepsilon_t \quad (1)$$

where A_{t-1} is the lagged total assets at the end of period t , S_t the sales during period t , ΔS_t is the change in sales from period $t - 1$ to t , and ε_t is the error term. Here, the abnormal level of CFO is calculated by subtracting the normal CFO, calculated using estimated coefficients from the corresponding industry-year model, from the actual CFO. Thus, the error term represents the abnormal level of CFO.

The normal level of discretionary expenses (DISEXP), a second variety of real activities manipulation, is expressed as a linear function of lagged sales (Roychowdhury, 2006). DISEXP is defined as the sum of advertising expenses, R&D expenses, and SG&A. The actual model for estimating the normal level of DISEXP is expressed as linear function of current sales. However, this model has issues if firms manage sales upward to increase earnings in a certain year, resulting in lower residuals, even when they do not manage discretionary expenses downwards. Hence, to avoid this problem, Roychowdhury (2006) suggests that DISEXP should be expressed as a function of lagged sales instead of current sales. The following regression estimates the normal level of DISEXP:

$$\frac{DISEXP_t}{A_{t-1}} = \alpha_0 + \alpha_1 \left(\frac{1}{A_{t-1}} \right) + \beta_1 \left(\frac{S_{t-1}}{A_{t-1}} \right) + \varepsilon_t \quad (2)$$

The abnormal level of discretionary expenses is calculated by subtracting the normal level of DISEXP, estimated with the model above, from the actual level of DISEXP.

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