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Earnings management research design

An evaluation of aggregate and specific accruals models

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Abstract

This study aims to evaluate whether accruals models are useful to detect earnings management in listed Swedish companies. We analyse the ability of aggregate and specific accruals models to detect manipulation, to provide unbiased estimates of discretionary behaviour and to identify known cases of accruals fraud. Our results show that both types of accruals models have limited usefulness in detecting manipulation at levels associated with fraudulent accounting, which is partly due to noise in the estimation procedure. While specific accruals models outperform aggregate accruals models, we argue that required detection rates for these models are higher if manipulation is spread across items. These findings contribute to recent studies criticising the ability of accruals models to detect earnings management by showing that specific accruals models may not be a preferable option to aggregate accruals models.

Tutor: Kenth Skogsvik

Keywords: *Earnings management, model design, accruals models, opportunistic behaviour.*

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1. Introduction

"As every past generation has had to disenthrall itself from an inheritance of truisms and stereotypes, so in our own time we must move on from the reassuring repetition of stale phrases to a new, difficult, but essential confrontation with reality. For the great enemy of the truth is very often not the lie - deliberate, contrived, and dishonest - but the myth - persistent, persuasive, and unrealistic." - John F. Kennedy

Research on earnings management has become a staple in the accounting literature with more than 8 000 published articles, of which nearly 600 are in leading accounting journals[1] (Elsevier, 2018). This elusive phenomenon, whereby managers engage in practices to shift earnings between periods to mislead stakeholders in the firm (Healey, 1985), is also attracting an increasing amount of interest as the number of published articles per annum has nearly doubled in the past ten years (Elsevier, 2018). The research design that has dominated the field is aggregate accruals models, which attempt to isolate the discretionary portion of working capital and depreciation accruals as a proxy for earnings management (Zang, 2012). The model developed by Jones (1991), whereby accruals are captured using gross property, plant and equipment and the change in sales, remains the starting point for methods that have evolved over nearly 30 years. In fact, two of the most commonly used models by researchers today have only made minor changes to the original Jones model, as the Modified Jones model replaced the change in sales with the change in cash sales (Dechow et al., 1995) and the Kothari model added a control for operational performance (Kothari et al., 2005). These models have now been so extensively used that they have become the de facto research design and their merits are rarely questioned (Christodoulou et al., 2018).

However, a series of recent articles on earnings management highlight a number of issues with accruals models that have been overlooked in previous research (Owens et al., 2017; Christodoulou et al., 2018; Jackson, 2018). Most notably, Jackson (2018) argues that different variations of the Jones model are unable to detect plausible instances of manipulation and should therefore be dropped as a proxy for earnings management and earnings quality. He even argues that researchers have shown a form of arrogance in assuming that they could detect manipulation that goes unnoticed even by those closest to the firm, such as auditors and equity analysts (Jackson, 2018). In a commentary paper, McNichols and Stubben, two influential

[1] Accounting Review, Journal of Accounting and Economics, Contemporary Accounting Research, Journal of Accounting Research and Review of Accounting Studies.

scholars within the field, acknowledge the recent findings on issues with accruals models and conclude the following:

"... we see two options: give up after considering the issues raised by Jackson (2018) and Christodoulou et al. (2018), or try to address the bias." - McNichols & Stubben (2018)

McNichols & Stubben (2018) propose that specific accruals models, that evaluate a single accrual rather than multiple accruals, could overcome some of the problems associated with aggregate accruals models. Revenue accruals would be an ideal candidate for a specific accrual in this context, as they are common across firms and represent a significant share of total discretion in earnings (Stubben, 2010). While specific accruals appear to be a promising alternative in the earnings management literature, these models have yet to be tested in light of recent findings on bias associated with aggregate accruals models. We therefore propose the following research question:

Are accruals models useful to detect earnings management in listed Swedish companies?

This research question is of interest to researchers and practitioners for three reasons. First, as the earnings management literature has become one of the most influential topics in the accounting literature (Jones, 2018), there is a need to thoroughly evaluate whether any existing model can demonstrate a sufficient level of reliability to warrant further use in research. Second, if it becomes widely accepted that established approaches to detect earnings management are exposed to significant bias, researchers should revisit results derived using these models and seek to support past findings with alternative research designs. This could have implications for the earnings management literature as well as related topics, such as earnings quality (Dechow et al., 2010). Third, if the bias associated with current models cannot be overcome to a sufficient extent, the field may need to seek an entirely different approach to identify discretion in financial reporting. However, the call for improved model designs in earnings management research has been voiced on numerous occasions (Healy, 1996; McNichols, 2000; Dechow et al., 2010), but has yet to result in any profound improvements (McNichols & Stubben, 2018). This would indicate that more radical innovation is needed in order to make meaningful contributions to the field.

We evaluate the ability of aggregate and specific accruals models to detect earnings management in three parts. First, we seed our main sample and artificial firms with fictitious sales through inflated accounts receivables. This allows us to analyse detection rates for known levels of manipulation, which is supported with Monte Carlo simulation for selected tests. Second, we analyse drivers of model performance by evaluating the application of accruals models, including the choice of accruals measure, the explanatory power of the models and the magnitude of implied discretion. Third, we provide context on plausible levels of manipulation and a qualitative interpretation of our previous findings by analysing known cases of accruals fraud. This part consists of an analysis of the listed search company Eniro and an overview of additional fraud cases. All our tests are conducted with a sample of Swedish non-financial and non-real estate firms listed on the Nasdaq Stockholm main market in the period 2005-2017.

This study makes three main contributions to the existing literature. First, we find that aggregate accruals models perform poorly in detecting plausible levels of earnings manipulation in line with recent studies (Jackson, 2018). We further show that specific accruals models, while associated with higher performance than aggregate accruals models, also display detection rates that limit their usefulness for drawing inferences on earnings management. Second, we show that both aggregate and specific accruals models are unable to capture variations in accruals and imply highly improbable levels of manipulation. We further show that traditional aggregate accruals measures are misspecified in relation to prevailing models as they fail to consider accrual generating processes. Hence, we propose a new aggregate accruals measure that outperforms existing measures, but still displays insufficient detection rates. Third, we provide context on the expected level of manipulation by analysing known cases of accruals fraud. A collection of such cases was previously lacking and provides a starting point for future studies.

This thesis comprises seven main sections. Section 2 will introduce asymmetric information, accrual accounting and earnings management, incentives to manipulate earnings, the accruals measures and models used in prior research as well as criticism of accruals models. Section 3 will outline our empirical questions, models and test design. Section 4 will present the selection, collection and quality analysis of our data as well as descriptive statistics and correlations. This is followed by the results and analysis of our empirical tests in three parts - *Detection of earnings management*, *Application of accruals models*, *Identification of accruals fraud* - in Section 5. Section 6 comprises additional tests through sensitivity analysis and robustness tests. Section 7 presents our concluding remarks, limitations and suggestions for future research.

2. Literature review

This section begins by introducing asymmetric information and accrual accounting, which show that managers can act opportunistically to influence reported earnings. Next, we define the concept of earnings management as well as the associated costs and incentives. We then discuss accruals measurement before outlining the evolution of accruals models to detect manipulation. The section ends with an overview of the recent criticism of accruals models.

2.1. Asymmetric information

Asymmetric information is when one party in a relationship has an informational advantage in relation to another party. This situation can arise when one party (the agent) is carrying out work on behalf of another party (the principal) and the principal has limited information on the behaviour or behavioural intent of the agent (Stiglitz, 2000). If the agent and the principal do not share goals or attitude towards risk, the agent can use its informational advantage to act opportunistically at the expense of the principal. According to agency theory, the principal might have to endure some opportunistic behaviour on behalf of the agent due to the trade-off between the cost of monitoring and losses arising from the conflict of interest. One principal-agent relationship that has been studied extensively in research is the interaction between shareholders (the principal) and managers (the agent) (Eisenhardt, 1989). In this context, managers can attempt to reduce conflicts of interest by sending signals (Spence, 2002).

According to signalling theory, managers choose whether and how they communicate information as signals to shareholders. These signals are then interpreted by the shareholders who will respond by sending feedback to managers. As managers favour sending signals that result in positive feedback, only costly signals will be viewed as credible by shareholders (Connelly et al., 2011). However, if the benefits outweigh the cost, managers may signal untruthful or misleading information to shareholders to serve their self-interest at the expense of firm-value maximization (Elitzur & Gavious, 2003). The primary way for managers in listed companies to credibly communicate with external stakeholders is through financial reports, where earnings is the most important item to shareholders (Hjelström et al., 2014). Hence, earnings is of particular interest for managers looking to show misleading information.

The concept of asymmetric information, through the lens of agency and signalling theory, shows that managers could benefit from exercising discretion over earnings. This discretion is made possible by accrual accounting.

2.2. Accrual accounting

Accrual accounting is the process of measuring non-cash assets and liabilities that represent anticipated future benefits and obligations. This method allows for income and expenses to be accounted for in the period they are earned or incurred, compared to cash accounting, where income and expenses are accounted for when cash is received or paid. Hence, a comprehensive measure of accruals in a particular year represents the net of all non-cash transactions recorded in the financial statements (Larson et al., 2018). Consequently, reported earnings can be viewed as comprising cash transactions and accruals used to communicate these transactions in financial reports (Teoh et al., 1998). The purpose of accruals is to more accurately portray the underlying performance of a firm to increase the usefulness of financial reports compared to cash accounting (Robinson et al., 2015). Due to the increased usefulness of accrual accounting, this method has become the foundation of the most established accounting standards, including both IFRS and U.S. GAAP (Paulsson, 2006; Bradshaw & Miller, 2008).

In the process of determining accruals the preparer of financial statements needs to exercise judgement, which introduces a level of subjectivity. This has been shown to lead to lower persistence of accrual earnings compared to cash flows (Sloan, 1996). Due to the subjectivity associated with determining accruals and their importance for earnings, accruals have attracted extensive attention from researchers in various fields (Basu, 1997; Fairfield et al., 2003). One branch of research has argued that managers can use the discretion inherent in accrual accounting to opportunistically advance or delay the recognition of income or expenses, thereby inflating or deflating earnings in a particular reporting period (Teoh et al., 1998). Examples of such misleading judgements include aggressive revenue recognition and capitalization of costs that should be expensed (Richardson et al., 2005). However, as accruals reflect temporary differences between earnings and cash flows, these will have to be offset in the future. Therefore, shifting accruals between periods is a zero-sum game over time, which implies that incentives for managers to engage in such activities should be transitory (Allen et al., 2013). In addition, this property of accruals implies that manipulation can be observed both during the initial manipulation and with the subsequent reversals.

As managers are not perfectly monitored by shareholders and can exercise judgement within the legal framework for financial reporting, there are both incentives and opportunity for managers to manipulate earnings.

2.3. Earnings management

"Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers." - Healy & Wahlen (1999)

The above definition of earnings management has been adopted by the majority of researchers within the field and emphasises the opportunistic intent of managers (Schipper, 1989; Tzur & Yaari 1999; Miller & Bahnson, 2002). Meanwhile, studies arguing that earnings management is merely a signal to improve the informativeness and usefulness of financial reports are in minority (Beneish, 2001; Sankar & Subramanyam, 2001). More recently, researchers have also started to consider manipulation of the underlying transactions, referred to as real activities manipulation. This has been defined as departures from normal operations at the potential expense of firm value maximization, for example through overproduction or price discounts (Roychowdhury, 2006). However, real activities manipulation is difficult to distinguish from ordinary business practices and is unrelated to financial reporting (Lo, 2008). Consequently, this study will focus on manipulation of accruals in line with the majority of past studies.

The opportunistic view of earnings management implies that manipulation of accruals reduces the quality of earnings, which violates the aim of financial reports to provide information that is useful for economic decision making (IASB, 2015). As financial reporting practices are enforceable by law, earnings manipulation can be a criminal offence that is punishable by up to six years in prison (SFS 1962:700, Chapter 11 5§ Brottsbalken). In addition, there are financial and reputational risks as investors will revise their financial projections and reduce their confidence in firms that have been caught managing earnings, leading to a decline in share price (Dechow et al., 1996). However, it should be noted that the definition of earnings management by Healy & Wahlen (1999) focuses on judgements in financial reporting that is distinguishable from fraudulent accounting, which is not within the legal framework (Sundvik, 2016). Regardless of the extent of manipulation, the cost of exposure can be severe implying a trade-off between benefits and costs (Zang, 2012).

As earnings management is a zero-sum game associated with large potential costs, the benefits need to be substantial. Previous studies within the field have therefore focused on circumstances where the incentives to manage earnings are more pronounced.

2.4. Incentives to manage earnings

Several situations where financial reporting data and earnings are of particular importance have been identified in prior literature on earnings management. These situations can be grouped into four categories (Dechow et al., 1996; Burgstahler & Dichev, 1997; Healy & Wahlen, 1999).

Capital market transactions. When the shares of a company are used as currency in a transaction, earnings are an important parameter in the valuation (Hjelström et al., 2014). This incentivises managers to increase earnings prior to the transaction to maximise firm value. Examples of such transactions include management buyouts (Perry & Williams, 1994; Mao & Renneboog, 2015), initial public offerings (Alhadab et al., 2015; Sletten et al., 2018), seasoned equity offerings (Cohen & Zarowin, 2010; Kothari et al., 2016) and mergers (Louis, 2004).

Earnings benchmarks. Earnings benchmarks are targets used to evaluate firm performance that have implications for share price development (Kasznik & McNichols, 2002). Hence, managers are incentivised to meet targets to ensure a positive response from capital markets (Graham et al., 2005). The three most important earnings benchmarks are reporting a profit, beating earnings from last year and beating analyst consensus estimates (Degeorge et al., 1999; Dechow et al., 2003; Brown & Caylor, 2005; Fang Li, 2010; Carvajal et al., 2017).

Contracting. Contracts between a firm and a counterparty can be based on financial reports. This situation arises when management compensation is tied to firm performance to align interests with shareholders (Watts & Zimmerman, 1990; Cheng & Warfield, 2005) and in the presence of debt covenants that limit the risk of creditors (DeFond & Jiambalvo, 1994; Sweeney, 1994). Earnings can also be used to communicate financial reliability in implicit contracts with customers and suppliers (Bowen et al., 1995; Dou et al., 2013).

Regulations. Some regulations come into force depending on financial reporting data. Examples include anti-trust regulations and industry-specific regulations, such as capital requirements (Jones, 1991; Byard et al., 2007; Godsell et al., 2017). Another regulatory incentive is taxes, where a change in the corporate tax rate can create incentives to manipulate earnings to minimise tax payments (Coppens & Peak, 2005; Sundvik, 2016).

Past studies have relied on models to identify discretion in relation to the situations outlined above. The first step in the application of these models is to choose a measure of accruals.

2.5. Measures of accruals

Defining an accruals measure is an integral part of earnings management research design as it sets the scope for detection of manipulation. It has been argued that the choice of accruals measure has often been made in an ad-hoc manner (Larson et al., 2018). Moreover, limited consideration has been applied to ensure a strong connection between the choice of accruals measure, earnings management incentives and the accruals generation process (Jackson, 2018). This issue has expressed itself in numerous research designs with accruals measures that are either incomplete or biased, leading to noisy measures of accruals (Richardson et al., 2005).

The majority of studies on earnings management have employed variations of two established accruals measures (Larson et al., 2018). The measure that dominates early research is calculated from the balance sheet and defines accruals as non-cash working capital less depreciation and amortisation expense, as seen in *Equation 1*. A comprehensive description of the items included in all variables is shown in *Appendix A*. This measure has been criticised for assuming that all changes in balance sheet working capital accounts are reflected in the income statement. This assumption does not hold in the case of non-operating events, such as mergers and acquisition or discontinued operations, which induces a bias in the measure (Hribar & Collins, 2002).

$$Accruals_t = \Delta Working\ capital_t - Depreciation\ expense\ and\ amortisation\ expense_t \tag{1}$$

Criticism of the balance sheet measure effectuated a shift towards a measure based on the cash flow statement calculated as net income less cash flow from operations, as displayed in *Equation 2*. The cash flow measure avoids bias from non-operating events as all accrual adjustments in the operating section of the cash flow statement are reflected in net income. However, the cash flow measure is also problematic as it includes items with non-linear properties, such as write-offs and impairments (Ball & Shivakumar, 2006), and non-operational items, such as interest costs (Richardson et al., 2005).

$$Accruals_t = Net\ income_t - Cash\ flow\ from\ operations_t \tag{2}$$

The balance sheet and the cash flow measures are still dominant in research on earnings management, often without a discussion on the potential impact of bias (Larson et al., 2018). When a measure of accruals has been selected the next step is to choose an accruals model.

2.6. Accruals models

The models used by researchers to detect earnings management have evolved over time. The first important step was taken by Healy (1985), who suggests dividing accruals into non-discretionary accruals and discretionary accruals, as seen in *Equation 3*.

$$\textit{Total accruals} = \textit{Non-discretionary accruals} + \textit{Discretionary accruals} \qquad (3)$$

Non-discretionary accruals arise naturally in firm operations, while discretionary accruals reflect management discretion and is considered a proxy for earnings management. Neither non-discretionary nor discretionary accruals are observable properties either ex ante or ex post, as that would require full disclosure of manipulation, which would render the behaviour meaningless (Healy, 1985). While estimating non-discretionary accruals is difficult in practice it remains the most common approach in research (Jackson, 2018). A selection of accruals models used to estimate non-discretionary accruals are categorised below and summarised in *Table 1*.

Constant accruals. Healy (1985) presented the first model to detect manipulation of accruals, where mean total accruals are compared across the partitioning test variable. This method estimates non-discretionary accruals at zero and assumes that earnings management occurs systematically in every period. DeAngelo (1986) developed this model by assuming non-discretionary accruals equal to total accruals in the previous year. Since both models implicitly assume that non-discretionary accruals are constant, they will be misspecified as accruals vary with underlying business activity (Dechow et al., 2012), which is visible through low power (Dechow et al., 1995).

Firm environment. Jones (1991) developed a model incorporating the economic environment of the firm that became the foundation for future model designs. The Jones model estimates non-discretionary accruals using a multiple regression model with lagged total assets, gross property, plant and equipment and changes in revenue as independent variables. However, the model implicitly assumes that revenue accruals are non-discretionary, which is problematic as revenue manipulation is one of the most common forms of earnings management (Stubben, 2010). Dechow et al. (1995) address this issue in the Modified Jones model by replacing the change in revenue with the change in cash revenue, thereby assuming that changes in credit sales reflect earnings management.

Table 1
Accruals models to detect earnings management

Article	Data	Accruals measure	Accruals model	Adj. R^2
Healy (1985)	U.S. 1964-1980	$Acc_{it} = \Delta WC_{it} - DP_{it}$ (Balance sheet measure)	$NonDisAcc_{it} = \Sigma_t Acc_{it} / T$	N/A
DeAngelo (1986)	U.S. 1973-1980	$Acc_{it} = NI_{it} - CFFO_{it}$ (Cash flow measure)	$NonDisAcc_{it} = AT_{it-1}$	N/A
Jones (1991)	U.S. 1961-1985	$Acc_{it} = \Delta WC_{it} - DP_{it}$ (Balance sheet measure)	$NonDisAcc_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta Rev_{it} + \lambda_3 PPE_{it} + \varepsilon_{it}$	23.2%
Dechow et al. (1995)	U.S. 1950-1991	$Acc_{it} = \Delta WC_{it} - DP_{it}$ (Balance sheet measure)	$NonDisAcc_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta CashRev_{it} + \lambda_3 PPE_{it} + \varepsilon_{it}$	15.1%
Dechow & Dichev (2002)	U.S. 1987-1999	$Acc_{it} = NI_{it} - CFFO_{it}$ (Cash flow measure)	$NonDisAcc_{it} = \lambda_0 + \lambda_1 CFFO_{it-1} + \lambda_2 CFFO_{it} + \lambda_3 CFFO_{it+1} + \varepsilon_{it}$	43.9%
McNichols (2002)	U.S. 1988-1998	$Acc_{it} = NI_{it} - CFFO_{it}$ (Cash flow measure)	$NonDisAcc_{it} = \lambda_0 + \lambda_1 CFFO_{it-1} + \lambda_2 CFFO_{it} + \lambda_3 CFFO_{it+1} + \lambda_4 \Delta Rev_{it} + \lambda_5 PPE_{it} + \varepsilon_{it}$	N/A
Kothari et al. (2005)	U.S. 1962-1999	$Acc_{it} = \Delta WC_{it} - DP_{it}$ (Balance sheet measure)	$NonDisAcc_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta CashRev_{it} + \lambda_3 PPE_{it} + ROA_{it} + \varepsilon_{it}$	N/A
Caylor (2010)	U.S. 2001-2005	$Acc_{it} = \Delta Rec_{it} - \Delta DRST_{it}$	$NonDisAcc(\Delta Rec)_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta Rev_{it} + \lambda_3 \Delta CFFO_{it+1} + \varepsilon_{it}$ $NonDisAcc(\Delta DRST)_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta Rev_{it+1} + \lambda_3 \Delta CFFO_{it} + \varepsilon_{it}$	36.0%
Stubben (2010)	U.S. 1988-2013	$Acc_{it} = \Delta Rec_{it}$	$NonDisAcc_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta RevQ123_{it} + \lambda_3 \Delta RevQ4_{it} + \varepsilon_{it}$	34.2%
Giedt (2018)	U.S. 2001-2013	$Acc_{it} = \Delta Rec_{it} - \Delta DRST_{it} - \Delta DRLT_{it}$	$NonDisAcc(\Delta Rec)_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta RevQ123_{it} + \lambda_3 \Delta RevQ4_{it} + \lambda_4 \Delta CashRev_{it+1} + \varepsilon_{it}$ $NonDisAcc(\Delta DRST)_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta Rev_{it+1} + \lambda_3 \Delta CashRev_{it} + \varepsilon_{it}$ $NonDisAcc(\Delta DRLT)_{it} = \lambda_0 + \lambda_1 (1/AT_{it-1}) + \lambda_2 \Delta Rev_{it+2} + \lambda_3 \Delta CashRev_{it} + \varepsilon_{it}$	41.7%

Acc is total accruals scaled by lagged total assets, *NonDisAcc* is non-discretionary accruals scaled by lagged total assets, ΔWC is the change in working capital, *DP* is depreciation and amortisation expense, *NI* is net income, *CFFO* is cash flow from operations and is scaled by lagged total assets in the accruals model, ΔRec is the change in accounts receivables, $\Delta DRST$ is the change in short-term deferred revenues, $\Delta DRLT$ is the change in long-term deferred revenues, *AT* is total assets, ΔRev is the change in revenues scaled by lagged total assets, *PPE* is gross property, plant and equipment scaled by lagged total assets, $\Delta CashRev$ is the change in cash sales scaled by lagged total assets, *ROA* is net income over lagged total assets, $\Delta RevQ123$ is the change in revenue in the first three quarters scaled by lagged total assets, $\Delta RevQ4$ is the change in revenue minus the change in revenue from the first three quarters scaled by lagged total assets, ε is the error term. The notation for accruals measures is simplified compared to the more detailed presentation in Appendix A for illustrative purposes.

The table shows model specifications for selected accruals models to detect earnings management. *Adj.* R^2 refers to average reported explanatory power for the accruals model regressions.

Cash flow realisation and accruals. Dechow & Dichev (2002) present a model that measures how working capital accruals map into realised cash flow from operations. The model relies on the notion that accruals are estimates of future cash flows and that realised cash flows should therefore match the previously recorded accrual. However, Dechow & Dichev (2002) do not distinguish between an intentional mismatch due to discretion and an unintentional mismatch due to changes in the economic environment of the firm. McNichols (2002) address this by including the variables gross property, plant and equipment and the change in revenue from the Jones model. However, inclusion of future cash flows in accruals models can still lead to biased estimates of discretion (McNichols & Stubben, 2018).

Performance matching. Previous studies have found a relationship between performance and accruals (Dechow et al., 1998). Kothari et al. (2005) therefore suggest controlling for performance in the Modified Jones model by deducting discretionary accruals from the firm in the same industry with the most similar level of return on assets. However, this method of performance matching can extract too much discretion when earnings are being managed, thereby decreasing the power of the test (Dechow et al., 2010). An alternative approach is to include return on assets as a variable in the Modified Jones model, which generates similar results to performance matching (Kothari et al., 2005) and has become the most widely used model specification in recent literature on earnings management (Jackson, 2018).

Specific accruals. Models based on a single accrual, rather than an aggregate measure of accruals as in the preceding models, are known as specific accruals models. These models address the main shortcomings of aggregate accruals models as they can identify manipulated items and are exposed less noise due to the inclusion of more relevant drivers (Stubben, 2010). Examples of specific accruals include the allowance for bad debt (McNichols & Wilson, 1988), loan loss provisions in the banking industry (Collins et al., 1995), loss reserves in the insurance industry (Nelson, 2000) and tax expense accruals (Phillips et al., 2003). Specific accruals should ideally be common across industries, subject to discretion and represent a large part of the earnings discretion available to firms (McNichols & Stubben., 2018). In light of this, revenue has received particular interest from researchers modelling specific accruals.

Revenue accruals. Stubben (2010) presents a model that measures non-discretionary changes in accounts receivables as a function of the change in revenue from the first three quarters and the change in revenue from the fourth quarter. By capturing the change in revenues in the last quarter in a different variable, the model accounts for the lower probability that this revenue will have been collected at year-end. Additional revenue models have been proposed by Caylor (2010) and Giedt (2018) that incorporate deferred revenue accruals and subsequent cash flow realisation. However, these additions have important drawbacks as low deferred revenues in most firms restricts the use of these models to certain industries and future cash flow realisation can lead to biased estimates of discretion (McNichols & Stubben, 2018).

While research designs to detect earnings management have evolved over time, researchers have failed to address some of the most pressing issues that can invalidate empirical results derived with accruals models.

2.7. Criticism of accruals models

While researchers have been aware that accruals models to detect earnings management suffer from important deficiencies, this has not had a noticeable effect on the use of these models in practice (Ball, 2013). In response, recent articles have more clearly illustrated the effect of model deficiencies on the ability to draw statistical inferences as measured by the rate of Type I errors (false positives) and Type II errors (false negatives) (Owens et al., 2017; Christodoulou et al., 2018; Jackson, 2018). A Type I error occurs when a true null hypothesis is rejected by the model, while a Type II error occurs when a false null hypothesis is not rejected by the model (Newbold et al., 2012). In the context of earnings management, a Type I error is identifying earnings management when it is not present while a Type II error is the failure to identify earnings management when it is present. In the following paragraphs, we will discuss potential sources of Type I and Type II errors in accruals models.

Alpha bias. Researchers assume that the estimation sample is free from earnings management when estimating non-discretionary accruals. However, when this assumption does not hold, the regression intercept will be distorted by the average amount of earnings management in the sample, which is known as an alpha bias. A positive (negative) alpha bias will cause non-discretionary accruals to be biased upwards (downwards), which makes it more difficult to detect income increasing (decreasing) earnings management. Hence, alpha bias can increase the risk of both Type I and Type II errors depending on the direction of the alpha bias and the manipulation (Christodoulou et al., 2018).

Beta bias. When there is covariance between discretionary accruals and an independent variable in the accruals model, this variable will capture some of the variation in discretionary accruals leading to a biased slope estimate, which is known as a beta bias. For example, this effect arises when cash flow from operations is used as an independent variable in an accruals model (e.g. Dechow & Dichev, 2002; McNichols, 2002; Caylor, 2010; Giedt, 2018), as the variable is negatively correlated with both non-discretionary and discretionary accruals via the accruals measure. Beta bias can either overstate or mask the true extent of discretionary accruals depending on the sign of the covariance. This problem can consequently give rise to both Type I and Type II errors with the extent of the bias depending on the choice of accruals measure and the independent variables in the accruals model (Christodoulou et al., 2018).

Idiosyncratic shocks. Christodoulou et al. (2018) show that accruals models are unable to distinguish management discretion from random estimation errors as a result of naturally occurring changes in the environment of the firm. Owens et al. (2017) further argue that firms will react differently to external events depending on their business model, and refer to changing economic circumstances and the individual firm response as idiosyncratic shocks. Researchers assume identical accruals generation processes across industries or over time in the application of accruals models. However, the presence of idiosyncratic shocks violate both of these assumptions. This gives rise to biased estimates of non-discretionary accruals from idiosyncratic shocks in the studied firm and in the estimation sample. Depending on the nature of the idiosyncratic shocks, this phenomenon can increase the risk of both Type I and Type II errors.

Omitted variable bias. The omission of variables that are correlated with discretionary accruals can induce bias when seeking to document a correlation with earnings management. If an independent variable is positively correlated with the omitted variable, earnings management can be incorrectly attributed to the independent variable. On the other hand, if the independent variable is negatively correlated with the omitted variable, earnings management can be unintentionally extracted from the independent variable. Even if there is no correlation between the independent variable and the omitted variable, the exclusion of the latter will inflate standard errors and make detection more difficult. Hence, omitted variables can result in both Type I and Type II errors (Dechow et al., 1995).

Alpha bias, beta bias, idiosyncratic shocks and omitted variable bias raise important concerns regarding the possibility to draw accurate inferences from the application of accruals models due to the increased risk of Type I and Type II errors. These concerns lay the foundation for our research question and empirical questions.

3. Method

This section begins with an introduction of our three empirical questions. Next, we discuss our selection and application of accruals models, before presenting our main regression model. The section ends with a description of the test design that will be used to evaluate our empirical questions. Throughout this section and in subsequent sections, we also highlight considerations related to the validity, comparability and reliability of our study.

3.1. Empirical questions

To answer our research question on whether accruals models are useful to detect earnings management in listed Swedish companies, we will evaluate one aggregate accruals model and one specific accruals model in three parts - *Detection of earnings management*, *Application of accruals models*, *Identification of accruals fraud* - each covered by an empirical question.

Detection of earnings management. Recent research has demonstrated that accruals models are subject to alpha bias, beta bias, idiosyncratic shocks and omitted variables bias. The main concern is that these biases could give rise to Type I errors (false positives) and Type II errors, (false negatives), which could impair the ability of accruals models to accurately detect earnings management (Owens et al., 2017; Christodoulou et al., 2018; Jackson, 2018). While it has been shown that certain adaptations of aggregate accruals models display a poor ability to detect manipulation as a result of these biases (Christodoulou et al, 2018), there is a need to expand this analysis to specific accruals models. While specific accruals models are considered a promising alternative to aggregate accruals models, it has yet to be evaluated to what extent they are subject to similar bias. Furthermore, it is warranted to document the extent of errors at different levels of manipulation to determine whether plausible levels of manipulation can be detected. We therefore propose the following:

Question 1: *Can accruals models detect plausible levels of earnings management due to Type I and Type II errors?*

Application of accruals models. The previously noted sources of bias can influence various stages in the application of accruals models, including the accruals model regressions and the properties of discretionary accruals (Christodoulou et al., 2018). However, past studies have not adopted a critical perspective in their application of accruals models, leading to limited documentation and articulation of the extent of biased estimates in the various stages (McNichols & Stubben, 2018). The indiscriminate reliance on past research designs has also extended into the choice of accruals measure that is seldom discussed or motivated (Larson et al., 2018). We argue that there is a need for a critical analysis of the application of accruals models and whether it contributes to noise, including an evaluation of the choice of accruals measure, the power of accruals model regressions and the magnitude of discretionary accruals. We therefore propose the following:

Question 2: *Does the application of accruals models contribute to noise resulting in biased estimates of discretionary accruals?*

Identification of accruals fraud. The most common approach to draw inferences on earnings management is to identify a relationship between discretionary accruals and a situation with a hypothesised incentive to inflate or deflate earnings (Teoh et al., 1998; Louis et al., 2008; Kim et al., 2012). However, as the actual manipulation remains unobservable, researchers turn to known cases of earnings management to evaluate accruals models (Dechow et al., 2003). Previous research has shown mixed evidence on the ability of accruals models to detect known manipulation, but these results are potentially distorted by bias in databases with enforcement actions (McNichols & Stubben, 2018). We argue that a more careful selection of known cases of accruals fraud could reduce bias and offer qualitative insights into the ability of accruals models to identify manipulation. We therefore propose the following:

Question 3: *Can accruals models identify known cases of earnings management?*

We aim for high validity in the operationalisation of our empirical questions to render a comprehensive and faithful representation of the ability of accruals models to detect earnings management. First, we analyse the fundamental performance of accruals models by analysing the rates of Type I and Type II errors in a controlled setting. Second, we analyse important drivers of performance in the application of accruals models. Third, we analyse known cases of fraud that enables a more nuanced interpretation of our results in the preceding parts.

3.2. Model specifications

This study employs and evaluates two accruals models to estimate non-discretionary accruals, one aggregate accruals model and one specific accruals model. In the next step, a main regression model is used to evaluate relationships with discretionary accruals. We now present and discuss our chosen models and the related variables.

3.2.1. Aggregate accruals model

We choose to employ an aggregate accruals model due to the important role of these models in the past literature on earnings management (McNichols & Stubben, 2018). While numerous aggregate accruals models have been proposed in research, we have chosen the alternative model specification proposed by Kothari et al. (2005), where ROA is added as a variable in the Modified Jones model. This model, hereafter referred to as the Kothari model, has become the most widely used accruals model in recent studies (Jackson, 2018), presumably due to its low risk of Type I and Type II errors compared to competing models (Kothari et al., 2005). Hence, this choice of model increases the comparability of our results as it allows us to evaluate the current state of the literature on earnings management. The Kothari model will be applied in three steps, the accruals model regression to estimate variable parameters is shown in *Equation 4*, the subsequent calculation of non-discretionary accruals is shown in *Equation 5* and the calculation of discretionary accruals is shown in *Equation 6*.

$$Acc_{it} = \lambda_{0t} + \lambda_{1t}\,(1/AT_{it-1}) + \lambda_{2t}\,\Delta CashRev_{it} + \lambda_{3t}\,PPE_{it} + \lambda_{4t}\,ROA_{it} + \varepsilon_{it} \tag{4}$$

$$NonDisAcc_{it} = \hat{\lambda}_{0t} + \hat{\lambda}_{1t}\,(1/AT_{it-1}) + \hat{\lambda}_{2t}\,\Delta CashRev_{it} + \hat{\lambda}_{3t}\,PPE_{it} + \hat{\lambda}_{4t}\,ROA_{it} \tag{5}$$

$$DisAcc_{it} = Acc_{it} - NonDisAcc_{it} \tag{6}$$

Acc_{it} is a dependent variable representing total accruals scaled by lagged total assets for firm *i* in year *t*. The value is calculated with the chosen accruals measure and then used to estimate the parameters in the accruals model regression in *Equation 4.* When estimating the parameters we use the cross-sectional approach, with an estimation sample consisting of all firms in the same industry in the same year. Our industry classification is based on the Global Industry Classification Standard (GICS), which has shown to result in less biased estimates of discretionary accruals compared to competing classifications (Hrazdil & Scott, 2011). The cross-sectional approach is the most common method in research as the alternative, the time-series approach that uses a pre-event window for each company, requires long data series that can induce survivorship bias (Subramanyam, 1996).

$NonDisAcc_{it}$ is a dependent variable representing non-discretionary accruals scaled by lagged total assets for firm i in year t. The value is estimated by applying *Equation 5*, with known parameter estimates and known values for all independent variables.

$DisAcc_{it}$ is a dependent variable representing discretionary accruals scaled by lagged total assets for firm i in year t. The value is estimated by applying *Equation 6*, with known total accruals and estimated non-discretionary accruals.

AT_{it} is an independent variable representing total assets for firm i in year t. This variable represents the scaled intercept and omission from the model can lead to lower power in the parameter estimates (Jackson, 2018). As this variable is an intercept, we do not have a hypothesised correlation between this variable and discretionary accruals.

$\Delta CashRev_{it}$ is an independent variable representing the change in net sales minus the change in accounts receivables scaled by lagged total assets for firm i in year t. This variable controls for changes in working capital. We expect this variable to be positively correlated with total accruals as most firms have positive working capital that increases with sales (Jones, 1991).

PPE_{it} is an independent variable representing gross property, plant and equipment scaled by lagged total assets for firm i in year t. This variable controls for accruals generated by depreciation expense. We expect this variable to be negatively correlated with total accruals as fixed assets lead to larger negative depreciation accruals (Jones, 1991).

ROA_{it} is an independent variable representing return on assets, calculated as net income over lagged total assets for firm i in year t.[2] This variable controls for performance as earnings increase before the corresponding cash flows are realised, leading to higher accruals (Dechow et al., 1998). We therefore expect this variable to positively correlated with total accruals.

ε_{it} is the error term in the accruals model regression for firm i in year t.

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[2] We note that this is not a consistent return measure of performance as the income measure in the numerator has no direct economic relationship with the capital measure in the denominator. However, we keep this variable definition and notation to enhance comparability with past research.

3.2.2. Specific accruals model

We choose to employ a specific accruals model based on revenue due to the higher explanatory power and lower noise of these models compared to aggregate accruals model (McNichols, 2000; Stubben, 2010). Our selected model was proposed by Stubben (2010), hereafter referred to as the Stubben model, and is based on accounts receivable accruals. As noted in section 2.6., this is the only revenue model that avoids bias from inclusion of realised future cash flows and only consists of accruals that are common across industries (McNichols & Stubben, 2018). While revenue accruals represent the largest and most frequently manipulated component of earnings, the Stubben model is more narrow in scope compared to the Kothari model. However, it has been suggested that the scope of the Stubben model could be expanded if used alongside other specific accruals models in a 'mosaic' approach (Giedt, 2018). The Stubben model will be applied in three steps, the accruals model regression to estimate variable parameters is shown in *Equation 7*, the subsequent calculation of non-discretionary accruals is shown in *Equation 8* and the calculation of discretionary accruals is shown in *Equation 9*.

$$Acc_{it} = \lambda_{0t} + \lambda_{1t}\,(1/AT_{it-1}) + \lambda_{2t}\,\Delta RevQ123_{it} + \lambda_{3t}\,\Delta RevQ4_{it} + \varepsilon_{it} \qquad (7)$$

$$NonDisAcc_{it} = \hat{\lambda}_{0t} + \hat{\lambda}_{1t}\,(1/AT_{it-1}) + \hat{\lambda}_{2t}\,\Delta RevQ123_{it} + \hat{\lambda}_{3t}\,\Delta RevQ4_{it} \qquad (8)$$

$$DisAcc_{it} = Acc_{it} - NonDisAcc_{it} \qquad (9)$$

Acc_{it}, $NonDisAcc_{it}$, $DisAcc_{it}$, AT_{it} and ε_{it} are defined analogously to the corresponding variables in the aggregate accruals model in section 3.2.1.

$\Delta RevQ123_{it}$ is an independent variable representing the change in revenue in the first three quarters scaled by lagged total assets for firm *i* in year *t*. We expect this variable to be positively correlated with accruals as revenue is a driver of accounts receivable (Stubben, 2010).

$\Delta RevQ4_{it}$ is an independent variable representing the change in total revenue minus the change in revenue in the first three quarters scaled by lagged total assets for firm *i* in year *t*.[3] We expect this variable to be positively correlated with accruals as revenue is a driver of accounts receivable (Stubben, 2010).

[3] $\Delta RevQ4$ is derived from the annual figures to avoid bias in relation to non-operating events where the sum of changes in revenue for all quarters do not add up to total change in revenue over the year.

3.2.3. Main regression model

We will use the regression model presented in *Equation 10* to test the ability of our models to detect earnings management. A main regression model is used to investigate the relationship between discretionary accruals (dependent) and our test variable (independent), while controlling for other factors that can influence discretion. We will only apply the main regression model in the tests of our first empirical question as other analysis is solely concerned with the levels of discretionary accruals derived using our accruals models. All variables in our accruals models, main regression model and discretionary accruals are winsorized at the 1st and 99th percentiles to reduce impact from outliers (Kothari et al., 2005).

$$DisAcc_{it} = \lambda_{0t} + \lambda_{1t}\, Test\ variable_{it} + \lambda_{2t}\, Size_{it} + \lambda_{3t}\, Leverage_{it} + \lambda_{4t}\, MarketBook_{it} + \\ + \lambda_{5t}\, CFFO_{it} + \lambda_{6t}\, Loss_{it} + \lambda_{7t}\, Analysts_{it} + \varepsilon_{it} \quad (10)$$

$DisAcc_{it}$ and ε_{it} are defined analogously to the corresponding variables in the aggregate accruals model in section 3.2.1. For the Kothari Model, the variable for discretionary accruals is denoted *Adj.CF* for the adjusted cash flow measure[4], *CF* for the cash flow measure and *BS* for the balance sheet measure. For the Stubben Model, the same variable is denoted *Rev.* As we are interested in detecting directional earnings management and not earnings quality, we will only conduct tests using non-absolute discretionary accruals (Dechow et al., 2010).

$Test\ variable_{it}$ is a generic independent test variable for firm *i* in year *t*. This variable will be replaced with non-generic variables defined in relation to our test design in section 3.3.1.

$Size_{it}$ is a control variable calculated as the natural logarithm of lagged market value of equity in year *t* for firm *i*. Previous research has found that large firms have high political costs and will therefore engage in more conservative financial reporting (Francis et al., 2005). We therefore expect this variable to be negatively associated with discretionary accruals.

$Leverage_{it}$ is a control variable calculated as lagged total debt over lagged total equity for firm *i* in year *t*. Previous research has found that higher leverage is associated with financial distress that incentivises managers to communicate a more positive view of financial performance to lenders (Becker et al., 1998). We therefore expect this variable to be positively associated with discretionary accruals.

[4] This measure will be defined in section 3.3.2.

$MarketBook_{it}$ is a control variable calculated as the lagged market value of equity over the lagged book value of equity for firm *i* in year *t*. Previous research has found that firms with high market-to-book ratios, a proxy for growth potential, are more keen to report consistent earnings increases (Chih et al, 2008). We therefore expect this variable to be positively associated with discretionary accruals.

$CFFO_{it}$ is a control variable calculated as cash flow from operations scaled by lagged total assets for firm *i* in year *t*. Previous research has found that high cash flow from operations is an indicator of strong financial performance, which reduces the need to engage in income increasing earnings management (Dechow et al., 1995). We therefore expect this variable to be negatively associated with discretionary accruals.

$Loss_{it}$ is a dummy control variable that equals one if reported earnings are negative and zero if earnings are not negative for firm *i* in year *t*. Previous research has found that negative earnings can incentivise managers to manipulate earnings to report a profit (Dechow & Dichev, 2002). We therefore expect this variable to be positively associated with discretionary accruals.

$Analysts_{it}$ is a control variable calculated as the number of analysts that have issued at least one earnings-per-share forecast for firm *i* in year *t*. Previous research has found that higher analyst coverage increases the importance of analyst forecasts, thereby incentivising managers to meet or beat consensus earnings (Choi, 2016). We therefore expect this variable to be positively associated with discretionary accruals.

3.3. Test design

In this section we will discuss the test designs that are used to evaluate our main empirical questions. It is divided into three main parts - *Detection of earnings management, Application of accruals models, Identification of accruals fraud*.

3.3.1. Detection of earnings management

The usefulness of statistical tests depend on their ability to correctly assess whether the null hypothesis should be rejected or not (Newbold et al., 2012). As discussed in section 2.7., this ability can be summarised with the risk of Type I errors (false positives) and Type II errors (false negatives). Assessing when accruals models have produced false positives or false negatives is inherently difficult as manipulation often remains unknown ex post. We therefore turn to seeding of earnings management, which involves introducing predetermined levels of manipulation in sample firms, thereby avoiding biases inherent in studies using databases with exposed discretionary behaviour (McNichols & Stubben, 2018). This evaluation will be carried out in three steps *(i) Main sample seeding, (ii) Monte Carlo simulation* and *(iii) Seeding in artificial firms.*

Main sample seeding. Seeding of known levels of discretion in the main empirical sample offers researchers considerably more flexibility when evaluating the rate of Type I and Type II errors in accruals models. This approach is therefore well established among researchers interested in research design topics within earnings management (Kothari et al., 2005; Stubben, 2010; Jackson, 2018). To apply this approach, researchers must decide on the financial statement item for seeding, the share of the sample to seed and the magnitude of seeding.

First, we choose to replicate the recognition of fictitious or premature sales by seeding an increase in accounts receivables and sales, which should be identified as discretionary accruals by our models.[5] Accounts receivables was chosen as it is the only accrual included in all our specifications of aggregate and specific accruals models. While booking of fictitious sales would normally reverse through negative accruals in subsequent periods, we assume that seeding is discrete to a specific period with no impact on future years. To avoid systematic introduction of alpha bias in our accruals models we therefore exclude seeded observations from our accruals model regressions (Christodoulou et al., 2018). However, as researchers are not always able to identify earnings management suspects, we also conduct a sensitivity test where we include seeded observations in accruals model regressions in section 6.1.4.

Second, the seeding of accounts receivables is conducted in a random subsample of firm years accounting for 5% of our main sample. The same subsample is used for different models and levels of seeding to enhance comparability. We have selected the share of seeded observations based on our expectation of the share of listed Swedish firms that might engage in earnings management. While we believe that managers would only engage in manipulation on a selective basis, this estimate is uncertain as the proportion of manipulating firms has not been explored in past research. We therefore conduct a sensitivity analysis with a share of seeded firms at 10% of our main sample in section 6.1.2.

[5] In untabulated results, we find that income decreasing seeding yields results that are qualitatively similar to the corresponding levels of income increasing seeding.

Third, we choose to seed the same amount of fictitious sales, ranging from 0.0% to 3.0% of lagged total assets for each individual firm year. While this makes the seeding comparable across firms we will primarily analyse the level of seeding through the average impact on earnings, which we believe is more informative. Seeded observations are captured with a dummy test variable, *Seeded*, in our main regression model, which takes on the value of one if the observation has been seeded and zero if it has not been seeded in firm *i* in year *t*, as seen in *Equation 11*. As we seed earnings increases through fictitious sales we expect this variable to be positively correlated with discretionary accruals. All other variables are defined analogously to the corresponding variable in the main regression model in section 3.2.3.

$$DisAcc_{it} = \lambda_{0t} + \lambda_{1t}\, Seeded_{it} + \lambda_{2t}\, Size_{it} + \lambda_{3t}\, Leverage_{it} + \lambda_{4t}\, MarketBook_{it} + \\ + \lambda_{5t}\, CFFO_{it} + \lambda_{6t}\, Loss_{it} + \lambda_{7t}\, Analysts_{it} + \varepsilon_{it} \qquad (11)$$

The seeding also affects other variables in our models. First, *ROA* increases in the Kothari model as net income increases in proportion to lagged total assets. Second, the Δ*RevQ123* and Δ*RevQ4* variables in the Stubben model both increase, reflecting the recognition of fictitious sales. While Stubben (2010) attributes all manipulation to fourth quarter revenue, we distribute the manipulation according to the relative share of revenue by quarter as incentives to manage earnings are present throughout the financial year (Zang, 2012). Third, the dummy control variable *Loss* is revised in cases where the seeding turns a loss into a net profit in the period. All other variables are either unrelated to fictitious sales or based on lagged metrics and therefore not affected by seeding in the same period. We also choose to exclude any tax effects from seeding as this could reduce comparability between different accruals measures.

There are three main drawbacks with seeding in our main sample. First, our accruals models regressions could be distorted by alpha bias if the average manipulation in our main sample is not zero (Christodoulou et al., 2018). However, while our main sample is likely to contain earnings management, we believe that bias in a particular direction is unlikely as most accruals reverse over time. Second, it is difficult to draw accurate inferences on error rates from seeding of a single random subsample as properties of the sample could influence results. We address this problem by conducting Monte Carlo simulations for selected levels of seeding. Third, seeding is most effective when the original level of discretionary accruals in each of the seeded firms is zero. As this problem is difficult to overcome when seeding real firms, we will conduct further tests where we seed artificial firms that have zero discretionary accruals prior to seeding.

Monte Carlo simulation. This method refers to the use of repeated random sampling of data in order to strengthen empirical results using the law of big numbers. The expectation is that errors will converge to zero given a sufficient number of repetitions (Mooney, 1997). While Monte Carlo simulation has been extensively used in quantitative fields, such as mathematics and physics, it has been less pervasive in business related topics (Hammersley, 2013). However, the usefulness of Monte Carlo simulation in evaluation of model performance has led to previous application in the earnings management literature (Kothari et al., 2005; Christodoulou et al., 2018). We employ Monte Carlo simulation to enhance the reliability of the results from seeding in our main sample. The Monte Carlo simulation is carried out at two selected levels of main sample seeding, 0.0% and 1.0% of lagged total assets, which are particularly important to draw conclusions on the rates of Type I and Type II errors based on findings in our initial tests. This is done by repeating our tests 100 times using different random subsamples obtained through sampling with replacement. Inferences about model ability can then be drawn by comparing the rejection rate of the null hypothesis to selected test proportions representing different levels of Type I and Type II error rates.

Seeding in artificial firms. To control for different levels of discretionary accruals in our subsample of seeded firms, we construct artificial firms with zero discretionary accruals that are added in the tests of our main regression model. This provides a situation with minimal noise that should maximise the ability of the models to detect seeded earnings and therefore yield the lowest possible Type II error rate. However, this method does not allow for tests of Type I errors as artificial firms display no noise in accruals that can give rise to false positives. The artificial firms account for 5% of our main sample and are seeded with fictitious sales in the range of 0.0% to 3.0% of lagged total assets, to enhance comparability with seeding of our main sample. We do not define other variables in the accruals models as the artificial firms are excluded from the accruals model regressions and the amount of seeding is expressed in relative terms. Moreover, we exclude control variables as we have full discretion over the accruals process and incorporating external factors could introduce bias (Spector & Brannick, 2011). Artificial firm observations are captured with a dummy test variable, *Artificial*, in our main regression model, which takes on the value of one if the observation is an artificial firm and zero otherwise for firm *i* in year *t*, as seen in *Equation 12*. $DisAcc_{it}$ and ε_{it} are defined analogously to the corresponding variables in the main regression model in section 3.2.3.

$$DisAcc_{it} = \lambda_{0t} + \lambda_{1t}\, Artificial_{it} + \varepsilon_{it} \qquad (12)$$

3.3.2. Application of accruals models

An appropriate research design founded in the accrual generation process is pivotal when using accruals models to detect earnings management. In fact, an inattentive choice of accruals measure or accruals model could exacerbate existing biases and lead to more misleading results (McNichols & Stubben, 2018). We will now discuss our test design related to three aspects in the application of accruals models *(i) Choice of accruals measure, (ii) Power of accruals model regressions* and *(iii) Magnitude of discretionary accruals.*

Choice of accruals measure. The choice of accruals measure is an important element in earnings management research design as it sets the scope for detection of manipulation (Larson et al., 2018). However, we claim that the two most commonly used accruals measures, the balance sheet and the cash flow measures, comprise accruals with no direct connection to variables in aggregate accruals models. This problem can be illustrated using the accruals components of the balance sheet measure in relation to the Kothari model. While the change in cash sales in the Kothari model could be expected to drive the change in working capital, and gross property, plant and equipment could similarly be expected to drive depreciation according to plan, there is no variable that can predict amortisation according to plan. This problem is exacerbated when using the cash flow measure as its broader definition of accruals should render the variables in the accruals model even less useful. Furthermore, the cash flow measure incorporates write-offs and impairments with non-linear properties that could further increase misspecification (Ball & Shivakumar, 2006).

To address these problems we propose a new aggregate accruals measure that we refer to as the adjusted cash flow measure, which is defined in *Equation 13*. We believe that this measure has three main benefits compared to any single aggregate accruals measure used in past research. First, there is a clear link between each of the accruals and the variables in the accruals model. The measure is similar to the balance sheet measure, but is better specified as it eliminates amortisation that is not captured by any of the variables in the Kothari model. Second, the selected items are collected from the cash flow statement to avoid bias associated with non-operating events (Hribar & Collins, 2002). Third, all items have linear properties as they exclude non-linear items such as write-offs and impairments (Ball & Shivakumar, 2006).

$$Accruals_{it} = \Delta Working\ capital_{it} - Depreciation\ expense_{it} \qquad (13)$$

The adjusted cash flow measure will be used alongside the balance sheet and cash flow measures for all empirical tests with the Kothari model. We have not developed an alternative accruals measure for the Stubben model as accounts receivables is logically consistent with the model variables and obtained from the cash flow statement (Stubben, 2010).

Power of accruals model regressions. The accruals model regression is used to estimate model parameters that are subsequently used to derive non-discretionary accruals. Analysing the power of these regressions is an established method to shed light on the predictive ability of accruals models and thereby assess the extent of misspecification (Jones, 1991; Dechow & Dichev, 2002). As illustrated in section 2.6., both aggregate and specific accruals models have displayed an adjusted R^2 of less than 50% in past research. This implies that a majority of the variation in accruals cannot be explained by the model variables, which should result in noisy estimates of discretionary accruals. To obtain a better understanding of the predictive ability of our chosen models, we will analyse power in three respects. First, we will analyse the explanatory power of the complete model and each of the parameters separately. Second, we will analyse the power of the models across the industries in our sample to assess inter-industry variation. Third, we will analyse the power of the models over time to assess the impact from extreme events.

Magnitude of discretionary accruals. Researchers have highlighted what they claim to be implausible magnitudes of discretionary accruals reported in many past studies on earnings management (Ball, 2013; Jackson, 2018). Ball (2013) argues that it is surprising that researchers have not been sceptical to empirical results implying that (i) manipulation occurs for every firm in every year, (ii) discretion drives a significant share of the variation in accruals and (iii) manipulation is possible in working capital items, such as inventory, that are typically easy to measure. He further suggests that scaled representation in relation to lagged total assets has contributed to the problem by obscuring the actual magnitude of discretionary accruals. We believe that the magnitude of discretionary accruals is an important factor in evaluating the performance of accruals models as noise in discretionary accruals could lead to increased risk of both Type I and Type II errors. Hence, we will analyse the magnitude of discretionary accruals in two respects. First, we will analyse the magnitude across the industries in our sample to assess inter industry variation. Second, we will analyse magnitude over time to assess the impact from extreme events.

3.3.3. Identification of accruals fraud

Analysing known cases of earnings management is an established method to evaluate the performance of accruals models (Dechow et al., 1995; Beneish, 1997). Previous studies analysing specific cases have found that accruals models perform poorly in detecting known cases of accruals manipulation (Beneish, 2016; Jackson, 2018). However, researchers have argued that the noise in discretionary accruals implies that accruals models are more suited to capturing earnings management across a portfolio of firms rather than in a single firm (McNichols & Stubben, 2018). We propose that studies on known instances of accruals fraud in single firms can make two main contributions in research design studies. First, it can shed light on how the random noise in accruals models exerts itself in practice and whether actual manipulation is still discernible. This provides an opportunity to make a qualitative interpretation of the risk of Type I and Type II errors. Second, known fraud cases can give an indication of what magnitudes of earnings manipulation are likely to be observed in practice among listed Swedish firms, which is important in the evaluation of detection rates.

We have three main requirements when searching for known cases of accruals fraud. More specifically we require that companies (i) are listed Swedish firms that have committed accruals fraud in the past 20 years, which excludes other types of violations such as insider trading, embezzlement and market abuse, (ii) issued a restatement of earnings pertaining to the accruals fraud by a known amount and (iii) are part of our main sample at the time of manipulation. To identify cases that meet these requirements, we gather information from four financial supervisory bodies, the Swedish Economic Crime Authority (Ekobrottsmyndigheten), Sweden’s Financial Supervisory Authority (Finansinspektionen) and the Swedish Inspectorate of Auditors (Revisorsinspektionen). In addition, we review a database with earnings restatements compiled by equity analyst Peter Malmqvist.

Due to the limited number of exposed accruals frauds on Nasdaq Stockholm, there was only one company that fulfilled all three requirements. The company was Eniro AB (Eniro), which engaged in premature revenue recognition in 2013. Our evaluation of Eniro will comprise a company overview, developments in relation to the manipulation and an analysis of discretionary accruals. As Eniro manipulated revenue accruals it is suitable for analysis with both the Kothari model and the Stubben model. To provide more context on expected levels of manipulation, we also analyse cases of accruals fraud that meet requirements (i) and (ii). The full list of identified firms that satisfy the first criteria is presented in Appendix B.

4. Empirics

This section begins with an outline of our sample selection and data collection processes followed by an analysis of data quality. We end the section by presenting descriptive statistics and Pearson correlations for the variables used in our accruals models and main regressions.

4.1. Sample selection

We restrict our sample to Swedish firms listed on the Nasdaq Stockholm main market in the period 2005-2018. As most research on earnings management has been undertaken in a public setting we believe that the effectiveness of the models should be evaluated in this context. We limit the time period to the years following the mandatory implementation of IFRS to ensure all firms in our sample are subject to similar accounting standards. This is warranted as the voluntary adoption of IFRS in the period 1991-2004 was characterised by deviations and weak enforcement (Hellman, 2011). Our delimitation resulted in a sample of 423 firms that was adjusted to derive the main sample used to conduct our empirical tests. Adjustments were made only if they were deemed important to allow us to conduct our empirical tests or to avoid bias. Furthermore, we do not believe that we have introduced bias by excluding firms with different propensity to manage earnings. The adjustments are detailed below and outlined in *Table 2*.[6]

Table 2
Sample selection

Criteria	**Adjustments**	**# of firms**
Delimitation*		423
1. Data available in Compustat	-41	382
2. Fiscal year end in December	-44	338
3. Reporting in SEK	-16	322
4. Non-financial and non-real estate companies	-56	266
5. Listed for two consecutive years or more	-34	232
6. Sufficient industry observations	-19	213
Total main sample	**-210**	**213**
Firm year observations		*1 654*

The table shows adjustments to our delimitation to derive our main sample as part of the sample selection process.
*Listed on Nasdaq Stockholm sometime in 2005-2018

First, we exclude 41 firms that are not available in Compustat Global Daily or lack data required to calculate discretionary accruals in all years. The majority of these firms are either foreign companies that may be exposed to different regulations than Swedish firms or companies that were recently listed and therefore have not filed two consecutive annual reports as listed firms. Hence, these firms would otherwise have been excluded from our sample.

[6] The year 2018 is excluded as annual reports for this period had not been released when we collected our data.

Second, we exclude 44 firms with a fiscal year end other than December. As the cross-sectional approach compares financial data within the same industry and year, it is important that time periods are consistent. Different time periods across firms could distort the effect from industry wide events and introduce bias in the estimation of discretionary accruals.

Third, we exclude 16 firms that do not report in SEK. Compustat Global Daily does not provide a function to translate between different currencies and any such attempts could potentially distort our measures of accruals without complete translation adjustments (Godfrey et al., 2010). Including the firms in a different currency without any adjustments would also distort their size in relation to other firms.

Fourth, we exclude 56 firms that are either financial firms, investment companies or real estate companies. Financial firms are excluded because their financial reports have a structure that does not allow for calculations of accruals (Berger, 2017). Investment companies and real estate companies are excluded because their earnings are driven by changes in market values of their asset portfolios leading to lower relevance of accruals (Liang & Riedl, 2014).

Fifth, we exclude 34 companies that have not been listed for two complete consecutive years. This is because lagging data is required to calculate accruals (Kothari et al., 2005; Stubben, 2010). Furthermore, we require that companies provide an IFRS compliant annual report for each year that they are included in the sample as certain data is collected from the notes. This excludes the year 2005 as lagging data for this period is prior to the implementation of IFRS.

Finally, we exclude 19 companies in industries that consistently have less than ten observations per year. While this is a common requirement in research (Kothari et al., 2005), we argue that ten observations could be too few to estimate parameters in accruals model regressions. We therefore include the *Materials* industry, despite having only eight to ten observations per year to analyse the potential impact of the number of observations on explanatory power.

Our final sample consists of 213 firms across five industries corresponding to 1 654 firm year observations, see *Table 3*. The average number of observations by industry is approximately 28, but varies considerably between industries with a minimum of eight observations in *Materials* and a maximum of 56 observations in *Industrials*. The same sample is used throughout all tests as the observations in our main sample have complete data for all variables.

Table 3
Firm observations by industry and year

GICS	Industry	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
15	Materials	10	9	9	9	10	10	10	10	10	8	9	8	**112**
20	Industrials	52	51	54	56	54	51	51	52	50	49	52	54	**626**
25	Consumer discretionary	15	16	17	18	17	18	21	22	22	22	23	27	**238**
35	Health care	18	19	19	20	18	17	18	21	21	21	23	26	**241**
45	Information technology	43	42	37	37	35	34	36	37	35	33	33	35	**437**
Total		**138**	**137**	**136**	**140**	**134**	**130**	**136**	**142**	**138**	**133**	**140**	**150**	**1 654**
Excluded industries (19 firms)														
10	Energy	2	2	2	2	2	2	2	2	3	3	1	1	**24**
30	Consumer staples	5	4	5	4	4	5	5	5	5	5	6	6	**59**
50	Telecom. services	3	3	3	3	3	4	4	4	3	3	4	4	**41**
55	Utilities	1	1	1	1	1	1	2	2	2	2	2	2	**18**
Total		**11**	**10**	**11**	**10**	**10**	**12**	**13**	**13**	**13**	**13**	**13**	**13**	**142**

The table shows firm observations in the main sample by industry and year as well as firms excluded due to insufficient industry observations.

4.1. Data collection

The empirics in our study are obtained from databases provided by Wharton Research Data Services. Compustat Global Daily is used to obtain annual and quarterly data from financial statements as well as security data, while IBES is used to obtain analyst estimates. We choose Compustat Global Daily as it has shown to be the most comprehensive database for listed international companies (Dai, 2012). In addition, data on listings and delistings on the Nasdaq Stockholm main market is obtained from the database provided by the Swedish House of Finance. Finally, we conduct a review to identify known cases of accruals fraud. Contributors of information in this search include Ekobrottsmyndigheten, Finansinspektionen, Revisors-nämnden and equity analyst Peter Malmqvist. All data from WRDS was collected in September 2018 while data from other sources was collected in September and October 2018.

4.3. Data quality

In order to ensure the integrity of our empirics we conduct data quality tests. First, we pick 200 random data points with financial statement data obtained from Compustat Global Daily and compare this to hand collected figures from financial reports. Second, we pick 50 random data points from the security data from Compustat Global Daily and compare with hand collected data from financial reports. Third, as there are few alternative databases on analyst coverage, we compare the most recent number of analyst estimates obtained from IBES with the number of analysts displayed on the investor relations page of 50 random firms. These tests reveal minor seemingly random discrepancies in less than three percent of cases, indicating that our data has high reliability and that our results should not be materially affected by issues with data quality.

4.4. Descriptive statistics

Descriptive statistics for the variables used in our accruals models as well as our main regression model are presented in *Table 4*. Our findings are similar to previous research with some exceptions. First, discretionary accruals have lower standard deviations ranging from 3.8% of lagged total assets in the Stubben model to 6.0% with the *CF* measure using the Kothari model. The mean of discretionary accruals is close to zero by construction. Second, the firms in our sample are smaller with an average market capitalisation of SEK 1.8 billion and less capital intensive with *PPE* of 35.6% of lagged total assets. Third, our sample displays higher profitability and higher cash generation with mean *ROA* of 2.8% and *CFFO* of 6.2% of lagged total assets respectively (Kothari et al., 2005; Stubben, 2010; Owens et al., 2017; Giedt, 2018). We can further conclude that the mean company in our sample has lagged total assets of SEK 13.5 billion, growth in cash sales of 6.1% per annum and a debt-to-equity ratio of 50.2%.

Table 4
Descriptive statistics

Metric	N	Mean	STD	Min	Q1	Q2	Q3	Max
Discretionary accruals								
DisAccAdj.CF	1 654	0.0001	0.0439	-0.1211	-0.0228	-0.0013	0.0231	0.1291
DisAccCF	1 654	0.0003	0.0601	-0.1851	-0.0290	0.0009	0.0320	0.1690
DisAccBS	1 654	0.0000	0.0579	-0.1691	-0.0303	-0.0006	0.0300	0.1709
DisAccRev	1 654	0.0000	0.0383	-0.1124	-0.0177	-0.0010	0.0159	0.1303
Kothari variables								
AccAdj.CF	1 654	-0.0131	0.0585	-0.1801	-0.0451	-0.0130	0.0140	0.1769
AccCF	1 654	-0.0357	0.0834	-0.3643	-0.0697	-0.0299	0.0032	0.2099
AccBS	1 654	-0.0220	0.0743	-0.2512	-0.0569	-0.0237	0.0084	0.2529
InvAT	1 654	0.0021	0.0038	0.0000	0.0002	0.0008	0.0022	0.0246
ΔCashRev	1 654	0.0606	0.2046	-0.5516	-0.0376	0.0479	0.1382	0.8100
PPE	1 654	0.3555	0.3332	0.0065	0.0960	0.2478	0.5187	1.4593
ROA	1 654	0.0275	0.1679	-0.7218	0.0092	0.0556	0.1016	0.3797
Stubben variables								
AccRev	1 654	0.0177	0.0657	-0.1361	-0.0113	0.0086	0.0350	0.3097
ΔRevQ123	1 654	0.0568	0.1810	-0.4670	-0.0272	0.0458	0.1302	0.7207
ΔRevQ4	1 654	0.0256	0.0939	-0.2386	-0.0150	0.0154	0.0537	0.4704
Control variables								
Size	1 654	7.4902	1.9398	3.4803	6.0832	7.1588	8.7701	12.2651
Leverage	1 654	0.5020	0.5427	0.0000	0.0495	0.3382	0.7827	2.6322
MarketBook	1 654	2.9640	2.9361	0.3051	1.2850	2.2252	3.5795	20.3600
CFFO	1 654	0.0616	0.1551	-0.6607	0.0281	0.0814	0.1310	0.4468
Loss	1 654	0.2219	0.4155	0.0000	0.0000	0.0000	0.0000	1.0000
Analysts	1 654	5.6560	7.4396	0.0000	1.0000	3.0000	7.2500	33.0000

DisAcc is discretionary accruals scaled by lagged total assets, *Acc* is total accruals scaled by lagged total assets, *InvAT* is inverse lagged total assets, *ΔCashRev* is the change in cash sales scaled by lagged total assets, *PPE* is gross property, plant and equipment scaled by lagged total assets, *ROA* is net income over lagged total assets, *ΔRevQ123* is the change in revenue in the first three quarters scaled by lagged total assets, *ΔRevQ4* is the change in revenue minus the change in revenue from the first three quarters scaled by lagged total assets, *Size* is the natural logarithm of lagged market capitalisation, *Leverage* is lagged total debt over lagged total equity, *MarketBook* is the lagged market capitalisation over lagged parent equity, *CFFO* is cash flow from operations scaled by lagged total assets, *Loss* equals one if reported earnings are negative and zero otherwise, *Analysts* is the number of analysts reporting at least one earnings-per-share forecast. Variables calculated using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

The table shows descriptive statistics for all variables used in the accruals models and main regression models.

4.5. Pearson correlations

The correlation coefficients for the variables used in our empirical tests are presented in *Table 5*, with results for our accruals models shown in Panel A and results for our main regression model shown in Panel B. Additional information on table notation and statistical tests is provided in the table descriptions of all tables. In Panel A, we expect the independent variables in our accruals models to be correlated with their respective measures of accruals with predicted signs, indicating that the variables contribute to the explanatory power of the models. This expectation is confirmed for all independent variables that are significant at the 1% level with expected signs. We also expect positive correlation between different measures of accruals as they are based on similar items from financial statements. Our results show positive correlations significant at the 1% level between all accruals measures, consistent with this expectation. In addition, we find that some independent variables are correlated at the 1% to 10% levels, but that correlations are not excessively high within the same models.

In Panel B, we expect discretionary accruals and control variables in our main regression model to be correlated with predicted signs. However, the results are mixed with only *CFFO* being significant at the 5% level for all accruals measures with the predicted sign. Some control variables are significant at the 5% level in relation to one measure of discretionary accruals, including *Analysts* in relation to *DisAccBS* as well as *Leverage* and *Loss* in relation to *DisAccRev*, but the coefficient has a negative sign for the latter two, which is not in line with previous research. We further conclude that of these variables only *Leverage* would be significant with a two-tailed test. This could be considered more appropriate given the finding of uncertainty regarding the coefficient sign. Despite the weak performance of the control variables we include them in the tests using our main regression model to avoid misspecification (Wooldridge, 2012). We also expect correlation between different measures of discretionary accruals as they are all intended to measure manipulation. This is confirmed as correlations between the different measures of discretionary accruals range from 0.21 to 0.72, with higher correlations between measures of aggregate accruals reflecting similarities in the definition of accruals for these measures. Furthermore, we expect limited correlation between the control variables as the opposite would indicate potential issues with multicollinearity. However, our results reveal significant correlations between some of our control variables, especially in relation to *Size*. We therefore conduct a robustness check for multicollinearity in section 6.2.1.

Table 5

Panel A

Pearson correlations - accruals models

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	AccAdj.CF	1.0000								
(2)	AccCF	0.6990***	1.0000							
(3)	AccBS	0.7420***	0.6333***	1.0000						
(4)	AccRev	0.9590***	0.6980***	0.7415***	1.0000					
(5)	InvAT	0.0745*	-0.0437	0.0413	0.0754*	1.0000				
(6)	ΔCashRev	0.1635***	0.0982***	0.1300***	0.1633***	0.0089	1.0000			
(7)	PPE	-0.2929***	-0.0689***	-0.1390***	-0.2936***	-0.1642***	-0.0400*	1.0000		
(8)	ROA	0.1368***	0.3742***	0.1430***	0.1360***	-0.3589***	0.3019***	-0.0191	1.0000	
(9)	ΔRevQ123	0.2332***	0.1624***	0.2361***	0.2325***	0.0108	0.9181***	-0.0476**	0.2927***	1.0000
(10)	ΔRevQ4	0.2384***	0.1349***	0.2152***	0.2377***	0.1042***	0.6349***	-0.0229	0.1982***	0.4612***

Acc is total accruals scaled by lagged total assets, *InvAT* is inverse lagged total assets, *ΔCashRev* is the change in cash sales scaled by lagged total assets, *PPE* is gross property, plant and equipment scaled by lagged total assets, *ROA* is net income over lagged total assets, *ΔRevQ123* is the change in revenue in the first three quarters scaled by lagged total assets, *ΔRevQ4* is the change in revenue minus the change in revenue from the first three quarters scaled by lagged total assets. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

Panel A shows Pearson correlations for variables in our accruals models. The significance levels indicate if the variables have a significant correlation in a t-test.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (2-tailed for InvAT, 1-tailed for all other variables), number of observations is 1 654.

Panel B

Pearson correlations - main regression model

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	DisAccAdj.CF	1.0000								
(2)	DisAccCF	0.7205***	1.0000							
(3)	DisAccBS	0.7126***	0.6204***	1.0000						
(4)	DisAccRev	0.3077***	0.2071***	0.3149***	1.0000					
(5)	Size	-0.0109	-0.0223	-0.0348*	0.0009	1.0000				
(6)	Leverage	-0.0269	-0.0257	-0.0390*	-0.0738***	0.1584***	1.0000			
(7)	MarketBook	-0.0042	-0.0292	-0.0097	0.0264	0.1859***	-0.0322*	1.0000		
(8)	CFFO	-0.2795***	-0.3834***	-0.2309***	-0.0932***	0.2513***	-0.0275	-0.0526**	1.0000	
(9)	Loss	-0.0045	-0.0190	-0.0098	-0.0479**	-0.3382***	0.0254	0.0069	-0.6002***	1.0000
(10)	Analysts	-0.0122	-0.0151	-0.0416**	-0.0188	0.8143***	0.2136***	0.0461**	0.1211***	-0.1814***

DisAcc is discretionary accruals scaled by lagged total assets, *Size* is the natural logarithm of lagged market capitalisation, *Leverage* is lagged total debt over lagged total equity, *MarketBook* is the lagged market capitalisation over lagged parent equity, *CFFO* is cash flow from operations scaled by lagged total assets, *Loss* equals one if reported earnings are negative and zero otherwise, *Analysts* is the number of analysts reporting at least one earnings-per-share forecast. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

Panel B shows Pearson correlations for variables in our main regression model. The significance levels indicate if the variables have a significant correlation in a t-test.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed), number of observations is 1 654.

5. Results and analysis

This section contains the results and analysis of our main empirical tests relating to our three empirical questions - *Detection of earnings management, Application of accruals models, Identification of accruals fraud.*

5.1. Detection of earnings management

The following paragraphs will outline our results on whether accruals models can detect plausible levels of earnings management due to Type I and Type II errors. We begin by presenting our findings from seeding in our main sample, followed by Monte Carlo simulations and seeding in artificial firms. We end by providing a preliminary conclusion on our first empirical question.

Main sample seeding. The results from our tests with seeding of fictitious sales in a random subsample of 5% of our main sample is presented in *Table 6*, with output from the main regression model for the test variable *Seeding* shown at various levels of seeding in Panel A and presentation of all variables in the main regression model at zero seeding in Panel B.

In Panel A, we present the results for our test variable *Seeding* at various levels of main sample seeding. The p-value shows if seeded firms have a significant relationship with discretionary accruals, which would indicate that the models are able to detect earnings management. The aim is to show a significant relationship at the lowest possible level of positive seeding as this would indicate high detection rates. For the Kothari model the *Adj.CF* measure outperforms the other metrics with significant detection at the 5% level for seeding at 1.0% of lagged total assets (denoted ∆ROA in the table), compared to seeding at 2.0% for the *BS* measure and the *CF* measure. The Stubben model exhibits similar performance to the *Adj.CF* measure with significant detection at the 5% level for seeding at 1.0% of lagged total assets. If expressed in relation to earnings for the average seeded firm, the Kothari model is able to detect manipulation of 20% to 35% of reported earnings, while the Stubben model is able to detect manipulation of about 20% of reported earnings (denoted %ROE in the table). These findings suggest that our specific accruals models and our proposed aggregate accruals model are better than traditional specifications of aggregate accruals models in detecting earnings management, which indicates a lower risk of Type II errors. While Type I errors can be analysed at zero seeding, with lower p-values indicating a higher error rate, these results cannot be generalised based on a single sample and will therefore be revisited in our Monte Carlo simulations.

Table 6

Panel A

Seeding of main sample - 5% seeded observations

			Kothari - Adj.CF			*Kothari - CF*			*Kothari - BS*			*Stubben - Rev*		
ΔROA	**ΔROE**	**%ROE**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	12.3%	-0.2023	0.4198	24.1%	-0.3143	0.3767	8.9%	-1.1481	0.1256	2.7%	-0.0704	0.4719
0.5%	1.0%	11.5%	12.3%	0.4220	0.3365	24.1%	0.2943	0.3843	8.8%	-0.3525	0.3622	2.8%	0.9936	0.1603
1.0%	2.0%	20.6%	12.4%	1.8915	0.0294**	24.1%	0.9025	0.1835	8.8%	0.4424	0.3291	2.9%	2.0613	0.0197**
1.5%	2.9%	28.0%	12.6%	2.9361	0.0017***	24.1%	1.5103	0.0656*	8.9%	1.2365	0.1082	3.2%	3.1298	0.0009***
2.0%	3.9%	34.2%	13.0%	3.8433	0.0001***	24.2%	1.9102	0.0281**	9.0%	1.9089	0.0282**	3.6%	4.1246	0.0000***
2.5%	4.9%	39.4%	13.4%	4.8798	0.0000***	24.3%	2.5171	0.0060***	9.1%	2.6995	0.0035***	4.2%	5.1943	0.0000***
3.0%	5.9%	43.8%	13.9%	5.9173	0.0000***	24.4%	3.1232	0.0009***	9.4%	3.4684	0.0003***	4.9%	6.2645	0.0000***
				N	*1 654*		*N*	*1 654*		*N*	*1 654*		*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

Panel A shows results for our test variable *Seeding* at various levels of seeding in 5% of our main sample. The p-value shows if seeded firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Panel B

Seeding of main sample - zero seeding

	Kothari - Adj.CF				*Kothari - CF*				*Kothari - BS*				*Stubben - Rev*			
	Coeff.	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**
Intercept	0.0085	0.0066	1.2876	0.1981	0.0208	0.0084	2.4783	0.0133**	0.0123	0.0089	1.3899	0.1647	0.0038	0.0060	0.6304	0.5285
Seeding	-0.0009	0.0044	-0.2023	0.4198	-0.0018	0.0056	-0.3143	0.3767	-0.0068	0.0059	-1.1481	0.1256	-0.0003	0.0040	-0.0704	0.4719
Size	0.0014	0.0010	1.3566	0.0875*	0.0021	0.0013	1.5912	0.0559*	0.0014	0.0014	1.0574	0.1452	0.0008	0.0009	0.8228	0.2054
Leverage	-0.0029	0.0019	-1.4799	0.0695*	-0.0046	0.0025	-1.8676	0.0310**	-0.0042	0.0026	-1.6068	0.0541*	-0.0053	0.0018	-2.9942	0.0014***
MarketBook	-0.0006	0.0004	-1.7154	0.0432**	-0.0014	0.0005	-3.0742	0.0011***	-0.0006	0.0005	-1.2316	0.1091	0.0001	0.0003	0.4017	0.3440
CFFO	-0.1279	0.0083	-15.355	0.0000***	-0.2435	0.0106	-22.930	0.0000***	-0.1417	0.0112	-12.661	0.0000***	-0.0473	0.0076	-6.2293	0.0000***
Loss	-0.0278	0.0032	-8.6731	0.0000***	-0.0562	0.0041	-13.767	0.0000***	-0.0345	0.0043	-8.0043	0.0000***	-0.0143	0.0029	-4.9011	0.0000***
Analysts	-0.0003	0.0002	-1.0409	0.1490	-0.0004	0.0003	-1.1487	0.1254	-0.0005	0.0003	-1.5728	0.0580	-0.0002	0.0002	-0.9364	0.1746
	Adj. R^2	*12.3%*	*N*	*1 654*	*Adj. R^2*	*24.1%*	*N*	*1 654*	*Adj. R^2*	*8.9%*	*N*	*1 654*	*Adj. R^2*	*2.7%*	*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise, *Size* is a control variable representing the natural logarithm of lagged market capitalisation, *Leverage* is a control variable representing lagged total debt over lagged total equity, *MarketBook* is a control variable representing lagged market capitalisation over lagged parent equity, *CFFO* is a control variable representing cash flow from operations scaled by lagged total assets, *Loss* is a control variable that equals one if reported earnings are negative and zero otherwise, *Analysts* is a control variable representing the number of analysts reporting at least one earnings-per-share forecast. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

Panel B shows results for all variables at zero seeding. The p-value shows if the variables have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (2-tailed for the intercept, 1-tailed for all other variables).

In Panel B, we present the results for all variables in the main regression model at zero seeding.[7] The p-value shows if the control variables have a significant relationship with discretionary accruals, which would indicate that they contribute to our models. To ascertain the relevance of the set of control variables we compare the explanatory power across our different models. The highest explanatory power is observed for the *CF* measure with an adjusted R^2 of 24.1%, followed by *Adj.CF* at 12.3%, *BS* at 8.9% and *Rev* at 2.7%. This suggests that the set of control variables is more relevant in relation to aggregate accruals models. An analysis of our control variables highlights mixed results compared to expectations. *CFFO* has a negative coefficient and is significant at the 1% level in all specifications of our models with the predicted sign. *Loss* also has a negative coefficient and is significant at the 1% level across all specifications of our models, but not with the predicted sign. However, as the *CFFO* and *Loss* variables are closely related to the accruals definition in the *CF* measure, it is possible that the higher explanatory power for this measure reflects that controls capture random residuals in discretionary accruals, which could indicate beta bias. *Leverage* has a negative coefficient and is significant at the 5% level for the *CF* measure and at the 1% level for the *Rev* measure, but not with the predicted sign. *MarketBook* has a negative coefficient and is significant at the 5% level for the *Adj.CF* measure and at the 1% level for the *CF* measure, but not with the predicted sign. *Size* and *Analysts* are not significant at the 5% level in any specification of our models. While the unexpected coefficient signs could warrant a two-tailed test, we note that the only variables that would no longer be significant at the 5% level with this approach are *MarketBook* for the *Adj.CF* measure and *Leverage* for the *CF* measure. As some of our control variables do not appear to capture the intended relationships, we assess their impact on our main tests by performing a sensitivity analysis without control variables in section 6.1.3.

Monte Carlo simulation. The results from our Monte Carlo simulations with seeding in a random subsample of 5% of our main sample is presented in *Table 7*, where we display our test variable *Seeding* at various levels of seeding. The p-value shows if the error rate is significantly higher than the selected test proportion, which would indicate excessive rates of either Type I or Type II errors. The aim is to solidify our results on the extent of Type I errors at zero seeding and Type II errors at seeding of 1.0% of lagged total assets across our models. For Type I errors, we identify an error rate that is significantly above our test proportion of 0.05 at the 5% level for all models. The test proportion is chosen at 0.05 as this is widely considered an acceptable

[7] We only present control variables at zero seeding as they are largely unaffected by different levels of seeding.

Table 7

Seeding of main sample – Monte Carlo simulations, error rates

			Kothari - Adj.CF			*Kothari - CF*			*Kothari - BS*			*Stubben - Rev*		
ΔROA	**ΔROE**	**%ROE**	**<0.05**	**Prop.**	**P-value**	**<0.05**	**Prop.**	**P-value**	**<0.05**	**Prop.**	**P-value**	**<0.05**	**Prop.**	**P-value**
Type I errors														
0.0%	0.0%	0.0%	23.0%	0.05	0.0000***	19.0%	0.05	0.0000***	23.0%	0.05	0.0000***	15.0%	0.05	0.0000***
0.0%	0.0%	0.0%	23.0%	0.10	0.0000***	19.0%	0.05	0.0046**	23.0%	0.10	0.0000***	15.0%	0.10	0.0734*
Type II errors														
1.0%	2.0%	27.8%	58.0%	0.40	0.3770	30.0%	0.40	0.0000***	44.0%	0.40	0.0008***	58.0%	0.40	0.3770
1.0%	2.0%	27.8%	58.0%	0.30	0.0072***	30.0%	0.30	0.0000***	44.0%	0.30	0.0000***	58.0%	0.30	0.0072***
			N	*100*		*N*	*100*		*N*	*100*		*N*	*100*	

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is discretionary accruals.

The table shows results from Monte Carlo simulations for our test variable *Seeding* at various levels of seeding in 5% of our main sample. The p-value shows if the error rate from the t-test, to assess if seeded firms have a significant relationship with discretionary accruals, is significantly higher than the test proportion using a binomial test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding, *<0.05* refers to the rejection rate for our null hypothesis on no earnings management at the 5% level, *Prop.* refers to a test proportion that represents a particular error rate.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Table 8

Seeding of artificial firms – 5% seeded observations

			Kothari - Adj.CF			*Kothari - CF*			*Kothari - BS*			*Stubben - Rev*		
ΔROA	**ΔROE**	**%ROE**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	0.0%	-0.0165	0.4934	0.0%	-0.0473	0.4811	0.0%	0.0030	0.4988	0.0%	0.0104	0.4959
0.5%	1.0%	16.2%	0.0%	1.0257	0.1526	0.0%	0.7153	0.2373	0.0%	0.7933	0.2139	0.0%	1.2077	0.1173
1.0%	2.0%	27.8%	0.2%	2.0680	0.0194**	0.1%	1.4780	0.0698*	0.1%	1.5837	0.0567*	0.3%	2.4050	0.0081***
1.5%	3.0%	36.6%	0.5%	3.1102	0.0010***	0.2%	2.2406	0.0126**	0.3%	2.3740	0.0089***	0.7%	3.6023	0.0002***
2.0%	4.0%	43.5%	0.9%	4.1524	0.0000***	0.5%	3.0032	0.0014***	0.5%	3.1643	0.0008***	1.3%	4.7796	0.0000***
2.5%	5.0%	49.1%	1.5%	5.1947	0.0000***	0.8%	3.7659	0.0001***	0.8%	3.9547	0.0000***	2.0%	5.9969	0.0000***
3.0%	6.1%	53.6%	2.1%	6.6369	0.0000***	1.1%	4.5285	0.0000***	1.2%	4.7450	0.0000***	2.8%	7.1942	0.0000***
			N	*1 738*		*N*	*1 738*		*N*	*1 738*		*N*	*1 738*	

Artificial is a test variable that equals one if the firm is artificial and seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is discretionary accruals.

The table shows results for our test variable *Artificial* accounting for 5% of our sample at various levels of seeding without control variables. The p-value shows if seeded artificial firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

rate of Type I errors (Goldberg, 1998). In a second test with a test proportion of 0.10, we conclude that the Stubben model has the lowest relative rate of Type I errors as it is the only model in our tests with an error rate that is not significantly above 10%. The results indicate that all accruals model are subject to excessive Type I error rates above the threshold of 5%. For Type II errors, the choice of test proportion is not apparent as there is no consensus on acceptable levels. In our initial test, we find an error rate that is significantly above a test proportion of 0.40 at the 5% level for the *CF* measure and the *BS* measure, but not for the *Adj.CF* measure or the *Rev* measure. We therefore conduct a second simulation where we identify an error rate that is significantly above a test proportion of 0.30 at the 5% level for all specifications of our models. These results indicate that the *BS* and *CF* measures are subject to Type II error rates in excess of 40% with seeding of 1.0% of lagged total assets, while the corresponding error rates for the *Adj.CF* and *Rev* measures are in excess of 30%. However, it should be noted that the rejection rates imply even lower detection rates for the *BS* and the *CF* measures. The interpretation is that all model specifications will fail to identify earnings management of 1.0% of lagged total assets, corresponding to 27.8% of reported earnings and ROE in our main sample, in more than 30% of cases.

Seeding in artificial firms. The results from our tests with seeding of artificial firms representing 5% of total observations is presented in *Table 8*, where we display our test variable *Artificial* at various levels of seeding. The p-value shows if seeded artificial firms have a significant relationship with discretionary accruals, which would indicate that the models are able to detect earnings management. The aim is to test our models in conditions that should minimise the extent of Type II errors. We find that the 1-tailed p-value is close to 0.50 at zero seeding for all our specifications of our models, which we interpret as evidence that our method for creating artificial firms has reduced noise to a minimum in line with our intentions. This is also observed in a consistent improvement in detection rates across all specifications of our models. The *Adj.CF* measure displays a decrease in p-value for different levels of seeding, but significance levels are unchanged. The *BS* and *CF* measures are now able to detect seeding at 1.5% of lagged total assets at the 5% level, which is an improvement from 2.0% of lagged total assets in the main sample. The Stubben model is now able to significantly detect seeding at 1.0% of lagged total assets at the 1% level instead of the 5% level. These results indicate that while performance is improved in an ideal setting, the improvement does not alter our main conclusions that the models are unable to detect seeing of less than 1.0% of lagged total assets or 27.8% of earnings.

Preliminary conclusion. The aim of this analysis has been to evaluate whether accruals models can detect plausible levels of earnings management due to Type I and Type II errors. For Type I errors, all models display excessive error rates above 5%, but the Stubben model exhibits the strongest relative performance with an error rate that is not above 10%. For Type II errors, none of our model specifications are able to detect manipulation below 25% of reported earnings, with an error rate of less than 30%. These results allow researchers to make an informed decision on whether a research design based on accruals models could be useful in different contexts. First, researchers must believe that manipulation will be at least 25% of reported earnings, which is equivalent to SEK 170 million for the average firm in our sample and five times the materiality threshold used by accountants (Vorhies, 2005). Second, unless the expected manipulation is materially above 25% of earnings, researchers need to accept failing to identify earnings management in more than 30% of cases as well as identifying manipulation when it is not there in at least 5% of cases. We believe that our results show that accruals models are unlikely to detect plausible levels of manipulation, but we will revisit this conclusion after assessing the level of manipulation in known cases of accruals fraud in section 5.3.

We draw three additional conclusions from the results in this section. First, our results support the view that the Stubben model displays a lower rate of Type I errors and does not involve a trade-off in terms of Type II errors in relation to our best specification of the Kothari model. However, current specific accruals models are likely to be unsatisfactory in most contexts as the Stubben model is unable to systematically detect earnings management of less than 25% of reported earnings and is limited to manipulation of accounts receivables. Second, the choice of accruals measure in aggregate accruals models has large implications for detection rates. Our results suggest that the balance sheet measure and the cash flow measure are subject to substantially higher risk of Type II errors than other model specifications, while not displaying lower Type I errors. Furthermore, we show that our adjusted cash flow measure leads to significantly improved results in terms of Type II errors, without increasing rates of Type I errors. Third, as numerous control variables were not significant across our models these may warrant further attention in future studies. This is particularly relevant in relation to specific accruals models as the Stubben model only displays an adjusted R^2 of 2.7%. Given the noise in discretionary accruals we also believe that new control variables should explicitly target potential sources of non-discretionary deviations from industry averages rather than attempt to capture reasons for discretion in reporting.

5.2. Application of accruals models

The following paragraphs outline our results on whether the application of accruals models contributes to noise resulting in biased estimates of discretionary accruals. We begin by presenting our findings on the power of accruals model regressions followed by an analysis on the magnitude of discretionary accruals. We end by providing a preliminary conclusion on our second empirical question.

Power of accruals model regressions. The results from our tests on the explanatory power of accruals models are presented in two separate tables. *Table 9* shows aggregate results by variable, while *Table 10* shows aggregate results by industry in Panel A and aggregate results by year in Panel B.

In *Table 9*, we present aggregate results for all variables in our accruals model regressions. The p-value shows if the variables have a significant relationship with the dependent accruals measure, which would indicate that they contribute to our models. For the Kothari model, the parameters refer to the model specification presented in *Equation 4* where λ1 is the scaled intercept, λ2 is *ΔCashRev*, λ3 is *PPE* and λ4 is *ROA*. Notably, none of the variables are significant at the 5% level, indicating that they do not contribute to explaining the accruals generation process. *ΔCashRev* also displays a negative sign with the *CF* measure, which is not in line with expectation. Moreover, the total explanatory power ranges from 18.7% to 30.3% indicating that the models only explain a minority of accruals. For the Stubben model, the

Table 9
Accruals model regressions – average by variables

	Kothari - Adj.CF		*Kothari - CF*		*Kothari - BS*		*Stubben - Rev*	
Variables	**t-stat**	**P-value**	**t-stat**	**P-value**	**t-stat**	**P-value**	**t-stat**	**P-value**
Intercept	-0.1482	0.4414	-0.8888	0.1890	-0.3886	0.3495	0.0977	0.4613
λ1	-0.1310	0.4481	0.0178	0.4929	-0.0664	0.4737	-0.0019	0.4992
λ2	0.2803	0.1951	-0.1122	0.2278	0.2671	0.1976	0.5001	0.1548
λ3	-0.5975	0.1382	-0.2118	0.2083	-0.4220	0.1687	1.4835	0.0359**
λ4	0.4948	0.1557	1.0026	0.0801*	0.5618	0.1442		
	Adj. R^2	*21.4%*	*Adj. R^2*	*30.3%*	*Adj. R^2*	*18.7%*	*Adj. R^2*	*50.6%*
	N	*60*	*N*	*60*	*N*	*60*	*N*	*60*

For the Kothari model, λ1 is the scaled intercept or *InvAT*, λ2 is *ΔCashRev*, λ3 is *PPE* and λ4 is *ROA*. For the Stubben model, λ1 is the scaled intercept or *InvAT*, λ2 is *ΔRevQ123* and λ3 is *ΔRevQ4*. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is total accruals.

The table shows aggregate results for all variables in our accruals model regressions. The p-value shows if the variables have a significant relationship with the dependent accruals measure in a t-test, with standard errors calculated under the assumption of independent observations. *N* is the number of regressions, the average number of observations by regression is approximately 28.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (2-tailed for the intercept and the scaled intercept, 1-tailed for all other variables).

parameters refer to the model specification presented in *Equation 7* where λ1 is the scaled intercept, λ2 is *ΔRevQ123* and λ3 is *ΔRevQ4*. While only one variable, *ΔRevQ4*, is significant at the 5% level, the Stubben model has the highest explanatory power of the models at 50.6%, which is also higher than previous research as presented in section 2.6. These findings indicate that specific accruals models are better than aggregate accruals models at explaining the accruals generation process, but that all specifications of our models introduce noise in discretionary accruals.

In Panel A of *Table 10*, we show aggregate results for all accruals model regressions by industry. The p-value indicates if the rejection rate is higher than the test proportion of 0.05, which would indicate that the models do not contribute to explaining total accruals. As the total p-value is significant at the 1% level across our models, we conclude that the models do not display sufficient explanatory power. The only discernible trend between industries across the models is that *Industrials* displays the highest explanatory power, which is significant at the 5% level across all model specifications apart from the *BS* measure. However, it is difficult to discern whether this reflects homogeneity in the accruals process or that *Industrials* has the highest number of firm observations. An argument in favour of the former interpretation is that *Materials*, which is below the commonly applied threshold of 10 observations in half of all years, does not display worse performance than other industries. This indicates that accruals models may be better specified for the accruals generation process in industrial companies.

In Panel B of *Table 10*, we show aggregate results for all accruals model regressions by year. The p-value indicates if the rejection rate is higher than the test proportion of 0.05, which would indicate that the models do not contribute to explaining total accruals. There are large variations in power between years with the Kothari model ranging from 2.6% to 51.0% and the Stubben model ranging from 21.8% to 69.0%, but there are no discernible trends between the years related to extreme events as seen in explanatory power and p-values. For example, we do not find evidence of lower performance during the financial crisis in 2008-2009. This indicates that the cross-sectional approach can lead to less noise in the presence of industry wide shocks that are unrelated to discretionary behaviour. Hence, a cross-sectional methodology may be preferable to time series analysis and panel data when estimating accruals in the presence of temporary systemic shocks.

Table 10

Panel A

Accruals model regressions – average by industry

			Kothari - Adj.CF				*Kothari - CF*				*Kothari - BS*				*Stubben - Rev*			
GICS	**Sectors**	**N**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**
15	Materials	9.33	19.9%	8.3%	0.05	0.0000***	61.8%	50.0%	0.05	0.0000***	36.5%	16.7%	0.05	0.0000***	70.5%	75.0%	0.05	0.0203***
20	Industrials	52.17	25.2%	83.3%	0.05	0.1182	24.2%	75.0%	0.05	0.0203**	14.6%	58.3%	0.05	0.0000***	49.2%	100%	0.05	0.7738
25	Consumer discretionary	19.83	33.7%	58.3%	0.05	0.0000***	31.2%	58.3%	0.05	0.0000***	17.0%	8.3%	0.05	0.0000***	40.9%	66.7%	0.05	0.0024***
35	Health care	20.08	15.9%	25.0%	0.05	0.0000***	15.8%	16.7%	0.05	0.0000***	13.2%	8.3%	0.05	0.0000***	42.5%	66.7%	0.05	0.0024***
45	Information technology	36.42	12.2%	16.7%	0.05	0.0000***	18.3%	50.0%	0.05	0.0000***	12.3%	25.0%	0.05	0.0000***	49.9%	91.7%	0.05	0.4598
Total		**27.57**	**21.4%**	**38.3%**	**0.05**	**0.0000*** **	**30.3%**	**50.0%**	**0.05**	**0.0000*** **	**18.7%**	**23.3%**	**0.05**	**0.0000*** **	**50.6%**	**80.0%**	**0.05**	**0.0000*** **

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is total accruals.

Panel A shows aggregate results for all accruals model regressions by industry. The p-value shows if the rejection rate for an F-test for overall significance, under the null hypothesis that the models do not contribute to explaining total accruals, is significantly higher than the test proportion using a binomial test with twelve observations per industry or 60 observations in total. *N* refers to the average number of industry observations. *<0.05* refers to the rejection rate for the null hypothesis that the models do not contribute to explaining total accruals at the 5% level, *Prop.* refers to a test proportion that represents a particular error rate.

***, **, * indicate significance at 1%, 5% and 10% levels respectively.

Panel B

Accruals model regressions – average by year

		Kothari - Adj.CF				*Kothari - CF*				*Kothari - BS*				*Stubben - Rev*			
Year	**N**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**	**Adj. R^2**	**<0.05**	**Prop.**	**P-value**
2006	27.60	30.8%	60.0%	0.05	0.0227**	51.0%	100%	0.05	0.5404	25.0%	20.0%	0.05	0.0000***	63.2%	100%	0.05	0.5404
2007	27.40	2.6%	20.0%	0.05	0.0000***	18.3%	20.0%	0.05	0.0000***	12.5%	20.0%	0.05	0.0000***	56.9%	80.0%	0.05	0.2261
2008	27.20	18.7%	20.0%	0.05	0.0000***	39.3%	60.0%	0.05	0.0227**	10.5%	20.0%	0.05	0.0000***	36.5%	60.0%	0.05	0.0227**
2009	28.00	26.8%	40.0%	0.05	0.0014***	20.9%	20.0%	0.05	0.0000***	23.5%	20.0%	0.05	0.0000***	50.9%	100%	0.05	0.5404
2010	26.80	34.8%	40.0%	0.05	0.0014***	37.3%	60.0%	0.05	0.0227**	36.9%	60.0%	0.05	0.0227**	57.8%	80.0%	0.05	0.2261
2011	26.00	18.7%	40.0%	0.05	0.0014***	32.4%	60.0%	0.05	0.0227**	21.2%	20.0%	0.05	0.0000***	33.7%	20.0%	0.05	0.0000***
2012	27.20	7.0%	20.0%	0.05	0.0000***	20.8%	0.0%	0.05	0.0000***	11.5%	0.0%	0.05	0.0000***	56.9%	80.0%	0.05	0.2261
2013	28.40	4.2%	40.0%	0.05	0.0014***	36.0%	80.0%	0.05	0.2261	8.7%	20.0%	0.05	0.0000***	21.8%	80.0%	0.05	0.2261
2014	27.60	16.1%	60.0%	0.05	0.0227**	21.1%	40.0%	0.05	0.0014***	14.7%	40.0%	0.05	0.0014***	69.0%	100%	0.05	0.5404
2015	26.60	35.2%	20.0%	0.05	0.0000***	35.1%	80.0%	0.05	0.2261	23.9%	40.0%	0.05	0.0014***	56.7%	100%	0.05	0.5404
2016	28.00	32.4%	40.0%	0.05	0.0014***	34.6%	60.0%	0.05	0.0227**	16.4%	0.0%	0.05	0.0000***	66.1%	100%	0.05	0.5404
2017	30.00	29.3%	60.0%	0.05	0.0227**	16.5%	20.0%	0.05	0.0000***	20.0%	20.0%	0.05	0.0000***	37.6%	60.0%	0.05	0.0227**
Total	**27.57**	**21.4%**	**38.3%**	**0.05**	**0.0000*** **	**30.3%**	**50.0%**	**0.05**	**0.0000*** **	**18.7%**	**23.3%**	**0.05**	**0.0000*** **	**50.6%**	**80.0%**	**0.05**	**0.0000*** **

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is total accruals.

Panel B shows aggregate results for all accruals model regressions by year. The p-value shows if the rejection rate for an F-test for overall significance, under the null hypothesis that the models do not contribute to explaining total accruals, is significantly higher than the test proportion using a binomial test with five observations per year or 60 observations in total. *N* refers to the average number of industry observations. *<0.05* refers to the rejection rate for the null hypothesis that the models do not contribute to explaining total accruals at the 5% level, *Prop.* refers to a test proportion that represents a particular error rate.

***, **, * indicate significance at 1%, 5% and 10% levels respectively.

Magnitude of discretionary accruals. The magnitude of discretionary accruals derived using our accruals models are presented in *Table 11*, with aggregate results by industry in Panel A and aggregate results by year in Panel B. Both panels display the share of observations with discretionary accruals above 25%, 50%, 75% and 100% of earnings in absolute terms.

Panel A and Panel B enable an analysis of the aggregate magnitudes of discretionary accruals. As previous research has found implausibly high levels of discretionary accruals in relation to earnings, we interpret models with lower magnitudes as less noisy. For the Kothari model, the *CF* and *BS* measures display the highest magnitudes where it is implied that more than 60% of firms manipulate 25% of ROE and more than 40% of firms manipulate 50% of ROE. The observed magnitudes are somewhat lower for the *Adj.CF* measure implying that 55.0% of firms manipulate 25% of ROE and 34.2% manipulate 50% of ROE. The Stubben model displays the lowest magnitudes with 45.6% of firms manipulating 25% of ROE and 28.1% manipulating 50% of ROE. These results show that estimated magnitudes of discretionary accruals are highly improbable for all model specifications, as it is implied that discretion in reporting enables a quarter of firms to manipulate 50% of earnings. However, the more narrow accruals measures, *Adj.CF* and *Rev*, display the lowest magnitudes and are therefore subject to the least noise.

In Panel A, we present aggregate magnitudes of discretionary accruals by industry. The only discernible trend is that *Information technology* consistently displays the highest magnitudes in relation to earnings. This could either reflect more noise or lower profitability amplifying the effect in relation to profits. We find that the primary reason for the high magnitude in relation to ROE is that *Information technology* firms in our sample display considerably lower average ROE at -4.5%, compared to the sample average at 5.1%. This suggests caution when comparing discretionary accruals in relation to total ROE for subsamples of the main sample.

In Panel B, we present aggregate magnitudes of discretionary accruals by year. The results show moderate variations between years with the share of firms with discretionary accruals of at least 25% of earnings ranging from 44.3% to 75.7% in the Kothari model and from 36.2% to 59.3% in the Stubben model. The year with the highest magnitude of discretionary accruals across all our specifications of the models is 2009, which is likely to reflect a combination of more extreme accrual behaviour and a lower denominator in terms of ROE during the financial crisis. The latter effect further supports the notion that it is difficult to compare discretionary accruals to ROE in relation to extreme performance.

Table 11

Panel A

AbsDisAcc % of AbsROE – by industry

			Kothari - Adj.CF				*Kothari - CF*				*Kothari - BS*				*Stubben - Rev*			
GICS	**Sectors**	**N**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**
15	Materials	9.33	55.4%	38.4%	21.4%	15.2%	57.1%	34.8%	24.1%	14.3%	63.4%	43.8%	33.0%	20.5%	21.4%	12.5%	8.9%	8.0%
20	Industrials	52.17	52.6%	31.8%	21.7%	16.1%	60.2%	38.7%	27.2%	20.3%	61.7%	40.1%	27.8%	22.2%	47.8%	29.4%	20.9%	15.7%
25	Consumer discretionary	19.83	57.1%	34.9%	24.8%	17.2%	65.1%	39.5%	28.6%	19.7%	62.2%	42.0%	28.6%	20.2%	37.8%	18.9%	13.0%	9.7%
35	Health care	20.08	47.7%	27.4%	21.2%	14.9%	60.6%	38.6%	29.9%	20.7%	51.9%	34.9%	26.1%	18.7%	34.9%	21.6%	14.1%	9.5%
45	Information technology	36.42	61.1%	39.8%	30.4%	24.3%	70.5%	49.7%	38.2%	30.7%	69.1%	48.5%	38.9%	30.7%	58.8%	38.9%	28.4%	22.7%
Total		**27.57**	**55.0%**	**34.2%**	**24.4%**	**18.2%**	**63.5%**	**41.4%**	**30.5%**	**22.6%**	**62.4%**	**42.1%**	**31.0%**	**23.5%**	**45.6%**	**28.1%**	**20.0%**	**15.2%**

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

Panel A shows aggregate results for the magnitude of discretionary accruals derived using our accruals models by industry, with the columns displaying the share of observations with discretionary accruals above 25%, 50%, 75% and 100% of earnings in absolute terms. *N* refers to the average number of industry observations.

Panel B

AbsDisAcc % of AbsROE – by year

		Kothari - Adj.CF				*Kothari - CF*				*Kothari - BS*				*Stubben - Rev*			
Year	**N**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**
2006	27.60	46.4%	23.9%	16.7%	15.9%	62.3%	36.2%	25.4%	18.8%	57.2%	35.5%	23.2%	18.1%	36.2%	25.4%	18.1%	13.8%
2007	27.40	56.2%	32.1%	23.4%	16.1%	62.8%	35.8%	26.3%	18.2%	65.0%	40.9%	28.5%	21.2%	46.0%	24.1%	16.1%	13.9%
2008	27.20	59.6%	33.8%	25.0%	19.9%	67.6%	43.4%	30.9%	23.5%	71.3%	43.4%	36.0%	27.2%	49.3%	30.1%	20.6%	14.7%
2009	28.00	65.7%	45.7%	34.3%	22.9%	67.1%	52.1%	37.9%	30.0%	75.7%	55.0%	42.9%	32.1%	59.3%	35.7%	27.9%	22.1%
2010	26.80	53.0%	35.8%	23.1%	19.4%	70.1%	41.8%	29.9%	23.1%	60.4%	40.3%	32.1%	27.6%	44.8%	30.6%	20.9%	17.2%
2011	26.00	56.2%	34.6%	22.3%	18.5%	65.4%	42.3%	31.5%	23.8%	56.2%	37.7%	26.9%	22.3%	42.3%	26.2%	20.0%	15.4%
2012	27.20	61.0%	42.6%	33.1%	26.5%	64.7%	44.1%	35.3%	28.7%	69.1%	46.3%	36.8%	29.4%	52.2%	37.5%	25.0%	19.1%
2013	28.40	59.2%	42.3%	28.9%	19.7%	66.9%	50.7%	38.7%	31.0%	62.7%	43.0%	28.9%	22.5%	48.6%	30.3%	24.6%	19.0%
2014	27.60	56.5%	33.3%	21.7%	15.2%	65.2%	37.7%	30.4%	22.5%	63.0%	41.3%	34.1%	23.9%	40.6%	21.0%	13.8%	11.6%
2015	26.60	56.4%	29.3%	24.1%	15.8%	62.4%	42.1%	28.6%	15.8%	58.6%	39.1%	27.1%	20.3%	42.1%	27.1%	21.1%	15.0%
2016	28.00	44.3%	25.7%	19.3%	15.0%	55.0%	37.9%	27.1%	19.3%	56.4%	45.0%	30.0%	21.4%	43.6%	22.9%	13.6%	10.0%
2017	30.00	46.0%	30.7%	20.7%	14.0%	53.3%	33.3%	24.0%	16.7%	53.3%	37.3%	25.3%	16.7%	42.0%	26.7%	18.0%	11.3%
Total	**27.57**	**55.0%**	**34.2%**	**24.4%**	**18.2%**	**63.5%**	**41.4%**	**30.5%**	**22.6%**	**62.4%**	**42.1%**	**31.0%**	**23.5%**	**45.6%**	**28.1%**	**20.0%**	**15.2%**

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

Panel B shows aggregate results for the magnitude of discretionary accruals derived using our accruals models by year, with the columns displaying the share of observations with discretionary accruals above 25%, 50%, 75% and 100% of earnings in absolute terms. *N* refers to the average number of industry observations.

Preliminary conclusion. The aim of this analysis has been to evaluate whether the application of accruals models contribute to noise resulting in biased estimates of discretionary accruals. We therefore analyse three important steps in the application of accruals models. First, the choice of accruals measure is a critical part of the research design that we argue has been neglected in previous research. We illustrate that traditional aggregate accruals measures, the *BS* and the *CF* measures, are exposed to bias that has not been addressed in past research. This suggests that researchers have prioritised comprehensive measures of accruals to capture multiple sources of manipulation (Larson et al., 2018), at the expense of model specification. Overall, the weak performance of the traditional measures compared to the *Adj.CF* and the *Rev* measures highlights the importance of carefully addressing all steps in the research design.

Second, our analysis on the power of accruals models reveals that none of our model specifications significantly contribute to explaining the accruals generation process. Moreover, none of the variables systematically contribute to explaining accruals in the Kothari model, while only one variable is significant at the 5% level in the Stubben model. These results show that the application of our aggregate and specific accruals models contribute to noise, which feed into the estimates of discretionary accruals. A comparison of explanatory power across models reveals that the Stubben model outperforms all specifications of the Kothari model, and that the *CF* measure has higher adjusted R^2 than the *Adj.CF* measure. However, while none of the variables are statistically significant in the Kothari model, we note that p-values for the *Adj.CF* measure are lower than the *CF* measure for all variables except *ROA*. This could indicate that the higher explanatory power of the *CF* measure reflects a relationship between large nonlinear accruals and *ROA*, rather than an ability to estimate non-discretionary accruals.

Third, our analysis on the estimated magnitude of discretionary accruals implies that about half of all firms manipulate 25% of ROE and that a quarter of all firms manipulate 50% of ROE. Furthermore, it should be noted that these rates vary across the models and that magnitudes are considerably higher for the *CF* and *BS* measures. These magnitudes are consistent with the levels of discretionary accruals observed in past research, that have been described as far from plausible (Ball, 2013; Jackson, 2018). For example, Ball (2013) argues that these levels of manipulation imply that most accruals would represent discretionary behaviour, which is an idea that he dismisses as absurd. Instead, it is clear that the application of accruals models results in considerable noise that manifests itself in discretionary accruals and hinders the ability of researchers to detect earnings management.

5.3. Identification of accruals fraud

The following paragraphs outline our results on whether accruals models can identify known cases of earnings management. We begin with an introduction to Eniro before discussing the nature and consequences of the exposed manipulation. We then evaluate the discretionary accruals derived for Eniro using our accruals models before presenting other cases of accruals fraud. We end by providing a preliminary conclusion on our third empirical question.

Eniro - background and development. Eniro is a Swedish search company with presence in the Nordics and Poland. The business idea is to provide high-quality local information through internet, phone communication and print to individuals and business. The majority of revenue is generated from advertisers who pay for exposure and rankings in the search services as well as products provided by Eniro. Another source of revenue consists of users paying for services and products that are not free of charge (Eniro, 2018). Eniro was a subsidiary of the Swedish telecommunications incumbent Telia until it was spun off and listed on the main market of the Stockholm stock exchange in 2000 (Telia AB, 2001). Following a series of acquisitions in the Nordic countries, Eniro expanded its presence and reported revenues of SEK 6.7 billion and net income of SEK 1.1 billion in 2006. In the coming years, financial performance started to deteriorate as Eniro was transitioning from the declining print business to digital channels as seen in *Table 12*. In 2009, Eniro announced that the print market was declining more rapidly than expected and therefore revised its financial targets for the following year (Eniro, 2010).

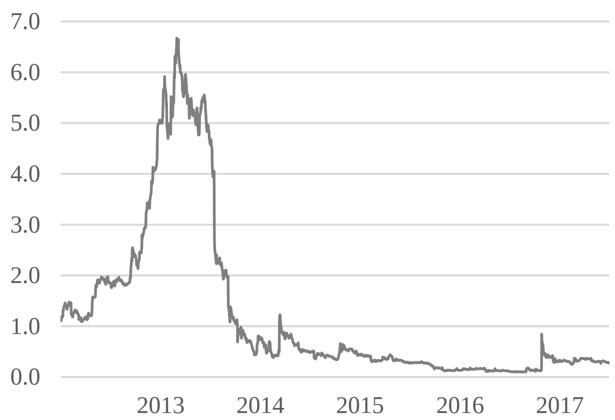
Table 12
Key financials - Eniro 2006-2017 (SEK million)

Year	$Sales_t$	$\%\Delta_t$	NI_t	$MVEQ_t$	ROE_t
2006	6 697	38.7%	1 054	16 480	22.7%
2007	6 443	-3.8%	1 305	9 412	25.5%
2008	6 645	3.1%	-315	1 736	-7.8%
2009	6 581	-1.0%	616	5 809	27.8%
2010	5 326	-19.1%	-4 620	2 710	-75.6%
2011	4 323	-18.8%	-213	1 147	-6.1%
2012	3 999	-7.5%	245	1 590	7.5%
2013	3 660	-8.5%	234	5 562	6.6%
2014	3 002	-18.0%	-1 662	1 019	-44.7%
2015	2 438	-18.8%	-1 125	726	-62.6%
2016	1 967	-19.3%	-862	260	-74.4%
2017	1 595	-18.9%	76	368	16.2%

%Δ represents the percentage change in sales, *NI* represents net income, *MVEQ* represents the market value of equity, *ROE* represents net income over lagged total equity.

The table shows key financials for Eniro in the period 2006-2017.

Figure 1
Market capitalization - Eniro Jan 2013-June 2018 (SEK billion)



The horizontal axis represents year and the vertical axis represents market capitalisation in SEK billion.

The figure shows the development in market capitalisation of Eniro in the period January 2013-June 2018 based on daily stock prices.

In the fall of 2010, Johan Lindgren was appointed new CEO of Eniro. Shortly thereafter, the company reported its worst annual financial performance ever with a revenue decline of 19.1% and a net loss of SEK 4.6 billion, which led to a fall in share price of 92% (Eniro, 2011). The negative financial development continued until 2012 when the CEO claimed that the transformation to a digital business model was complete, which would provide a platform for improved performance. This was followed up with positive news and aggressive financial targets in the quarterly reports of 2013 (Eniro, 2013a; 2013b; 2013c). Investors responded forcefully and in the beginning of 2014 the market capitalisation of Eniro had increased by more than 500% in about a year, see *Figure 1*. Since his appointment as CEO, Johan Lindgren had gradually increased his holding of shares in Eniro. After purchasing an additional equity stake in 2013, his total position in the company was more than 300 000 shares and more than 140 000 synthetic shares (Eniro, 2014a). The CEO later sold a substantial part of this holding in March 2014, only days after the share reached an all-time high of SEK 66 per share (Finansinspektionen, 2018).

Following the peak in the beginning of 2014, the share price of Eniro declined as the first two quarterly reports of 2014 revealed weak financial performance in digital channels (Eniro 2014b; 2014c). In August 2014, it was announced that the CEO Johan Lindgren was replaced effective immediately (Eniro 2014d) and in the following month Eniro revealed issues with their financial reporting due to early revenue recognition. As a consequence, revenue and EBITDA for 2013 were revised downwards with SEK 58 million, along with a smaller restatement for the first half of 2014, and projected EBITDA for 2014 was revised from SEK 850 million to SEK 700 million. The early revenue recognition was identified in an internal investigation requested by the board of Eniro and carried out by its auditor PWC (Eniro, 2014e). In connection with the internal investigation, the board of Eniro reported the former CEO Johan Lindgren to the police for suspected fraud (Eniro, 2014f), filed a lawsuit against him and stripped him of his severance package (Eniro, 2015a). On the annual shareholder meeting for the financial year 2014, the former CEO Johan Lindgren was not discharged from liability (Eniro, 2015b). However, in the end the former CEO was not prosecuted, as it could not be determined who was responsible for the fraudulent reporting (TT, 2016). Following the unravelment of the manipulation the share price of Eniro went into free fall and had not recovered by the end of 2017.

Discretionary accruals in Eniro. The results from our analysis of discretionary accruals in Eniro are presented in *Figure 2*, with a comparison of actual and estimated manipulation shown in Panel A, discretionary accruals in Eniro over time shown in Panel B and the net income impact from discretionary accruals expressed in SEK million shown in Panel C.

In Panel A, we present the actual manipulation compared to estimated discretionary accruals from our accruals models for Eniro in 2013 expressed as a percentage of reported ROE in absolute terms. The actual revenue manipulation amounted to SEK 58 million in this period, which corresponds to 24.8% of ROE.[8] However, there are meaningful discrepancies between the actual manipulation and the estimates of discretionary accruals. In the Kothari model, the *Adj.CF* and the *BS* measures both overstate the manipulation by more than two times, while the *CF* measure understates it at less than a third of the actual manipulation. The Stubben model estimates nearly two times the actual manipulation, but as this prediction concerns income decreasing manipulation the actual error was even larger. These results show that none of the models were able to identify the actual extent of the earnings management through early recognition in Eniro.

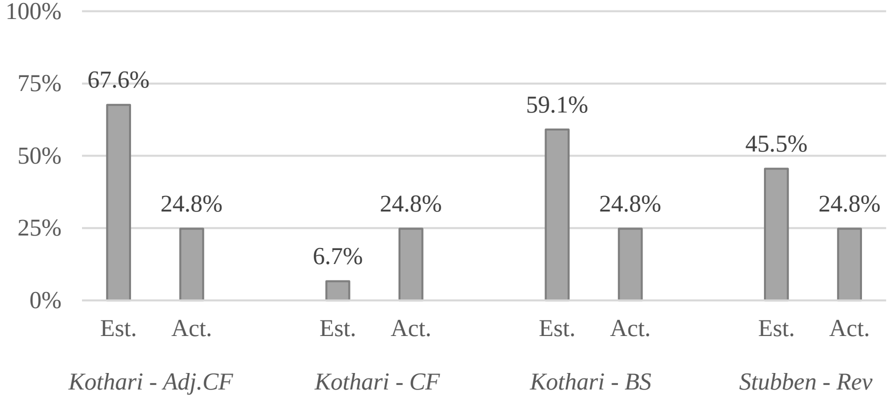
In Panel B, we present discretionary accruals for Eniro over time in the period 2006-2017. If the models were well specified we would only expect to see positive discretionary accruals in the years of manipulation 2013 and 2014 as well as the subsequent negative reversals. Instead, we identify large fluctuations in discretionary accruals over the years across all specifications of our models. Interestingly, discretionary accruals are on average closest to zero in 2013, implying that the models consider all other years to be more likely to reflect earnings management than the year when we know that manipulation occurred. A qualitative comparison across the different models shows that the Kothari model generates more volatile results, particularly the *CF* measure seems to amplify patterns seen in the other measures, while the Stubben model is the least volatile. There are also discrepancies in the expected direction of manipulation across models in certain years. While we cannot ascertain that Eniro has not manipulated results in other years, we do not expect this to be impactful enough to considerably influence our results. Hence, these findings yield qualitative support to the proposition that accruals models generate noisy estimates of discretionary accruals.

[8] The actual impact on net income is expected to be somewhat lower due to taxes, but the effect on taxes was not disclosed by Eniro.

Figure 2

Panel A

AbsDisAcc % of AbsROE - Eniro 2013

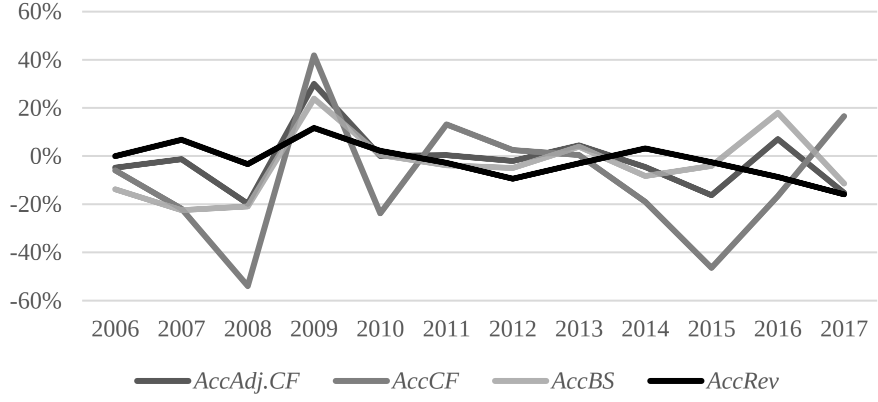


Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The horizontal axis represents estimated and actual manipulation for each accruals measure and the vertical axis represents discretionary accruals in relation to ROE.

Panel A shows actual manipulation compared to estimated discretionary accruals as a percentage of ROE in absolute terms for Eniro in 2013.

Panel B

Discretionary accruals over time - Eniro 2006-2017, impact on ROE (%)

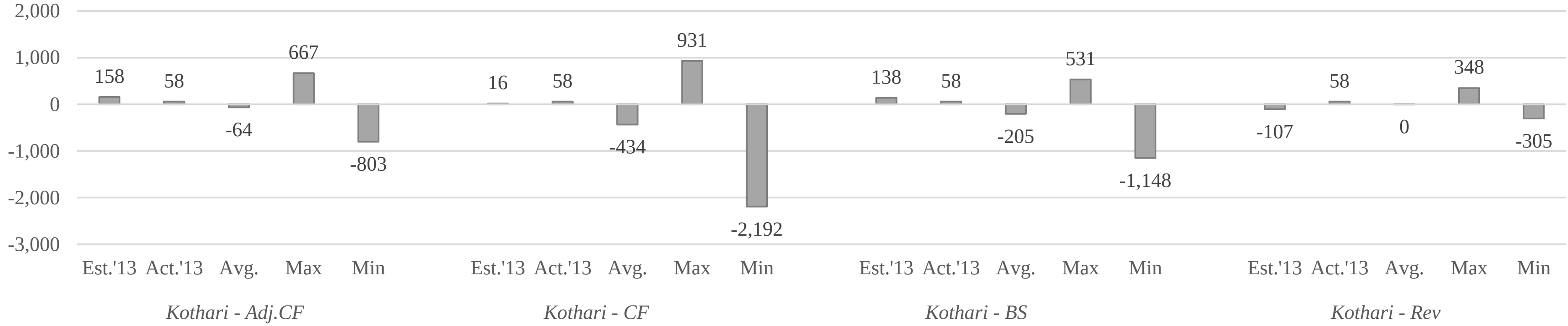


Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The horizontal axis represents year and the vertical axis represents impact on ROE.

Panel B shows the implied impact on ROE from estimated discretionary accruals for Eniro in the period 2006-2017.

Panel C

Discretionary accruals - Eniro 2006-2017, impact on net income (SEK million)



Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The horizontal axis represents estimated and actual manipulation in 2013 as well as the average, maximum and minimum of estimated discretionary accruals for each accruals measure in the period 2006-2017 and the vertical axis represents impact on net income in SEK million.

Panel C shows the implied impact on net income in SEK million from our estimated discretionary accruals in the period 2006-2017.

In Panel C, we present the implied impact on net income in SEK million from discretionary accruals in the period 2006-2017. This illustrates what the noise in discretionary accruals can imply in monetary terms. We find that all our model specifications yield discretionary accruals that are significantly larger than the actual manipulation. The *CF* measure has the most extreme outliers, with a maximum of SEK 0.9 billion and a minimum of negative SEK 2.2 billion. The Stubben model has the least extreme outliers, with a maximum and minimum of approximately SEK 300 million. However, discretionary accruals of more than SEK 300 million is still substantial in comparison to the actual manipulation of SEK 58 million. As accruals reverse over time, we would also expect average discretionary accruals to be close to zero over the twelve years in our study. In this respect, the *CF* and *BS* measures both perform poorly with average implied manipulation of negative SEK 434 million and negative SEK 205 million respectively. The *Adj.CF* and *Rev* measures yield lower average accruals of negative SEK 64 million and less than SEK 1 million respectively. Overall, these results show that the magnitude of discretionary accruals can be substantial in monetary terms across all our model specifications, with the *CF* and *BS* measures seemingly being particularly problematic.

Additional cases of earnings management. Selected financial information from the period of manipulation for the additional five known cases of accruals fraud is presented in *Table 13*. All the cases concern accruals fraud through manipulation of accruals and are therefore relevant to evaluate plausible levels of discretion in practice. The cases can be categorised based on the level of manipulation in relation to reported earnings in absolute terms (denoted %ROE in the table). First, three cases have manipulated 21% to 35% of ROE, which is similar to the manipulation in Eniro at 25% of ROE. Second, one case managed more than 100% of ROE

Table 13
Additional cases of accruals fraud (SEK million)

Firm	Year	EM_t	NI_t	EQ_{t-1}	ROE_t	$\%ROE_t$
ABB AB	2002	180	-	-	-	-
Intrum Justitia AB	2002	80	253	528	48%	32%
CDON AB	2012	32	-152	417	-36%	21%
Oniva Online Group AB	2013	83	63	78	81%	>100%
Eltel AB	2015	150	430	2 549	17%	35%

EM is the level of earnings manipulation, *NI* is the reported net income including manipulation, *EQ* is the book value of equity, *ROE* is the net income over lagged equity, *%ROE* is the absolute earnings manipulation over absolute reported net income including manipulation.

The table shows the level of accruals manipulation and other selected financial information expressed in SEK million in additional cases of accruals fraud.

Sources: ABB AB (2004); CDON AB (2013); Eltel AB (2017); Intrum Justitia AB (2003); Oniva Online Group AB (2014).

with manipulation enabling the report of a profit instead of a loss, which makes the result more difficult to interpret in relation to earnings. The manipulation in ABB cannot be analysed in relation to earnings as the manipulation occurred in the Italian branch, which is not reported separately in group accounts. In summary, we find that the majority of identified known cases of accruals fraud display manipulation of 21% to 35% of ROE, while the case where manipulation is used to turn net income positive can extend beyond 100% of ROE. However, given the limited number of cases it is difficult to generalise from these results.

Preliminary conclusion. The aim of this analysis has been to evaluate whether accruals models can identify known cases of earnings management. Eniro provides an interesting opportunity to qualitatively assess the ability of accruals models in this context, as it concerns accounting fraud through early recognition of revenues that can be detected with both aggregate and specific accruals models. Our results show that the models were unable to identify income increasing manipulation in Eniro at 25% of ROE, with the estimated discretionary accruals for this period ranging from 68% of ROE to negative 46% of ROE. The noise can also be illustrated with the most extreme values of discretionary accruals that range from SEK 931 million to negative SEK 2.2 billion over the sample years, compared to the actual manipulation of SEK 58 million. While Eniro exhibit extreme financial performance during this period, these levels of noise in discretionary accruals certainly appear problematic. In line with our previous findings, the specific accruals model generally outperforms the aggregate accruals model as shown by lower volatility in discretionary accruals.

The developments in Eniro illustrate the potential consequences from aggressive accruals manipulation for management, the company and investors. While it is difficult to relate the consequences of the manipulation to its magnitude, we argue that the illegal manipulation at 25% of ROE in Eniro was substantial. This is supported by an overview of the level of manipulation in other known cases of illegal accruals manipulation, where the majority of firms have manipulated 21% to 35% of ROE. While research on earnings management generally regards manipulation as driven by a malicious intent of managers (Healy & Wahlen, 1999), many scholars state explicitly that they do not refer to illegal activities, which they instead consider as fraudulent accounting (Sundvik, 2016). Consequently, we expect the identified level of manipulation in our fraud cases to represent fraudulent accounting rather than earnings management. This has implications for what can be considered as plausible levels of earnings management for a wider set of firms.

5.4. Concluding analysis

Our aim has been to evaluate if accruals models are useful to detect earnings management in listed Swedish companies. This research question has been analysed in three parts - *Detection of earnings management, Application of accruals models, Identification of accruals fraud* - with both aggregate and specific accruals models. Our results suggest that 25% of ROE represents a critical level of manipulation that is useful to contextualise our findings. First, our accruals models are unable to identify seeded manipulation at 25% of ROE due to Type II error rates of at least 30% and excessive rates of Type I errors, which we argue would not be acceptable to researchers in most contexts. Second, our models estimate that approximately 50% of observations in our sample display discretionary accruals at 25% of ROE in absolute terms, which indicates that the excessive error rates reflect noise in accruals models that disguises actual manipulation. Third, known cases of accruals manipulation in Sweden imply that manipulation at 25% of ROE would not be considered plausible levels of earnings management, but rather as fraudulent accounting that goes beyond judgements in financial reporting. Overall, these findings suggest that the usefulness of our accruals models to detect plausible levels of earnings management is limited.

While performance was unsatisfactory for all models with seeding at 25% of ROE, our specific accruals model outperforms our aggregate accruals model across all tests. However, this does not necessarily imply that specific accruals are a preferable alternative for future research on earnings management. We identify a number of issues with specific accruals models that would have to be addressed for these models to be useful to researchers. As specific accruals models are limited in scope, researchers will need to develop models incorporating different accruals in a mosaic approach (Giedt, 2018). Given the large number of accruals that are subject to discretion it is not clear if such an approach would be feasible in practice. Moreover, as manipulation can be spread across different items in financial statements, the required detection rates for specific accruals models need to be higher than for aggregate accruals models. While it is not clear to what extent different accruals are manipulated simultaneously in practice, the implication for detection rates can be illustrated with a situation where manipulation is spread evenly across three specific accruals. In this situation an aggregate accruals model only needs to detect the total level of manipulation, while each specific accruals model needs to detect a third of the total manipulation. As the specific accruals model in our study exhibits excessive Type I and Type II error rates at plausible levels of total manipulation, this indicates that considerable improvements in model design are required to capture fractions of total manipulation. Suggestions to improve models include accounting for additional factors in the firm environment, such as cash collection policies (McNichols & Stubben, 2018). However, as the benefits from these initiatives are uncertain it is likely that more novel approaches are needed to reach sufficient detection rates for both specific and aggregate accruals models.

When interpreting our results it is also important to note that we have aimed to test our models in an ideal setting by evaluating multiple model specifications and actively correcting for bias in established methods. Examples of this include our new proposed accruals measure and using artificial firms to test for Type II errors. In practice, most studies on earnings management are likely to display lower detection rates for two reasons. First, our results show that common research design choices can significantly impair model performance as displayed by low detection rates for traditional aggregate accruals measures. Second, an important issue that cannot be evaluated when seeding earnings management is correlated omitted variables. This is because our seeding is random and thereby expected to be uncorrelated with external factors that can otherwise result in false positives. Overall, the inability to detect manipulation in an ideal setting is further evidence that the models have limited usefulness in practice.

6. Additional tests

This section presents the results from additional empirical tests. We begin by presenting effects from alternative assumptions in sensitivity analyses followed by an evaluation of common issues in the application of linear regression models in robustness tests.

6.1. Sensitivity analysis

We conduct four main tests to analyse if our results are sensitive to alternative model assumptions. These tests consist of an application of the Modified Jones model, seeding in 10% of our main sample, exclusion of control variables and inclusion of seeded firms in the accruals model regressions.

6.1.1. Modified Jones model

We have chosen to test an additional aggregate accruals model to further increase the comparability of our findings. For this purpose, we choose the Modified Jones model as it is the most cited accruals model in earnings management research, which enhances our ability to evaluate the performance of past research designs (Christodoulou et al., 2018). We do not test an additional specific accruals model as the only difference between the Stubben model and alternative revenue models is the introduction of subsequent realisation of cash flows, which can give rise to bias (McNichols & Stubben, 2018). We use the Modified Jones model to repeat selected tests in our first two empirical questions. The results from our tests with seeding of fictitious sales in a random subsample of 5% of our main sample is presented in *Appendix C* and the magnitudes of discretionary accruals in relation to ROE in absolute terms are presented in *Appendix D*. In our tests relating to main sample seeding, the Modified Jones model yields qualitatively similar results with slight improvements in detection rates as observed in lower p-values for given levels of seeding and ability to detect seeding at 0.5% lower share of lagged total assets with the *CF* measure. The control variables are also qualitatively similar with the main differences that *MarketBook* is no longer significant at the 5% level for the *Adj.CF* and *CF* measures, while *Leverage* becomes significant at the 5% level for all model specifications, but not with the expected sign. Furthermore, we observe that the magnitudes of discretionary accruals are similar between the Modified Jones model and the Kothari model, indicating that the models have similar exposure to noise. Overall, as the performance of the Modified Jones model is similar to the Kothari model, we do not revise our main conclusions.

6.1.2. Seeding in 10% of the main sample

In our main tests we seeded 5% of our main sample as this is the share of companies that we expect to engage in earnings management. However, as this share is not observable in practice, we conduct a sensitivity test where we seed fictitious sales in a random subsample of 10% of our main sample. The results from the main regression model for the test variable *Seeding* at various levels of seeding are presented in *Appendix E*. We find that increasing the share of seeded observations does not lead to systematic changes in p-values and does not result in changes in significance levels in any of our models. Overall, as the differences from increasing the share of seeding in the sample is not material we do not revise our main conclusions.

6.1.3. Exclusion of control variables

Some of our control variables were not correlated with the dependent variable in our main test. To determine whether the controls contribute to the detection rates in our specifications of the models we therefore conduct a sensitivity test where we seed fictitious sales in a random subsample of 5% of our main sample without control variables. The results from the main regression model for the test variable *Seeding* at various levels of seeding are presented in *Appendix F*. We find that all specifications of the Kothari model display weaker performance without control variables as they are only able to detect seeding at 0.5% higher share of lagged total assets than before, while significance levels in the Stubben model are unaffected. This suggests that the control variables can have an important function in aggregate accruals models even if they are not statistically significant. We interpret these findings as support for including these variables in earnings management studies, but further research is needed to assess if they should be included in accruals models or main regression models (Christodoulou et al., 2018).

6.1.4. Inclusion of seeded firms in accruals model regressions

Observations suspected to be associated with earnings management are normally removed from accruals model regressions to prevent alpha bias (Christodoulou et al., 2018). However, as researchers cannot expect to remove all manipulating firms we conduct a sensitivity test where we seed fictitious sales in a random subsample of 5% of our main sample after including the seeded observations in the accruals models. The results from the main regression model for the test variable *Seeding* at various levels of seeding are presented in *Appendix G*. We find that the *Adj.CF* and *BS* measures display weaker performance as they are only able to detect seeding at 0.5% higher share of lagged total assets than before, while significance levels for the *CF* and *Rev* measures are unaffected. We interpret these findings as support for excluding observations suspected of discretion from accruals models in earnings management studies.

6.2. Robustness tests

We have investigated potential issues in the application of linear regression models that can give rise to incorrect statistical inferences. This review consists of tests for heteroscedasticity, multicollinearity and non-linearity in our main regression model.

6.2.1. Heteroscedasticity

Heteroscedasticity is the presence of non-constant variance in error terms, which leads to biased estimates of standard errors that invalidate conclusions on significance levels (Cohen et al., 2002). While scaling of our variables is intended to reduce heteroscedasticity (Kmenta, 1986), we also conduct a test proposed by White (1980) that does not impose any formal structure for the nature of the heteroscedasticity. The results of the test can be found in *Appendix H,* and show that the null hypothesis of no heteroscedasticity is rejected at the 1% level for all model specifications. To analyse the impact on our findings, we conduct a robustness test using Eicker-Huber-White standard errors that is superior to other corrections as it does not place any restrictions on the nature of the heteroscedasticity (Hayes & Cai, 2007). The results from our tests with seeding of fictitious sales in a random subsample of 5% of our main sample is presented in *Appendix I.* We find slight inflations in p-values across all model specifications, but this only leads to a change in significance level for the *BS* measure that is able to detect seeding at 0.5% higher share of lagged total assets than with normal standard errors. Moreover, the only change in control variables is that *MarketBook* is no longer significant at the 5% level for the *Adj.CF* measure and that *Analysts* becomes significant at the 5% level with the *BS* measure, but not with the predicted sign. We therefore conclude that the integrity of our main conclusions are not materially affected by heteroscedasticity.

6.2.2. Multicollinearity

Multicollinearity is the presence of correlations between independent variables in a multiple regression model, which can invalidate the results from statistical tests as the independent contribution of each variable cannot be distinguished (Farrar & Glauber, 1967). To test for multicollinearity we examine Tolerance Levels and Variance Inflation Factors (VIF). The Tolerance Level for an independent variable is the proportion of the explained variance in the dependent variable that is not captured by other independent variables and the VIF is the inverse of the Tolerance Level. The results of these tests for our main regression models at zero seeding can be seen in *Appendix J*. A VIF below ten is generally not seen a problematic (Wooldridge, 2012), but a more conservative view is that VIF should be below four (O'Brien, 2007). The VIF value is below four for all variables and the majority of variables display values between one and two. Two variables have slightly higher VIF, *Size* at 3.68 and *Analysts* at 3.26, which was expected as these variables were found to be highly correlated in section 4.5. While this could affect the results for these variables we conclude that inferences for our empirical questions are not materially affected by multicollinearity.

6.2.3. Non-linearity

Non-linearity is when the dependent variable is not a linear function of the independent variables and an error term. As non-linear relationships are not captured with linear regression models this can lead to biased estimates and failure to identify an existing relationship (Newbold et al., 2012). To test for non-linearity we conduct a lack-of-fit F-test that investigates the null hypothesis that the there is no lack of fit for the linear regression (Su & Wei, 1991). The results of these tests for our main regression models at zero seeding can be seen in *Appendix K*. We find that the variables across all of our models are not significant and we therefore do not reject the null hypothesis of fit in the linear regressions. Hence, we conclude that the inferences from our empirical questions are not materially affected by non-linearity.

7. Concluding remarks, limitations and suggestions for future research

Accruals models have been pervasive in the earnings management literature for nearly three decades. However, recent studies have shown that common specifications of aggregate accruals models are subject to bias that can result in incorrect inferences on earnings management (Owens et al., 2017; Christodoulou et al., 2018; Jackson, 2018). It has been proposed that specific accruals models could potentially alleviate the bias, but this has yet to be tested in light of recent findings (McNichols & Stubben, 2018). Our study therefore aims to investigate whether accruals models are useful to detect earnings management in listed Swedish companies. To answer this question, we have analysed one aggregate accruals model and one specific accruals model in three parts covering the detection rate for various levels of manipulation, the noise in discretionary accruals and known cases of manipulation.

Our results indicate that both aggregate and specific accruals models are unable to detect manipulation equivalent to 25% of ROE with an acceptable risk of making incorrect inferences. This reflects noise in accruals models implying discretion at 25% of ROE in absolute terms for half of all firms, which seems highly improbable. Furthermore, we do not believe that 25% of ROE is a plausible level of earnings management across a wider set of firms, as this magnitude of manipulation is associated with known cases of fraudulent accounting. We therefore conclude that the usefulness of accruals models is limited and that researchers should seek to use alternative research designs in studies on earnings management. While our results show that specific accruals models outperform aggregate accruals models, this does not necessarily imply that specific accruals models are more useful as they are less relevant when discretion is spread over multiple accruals. Moreover, we find that our proposed measure of accruals has a higher detection rate than traditional measures, indicating that our measure is a preferred option if aggregate accruals models is the only possible research design.

We acknowledge that this study has numerous limitations. Our results are based on a sample of Swedish non-financial and non-real estate firms listed on the Nasdaq Stockholm main market in 2005-2017. Hence, our findings are not directly comparable to studies on U.S. data as these firms are subject to different accounting standards (Hughes et al., 2017) and might have different propensity to engage in earnings management (Segelod, 2000; Lubatkin et al., 2005). We further limit ourselves to accruals earnings management and therefore do not provide an evaluation of all methods managers can use to manipulate earnings, which include altering real transactions (Roychowdhury, 2006) and distorting non-financial measures (Brazel et al., 2009).

While multiple accruals models have been proposed in research, we only conduct tests with the Kothari and Stubben models, as well as selected tests with the Modified Jones model. While other prevalent models share traits with our selected models, all of our conclusions refer only to our chosen model specifications. Furthermore, we do not evaluate the extent of earnings management among listed Swedish firms, but rather evaluate the ability of accruals models to detect known levels of manipulation. While we conduct a thorough search to find known cases of accruals fraud, we cannot ascertain that our list is comprehensive and we therefore exercise caution in the interpretation of these findings. In addition, our findings in the analysis of Eniro are not generalizable, but rather used to illustrate the noise in accruals models.

We have a number of suggestions for future research within the topic of earnings management that are beyond the scope of this thesis. First, our findings support the notion that researchers should strive to develop new improved methods to detect earnings management, preferably adopting novel approaches rather than incremental improvements of existing models. Second, more research is needed to determine what levels of earnings management could be expected in practice. This would be useful not only to evaluate research designs in relation to earnings management, but also to investigate the relevance of this phenomenon following increased regulation in Europe (Gao & Sidhu, 2018) and the U.S. (Baranek, 2018). Furthermore, insights into the frequency of simultaneous manipulation of multiple accruals would contribute to an evaluation of the usefulness of specific accruals models. Third, our findings support the proposition by McNichols & Stubben (2018) that a significant relationship with discretionary accruals is not sufficient to draw inferences on earnings management. We argue that this can have implications for prior research, as researchers may want to revisit past findings and evaluate whether conclusions can be supported with alternative research designs.

This thesis and preceding articles evaluating the flaws in accruals models to detect earnings management illustrate the importance of constantly questioning assumptions and logic in empirical research design. Jackson (2018) argues that researchers have taken a leap of faith in assuming that discretionary accruals reflect manipulation rather than ordinary deviations from industry averages. This fallacy has up until recently governed earnings management research and is the result of overlooking or ignoring important shortcomings in the models. We argue that researchers should dismiss the myth that discretionary accruals are unproblematic and that this field should have an essential confrontation with reality.

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Appendices

Appendix A

Variable definitions, sources and items

Variable	Definition	Source[φ]	Compustat Global Daily items
$AccAdj.CF_t$	Change in working capital minus depreciation of fixed assets according to plan, scaled by lagged total assets	Cash flow statement	$(WCAPOPC_t - DFXA_t) / AT_{t-1}$
$AccCF_t$	Net income before extraordinary items less cash flow from operations excluding extraordinary items, scaled by lagged total assets	Cash flow statement	$(IBC_t - OANCF_t + XIDOC_t) / AT_{t-1}$
$AccBS_t$	Change in non-cash current assets minus the change in non-debt current liabilities minus depreciation and amortisation, scaled by lagged total assets	Balance sheet	$(\Delta ACT_t - \Delta CHE_t - (\Delta LCT_t - \Delta DLC_t) - DP_t) / AT_{t-1}$
$AccRev_t$	Change in accounts receivables, scaled by lagged total assets	Cash flow statement	$RECCH_t / AT_{t-1}$
AT_t	Total assets	Balance sheet	AT_t
$\Delta CashRev_t$	Change in net sales minus the change in receivables, scaled by lagged total assets	Multiple[φφ]	$(\Delta SALE_t - \Delta RECT_t) / AT_{t-1}$
PPE_t	Gross property, plant and equipment, scaled by lagged total assets	Notes	$PPEGT_t / AT_{t-1}$
ROA_t	Net income before extraordinary items, scaled by lagged total assets	Cash flow statement	IBC_t / AT_{t-1}
$\Delta REVQ123_t$	Change in revenue from the first three quarters in the financial year, scaled by lagged total assets	Income statement	$\Delta REVTQ_{t,Q1\text{-}Q3} / AT_{t-1}$
$\Delta REVQ4_t$	Change in revenue minus the change in revenue from the first three quarters, scaled by lagged total assets	Income statement	$(\Delta REV_t - \Delta REVTQ_{t,Q1\text{-}Q3}) / AT_{t-1}$
$Size_t$	Natural logarithm of the product of shares outstanding and closing share price at year end for all share classes	Other	$\ln(CSHOC_{t-1} \times PRCHD_{t-1})$
$Leverage_t$	Debt-to-equity ratio calculated as the sum of long-term and short-term debt over equity including NCI	Balance sheet	$(DLTT_{t-1} + DLC_{t-1}) / (SEQ_{t-1} + MIBT_{t-1})$
$MarketBook_t$	Shares outstanding multiplied by closing share price at year end for all share classes over parent equity	Multiple[φφφ]	$(CSHOC_{t-1} \times PRCCD_{t-1}) / SEQ_{t-1}$
$CFFO_t$	Cash flow from operations, scaled by lagged total assets	Cash flow statement	$OANCF_t / AT_{t-1}$
$Loss_t$	Reports if net income before extraordinary items is negative	Cash flow statement	IBC_t
$Analysts_t$	Number of analysts reporting at least one earnings-per-share forecast	IBES database	EPS_t[φφφφ]

The table shows definitions, sources and items for the input variables included in the main adaptions of our accruals models and main regression models.

[φ] Total assets are always obtained from the balance sheet, [φφ] Balance sheet and income statement, [φφφ] Balance sheet and other, [φφφφ] Refers to IBES ticker

Appendix B

Identified cases of accruals fraud in Sweden

Firm	Years	Criteria (i)	Criteria (ii)	Criteria (iii)
		Accruals fraud in listed firm	*Restatement of known amount*	*Part of our main sample*
ABB Ltd	2002	x	x	
Intrum Justitia AB	2002	x	x	
Ericsson AB	2005	x		
FlyMe Europe AB	2006-2007	x		
Stora Enso AB	1999-2011	x		
Saab AB	2011	x		
Panaxia AB	2012	x		
CDON AB	2012	x	x	
Värmlands Finans AB	2012	x		
Oniva Online Group AB	2013	x	x	
Eniro	2013-2014	x	x	x
Eltel AB	2015	x	x	

The table shows to what extent the identified cases of accruals fraud in listed Swedish firms satisfy our criteria. *Years* refers to the period of known manipulation.

Sources: Engshagen, I. 2018, Finansinspektionen, 22 October, Stockholm; Lundin, H. 2018, Ekobrottsmyndigheten, 25 October, Stockholm; Malmqvist, P. (2018); Ranta, C. 2018, Revisorsnämnden, 22 October, Stockholm.

Appendix C

Panel A

Seeding of main sample – 5% seeded observations, Modified Jones model

			Modified Jones - Adj.CF			*Modified Jones - CF*			*Modified Jones - BS*		
ΔROA	**ΔROE**	**%ROE**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	12.8%	0.1753	0.4304	20.5%	-0.2965	0.3834	9.7%	-0.7501	0.2267
0.5%	1.0%	11.5%	12.9%	1.2678	0.1025	20.4%	0.4329	0.3326	9.6%	0.0487	0.4806
1.0%	2.0%	20.6%	13.0%	2.3524	0.0094***	20.5%	1.1639	0.1223	9.6%	0.8479	0.1983
1.5%	2.9%	28.0%	13.3%	3.4374	0.0003***	20.5%	1.8921	0.0293**	9.7%	1.6388	0.0507*
2.0%	3.9%	34.2%	13.7%	4.3522	0.0000***	20.8%	2.3468	0.0095***	9.8%	2.2812	0.0113**
2.5%	4.9%	39.4%	14.1%	5.4232	0.0000***	20.9%	3.0730	0.0011***	10.0%	3.0678	0.0011***
3.0%	5.9%	43.8%	14.7%	6.4893	0.0000***	21.1%	3.7991	0.0001***	10.3%	3.8498	0.0001***
				N	*1 654*		*N*	*1 654*		*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF* and the balance sheet measure are denoted *BS.* The dependent variable is discretionary accruals.

Panel A shows results for our test variable *Seeding* at various levels of seeding in 5% of our main sample using the Modified Jones model. The p-value shows if seeded firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Panel B

Seeding of main sample – zero seeding, Modified Jones model

	Modified Jones - Adj.CF				*Modified Jones - CF*				*Modified Jones - BS*			
	Coeff.	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**
Intercept	0.0126	0.0068	1.8407	0.0658	0.0446	0.0100	4.4596	0.0000***	0.0173	0.0092	1.8895	0.0590*
Seeding	0.0008	0.0046	0.1753	0.4304	-0.0020	0.0067	-0.2965	0.3834	-0.0046	0.0061	-0.7501	0.2267
Size	0.0010	0.0010	0.9929	0.1604	-0.0007	0.0015	-0.4304	0.3335	0.0010	0.0014	0.7313	0.2323
Leverage	-0.0046	0.0020	-2.2669	0.0118**	-0.0114	0.0029	-3.8641	0.0001***	-00069	0.0027	-2.5456	0.0055***
MarketBook	-0.0002	0.0004	-0.4095	0.3411	-0.0004	0.0006	-0.6881	0.2457	-0.0001	0.0005	-0.2561	0.3990
CFFO	-0.1318	0.0086	-15.286	0.0000***	-0.2223	0.0127	-17.574	0.0000***	-0.1472	0.0116	-12.696	0.0000***
Loss	-0.0369	0.0033	-11.112	0.0000***	-0.0882	0.0049	-18.123	0.0000***	-0.0439	0.0045	-9.8484	0.0000***
Analysts	-0.0002	0.0003	-0.9091	0.1817	0.0001	0.0004	0.1854	0.4265	-0.0005	0.0003	-1.3309	0.0917*
	Adj. R^2	*12.8%*	*N*	*1 654*	*Adj. R^2*	*20.5%*	*N*	*1 654*	*Adj. R^2*	*9.7%*	*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise, *Size* is a control variable representing the natural logarithm of lagged market capitalisation, *Leverage* is a control variable representing lagged total debt over lagged total equity, *MarketBook* is a control variable representing lagged market capitalisation over lagged parent equity, *CFFO* is a control variable representing cash flow from operations scaled by lagged total assets, *Loss* is a control variable that equals one if reported earnings are negative and zero otherwise, *Analysts* is a control variable representing the number of analysts reporting at least one earnings-per-share forecast. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF* and the balance sheet measure are denoted *BS.* The dependent variable is discretionary accruals.

Panel B shows results for all variables at zero seeding using the Modified Jones model. The p-value shows if the variables have a significant relationship with discretionary accruals in a t-test.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (2-tailed for the intercept, 1-tailed for all other variables).

Appendix D

Panel A

AbsDisAcc % of AbsROE – by industry, Modified Jones model

			Modified Jones - Adj.CF				*Modified Jones - CF*				*Modified Jones - BS*			
GICS	**Sectors**	**N**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**
15	Materials	9.33	66.1%	41.1%	24.1%	15.2%	75.0%	53.6%	33.0%	22.3%	75.9%	48.2%	34.8%	25.9%
20	Industrials	52.17	53.7%	32.6%	21.1%	16.0%	60.9%	41.4%	29.6%	22.4%	58.5%	40.7%	28.9%	21.7%
25	Consumer discretionary	19.83	56.7%	35.3%	25.6%	17.6%	64.7%	41.6%	30.7%	22.3%	63.9%	40.8%	31.1%	21.4%
35	Health care	20.08	47.7%	27.4%	20.3%	14.9%	63.5%	41.9%	29.9%	21.2%	53.5%	36.5%	26.1%	19.1%
45	Information technology	36.42	63.2%	40.3%	30.0%	24.7%	77.3%	54.2%	41.0%	32.0%	70.3%	48.7%	37.8%	29.7%
Total		**27.57**	**56.6%**	**34.8%**	**24.2%**	**18.3%**	**67.1%**	**45.7%**	**33.0%**	**24.7%**	**62.8%**	**42.7%**	**31.6%**	**23.7%**

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

Panel A shows aggregate results for the magnitude of discretionary accruals derived using the Modified Jones model by industry, with the columns displaying the share of observations with discretionary accruals above 25%, 50%, 75% and 100% of earnings in absolute terms. *N* refers to the average number of industry observations.

Panel B

AbsDisAcc % of AbsROE – by year. Modified Jones model

		Modified Jones - Adj.CF				*Modified Jones - CF*				*Modified Jones - BS*			
Year	**N**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**	**25%**	**50%**	**75%**	**100%**
2006	27.60	50.7%	28.3%	18.1%	15.9%	76.8%	47.8%	29.7%	25.4%	61.6%	39.1%	25.4%	20.3%
2007	27.40	59.9%	31.4%	24.1%	16.8%	65.0%	46.0%	29.9%	23.4%	63.5%	41.6%	27.7%	21.2%
2008	27.20	58.8%	36.0%	25.0%	19.1%	77.2%	47.8%	35.3%	26.5%	67.6%	48.5%	38.2%	29.4%
2009	28.00	66.4%	46.4%	33.6%	22.9%	75.0%	57.1%	42.9%	35.7%	72.1%	52.1%	44.3%	31.4%
2010	26.80	55.2%	37.3%	23.9%	21.6%	67.9%	47.0%	37.3%	27.6%	59.0%	42.5%	31.3%	25.4%
2011	26.00	59.2%	37.7%	22.3%	19.2%	71.5%	50.0%	33.1%	21.5%	63.1%	40.0%	27.7%	21.5%
2012	27.20	61.8%	40.4%	31.6%	23.5%	64.0%	44.9%	38.2%	27.9%	66.9%	47.1%	37.5%	27.9%
2013	28.40	60.6%	42.3%	28.2%	20.4%	71.8%	56.3%	40.1%	31.0%	60.6%	41.5%	28.9%	21.8%
2014	27.60	60.1%	33.3%	21.0%	15.9%	65.9%	40.6%	29.7%	23.2%	63.8%	41.3%	34.1%	27.5%
2015	26.60	57.1%	31.6%	24.1%	15.8%	61.7%	39.1%	30.1%	19.5%	60.2%	39.8%	28.6%	21.1%
2016	28.00	45.0%	24.3%	18.6%	14.3%	60.0%	39.3%	26.4%	17.1%	62.1%	44.3%	28.6%	20.0%
2017	30.00	45.3%	29.3%	20.0%	14.7%	50.0%	33.3%	24.0%	18.0%	54.0%	35.3%	26.7%	17.3%
Total	**27.57**	**56.6%**	**34.8%**	**24.2%**	**18.3%**	**67.1%**	**45.7%**	**33.0%**	**24.7%**	**62.8%**	**42.7%**	**31.6%**	**23.7%**

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

Panel B shows aggregate results for the magnitude of discretionary accruals derived using the Modified Jones model by year, with the columns displaying the share of observations with discretionary accruals above 25%, 50%, 75% and 100% of earnings in absolute terms. *N* refers to the average number of industry observations.

Appendix E

Seeding of main sample - 10% seeded observations

			Kothari - Adj.CF			*Kothari - CF*			*Kothari - BS*			*Stubben - Rev*		
ΔROA	**ΔROE**	**%ROE**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	11.5%	-0.5987	0.2747	22.5%	-0.5996	0.2744	8.4%	-1.2168	0.1119	2.8%	-0.4328	0.3326
0.5%	1.0%	12.8%	11.6%	0.5818	0.2804	22.5%	0.0804	0.4680	8.2%	-0.3837	0.3506	2.8%	0.7649	0.2222
1.0%	2.0%	22.6%	11.7%	1.7683	0.0386**	22.5%	0.7691	0.2210	8.0%	0.4414	0.3295	3.1%	1.9706	0.0245**
1.5%	3.1%	30.5%	12.1%	2.9526	0.0016***	22.7%	1.4672	0.0713*	8.2%	1.2559	0.1047	3.5%	3.1918	0.0007***
2.0%	4.1%	36.9%	12.6%	4.1024	0.0000***	22.9%	2.0841	0.0187**	8.4%	2.0359	0.0210**	4.0%	4.3613	0.0000***
2.5%	5.1%	42.3%	13.2%	5.2850	0.0000***	23.1%	2.7555	0.0030***	8.6%	2.8556	0.0022***	4.7%	5.5590	0.0000***
3.0%	6.1%	46.8%	13.9%	6.4597	0.0000***	23.3%	3.4236	0.0003***	8.9%	3.6646	0.0001***	5.6%	6.7729	0.0000***
				N	*1 654*		*N*	*1 654*		*N*	*1 654*		*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

The table shows results for our test variable *Seeding* at various levels of seeding in 10% of our main sample. The p-value shows if seeded firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Appendix F

Seeding of main sample - 5% seeded observations, exclusion of control variables

			Kothari - Adj.CF			*Kothari - CF*			*Kothari - BS*			*Stubben - Rev*		
ΔROA	**ΔROE**	**%ROE**	**Adj.R^2**	**t-stat**	**P-value**	**Adj.R^2**	**t-stat**	**P-value**	**Adj.R^2**	**t-stat**	**P-value**	**Adj.R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	0.0%	-0.4930	0.3111	0.0%	-0.6878	0.2458	0.0%	0.0639	0.4745	0.0%	-0.2285	0.4096
0.5%	1.0%	11.5%	0.0%	0.4914	0.3116	0.0%	-0.1558	0.4381	0.0%	-0.6517	0.2573	0.0%	0.8241	0.2050
1.0%	2.0%	20.6%	0.1%	1.4764	0.0700*	0.0%	0.3759	0.3535	0.0%	0.1122	0.4553	0.2%	1.8820	0.0300**
1.5%	2.9%	28.0%	0.3%	2.4567	0.0071***	0.0%	0.9074	0.1822	0.0%	0.8753	0.1908	0.5%	2.9405	0.0017***
2.0%	3.9%	34.2%	0.6%	3.4308	0.0003***	0.1%	1.4384	0.0752*	0.1%	1.6371	0.0509*	0.9%	3.9996	0.0000***
2.5%	4.9%	39.4%	1.1%	4.4049	0.0000***	0.2%	1.9691	0.0246**	0.3%	2.3956	0.0084***	1.5%	5.0592	0.0000***
3.0%	5.9%	43.8%	1.7%	5.3798	0.0000***	0.3%	2.4992	0.0063***	0.5%	3.1317	0.0009***	2.2%	6.1192	0.0000***
				N	*1 654*		*N*	*1 654*		*N*	*1 654*		*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

The table shows results for our test variable *Seeding* at various levels of seeding in 5% of our main sample without control variables. The p-value shows if seeded firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Appendix G

Seeding of main sample – 5% seeded observations, inclusion of seeded firms in accruals models

			Kothari - Adj.CF			*Kothari - CF*			*Kothari - BS*			*Stubben - Rev*		
ΔROA	**ΔROE**	**%ROE**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	12.4%	-0.3837	0.3506	24.7%	0.0977	0.4611	8.8%	-0.7675	0.2214	2.8%	-0.0633	0.4748
0.5%	1.0%	11.5%	12.4%	0.4852	0.3138	24.7%	0.6048	0.2727	8.8%	-0.1696	0.4327	2.8%	0.8787	0.1899
1.0%	2.0%	20.6%	12.4%	1.3559	0.0877*	24.7%	1.1115	0.1333	8.8%	0.4311	0.3332	3.0%	1.8234	0.0342**
1.5%	2.9%	28.0%	12.6%	2.2260	0.0131**	24.7%	1.6118	0.0536*	8.8%	1.0332	0.1508	3.2%	2.7687	0.0028***
2.0%	3.9%	34.2%	12.8%	2.9655	0.0015***	24.8%	1.9025	0.0286**	8.9%	1.5233	0.0639*	3.5%	3.6368	0.0001***
2.5%	4.9%	39.4%	13.0%	3.8268	0.0001***	24.9%	2.3967	0.0083***	9.0%	2.1248	0.0169**	4.0%	4.5719	0.0000***
3.0%	5.9%	43.8%	13.4%	4.6702	0.0000***	25.0%	2.8866	0.0020***	9.2%	2.7237	0.0033***	4.5%	5.5017	0.0000***
			N	*1 654*		*N*	*1 654*		*N*	*1 654*		*N*	*1 654*	

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

The table shows results for our test variable *Seeding* at various levels of seeding in 5% of our main sample with inclusion of seeded firms in our accruals models. The p-value shows if seeded firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Appendix H

Heteroscedasticity

	Kothari - Adj.CF		*Kothari - CF*		*Kothari - BS*		*Stubben - Rev*	
	Stat.	**P-value**	**Stat.**	**P-value**	**Stat.**	**P-value**	**Stat.**	**P-value**
White's test	294.255	0.0000***	332.153	0.0000***	229.964	0.0000***	182.418	0.0000***
	R^2	*17.8%*	*R^2*	*20.1%*	*R^2*	*13.9%*	*R^2*	*11.0%*
	N	*1654*	*N*	*1654*	*N*	*1654*	*N*	*1654*

Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

The table shows results for White's test for heteroscedasticity under the null hypothesis that heteroscedasticity is not present.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Appendix I

Panel A

Seeding of main sample - 5% seeded observations, Eicker-Huber-White standard errors

			Kothari - Adj.CF			Kothari - CF			Kothari - BS			Stubben - Rev		
ΔROA	**ΔROE**	**%ROE**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**	**Adj. R^2**	**t-stat**	**P-value**
0.0%	0.0%	0.0%	12.3%	-0.1772	0.4297	24.1%	-0.2749	0.3917	8.9%	-0.9576	0.1692	2.7%	-0.0648	0.4742
0.5%	1.0%	11.5%	12.3%	0.7437	0.2286	24.1%	0.2566	0.3988	8.8%	-0.2930	0.3848	2.8%	0.9323	0.1757
1.0%	2.0%	20.6%	12.4%	1.6741	0.0472**	24.1%	0.7840	0.2166	8.8%	0.3659	0.3573	2.9%	1.9382	0.0264**
1.5%	2.9%	28.0%	12.6%	2.6131	0.0046***	24.1%	1.3064	0.0958*	8.9%	1.0165	0.1548	3.2%	2.9498	0.0016***
2.0%	3.9%	34.2%	13.0%	3.4477	0.0003***	24.2%	1.6491	0.0497**	9.0%	1.5588	0.0596*	3.6%	3.8908	0.0001***
2.5%	4.9%	39.4%	13.4%	4.4096	0.0000***	24.3%	2.1611	0.0154**	9.1%	2.1873	0.0145**	4.2%	4.9109	0.0000***
3.0%	5.9%	43.8%	13.9%	5.3845	0.0000***	24.4%	2.6656	0.0039***	9.4%	2.7948	0.0027***	4.9%	5.9351	0.0000***
			N	*1 654*		*N*	*1 654*		*N*	*1 654*		*N*	*1 654*	

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is discretionary accruals.

Panel A shows results for our test variable *Seeding* at various levels of seeding in 5% of our main sample with Eicker-Huber-White standard errors. The p-value shows if seeded firms have a significant relationship with discretionary accruals in a t-test. *ΔROA* refers to level of seeding as a percentage of lagged total assets, *ΔROE* refers to the level of seeding as a percentage of equity, *%ROE* refers to the level of seeding expressed as a share of reported earnings post seeding.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (1-tailed).

Panel B

Control variables - seeding of main sample, zero seeding, Eicker-Huber-White standard errors

	Kothari - Adj.CF				Kothari - CF				Kothari - BS				Stubben - Rev			
	Coeff.	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**	**Coeff.**	**STD**	**t-stat**	**P-value**
Intercept	0.0085	0.0069	1.2317	0.2182	0.0208	0.0090	2.3250	0.0202**	0.0123	0.0091	1.3516	0.1767	0.0038	0.0066	0.5691	0.5694
Seeding	-0.0009	0.0050	-0.1772	0.4297	-0.0018	0.0064	-0.2749	0.3917	-0.0068	0.0071	-0.9576	0.1692	-0.0003	0.0043	-0.0648	0.4742
Size	0.0014	0.0010	1.3332	0.0913*	0.0021	0.0013	1.5502	0.0607	0.0014	0.0014	1.0493	0.1471	0.0008	0.0010	0.7659	0.2220
Leverage	-0.0029	0.0021	-1.3604	0.0870*	-0.0046	0.0028	-1.6665	0.0479**	-0.0042	0.0029	-1.4684	0.0711*	-0.0053	0.0018	-2.9792	0.0015***
MarketBook	-0.0006	0.0005	-1.2650	0.1030	-0.0014	0.0007	-2.0166	0.0220**	-0.0006	0.0007	-0.9251	0.1776	0.0001	0.0005	0.2694	0.3939
CFFO	-0.1279	0.0125	-10.217	0.0000***	-0.2435	0.0175	-13.892	0.0000***	-0.1417	0.0164	-8.6276	0.0000***	-0.0473	0.0095	-4.9625	0.0000***
Loss	-0.0278	0.0037	-7.4485	0.0000***	-0.0562	0.0049	-11.476	0.0000***	-0.0345	0.0047	-7.2840	0.0000***	-0.0143	0.0033	-4.3553	0.0000***
Analysts	-0.0003	0.0002	-1.2507	0.1056	-0.0004	0.0003	-1.3530	0.0881*	-0.0005	0.0003	-1.8462	0.0325**	-0.0002	0.0002	-1.0669	0.1431
	Adj. R^2	*12.3%*	*N*	*1 654*	*Adj. R^2*	*24.1%*	*N*	*1 654*	*Adj. R^2*	*8.9%*	*N*	*1 654*	*Adj. R^2*	*2.7%*	*N*	*1 654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev.* The dependent variable is discretionary accruals.

Panel B shows results for all variables at zero seeding with Eicker-Huber-White standard errors. The p-value shows if the variables have a significant relationship with correlated with discretionary accruals in a t-test.

***, **, * indicate significance at 1%, 5% and 10% levels respectively (2-tailed for the intercept, 1-tailed for all other variables).

Appendix J
Multicollinearity

	Kothari - Adj.CF		*Kothari - CF*		*Kothari - BS*		*Stubben - Rev*	
	Tolerance	**VIF**	**Tolerance**	**VIF**	**Tolerance**	**VIF**	**Tolerance**	**VIF**
Seeding	0.990	1.010	0.990	1.010	0.990	1.010	0.990	1.010
Size	0.272	3.682	0.272	3.682	0.272	3.682	0.272	3.682
Leverage	0.948	1.055	0.948	1.055	0.948	1.055	0.948	1.055
MarketBook	0.909	1.100	0.909	1.100	0.909	1.100	0.909	1.100
CFFO	0.629	1.590	0.629	1.590	0.629	1.590	0.629	1.590
Loss	0.593	1.688	0.593	1.688	0.593	1.688	0.593	1.688
Analysts	0.307	3.260	0.307	3.260	0.307	3.260	0.307	3.260
	N	*1654*	*N*	*1654*	*N*	*1654*	*N*	*1654*

Seeding is a test variable that equals one if earnings are seeded with fictitious sales and zero otherwise, *Size* is a control variable representing the natural logarithm of lagged market capitalisation, *Leverage* is a control variable representing lagged total debt over lagged total equity, *MarketBook* is a control variable representing lagged market capitalisation over lagged parent equity, *CFFO* is a control variable representing cash flow from operations scaled by lagged total assets, *Loss* is a control variable that equals one if reported earnings are negative and zero otherwise, *Analysts* is a control variable representing the number of analysts reporting at least one earnings-per-share forecast. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*.

The table shows results from our tests for multicollinearity. VIF is the inverse of the tolerance level and a value below ten is generally seen as indicating limited effect from multicollinearity.

Appendix K
Non-linearity

	Kothari - Adj.CF		*Kothari - CF*		*Kothari - BS*		*Stubben - Rev*	
	F-stat	**P-value**	**F-stat**	**P-value**	**F-stat**	**P-value**	**F-stat**	**P-value**
Size	0.917	0.676	1.064	0.423	0.931	0.651	0,675	0.971
Leverage	0.453	1.000	0.490	1.000	0.505	1.000	0.450	1.000
MarketBook	0.538	0.997	0.660	0.965	0.710	0.932	0.700	0.940
CFFO	0.357	1.000	0.276	1.000	0.287	1.000	0.566	0.993
Analysts	1.089	0.337	1.053	0.387	0.806	0.772	0.389	0.999
	N	*1654*	*N*	*1654*	*N*	*1654*	*N*	*1654*

Size is a control variable representing the natural logarithm of lagged market capitalisation, *Leverage* is a control variable representing lagged total debt over lagged total equity, *MarketBook* is a control variable representing lagged market capitalisation over lagged parent equity, *CFFO* is a control variable representing cash flow from operations scaled by lagged total assets, *Analysts* is a control variable representing the number of analysts reporting at least one earnings-per-share forecast. Accruals using the adjusted cash flow measure are denoted *Adj.CF*, the cash flow measure are denoted *CF*, the balance sheet measure are denoted *BS* and revenue accruals are denoted *Rev*. The dependent variable is discretionary accruals.

The table shows results from our tests of non-linearity. The p-value shows if the linear relationship between the dependent and the independent variable is poor using a lack-of-fit F-test. This tests excludes the dichotomous variables *Seeding* and *Loss* as linearity can only be tested for variables with at least three different outcomes.

***, **, * indicate significance at 1%, 5% and 10% levels respectively.