DETECTING EARNINGS MANAGEMENT: A COMPARISON OF ACCRUAL AND REAL EARNINGS MANIPULATION MODELS

Abstract

The use of models for detecting earnings management in the academic literature, using accrual and real manipulation, is commonplace. The purpose of the current study is to investigate the power of these models in a UK sample of 19,424 firm-year observations during the period 1991-2018. We include artificially induced manipulation of revenues and expenses between zero and 10 percent of total assets to random samples of 500 firm-year observations within the full sample. We use two alternative samples, one with no reversal of manipulation (sample 1) and one with reversal in the following year (sample 2). We find that the traditional real earnings manipulation models (Roychowdhury, 2006) have lower power than accrual earnings management models, when manipulating discretionary expenses and revenues. Furthermore, the real earnings manipulation model to detect overproduction has high misspecification, resulting in artificially inflating the power of the model. Modified real manipulation models (Srivastava, 2019) are used as robustness and we find these to be more misspecified in some cases but less in others. We extend the analysis to a setting in which earnings management is known to occur, i.e. around benchmark-beating. and find consistent evidence of accrual and some forms of real manipulation in this sample using all models examined.

Keywords: accrual manipulation; real accounts manipulation; earnings management detection

JEL: C18; C53; M40

1. Introduction

Earnings management by firms can be conducted using accrual or real manipulation (e.g., Dechow et al., 1995; Cohen et al., 2008; Cohen et al., 2010; Zang, 2012; Gao et al., 2017; Ipino and Parbonetti, 2017). Most of these studies use well-established proxies of accrual and real manipulation. Although previous empirical research widely uses discretionary accruals as a proxy of accrual earnings management (Xie, 2001; Capalbo et al., 2014; Kothari et al., 2016; Ravenda et al., 2018), the models measuring discretionary accruals (proxy for accrual manipulation) have previously been tested in the literature and found to have misspecification and low power, especially in samples of firms with extreme performance (e.g. Dechow et al., 1995; Kothari et al., 2005; Dechow et al., 2010). Recently, there are some studies that examine the power and specification of real manipulation models (Srivastava, 2019; Cohen et al., 2020; Siriviriyakul, 2021). However, evidence on the detection abilities of accrual manipulation models as compared to real manipulation models is scarce. To close this gap, this study compares the abilities of relative models for detecting accrual-based and real earnings manipulation by comparing the power of these models in a UK sample of 19,424 firm-year observations during the period 1991-2018.

The power of the test statistics is evaluated by comparing the frequency with which accrual and real manipulation models generate type II errors. Type II errors occur when the null hypothesis of earnings management systematically managed is not rejected by the relative models to detect accrual and real earnings manipulation. We artificially apply different levels and types of manipulation using accrual earnings management and real earnings. Specifically, we artificially include revenue recognition manipulation, as well as manipulation of expenses using either accruals or real accounts (e.g., discretionary expenses and overproduction). We provide results in randomly selected samples of 500 firms with no reversal of manipulation (Sample 1) as well as with reversal of manipulation in the subsequent year (Sample 2).

Although the models to detect real earnings management proposed by Roychowdhury (2006) are widely used in previous empirical studies, we find that they generate low power compared to accrual earnings management models. Specifically, for manipulation of discretionary expenses (such as research development expenses) and revenue manipulation, real earnings manipulation models have lower power than accrual earnings management models. The real earnings manipulation model to detect overproduction also experiences high misspecification of tests, resulting in artificially inflating the power of the model. We also investigate an alternative real earnings management model to detect discretionary expense manipulation (Kothari et al., 2016) that generates higher power than the Roychowdhury (2006) model.

In further tests, we assess the power of modified real manipulation models proposed by Srivastava (2019) and find improvements in detection rates and power of the models for both cashflow and discretionary manipulation in samples with no reversal (Sample 1) but the misspecification is exacerbated in samples with reversal (Sample 2).

As robustness, we also extend the analysis to a setting in which earnings management is known to occur, i.e. around benchmark-beating. We find consistent evidence of accrual and some forms of real manipulation in this sample using all models examined.

The current study contributes to the literature in the following ways. First, it extends the literature examining the power and specification of earnings management models. Prior literature has focused on accrual manipulation models only (e.g., Dechow et al., 1995; Peasnell et al., 2000; Kothari et al., 2005) or real earnings management models only (e.g. Srivastava, 2019; Cohen et al., 2020; Siriviriyakul, 2021). However, no study has assessed both accrual and real manipulation models in the same sample to compare their relative effectiveness in detecting manipulation. In this study, we provide a comparison of the ability of accrual and real manipulation to detect artificially-induced manipulation in the same sample of UK firms across an extended period of time, namely 1991-2018 with different levels of manipulation (0-10% of total assets). The findings raise concerns that real manipulation may be over-estimated in certain contexts in prior research.

Furthermore, the study provides insight into the effectiveness of the models that incorporate reversal (e.g., Dechow et al., 2000; Vorst, 2016; Srivastava, 2019) in different situations. Some of these models out-perform models with no reversal of the manipulation in the following year, but suffer from lower power when the reversal does not occur in the following year.

Furthermore, recent studies measuring the power and specification of real manipulation models are conducted on US samples; this study extends the tests to a UK context (e.g. Peasnell et al., 2000), while incorporating both types of manipulation.

The findings from the study are useful to academics and other stakeholders interested in investigating the prevalence of earnings management using alternative techniques. It highlights the current issues with models used to detect earnings management. Therefore, we caution academics who study the substitution between accrual and real manipulation (e.g., Cohen et al., 2008; Cohen et al., 2010; Cohen and Zarowin, 2010; Ibrahim et al., 2011; Zang, 2012; Gao et al., 2017; Ipino and Parbonetti, 2017; Owusu et al., 2020) that the findings may be biased due to the differential ability of the accrual and real manipulation models to detect manipulation of different magnitudes and under different assumptions (reversal or no reversal).

The study proceeds as follows. The next section provides the literature review and hypothesis development, followed by a description of the methodology and research design in section 3. Section 4 presents the empirical results and section 5 concludes.

2. Literature review and hypothesis development

2.1 Detection of accrual manipulation

Established proxies of accrual manipulation in the literature are based on the Jones (1991) model. Several modifications have been proposed over the years (e.g., Modified Jones model in Dechow et al., 1995; Peasnell et al., 2000; Dechow and Dichev, 2002; Francis et al., 2005; Kothari et al., 2005; Dechow et al., 2012; Byzalov and Basu, 2019). However, Dechow et al. (2010) argue that the modifications can induce estimation errors of discretionary accruals. Gerakos (2012) suggests that improvements in estimating discretionary accruals since Dechow and Dichev (2002) is questionable.

Prior research investigates the power and specification of these discretionary accrual models by using random samples with no expectation of manipulation, those with artificially added manipulation, and/or samples of firms that have allegedly manipulated profits. Most of these studies use US samples. For example, Dechow et al. (1995) compare several discretionary accrual models and provide evidence that discretionary accrual models are well specified when using a random sample but generate type II errors for firms with extreme financial performance. Kothari et al. (2005) examine the specification and power of tests based on performance-matched discretionary accruals and find better detection when the earnings management levels are not expected to vary with performance. Stubben (2010) run a similar analysis and find that accrual models are not effective in detecting a mix of revenue- and expense-related misstatements in firms subject to enforcement actions by the Securities and Exchange Commission. Dechow et al. (2012) investigate accrual models that incorporate reversal of the manipulation and find that this increases the power of the tests by around 40% and mitigate model misspecification from correlated omitted variables.

Limited studies examine these issues in non-US samples. For example, Peasnell et al. (2000) examine the Jones model, the modified Jones model and introduce a new specification (Margin model) in a UK sample and find that the three models are well-specified in a random sample of firm-years. They also find that the Jones and modified Jones model are more powerful than the margin model in detecting revenue and bad-debt manipulation but less powerful in detecting non-bad debt expense manipulation. In a Spanish context, Jaime and Noguer (2004) find that the models examined (including Jones, modified Jones, and margin model) are well-specified in a random sample. Similarly, they find different models are better able to detect different types of manipulation when artificially induced manipulation is added, with no model performing better in all contexts.

2.2 Detection of real manipulation

Earnings management through real accounts has emerged as an alternative to accrual manipulation following the findings of a survey by Graham et al. (2005) indicating that top executives prefer real earnings manipulation to discretionary accruals.

Models used in the academic literature to detect real manipulation were proposed by Roychowdhury (2006) using the following mechanisms: revenue manipulation, overproduction and reduction in discretionary expenses (e.g. research and development expenses). In his paper, he tests these models by comparing the magnitude of manipulation between suspect firms that meet/beat earnings benchmarks and the rest of the sample. He finds evidence consistent with firms trying to boost earnings to meet their benchmarks by using real manipulation methods. Further modifications to the models have been proposed (e.g., Cohen et al., 2010; Srivastava, 2019; Siriviriyakul, 2021) with some focusing exclusively on one of the real manipulation mechanisms, namely discretionary expenses (e.g., Vorst, 2016; Kothari et al., 2016). For example, Vorst (2016) proposes an adjusted proxy of abnormal discretionary expenses that incorporates the effect of reversal. He finds that reversal of abnormal reduction in discretionary expenses is indicative of real accounts manipulation, implying less misspecification of a measure that takes into account lagged discretionary expenses.

Limited previous literature has systematically tested whether these proposed real manipulation measures suffer from misspecification. One notable exception is the study by Cohen et al. (2010), in which they find misspecification in the traditional models proposed by Roychowdhury (2006), especially in samples with extreme performance. They compare these models to performance-matched ones and find that neither approach is consistently more powerful than the other in detecting artificially added manipulation ranging from 1 to 10% of lagged assets. Recently, Srivastava (2019) argues that the traditional models are not able to distinguish between firm performance and its competitive strategy. Specifically, he finds these measures to be strongly associated with future revenue growth. He suggests improvements by controlling for differences in size, growth and other measures and finds these measures to be less misspecified. Siriviriyakul (2021) assess the traditional measures and find that they exhibit persistence and vary with performance. She finds that modifications proposed by Vorst (2016) and Kothari et al. (2016) are the most effective in capturing real manipulation. However, using simulated added manipulation, she finds that the power of the models depends on whether real manipulation subsequently reverts.

Prior literature has not systematically investigated misspecification of accrual and real manipulation models in the same sample. Since accruals are aggregate measures (e.g., include receivables, payables, and other accounts), while real accounts tend to be more specific (e.g., overproduction relates to production expenses), this may imply that models to detect real earnings management may be better specified. For example, receivables and tax accruals may behave differently with respect to firm revenues (used to capture normal levels of accruals) but the coefficient on revenues is forced to be the same. In this case, accrual manipulation models would contain errors. We discuss potential errors in the models in the next section.

On the other hand, real earnings management could be wrongly detected by the models in the case of prudent business decisions or strategy differences which would create an omitted variable problem (Srivastava, 2019; Siriviriyakul, 2021). In line with this, Lennox and Yu (2019) find that detection of manipulation by firms overstating earnings through manipulating cash flows is more difficult than when cash flow manipulation is not used. Similarly, Kothari et al. (2016) document that managers select real manipulation methods to inflate earnings that tend to be more opaque to escape from scrutiny from auditors or regulators. On the other hand, Pappas et al. (2019) find that lenders possess private information that may allow them to correctly identify real manipulation.

To add to this, limited research has investigated the complementarity of both manipulation methods in different settings such as around meeting earnings benchmarks (e.g. Cohen et al., 2008; Cohen et al., 2010; Zang, 2012), around seasoned equity offerings (e.g. Cohen and Zarowin, 2010; Ibrahim et al., 2011), in relation to factors such as government intervention and debt ratio (e.g. Gao et al., 2017), and around adoption of new standards (e.g. Cohen et al., 2008; Ipino and Parbonetti, 2017). These studies indicate that real manipulation is more difficult to be detected by outsiders than accrual manipulation as it may be confused with changes in normal operating decisions.

Given the above discussion, it is an empirical issue as to which model, accruals or real accounts manipulation, would be more effective in capturing cases of manipulation. We therefore formulate the hypothesis as follows:

H_1: *The detection ability of real earnings management models is different from that of accrual-based earnings management models.*

3. Research Design

3.1 Testing the hypothesis

To examine the detection ability of accrual-based and real earnings management models, we compare the frequency with which these models generate type II errors (i.e., incorrectly reject the null hypothesis of no earnings management when it is false).

We use a similar framework to that introduced by McNichols and Wilson (1988) to detect earnings management, as follows:

$$DA_t = a_0 + a_1 PART_t + \sum_{k=0}^{n} a_3 X_{kt} + \varepsilon_t \quad (1)$$

$$RE_t = b_0 + b_1 PART_t + \sum_{k=0}^{n} b_3 X_{kt} + e_t \quad (2)$$

Where *DA* is discretionary accruals and *RE* is real earnings management); *PART* is an indicator variable that is set as 1 when earnings management exists in the observation, 0 otherwise; X_k is other sources of earnings management; ε is the error term.

In the equations above, the coefficient a_0 (b_0) represents mean values of discretionary accruals (real earnings management) when *PART* is equal to zero, and a_0+a_1 (b_0+b_1) indicates mean discretionary accruals (real earnings management) when *PART* is equal to 1 (observations with earnings management present).

Under the ordinary-least square (OLS) assumption, $\hat{a}$ and $\hat{b}$ are the best linear unbiased estimates of a_1 and b_1 in equations (1) and (2). Furthermore, the standard errors of $\hat{a}$ and $\hat{b}$ are:

$$SE(\hat{a}) = S_{\varepsilon}/\sqrt{(n-1) * s_{PART}} \quad (3)$$

$$SE(\hat{b}) = S_{e}/\sqrt{(n-1) * s_{PART}} \quad (4)$$

Where *n* is the total number of observations including *PART*=0 and *PART*=1; S_{ε}, S_e are standard errors of the regressions; S_{PART} is the standard deviation of *PART*. Accordingly, the null hypothesis of no earnings management is rejected if $\hat{a}$ and $\hat{b}$ are statistically different from zero at conventional levels. As a result, the power of a t-test for earnings management is improved by the coefficients of a and b (i.e., the signed magnitude of hypothesized earnings manipulations), total number of observations (*n*) and standard deviation of $PART$ (s_{PART}). In contrast, the power of the test is reduced by standard error ($S_{\varepsilon}, S_{\gamma}$) of the regression that represent other determinants of earnings management in the regression models.

Unfortunately, researchers cannot directly observe discretionary accruals or real earnings management. Hence, they rely on a proxy of estimated discretionary accruals or real earnings manipulation. Accordingly, there are measurement errors in estimating the proxy of discretionary accruals (*DAP*) or real earnings management (*REM*).

$$DAP_t = DA_t - \mu + \eta \quad (5)$$

$$REM_t = RE_t - \varrho + ð \quad (6)$$

Where μ and ϱ represent the amount that is excluded from *PART* that relates to discretionary accruals and real earnings management, respectively; η and ð represent the amount that is included in *PART* that relates to non-discretionary accruals and normal operating activities, respectively; other variables are as previously defined.

The three types of problems causing misspecification in the estimates of equations (5) and (6) (see Dechow et al., 1995; Dechow et al., 2012) are below:

Problem 1: Unintentionally removing some or all the earnings manipulation from DAP and REM

The first problem is that the omission of μ and ϱ could cause biased estimates and low power of the tests. Indeed, μ and ϱ representing discretionary accruals and abnormal operating accounts are unintentionally removed from *DAP* and *REM* in the estimation of (5) and (6), respectively. Accordingly, $\hat{a}_1$ could be biased towards zero. This bias might reduce the power of the test (i.e., rejecting null hypothesis of no earnings management when it is false).

Problem 2: Inclusion of correlated variables in DAP and REM

The second problem is that η and ð indicating normal accruals and normal operating activities may unintentionally remain in *DAP* and *REM*, respectively. This presence of correlated η and ð might result in biased $\hat{a}_1$ and $\hat{b}_1$ not equal to zero even when the true a_1 and b_1 equals to zero. As a result, the type I errors (i.e., not rejecting null hypothesis of no earnings management when it is true) increases.

Problem 3: Inclusion of uncorrelated variables in DAP and REM

The third problem is the inclusion of uncorrelated η and ð with *DAP* and *REM*. When η and ð are left in normal accruals or normal operating activities but not correlated with *DAP* and *REM*, $\hat{a}_1$ and $\hat{b}_1$ are not biased. However, the presence of uncorrelated η and ð increase standard errors of estimated coefficients of $\hat{a}_1$ and $\hat{b}_1$. Accordingly, the type II error is higher, resulting in lowering the power of the test.

Reducing either above-mentioned problem could increase other problems, hence, there is a trade-off between balancing the three problems of misspecification. For example, if researchers correctly conceive the determinants of normal accruals or normal operating accounts, this can expand the first problem. In contrast, the inclusion of too few determinants could lead to the second and the third problem.

3.2 Measuring earnings management

3.2.1 Measuring accrual earnings management

We use three alternative models to detect accrual earnings management. First, the cross-sectional modified Jones model (Dechow et al., 1995) is applied to estimate discretionary accruals. In which, the cross-sectional measure of non-discretionary accruals (*NDA*) for each year and industry combination is used to estimate the parameters of the model. The modified Jones model is applied to measure non-discretionary accruals (NDA) during the event period when earnings management is hypothesized.

$$NDA_t = \alpha_1\left(\frac{1}{A_{t-1}}\right) + \alpha_2\left(\frac{\Delta REV_t - \Delta REC_t}{A_{t-1}}\right) + \alpha_3\left(\frac{PPE_t}{A_{t-1}}\right) \quad (7)$$

Where ΔREV_t is the change in revenue from year t-1 to t; ΔREC_t is the change in receivables from year t-1 to t; PPE_t is gross property, plant, equipment in year t; A_{t-1} is total assets in year t-1.

The parameters in Eq. (7) during the estimation period when no systematic earnings management is hypothesized are obtained from the original Jones model (Jones, 1991), which uses an estimation portfolio of firms within the same industry and year. In the modified Jones model, it is assumed that all the changes in credit sales result from earnings management (Dechow et al., 1995). Discretionary accruals (*DAP*) are estimated by subtracting non-discretionary accruals (*NDA*) from total accruals (*TA*).

Kothari et al. (2005) show that the correlation between performance and accruals can result in misspecification of commonly used discretionary accrual models (e.g., Jones, 1991 and the modified Jones model). Therefore, in this study, our second model is that based on Kothari et al. (2005) model. To control for firm performance in estimating discretionary accruals, the current year's return on assets (*ROA*) is added to the modified Jones model as an additional regressor (Kothari et al., 2005). Accordingly, return on assets for the current year is added to equation (7) to estimate normal discretionary accrual as follows:

$$NDA_t = \alpha_1 \left(\frac{1}{A_{t-1}}\right) + \alpha_2 \left(\frac{\Delta REV_t - \Delta REC_t}{A_{t-1}}\right) + \alpha_3 \left(\frac{PPE_t}{A_{t-1}}\right) + \alpha_4 \left(ROA_t\right) \quad (8)$$

Where ROA_t is earnings deflated by total assets in year t. Discretionary accruals (*DAP*) are estimated by subtracting non-discretionary accruals (*NDA*) estimated from Eq. (8) from total accruals (*TA*).

Third, we also use the Dechow and Dichev (2002) model as modified by McNichols (2002) and Francis et al. (2005). Dechow and Dichev (2002) (hereafter, DD) introduce a new measure for earnings quality. DD indicate that earnings quality is the relation between accruals and cash flows, in which accruals adjust cash flows over time. Moreover, cash flow realization in the prior period t-1 and next period t+1 is assumed to be reflected in current year accruals. Accordingly, accruals of firms unrelated with cash flow realizations are treated as low quality of accruals. However, McNichols (2002) indicates the limitation of DD's (2002) model in not considering the effect of long-term accruals on estimating discretionary accruals. Therefore, McNichols (2002) extends the DD model by including the change in revenues and property, plant and equipment (*PPE*) as additional explanatory variables in the estimation of discretionary accruals. Following Dechow and Dichev (2002) and McNichols (2002) and Francis et al. (2005), we estimate non-discretionary accruals by using the model (hereafter the Modified DD model) as follows:

$$NDA_t = \alpha_1 + \alpha_2 \left(\frac{\Delta REV_t - \Delta REC_t}{A_{t-1}}\right) + \alpha_3 \left(\frac{PPE_t}{A_{t-1}}\right) + \alpha_4 \left(\frac{CFO_{t-1}}{A_{t-1}}\right) + \alpha_5 \left(\frac{CFO_t}{A_{t-1}}\right) + \alpha_6 \left(\frac{CFO_{t+1}}{A_{t-1}}\right) \quad (9)$$

Where CFO_{t-1} is the cash flow from operation in year t-1; CFO_t is the cash flow from operation in year t; CFO_{t+1} is the cash flow from operation in year t+1 and all other variables are as previously defined. All measures are scaled by lagged assets. Discretionary accruals (*DAP*) are estimated by subtracting non-discretionary accruals (*NDA*) estimated from Eq. (9) from total accruals (*TA*).

Total accruals *(TA)* for the three models of detecting accrual earnings management are computed as below:

TA_t = (ΔCA_t - ΔCL_t - $\Delta Cash_t$ + ΔSTD_t - Dep_t) / A_{t-1} (10)

where ΔCA_t = change in current assets from year t-1 to t, ΔCL_t = change in current liabilities from year t-1 to t, $\Delta Cash_t$ = change in cash and cash equivalents from year t-1 to t, ΔSTD_t = change in short term debt from year t-1 to t, Dep_t = depreciation and amortization expense in year t, and A_{t-1}= total assets in year t-1.

3.2.2 Measuring real earnings management

Following previous studies (Roychowdhury, 2006; Cohen et al., 2008; Gunny, 2010; Ibrahim et al., 2011; Athanasakou et al., 2011; Pappas et al., 2019), the measures of real earnings manipulation are based on three types of real earnings management. Although there are several recent studies that have tried to improve detection of real manipulation, the traditional measures developed by Roychowdhury (2006) are the most widely applied in accounting research. Therefore, in this study, we focus on evaluating the effectiveness of detecting REM using Roychowdhury (2006)'s model, although we present in the robustness section analysis using alternative measures developed by Srivastava (2019).

First, we use a model of revenue manipulation which is conducted by accelerating the timing of sales (i.e., offering price discounts or more lenient credit terms, which results in abnormally low cash from operations). The model used is as follows:

$$\frac{CFO_t}{A_{t-1}} = \alpha_0 + \alpha_1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{REV_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \varepsilon_t \quad (11)$$

Where REV_t is net revenue in year t; all other variables are as previously defined.

Second, we use a model to capture changes in discretionary expenditures such as research and development (R&D), advertising and selling, general and administrative expenses, which leads to abnormal discretionary expenses. The model used is as follows:

$$\frac{DISEXP_t}{A_{t-1}} = \alpha_0 + \alpha_1\frac{1}{A_{t-1}} + \beta_1\frac{REV_{t-1}}{A_{t-1}} + \varepsilon_t \quad (12)$$

Where: $DISEXP_t$ is the discretionary expenses measured as the sum of research and development (R&D), advertising and selling, general and administrative expenses in year t; all other variables are as previously defined.

Third, we model overproduction which is implemented by overproducing goods to lower cost of goods sold. The model used is as follows:

$$\frac{PROD_t}{A_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{t-1}} + \beta_1 \frac{REV_t}{A_{t-1}} + \beta_2 \frac{\Delta REV_t}{A_{t-1}} + \beta_3 \frac{\Delta REV_{t-1}}{A_{t-1}} + \varepsilon_t \quad (13)$$

Where $PROD_t$ is production costs in year t; ΔREV_{t-1} is revenues in yeat t-1 and all remaining variables are as previously defined. The use of production costs instead of costs of goods sold could help reduce the confounding effect of accrual-based earnings management. For instance, managers of firms may delay the write-off of obsolete inventory at the end of the year (accrual-based earnings management). This results in abnormally low cost of goods sold. However, this does not influence production costs since lower cost of goods sold will offset higher inventory costs.

Abnormal real activities estimated by the Roychowdhury (2006) models are measured as the difference between actual and normal real activities. This includes abnormal cash from operating activities (REM_{CFO}), reduction of discretionary expenses (REM_{DISEXP}) and overproduction (REM_{PROD}).

3.3 Sample selection

The sample in the study includes all "dead" and "alive" firms listed on London Stock Exchange from 1991-2018 with all available data for the computation of the discretionary accrual models and the real earnings management models. The estimation of cross-sectional model requires at least ten observations per each industry/year combination. Therefore, each industry/year group having less than ten observations is excluded from the sample. We classify firms into industries according to the FTSE classification using the 2-digit SIC code. Previous studies do not remove banks and financial institutions in calculating earnings management (e.g., Dechow et al., 1995; Kothari et al., 2016), hence, in the sample, we do not eliminate these firms. Furthermore, to avoid extreme observations causing noisy estimation, we remove observations at the top and bottom one percent of continuous variables. Table 1, panel A illustrates the sampling procedure of the study. The final sample comprises 19,424 observations.

Moreover, panels B and C of table 1 show the yearly and industry distribution of the full sample. In panel B, we see a somewhat even distribution across sample years 1991-2018, with the highest number of observations in year 2006 (N=980) and the lowest in year 1991 (N=178). Panel C indicates that the industry with the highest number of observations is Manufacturing (N=7,467), followed by Services (N=6,218). Both industries constitute 70% of the sample with the remaining 30% distributed across the remaining 7 industries.

((Table 1 here))

To evaluate the accrual and real earnings management models in terms of type II errors (i.e., not rejecting the null hypothesis of no earnings management when it is false), we create two randomly selected sub-samples within the full sample as follows:

(1) Sample 1 is a random sample of 500 firm-years selected from the full sample without replacement. We follow Brown and Warner (1985) and Dechow et al. (1995)'s approach to investigate type II errors for earnings management models. Since we use cross-sectional non-discretionary accrual models instead of the time-series model in Dechow et al. (1995), to avoid the assumption that accruals fully reverse in the following year (as in Dechow et al., 1995), this sample is selected whereby each firm is included in the sample only once if randomly selected and all other observations of the selected firm are deleted. Accordingly, there is no assumption of full reversal of earnings manipulation in the next fiscal year. We assign a value of *PART = 1* to the random sample of 500 firm-years, and *PART = 0* to the remaining observations. We choose 500 firm-years as our random sample, to keep it large enough and close to the sample size in Dechow et al. (1995), while considering our smaller full sample. They select a random sample of 1,000 observations from the full sample of 168,771.[1]

(2) Sample 2 is a random sample of 500 firm-year observations using the same sample selection methodology as Dechow et al. (1995) whereby we randomly select 500 firm-years from the full sample. Sample 2 is different from sample 1 in that firm-years in sample 2 can appear in consecutive years, whereas in sample 1, the firm observations appear in only one specific year. We therefore assume that discretionary accruals and abnormal operating accounts fully reverse in the following fiscal period. As above, we assign a value of *PART = 1* to the random sample, and *PART = 0* to the remaining 18,924 observations.

3.4 Types of manipulation

To evaluate the rejection frequency using one-tailed t-tests at significant levels between real earnings management and accrual earnings management models, we adopt a similar approach to Brown and Warner (1985) and Dechow et al. (1995) by using artificially induced earnings management where a known amount and timing of earnings management is added to sample (1) and (2). With the given level of artificially induced earnings management in the given samples, the failure to reject the null hypothesis of no earnings management when it is false

[1] We also run analyses using samples of 100 firm-years and find similar results.

generates type II errors. The procedure is implemented by artificially introducing accrual and real account manipulation ranging from zero percent to 10 percent of lagged assets to sample (1) and sample (2).

The three manipulation types of accruals are as follows:

(1) *Revenue manipulation:* e.g., premature recognition of revenues with assumption that all costs are fixed. This approach is applied by adding the pre-determined amount of earnings management (zero to 10 percent of lagged assets) to total accruals, revenues, and receivables in the year of earnings management occurring.

(2) *Expense manipulation:* e.g., reduction of accrued discretionary expenditure. This approach is conducted by adding an assumed amount to total accruals. Since the accrual model does not use expenses to estimate non-discretionary accruals, none of the other variables in the model are affected.

(3) *Overstated asset:* e.g., understated allowance for obsolete inventory. When a firm engages in overproducing goods, the assumption concerning the component of accruals managed is that the firm might overstate assets through understating the expense allowance for obsolete inventory. Accordingly, this type of accrual manipulation increases inventory and decreases cost of goods sold in the manipulation year. Thus, this approach is implemented by adding an assumed amount to total accruals only in the earnings management year. Because the model does not apply cost of goods sold to estimate non-discretionary accruals, none of other variables are affected. Therefore, this manipulation has a similar effect as (2) above.

The three assumptions for real earnings manipulation are based on the three types of real earnings manipulation, namely revenue manipulation, reduction of discretionary expenses and overproduction. The three manipulation types are as follows:

(1) *Revenue manipulation:* e.g., price discounts. When firms offer price discounts to customers, both cash flows from operations and sales increase. It is assumed that the increase in cash from operations and sales is the same. Accordingly, this approach is implemented by adding the assumed amount of revenue manipulation to cash flow from operations and revenues in the earnings management year.

(2) *Expense manipulation:* e.g., reduction of discretionary expenses. It is assumed that all discretionary expenses are paid by cash. This approach is conducted by adding an assumed amount of expense manipulation to discretionary expenses in the earnings management year.

Since the models do not use expenses to estimate normal discretionary expense, none of the other variables in the model are adjusted.

(3) *Overproduction:* When a firm overproduces goods relative to demand, there is higher production and holding costs of over-produced goods that are not recovered in the same period as sales. Thus, this approach is implemented by adding the assumed amount of overproduction to production costs in the earnings management year. Since all other variables in the model to estimate normal production costs are not affected, none of the other variables in the model are adjusted.

It is noted that for sample (1), there is no assumption of full reversal of artificially induced earnings management in the following period since there are no firms with consecutive years in the sample. To the sample of random firm-years (sample 2), it is assumed that accruals and abnormal operating accounts fully reverse in the next year.

The empirical tests follow the framework illustrated in section 3.1, which is applied to the two samples described above. Firm-years in the two samples represent the event year used to test earnings management. To estimate the cross-sectional non-discretionary accruals and normal operating activities, firm-years are matched with remaining firm-years in the full sample to form an estimation portfolio of firms within the same industry and year combination. All firms have at least 10 observations in their estimation portfolio.

4. Discussion of results

4.1 Descriptive statistics

Panel A, table 2 presents the descriptive statistics for the full sample of 19,424 firm-years from 1991-2018. From the table, we see that firm characteristics are broadly similar to previous studies (e.g., Ball and Shivakumar, 2005; Roychowdhury, 2006). Firms are somewhat smaller than in prior literature using UK samples, with mean total sales of £140M, compared to £432 in Ball and Shivakumar (2005). Mean cash from operations is £14M compared to £12.5M in Ball and Shivakumar (2005). Accruals are on average negative (-5.5M) as in the US sample in Roychowdhury (2006). In fact, the scaled values of accruals, production expenses, and discretionary expenses are similar to the values in Roychowdhury (2006) (Mean $Accrual_t/A_{t-1}$, $PROD_t/A_{t-1}$, and $DISEXP_t/A_{t-1}$ is -4.6, 74.9, and 37.3, respectively, similar to -4.31, 98.99 and 36.63 in the US sample of Roychowdhury, 2006).

Panel B of table 2 reports the model parameters of normal level of accruals, cash from operations, discretionary expenses, and production costs. The full sample is used to estimate the coefficients of the models. The table presents the mean coefficients across industry-year combinations. Moreover, the t-statistics are estimated from standard errors of the coefficients across industry-years. For the sake of comparison, all models include an unscaled intercept (α_0). As noted by Roychowdhury (2006), including a non-scaled intercept leaves the mean abnormal *CFO* for every industry-year equal to zero and this inclusion does not materially affect the results.

((Table 2 here))

The coefficients of non-discretionary accruals for the modified-Jones model include changes in revenues, property, plant, and equipment (PPE_{t-1}/A_{t-1}). Moreover, the Kothari et al., (2005) model augments the modified-Jones model to add current year's return on asset (ROA). As shown in panel B of table 2, the mean coefficient of property, plant, and equipment (PPE_{t-1}/A_{t-1}) is negative (-0.016) and statistically significant at 1 percent, which indicates income-decreasing income accruals (i.e., depreciation expenses). Furthermore, the average coefficient of change in revenues is negative (-0.010). The expected sign for changes in revenues ($\Delta REV_t/A_{t-1}$) coefficients is ambiguous since changes in revenues affect both income-increasing accruals such as receivables and income-decreasing accruals such as account payables (see Jones, 1991). The average coefficient on return on asset is positively significant (0.104) at 1 percent level, indicating that a higher current year's return on asset implies higher non-discretionary accruals. As for the Modified DD model, the average coefficients on CFO_{t-1} and CFO_{t+1} are positive (0.145, 0.098, respectively). Moreover, the coefficient of CFO_t is negative (-0.319), significant at 1 percent level. Furthermore, the average coefficients of change in revenues ($\Delta REV_t/A_{t-1}$) and property, plant, and equipment (PPE_{t-1}/A_{t-1}) are 0.008 and -0.034, significant at 1 percent level. The expected sign of all coefficients shown in Panel B, table 2 are consistent with results by the DD model and the McNichols (2002)'s model.

As for the normal level of cash from operations, discretionary expenses and production costs, the mean coefficients in Panel B are statistically significant and comparable with those presented by Roychowdhury (2006), Zang (2012) and Gunny (2010). The adjusted R^2 of normal cash from operations, discretionary expenses and production costs is 32.4%, 28.9% and 77.4%, respectively. The explanatory power of the models is reasonable in explaining the variance of the independent variables in the models. Furthermore, the adjusted R^2 of normal accruals is 20% which is nearly equal to that in Jones (1991) and is lower than the 28% in Roychowdhury (2006).

Panel C, table 2 presents that the mean values of accrual-based earnings management (DAP_t) for the discretionary accrual measure (e.g., the modified-Jones model, the performance-matched discretionary accrual model, and the modified DD model) and real earnings management *(*RM_{CFO}, RM_{PROD}, RM_{DISEXP}*)* are all equal to zero. The t-statistics show that all mean values are not significantly different from zero. Therefore, there is no systematic evidence of earnings management in the full sample. As shown in panel C, table 2, the standard deviations of *DAP* for the modified-Jones model, Kothari et al., (2005) model, and the modified DD model are 0.324, 0.317, and 0.123, respectively. Moreover, the standard deviation (SD) of the RM_{DISEXP} model is highest (0.542), and the lowest SD is for the RM_{CFO} with 0.299. As shown in Cohen et al. (2020), the SD of RM_{CFO} and RM_{DISEXP} are 0.520 and 0.400, respectively. The SD of the RM_{PROD} model is 0.409 that is similar to the result shown in. The descriptive statistics provide consistent results with Cohen et al. (2020), in which the REM measure of discretionary expenditures exhibit the highest variation.

4.2 Testing for bias in estimates of discretionary accruals and real earnings management

4.2.1 Sample 1: firms with artificially induced earnings management with no reversal

Before examining the power of the models, we test for bias in the estimates of discretionary accruals and real earnings management. As noted by Dechow et al. (1995), with a large number of independent observations (*PART*=1), unbiased estimators of the earnings management models should be equal to the magnitudes of income-increasing accruals. Table 3, panel A presents the results of estimates at magnitudes of accrual earnings management with artificially induced accrual manipulation to sample 1 ranging from zero to 10 percent of lagged assets. As presented in the preceding discussion, there is no assumption of full reversal of discretionary accruals or abnormal operating activities in the following fiscal year since each firm is randomly selected only once in year t.

The three types of accrual manipulation provide similar results, so we only include the results of coefficient estimates on *PART* for revenue manipulation activities. The results indicate that the modified Jones model (Dechow et al., 1995), Kothari et al. (2005) model and the modified DD model applied to estimate *DAP* do not appear to suffer biased estimates of abnormal accruals. The mean estimators are nearly equal to the artificially induced manipulation from zero percent to 10 percent of lagged assets. In addition, the modified-Jones model generates the t-statistics of mean coefficient on *PART* statistically different from zero when 3 percent of lagged assets ($p<0.05$) or more is artificially added to the model. The Kothari et al., (2005) model and the modified DD model have statistically significant mean coefficients on *PART* that is different from zero with artificially added amount of 2 percent of lagged assets or greater, at p-value<0.05. Compared to the time-series modified-Jones model by Dechow et al. (1995), the cross-sectional modified-Jones model in this study experiences a much higher rejection rate. For instance, the rejection rate presented in Dechow et al. (1995) is less than 30 percent for earnings manipulation of 5 percent of lagged assets, reaching 100 percent with artificially added earnings manipulation of 50 percent of lagged asset.

((Table 3 here))

Panel B presents results for all real manipulation models. The first column provides results of coefficient estimates on *PART* including artificially induced revenue manipulation from zero percent to 10 percent of lagged assets using sample 1. There appears to be misspecification in the model estimating abnormal cash flows as the sign of the estimators is negative with the induced earnings management from 0% to 6% of lagged assets and positive with the induced amount from 7% to 10% of lagged assets. Moreover, the coefficient estimate of REM_{CFO} is only statistically significant at the induced amount from 0% to 2% and 10% of lagged assets. The results indicate that the REM_{CFO} model gives biased estimators for artificially induced cash revenue manipulation from 0% to 10% of lagged assets.

In the preceding discussion, REM_{CFO} is influenced by other real earnings management activities (e.g., overproduction and reduction of discretionary expenses). Hence, the biased estimates of REM_{PROD} and REM_{DISEXP} might result in biased estimates of REM_{CFO}. In detail, both REM_{PROD} and REM_{DISEXP} are overestimated even with no manipulation (coefficient on *PART* = 0.035 and 0.034, for REM_{PROD} and REM_{DISEXP}, respectively when no manipulation is added). It indicates that abnormal cashflows are affected by the average of these real earnings manipulation. Accordingly, the mean REM_{CFO} are nearly underestimated by about -0.057 at zero manipulation.

The second column of table 3, Panel B, shows results of coefficient estimates on *PART* with artificially induced discretionary expense manipulation ranging from zero percent to 10 percent of lagged assets. In detail, the estimates of REM_{DISEXP} are overestimated by around 3.5% for the induced amount from 0% to 10% of lagged assets. Furthermore, the mean abnormal discretionary expenditures are statistically different from zero when the induced manipulation is between 7% to 10% of lagged assets. Additionally, the discretionary expense model experiences the highest value of standard error (0.020). This indicates that it is probable that this model suffers misspecification from omitting determinants of normal level of discretionary expenses (problem 2).

The third column documents the results of coefficient estimates on *PART* including artificially induced overproduction ranging from zero percent to 10 percent of lagged assets. The coefficient estimate of REM_{PROD} are overestimated by about 3% for all levels of induced earnings management. For example, when the induced manipulation is 1% of total assets, the coefficient on *PART* is equal to 0.044, which indicates manipulation of 4.4% of lagged assets. Moreover, the coefficients of *PART* are significantly different from zero at all levels of artificially induced earnings management. Importantly, when there is 0% of artificially induced manipulation, the coefficient on PART is 3.4% and statistically significant at the 5% level. It may be that the correlated inclusion of determinants of normal production leads to coefficients on *PART* that are not equal to zero even when there is no induced real earnings management in the model.

The results from table 3 (panels A and B) indicate that compared to real earnings management models, the discretionary accruals model has lower standard errors (0.012), suggesting that this model is more effective in generating normal accruals and suffer less bias caused by omitting determinants of normal accruals.

4.2.2 Sample 2: Sample of firm-years with artificially induced earnings management with reversal

Table 4 illustrates the results of coefficient estimates on *PART* using a random sample of 500 firm-year observations (sample 2) with artificially induced earnings manipulation from zero percent to 10 percent of lagged assets in year t. Since the random sample of firm-year includes firm-years with consecutive years, the assumption of the tests is that accruals and real operating manipulation activities fully reverse in the next year. The approach is implemented by adding induced earnings manipulation from zero percent to 10 percent of lagged assets to the random sample in year t and subtracting the same amount in year t-1.

Table 4, Panel A, presents the results of the estimates of the coefficients on *PART* with different magnitudes of artificially induced accrual manipulation ranging from zero percent to 10 percent of lagged assets using sample 2. As shown in the table, the estimators of accrual earnings management for the modified-Jones model and Kothari et al., (2005) model have quite low bias, which is the same as the result in panel A, table 3. The consistent findings indicate that the modified Jones model (Dechow et al., 1995), the performance-matched discretionary accrual model, and the modified DD model are well specified once applied to the random sample of firm-years and the sample of firms selected at random in an event year, t.

((Table 4 here))

The first column of table 4, panel B, provides the results of the coefficient estimates on *PART* including artificially induced revenue manipulation from zero percent to 10 percent of lagged assets in sample 2. The estimator of abnormal cash from operations is underestimated by about one percent and the coefficients on *PART* are statistically different from zero when induced manipulation is between 3% to 10% of lagged assets. The explanation is that the estimates of REM_{DISEXP} and REM_{PROD} in the random sample of firm-years are less biased, hence, REM_{CFO} might be not affected by the biased estimates of overproduction and reduction of discretionary expenses.

Nevertheless, the signs of coefficients on *PART* are all positive for all level of induced earnings management. In Roychowdhury (2006)'s paper, it is shown that suspect firms (i.e., firms that have high incentives to engage in earnings management) engaging in revenue manipulation have abnormal low cash from operations compared to other firms in the same industry. This unexpected sign of REM_{CFO} could be due to the inclusion of contemporaneous sales and sales changes to estimates of normal levels of cash flows from operations. However, once firms engage in revenue manipulation such as offer price discounts or channel stuffing, the model removes part of earnings management from the abnormal cash from operations proxy. As a result, the model for detecting revenue manipulations provides ambiguous signs of the estimators.

In column 2, we find that the estimate of REM_{DISEXP} is biased by about 0.5% at all levels of induced earnings management from 0% to 10% of lagged assets. The result indicates that when the sample has full reversal in the following fiscal year, the inclusion of other determinants for REM_{DISEXP} is relevant but not correlated with *PART*. Therefore, this could result in unbiased estimators for REM_{DISEXP} but the standard error of the model is higher (0.22) than the previous result (0.20).

In the third column, we find that the estimate of REM_{PROD} is underestimated by around 2% at all levels of induced real earnings management. This is contrary to the results in the sample of 500 firms at random from year t in the previous section, which are overestimated by 3% for all rates of artificially induced overproduction. This is because in this simulation, the full amount of REM_{PROD} is reversed in the next fiscal year. Therefore, omitted variables in measuring

REM_{PROD} is not correlated with *PART* (see problem 3, section 3.1). This is explained by the higher standard error in this sample (0.019) in comparison with the previous sample (0.017). As a result, while the estimates of *REM_{PROD}* in sample 1 is statistically significant for all levels, the estimate of *REM_{PROD}* in sample 2 is statistically different from zero only when manipulation is between 6% to 10%.

4.3 Power of tests for detecting artificially induced earnings management

Tables 5 and 6 provide further evidence on the ability of the models to detect earnings management. The results presented are the frequency with which the null hypothesis of no earnings management is rejected. In particular, the first column in table 5 presents the power of the test for *DAP* model for assumed sources of accrual manipulation in sample 1. Since the three assumptions of accruals managed give similar results, we only present results using revenue manipulation. The rejection rates of different models are calculated by using a one-tailed test at the five percent level. Therefore, the results show the frequency with which the discretionary accruals model and real earnings management models reject the null hypothesis of no earnings management using a one-tailed t-test at the 5% level. The results indicate that both the modified Jones model and Kothari et al., (2005) model generate rejection frequencies for the null hypothesis of no earnings management about 100% for artificially induced earnings management of around 5 percent of lagged assets or greater. In contrast, the power of the test using the modified DD model is 100% with the artificially induced earnings management of 4 percent of lagged assets. The high rejection frequency for the null hypothesis of no earnings management of the discretionary accrual model is related to the unbiased estimates of earnings management and low standard errors as shown in table 3, Panel A. Moreover, at the low levels of induced accrual manipulation such as 2 percent of lagged assets, the power of the test of the modified Jones model is 48%. In comparison with the time-series modified Jones model (Dechow et al., 1995), the cross-sectional modified Jones model has higher power for detecting accrual manipulation. For instance, Dechow et al. (1995) report rejection rates of 30% for artificially induced earnings management equal to 5 percent of lagged assets. Similarly, at the artificially induced earnings manipulation of 2 percent of lagged assets, the power of the test of Kothari et al., (2005) model is 53%. The power of the test using the modified DD model generates 78% at the artificially induced earnings manipulation of 2 percent of lagged asset. Among the three models to detect accrual earnings management, the modified DD model has the highest power to detect accrual earnings management. The higher power of the modified

DD model than the other traditional discretionary accrual models is due to the low standard error as shown in panel A, table 3.

The second column of table 5 shows the results of the power of REM_{CFO} model for detecting real earnings management, which uses artificially induced earnings management from zero percent to 10 percent of lagged assets. At the low level of artificially induced earnings management ranging from zero percent to 2 percent of lagged assets, the frequency of rejection for the null hypothesis of no earnings management is higher than that of the *DAP* model (ranges from 80% to 98%). Furthermore, the power of REM_{CFO} model is lower than that of *DAP* model for levels of induced earnings management from 3 percent to 10 percent of lagged assets. Specifically, the power of REM_{CFO} model achieves 71% for artificially induced earnings management at 10 percent of lagged asset. The lower power of the REM_{CFO} model is due to high biased estimates of earnings management as shown in table 3, Panel B.

The third column in table 5 gives the results of the power function for detecting discretionary expense manipulation. At rates of artificially induced earnings management of zero and 1 percent of lagged asset, the power of REM_{DISEXP} model is 53% and 34%, respectively. This is higher than the power of the *DAP* model possibly due to the bias in estimates as discussed in table 3, Panel B. Moreover, the results of the power test of REM_{DISEXP} model are lower than those of the *DAP* model for levels of artificially induced earnings management above 2 percent of lagged assets. Surprisingly, the rejection frequency is only 8% with induced manipulation of 3 percent and 4 percent of lagged assets, indicating very low power. The rejection frequency for the null hypothesis of no earnings management reaches 95% for artificially induced earnings management at 10 percent of lagged assets. The lower power than the *DAP* model is because the model has a higher standard error as shown in table 3, Panel B.

The last column in table 5 provides the power function of REM_{PROD} model for detecting real earnings management using the magnitude of the induced earnings management from zero percent to 10 percent of lagged asset. The REM_{PROD} model has higher power than the *DAP* model for all levels of induced earnings management. In detail, the rejection frequencies for the null hypothesis of no earnings management of REM_{PROD} model reaches nearly 100% for artificially induced earnings management of 3 percent of lagged assets and greater. The higher power function of REM_{PROD} model is due to upward biased estimates of earnings management in table 3, Panel B. Importantly, the rejection rate at the magnitude of no induced earnings manipulation is 64% indicating the misspecification of the model, in line with the results of the bias in estimators discussed earlier.

In general, using sample 1, the *DAP* model dominates real earnings management models except that the power of *DAP* model is lower than the REM_{PROD} model at the level of artificially induced earnings management from 1 percent to 5 percent of lagged assets. However, the high power of REM_{PROD} is due to upward bias in estimates of earnings management.

((Table 5 here))

Table 6 provides the power of the test of accrual earnings management model and real earnings manipulation at detecting artificially induced earnings management ranging from zero percent to 10 percent of lagged asset using sample 2. It is assumed that there is full reversal of artificially induced earnings management in the next fiscal year. All rejection rates are calculated at the five percent level using a one-tailed test.

The first column and second column of table 6 provides the results of the power of the modified-Jones model, Kothari et al., (2005) model and the modified DD model for different levels of induced manipulation ranging from zero to 10 percent of lagged assets. The rejection rates of the modified-Jones model of the random sample of firm-years are slightly higher than that of the sample of firms at random in year t due to reduction of standard errors. In detail, the rejection rates of the null hypothesis of no accrual earnings manipulation are close to 100% around induced manipulation of 4 percent of lagged assets and greater. Moreover, at low levels of induced earnings management such as 2 percent of lagged assets, the rejection frequency is 54%. The result indicates that the cross-sectional accrual-based earnings management model improves the power of the models and controls for the full reversal of discretionary accruals in the next fiscal year. In contrast, the Kothari et al., (2005) model has slightly lower power of the test for the sample (2) than that of sample (1) with the artificially induced earnings management from zero percent to 3 percent of lagged asset because of higher standard errors shown in panel A, table 4. At the induced earnings manipulation of 5 percent of lagged asset or greater, the rejection rates of the performance-matched discretionary accrual model are equal to 100%. Moreover, the power of the modified DD model using sample (2) are approximately equal to that of using sample (1). In detail, the power of the modified DD model is 100% at the induced earnings manipulation of 4 percent of lagged asset or greater. Consistent with the results shown in table 5, the power of the modified DD model is higher than the remaining models to uncover accrual earnings management when using sample (2) in the study.

As shown in the third and fourth column of table 6, both REM_{CFO} and REM_{DIEXP} models have higher power of the tests compared to those of sample 1. In detail, the rejection frequencies of

REM_{DISEXP} model generates nearly 100% for artificially induced earnings management of 8 percent of lagged assets. The improvement in the power REM_{DIEXP} is likely due to less biased estimates of earnings management as shown in table 4, panel B. Moreover, the REM_{CFO} model reaches the power of 99% for artificially induced earnings manipulation at 4 percent of lagged assets. In comparison with the power of sample 1, the power of the test to detect revenue manipulation for sample 2 significantly improves due to unbiased estimates of earnings management as shown in table 4, panel B.

The final column of table 6 shows the results of the power of REM_{PROD} model for detecting real earnings manipulation. In comparison with the power of REM_{PROD} model of sample 1, the power of REM_{PROD} model of sample 2 is lower. This may be because of the downward bias in the estimate of earnings management (see table 4, panel B) resulting in reducing the power of the test. The power of the REM_{PROD} model reaches 99% rejection rate for the artificially induced earnings management at 10 percent of lagged assets.

((Table 6 here))

4.4 Alternative model to detect abnormal research and development expenses (R&D)

Graham et al., (2005) indicate that reduction in investment of R&D expenses or selling, general and administrative (SG&A) expenditures is one of the most preferred technique to overstate earnings. The modelling of discretionary expenses including advertising, R&D and SG&A expenses by Roychowdhury (2006) as a function of lagged revenue exposes limitations of the model through omitted variables. Some prior studies measure the normal level of R&D by including lagged R&D to control for firms' opportunity for R&D expenditure in the current year (see Gunny, 2010; Kothari et al., 2016). Indeed, Darrough and Rangan (2005) explain that firms might use lagged R&D as a starting point for setting the budget for current year R&D. Therefore, the model for normal discretionary expenses by Roychowdhury (2006) may experience problem 2 since it excludes relevant previous year R&D in the model. Accordingly, there may be biased estimates and low power of the tests for estimating discretionary expenses. In this section, we modify the model proposed by Roychowdhury (2006) for estimating discretionary expenses by including lagged R&D expenses in the model. As a result, the model to estimate the normal level of R&D expense is as below:

$$\frac{R\&D_t}{A_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{t-1}} + \beta_1 \frac{REV_{t-1}}{A_{t-1}} + \beta_2 \frac{R\&D_{t-1}}{A_{t-1}} + \varepsilon_t \quad (14)$$

Where $R\&D_t$ is research and development, advertising and selling, administrative expenses in year t; $R\&D_{t-1}$ is research and development, advertising and selling, administrative expenses in year t-1; all other variables are as previously defined.

We use samples 1 and 2 with artificially added real earnings manipulation from zero percent to 10 percent of lagged assets to test for the bias of the estimates of the real manipulation measure. The assumption concerning reduction in recognition of R&D expense is used in the simulation. Specifically, we subtract the assumed amount of real earnings manipulation in the earnings management year. As for sample 1, there is no assumption of full reversal in the next year. In contrast, the full reversal is applied in the following year in sample 2.

The results are similar across samples 1 and 2. Therefore, we present results only for sample 1. Table 7 presents results for testing the bias in estimates of abnormal levels of R&D expenses. From the table, we see that the coefficient on *PART* is close to the induced amount of manipulation for all levels, with significant coefficients at all levels of manipulation. Only when there is no added manipulation (zero percent) is the coefficient on *PART* not significant (p-value = 0.841). This is a significant improvement from the results in table 4, Panel B, where the coefficients are only significant at manipulation levels of 5% and above.

((Table 7 here))

Table 8 shows the rejection rates at alternative levels of induced earnings management. All rejection rates are calculated at a 5% significance level using one-tailed tests. Due to unbiased estimates of real earnings management and low standard errors, the alternative model generates high power of the test to detect abnormal R&D expenses. At the level of induced earnings management of one percent of lagged asset, the rejection frequency with which the null hypothesis of no earnings management is rejected is 80%. From the induced earnings management ranging from two percent and greater, the power reaches 100%. In comparison with the previous results of the power test for REM_{DISEXP} in table 5, the rejection rates for the alternative model to detect abnormal level of R&D expenditures are higher.

((Table 8 here))

Therefore, the alternative model for detecting abnormal R&D expenditures by adding lagged R&D expenses to the model estimating normal R&D expenditures by Roychowdhury (2006) generates unbiased estimates of real earnings management as well as high power of tests to detect abnormal R&D expenditures. This significant improvement in the new model results from reducing measurement errors. Future research could focus on developing effective models for detecting the remaining types of real earnings management such as overproduction and revenue manipulation.

5. Robustness testing

In this section, we include several robustness tests to ensure our results are not due to methodological or sample issues.

First, in the main analyses, we include financial firms in the sample, which have different regulatory and financial reporting requirements. As robustness, we exclude all financial firms and find the (untabulated) results are qualitatively similar. Specifically, both the modified-Jones model and the Kothari et al., (2005) model generate rejection frequencies for the null hypothesis of no income-increasing earnings management at 100% for artificially induced accrual manipulation of around 5 percent of lagged total assets or greater. As for the modified DD model by Francis et al. (2005), the power of the test generates 100% detection for artificially induced accrual manipulation of around 4 percent of lagged total assets or greater. In addition, the power of the tests to detect accrual earnings management have higher power in comparison to real earnings management models.

Second, Hribar and Collins (2000) find that there are articulation problems when calculating accruals using balance sheet accounts. As an alternative, we measure total accruals as the difference between net income and cash from operations. The (untabulated) results are similar to those reported in the main analyses.

Third, in the main analyses, our measure of discretionary accruals in Equation (8) uses the current year performance of the firm (ROA), which may be problematic given that accruals will be part of the current year performance. As additional robustness, we rerun all analyses using lagged ROA instead. The (untabulated) results are again similar to those reported in the main analyses.

Fourth, we use recently introduced alternative measures of real earnings manipulation as in Srivastava (2019), which are shown to be more robust than the Roychowdhury (2006) variables. Specifically, Srivastava (2019) argues that the real manipulation models do not control for the competitive strategy of the firm and include five new variables into the Roychowdhury (2006) models. These are: 1) Log market value as a proxy for size 2) Lagged ROA; 3) Market to book value as a proxy for growth; 4) Future revenue (t+1); and 5) Lagged value of the dependent variable (i.e., cash from operations, discretionary expenses, and production costs in equations

11, 12, and 13, respectively). We rerun all analyses using the three alternative variables for: REM_{CFO}, REM_{DISEXP}, and REM_{PROD}. The results are presented in tables (9) and (10).

Table 9 (Panel A) replicates the results presented in table 3 (Panel B) for sample 1. The model for REM_{CFO} suffers less misspecification and the coefficients are closer to the amount of manipulation added to the sample and the coefficients are significant for manipulation of 2% and above. Therefore, there is improvement from using this model and its accuracy is similar to that of accrual manipulation models. As for REM_{DISEXP} there is less bias and the coefficients are close to the manipulation amount added. Furthermore, the variable *PART* is significant for manipulation of 3% or above of lagged assets. In the third column, we find that the estimate of REM_{PROD} is underestimated by around 4% at all levels of induced real earnings management. Furthermore, the estimates of REM_{PROD} in sample 1 are only statistically significant when manipulation is between 8% and 10%. These results contrast with those in table 3, where REM_{PROD} is significant at all levels of manipulation. Therefore, the real manipulation models for REM_{CFO} and REM_{DISEXP} have less misspecification than before. However, REM_{PROD} has more misspecification than the accrual models shown in table 3 (Panel A).

Table 9 (Panel B) replicates the results presented in table 4 (Panel B) for sample 2 which includes reversal of the manipulation in the following period. The coefficients for REM_{CFO} are under-estimated by around 2% and are significant only when manipulation is 5% or more. This indicates poor specification as compared to the earlier results where the coefficients were closer to the value of added manipulation. The coefficients for REM_{DISEXP} are misspecified by about 1% and are only significant when manipulation is 7% or above, again showing worse performance than results in table 4 (Panel B). Finally, REM_{PROD} shows very poor specification with coefficients on *PART* between 30-40% for all levels of manipulation. Therefore, all alternative models perform worse than the original models in sample 2. This also indicates more misspecification than accrual models. This is likely due to the reversal of manipulation in the following year in this sample, which causes misspecification in models that include lagged variables to determine normal levels of cashflows, discretionary expenses, and production.

((Table 9 here))

Table 10 replicates the results shown in tables 5 and 6. The results in panel A for sample 1 show that the rejection rates are equal to 100% at manipulation rates of 4% or more for both REM_{CFO} and REM_{DISEXP} but only approaches 88% at the highest level of manipulation for REM_{PROD}. This shows improvement from results in table 5 for both REM_{CFO} and REM_{DISEXP} but not for

REM_{PROD}. In fact, the rejection rates for *REM_{CFO}* and *REM_{DISEXP}* are higher than those for all discretionary accrual measures. In contrast, rejection rates for *REM_{PROD}* are lower than those for all measures of discretionary accruals. This corroborates the findings in table 9 that the Srivastava (2019) models perform better than the accrual models for some accounts (*REM_{CFO}* and *REM_{DISEXP}*) but not for others (*REM_{PROD}*).

The results in panel B repeats the analyses in sample 2. We find the rejection rate for *REM_{PROD}* is 100% at all levels of manipulation, but this is due to bias in the coefficients as seen in table 9. In addition, the rejection rate exceeds 90% only at 8% of manipulation for *REM_{CFO}* and 89% at 10% manipulation for *REM_{DISEXP}*. This indicates worse rejection rates for the alternative measures in sample 2 compared to the models in table 6 as well as discretionary accruals.

((Table 10 here))

Overall, the results provide mixed interpretation showing better performance of real manipulation models than accrual models in some cases (e.g., *REM_{CFO}* and *REM_{DISEXP}* in sample 1) but worse performance in other instances (e.g., *REM_{CFO}* and *REM_{DISEXP}* in sample 2 and *REM_{PROD}* in sample 1).

Finally, we use an alternative context to investigate the power of the accrual and real manipulation models, namely meeting/beating earnings benchmarks. Prior evidence shows that firms have incentives to manipulate earnings to meet or beat prior year's earnings as well as to avoid reporting losses (e.g. Burgstahler & Dichev, 1999; Roychowdhury, 2006; Zang, 2012). We therefore use this context to investigate the models described above through the following regression:

$$\mathrm{EM}_{\mathrm{it}} = \beta_0 + \beta_1\,\mathrm{SUSPECT}_{\mathrm{it}} + \beta_2\,\mathrm{SIZE}_{\mathrm{it}} + \beta_3\,\mathrm{BIG4}_{\mathrm{it}} + \beta_4\,\mathrm{ROA}_{\mathrm{it}} + \beta_5\,\mathrm{LEV}_{\mathrm{it}} + \beta_6\,\mathrm{M/B}_{\mathrm{it}} + \sum_j \beta_j\,\mathrm{INDUSTRY}_{\mathrm{DUMMY}_{\mathrm{it}}} + \sum_k \beta_k\,\mathrm{YEAR}_{\mathrm{DUMMY}_{\mathrm{it}}} + \varepsilon_{\mathrm{it}} \tag{15}$$

The dependent variable (EM) is the different accrual/real earnings management measure using the alternative models illustrated in section 3.2 as well as the Srivastava (2019) models above.

Following Cohen et al., (2008), SUSPECT is set as 1 for firm-year observations with net income before extraordinary items scaled by total assets that lies in the interval [0, 0005), or the change in net income before extraordinary items scaled by total assets that lies in the interval [0, 0005), 0 otherwise.

We include control variables to account for firm size, firm performance (Roychowdhury, 2006) and growth opportunities (Bartov et al., 2002; Kaznik & McNichols, 2002). SIZE is the natural logarithm of total assets. Big4 is an indicator variable set equal 1 if the auditor is a Big 4 firm, 0 otherwise. ROA is return on assets, calculated as income before extraordinary items divided by lagged total assets. LEV is measured as long-term debt divided by total assets. M/B is market-to-book ratio, calculated as the market value of equity divided by the book value of common shareholders' equity. The model is estimated by using a probit regression with heteroscedasticity-robust standard errors. The results are presented in table 11.

((Table 11 here))

The sample is reduced due to data requirements of the control variables. In the first three columns, we find evidence of accrual manipulation at similar levels using the modified Jones model (Coefficient on Suspect = 0.010, significant at the 1% level), the Kothari et al. (2005) model (Coefficient on Suspect = 0.010, significant at the 1% level) and the DD model (Coefficient on Suspect = 0.006, significant at the 1% level). In terms of real manipulation, there is less evidence of this occurring in this sample and there are some differences between the alternative models. Specifically, there is no evidence of manipulation using cashflows or overproduction. However, there is evidence of reducing discretionary expenses but the magnitude is different using the alternative models (Coefficient on Suspect = 0.031 and 0.009, significant at the 1% level using the Roychowdhury (2006) models and the Srivastava (2019) models, respectively). Therefore, there appears to be less evidence of real manipulation (1-3% of total assets for discretionary expenses) compared to accrual manipulation (6-10% of total assets) and there are differences across the different models. This is in line with our earlier evidence that accrual manipulation may be easier to be detected using the current models than real manipulation.

6. Discussion and conclusion

The study compares the ability of the commonly used models to detect accrual earnings management (e.g., modified-Jones model, Kothari et al., (2005) model and the modified DD model) and real earnings manipulation in random samples with artificially induced manipulation ranging from zero percent to 10 percent of lagged assets. With respect to accrual earnings management, we find that the modified DD model by Francis et al. (2005) has higher power than the modified-Jones model or the Kothari et al., (2005) model in detecting accrual earnings management due to lower standard errors of the estimates of earnings management. Moreover, in comparison with the time-series modified Jones model using a US sample of firm-years, the cross-sectional modified Jones model using the sample of listed firm-years in the UK provides higher power tests of earnings management. In detail, the cross-sectional modified Jones model in this study generates the power of the tests above 48% with the induced earnings management of 2 percent of lagged assets. In addition, the cross-sectional modified Jones model has 100 percent of power for testing upward earnings management at manipulation of 5 percent of lagged assets and above. In contrast, at the artificially induced earnings manipulation of 10 percent of lagged asset, the time-series modified Jones model by Dechow et al. (1995) has the power of the test of nearly 35 percent. Additionally, the Kothari et al., (2005) model using the UK sample in this study has higher power than that using the US sample by Kothari et al. (2005). In particular, where the added earnings manipulation is 2 percent of lagged assets, the Kothari et al. (2005) model using the UK sample in this study has the power of the test about 53 percent, compared to nearly 30 percent for the performance-matched discretionary accrual model by Kothari et al. (2005) using a US sample.

Compared to real earnings manipulation, the power of the tests for accrual-based earnings management (e.g., the modified-Jones model, Kothari et al., (2005) model, and the modified DD model) dominate that for real earnings manipulation. Furthermore, while the three accrual models used (the modified-Jones model, Kothari et al., (2005) model, and the modified DD model) provide unbiased estimates of earnings management when applied to the sample of firms selected at random in year t (sample 1) as well as the random sample of firm-years (sample 2), real earnings management models experience biased estimates for earnings management in the sample of firms at random in year t (sample 1). Correspondingly, the power of real earnings manipulation is affected by biased estimates of earnings management. Specifically, the downward bias in estimates of expense manipulation result in low power tests of the normal discretionary expenses model. In contrast, the upward bias in estimates of overproduction leads to high power of the normal production model. Furthermore, the high bias in estimates of revenue manipulation cause low power of tests for detecting revenue manipulation.

The implication of this study is that when the models to detect real earnings management are applied for a given sample of firms at random, there are biases in estimates of real earnings management, resulting in an ambiguous power of the tests. Moreover, the power for detecting accrual earnings management is higher than that for detecting real earnings manipulation.

The findings of this study indicate that for academics and in practice, real earnings management is more difficult to be detected by outside stakeholders. Up to now, there has been no systematic evidence evaluating the ability of existing models to detect real earnings management. The study contributes to evaluating the power issues related to the measurement of real earnings manipulation activities. The findings of this study provide a warning to academics about the use of academic models of real manipulation. Specifically, although prior studies widely apply the Roychowdhury (2006) model to detect real earnings manipulation in the US context (e.g. Cohen et al., 2010; Zang, 2012), in the UK context (e.g. Alhadab et al., 2015; Alhadab and Clacher, 2018; Haga et al., 2018), and in other settings (e.g. Achleitner et al., 2014 in Germany), the misspecification and the ability of the models to detect real earnings manipulation is questionable. We investigate an alternative model to detect abnormal research and development (R&D) expenditures by adding last year's R&D amount. The alternative model provides higher power and less misspecification than the Roychowdhury (2006) Model. We also investigate recently proposed models in Srivastava (2019) and find these are better able to detect manipulation in some contexts (e.g., revenue manipulation and reduction in discretionary expenses in sample 1 with no reversal) but perform worse in other cases (e.g., revenue manipulation and reduction in discretionary expenses in sample 2 with reversal). Further research should focus on developing better models to uncover real earnings management.

As with all research, this study has limitations. First, firms may systematically manipulate real accounts and therefore the random sample includes actual manipulation of cashflows, discretionary expenses, and production costs.

Second, prior evidence indicates the models to detect earnings management are misspecified, especially for firms with extreme performance. We do not investigate this issue. Furthermore, in the current study, we do not attempt to make improvements to the accrual and real manipulation models in the literature except for discretionary expenses. This is left for future research.

In addition, we focus on the UK context rather than conduct a cross-country analysis to avoid confounding effects of financial reporting or legislative environment differences; therefore, our results may not be generalizable to other contexts.

Furthermore, although prior studies have applied the industry cross-sectional models to examine real earnings management, Ecker et al. (2013) and Haga et al. (2015) show that using this grouping method is subject to sample attrition and may result in biased samples. Therefore, we decide not to use alternative groupings of accrual and real manipulation models to compare our results to prior work that predominantly use the industry grouping methodology.

Another important issue relates to the methodology in the models tested whereby the residual of the regressions presented is taken to represent abnormal levels that proxy for manipulation.

Chen et al. (2018) and Christodoulou (2018) show that this method generates biased coefficients with both Type I and Type II errors. However, we do not expect any systematic differences between accrual and real manipulation models which may affect our results.

Finally, whereas previous studies examining the power of specification of earnings management models have used both simulated samples as well as samples of real earnings management cases, we do not present results based on this second sample. Identifying firms that have managed earnings in a UK sample is not as straightforward as in the US, where the Securities and Exchange Commission (SEC) report the Accounting and Auditing Enforcement Releases (AAERs) that include firms that have allegedly manipulated profits. We do however test the models in the context of a previously documented incentive to manipulate earnings, namely meeting/beating earnings benchmarks.

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