ACCRUAL EARNINGS MANAGEMENT, REAL EARNINGS MANAGEMENT, AND INFORMATION UNCERTAINTY

By

Thi Thu Ha Nguyen

Kingston University

Kingston Business School

Thesis submitted for the degree of

Doctor of Philosophy

ABSTRACT

The aim of this thesis is to contribute to the research on earnings management, by first investigating models of real earnings management, then extending the literature by examining both accrual and real earnings management within the context of information uncertainty. The thesis comprises of three main studies which analyse secondary data of firms with available data that are listed on the London Stock Exchange during the period from 1992 to 2018.

In the first empirical chapter, the relative performance of models to detect accrual earnings management and real earnings management is evaluated by comparing the power of widely used models. The power of test statistics of earnings management detection models is evaluated through examining the frequency with which detection models of accrual earnings management and real earnings management generate type II errors. I adopt a similar approach to that used by Dechow et al. (1995) and Brown and Warner (1985) in which I randomly select a sample of firm-year observations and artificially add accrual manipulation and real earnings management with the magnitude ranging from 0 percent to 10 percent of lagged assets. I compare the bias in the estimates of accrual earnings management generated by Dechow et al. (1995), Kothari et al. (2005), Modified Dechow and Dichev (2002) model and real earnings management produced by the Roychowdhury (2006) models. The results show that the detection models for real earnings management generates larger biased estimates of real earnings management activities compared to models to detect accrual-based earnings management. Among the three types of real earnings management activities, the power of the model for detecting real-based sales manipulation is lowest due to the biased estimates. Moreover, the power of the model for uncovering abnormal research and development (R&D) expenditure is improved when lagged R&D expenditures is added to the existing model.

The second empirical chapter investigates the role of information uncertainty in explaining the opportunistic behaviour of managerial discretion when firms have high incentives to manage earnings (i.e., meeting/beating earnings benchmarks). To address endogeneity, in which there are potential differences in characteristics of suspect firms (i.e., those beating earnings expectations) and non-suspect firms (i.e., those missing earnings expectations), I apply propensity score matching (PSM) developed by Rosenbaum and Rubin (1983) (Shipman et al., 2016). More specifically, suspects are matched with non-suspects (by one-

to-one matching without replacement) that have the closest propensity-matching score. These scores are based on a range of different firm characteristics. In addition, this study also uses Heckman (1979) selection model that depends on a particular functional form to give an indirect estimate of suspect firms' treatment effects. This empirical evidence contributes to the existing literature by determining the condition in which accrual-based earnings management occurs. Under the condition of high information uncertainty, managerial opportunistic behaviour is unobservable and difficult to detect by market participants; hence, the result shows that when facing high information uncertainty, managers of firms beating earnings expectation are more likely to use discretionary accruals. Moreover, managers of suspect firms also engage in earnings smoothing under the condition of high information uncertainty. In addition, this study contributes to the literature by exploring the role of information uncertainty in managers' decisions to use accrual earnings management compared to real earnings management.

The last empirical chapter examines the effect of information uncertainty on the long-run performance of firms meeting/beating earnings expectations. There is mixed evidence about whether market participants are irrationally over-optimistic about the information contained within earnings announcements. The evidence provided in this chapter contributes to our knowledge on the interaction effect of information uncertainty on the mispricing of investors. Indeed, empirical results show that firms meeting/beating earnings benchmarks underperform in the long-run period under high information uncertainty compared to low information uncertainty, after controlling for variables such as firm size, market-to-book ratio, capital expenditures, and sales growth in the fiscal year that earnings are announced. The results are robust after using alternative measures of stock performance. The evidence overall suggests that the condition of information uncertainty is necessary for explaining irrational behaviour of investors. These findings indicate that future underperformance may follow managed earnings under high information uncertainty.

ACKNOWLEDGEMENTS

To make my PhD thesis possible, my Mum and my Dad are always the sources of inspiration for me to overcome obstacles on the road to my achievements I have made. Their endless love, encouragement and understanding give me huge motivation for completing my PhD thesis. They are always in my heart, and I would like to express my gratitude for never leaving me alone whatever I get in my life, success, or failure. I also thank my husband for his patience in this long journey to complete my PhD thesis.

I would like to wholeheartedly thank my supervisors, Professor Salma Ibrahim, and Dr George Giannopoulos, without them I cannot go this far. They not only have shared me with their expertise, knowledge, but also have helped me overcome difficult time during my PhD journey. Absolutely, the experience that I have had when working with my supervisors is absolutely one of the best, I get out of my PhD study.

I would also like to thank Kingston University, Kingston Business School in general for giving excellent research environment, facilities, and necessary support during my study here. Especially, I am so thankful to Kingston Business School to provide me the full-funded studentship. Without this generous funding, I would not be able to achieve my dream about pursuing PhD program. I would like to thank the research panel committees and administrative staffs at Kingston University, Kingston Business School who conducted all paperwork and procedures related to my thesis.

I am also thankful to many other people who in one way or the other contribute to my PhD journey. The feedback and comments I received from faculty, discussants and participants at conferences are valuable for me. Finally, I also thank my friends for their interests in my work or simply be there for me.

Table of contents

List of tables

List of figures

List of Abbreviations

Abbreviation	Meaning
A	Total asset
A/R	Account receivable
REM_{CFO}	Abnormal cash flows
REM_{DISEXP}	Abnormal discretionary expenditure
REM_{PROD}	Abnormal production costs
A_REAL	Total real earnings management
A_ROA	Adjusted return on asset
BENCH	Benchmark
BHAR4F	Fama-French four-factor model
BHRR	Buy-and-hold return
BHSAR	Buy-and-hold size-adjusted returns
CA	Current assets
CAPEX	Capital expenditures
CFO	Cash flow from operations
CL	Current liabilities
COGS	Cost of goods sold
DAP	Discretionary accruals
DD	Dechow and Dichev
DEP	Depreciation and amortization expense
DISEXP	Discretionary expenses
DSRI	Days' sales in receivable
DTR	Discretionary accruals to real earnings management
EM	Earnings management
EPS	Earnings per share
GAAP	Generally Accepted Accounting Principles
IAS	International Accounting Standards
IFRS	International Financial Reporting Standard
IMR	Inverse mill ratio
INVT	Inventory
IPO	Initial public offering
IU	Information uncertainty
LEV	Leverage
M/B	Market to book value
NDA	Non-discretionary accruals
NON_SUSPECT	Non-suspect firms
NRA	Normal real activities
NRV	Net realisable value
OLS	Ordinary least square regression
PPE	Property, plant, equipment
PROD	Production costs
PSM	Propensity score matching

R&D	Research and Development
REC	Receivables
REM	Real earnings management
REV	Revenue
ROA	Return on Asset
SD	Standard deviation
SE	Standard error
SEO	Secondary equity offering
SGAI	Sales, general, and administrative expenses index
SGI	Sales growth index
SHARE	Share outstanding
SIG_CFO	Standard deviation of operating cash flows
SIZE	Firm size
SMOOTHING	Income smoothing
SPREAD	Bid ask spread
STD	Short term debt
SUSPECT	Suspect firms
TA	Total accruals
TATA	Total accruals to total assets
TOA	Total operating activities
UK	United Kingdom
US	United State
VOLATILITY	Stock return volatility
VOLUME	Trading volume

CHAPTER 1: THESIS INTRODUCTION

1.1 Background of the thesis

This thesis aims at contributing to earnings management research in different ways. First, the thesis contributes to the strand of research on the evaluation of academic models to detect earnings management by comparing the specification and power of the accrual-based and real-based earnings management models. The most notable models to detect real activities can be found in the study conducted by Roychowdhury (2006), which develops three models to capture three activities of real earnings management. Although the Roychowdhury (2006) model is widely applied in accounting research, until now, to my knowledge there have been lack empirical evidence about the specification as well as power of these models for uncovering real earnings management activities. 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; Siriviyakul, 2021). However, no study has assessed both accrual and real manipulation models in the same sample to compare their relative effectiveness in detecting manipulation. Importantly, 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 perform better when there is no reversal of the manipulation in the following year but suffer from lower power when the reversal does not occur in the following year. Therefore, the findings of the study contribute to the literature on the substitution/complementarity 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) by comparing the effectiveness of the current models of accrual and real manipulation as proxies of earnings management in the same sample with similar levels of manipulation.

Secondly, recent literature provides evidence that managers of firms trade-off between accrual earnings management and real earnings management based on their own relative costs (see Cohen et al., 2010; Zang, 2012). This study extends previous studies by introducing the role of IU on managerial choices of selecting accrual earnings management versus real earnings management. In addition, this study compares the trade-off between

accrual and real manipulation in a context that has never been investigated before, as far as my knowledge is concerned.

Finally, previous literature provides pervasive evidence about discontinuity in earnings distribution around prominent benchmarks (e.g., Burgstahler and Dichev, 1997; Holland and Ramsay, 2003). There is the large number of empirical studies about the subsequent consequences of earnings management. However, findings of these studies are not conclusive. This study provides evidence that IU plays a role in explaining the managerial discretion in beating/meeting earnings benchmarks. The results of this study indicate under high IU, managers of firms manage earnings to meet and beat earnings benchmarks to mislead investors about subsequent firms' performance. Therefore, there is negative relationship between benchmark beaters and long-run performance under high IU.

This thesis includes three empirical chapters. The first empirical chapter of this thesis focuses on comparing the relative performance of accrual and real earnings management models by evaluating specification and power of commonly applied earnings management models. Real earnings management activities are similar to normal business activities of firms; hence, market participants may find it hard to detect such behaviour than accrual earnings management. It is expected that real earnings management is more difficult to be detected than accrual earnings management in theory and in practice.

The second empirical chapter of this thesis examines the effect of information uncertainty on accrual earnings management. Moreover, in this chapter, the role of information uncertainty (hereafter IU) on managerial choice between accrual earnings management and real earnings management is investigated.

The third empirical chapter of this thesis examines the effect of IU on subsequent performance of firms meeting/beating earnings benchmarks. When the IU is high, outside market participants do not have sufficient resources to assess the accuracy of reported earnings that are managed by managers (Schipper, 1989; Warfield et al., 1995). Accordingly, managers of firms have more opportunities to manage earnings to meet earnings benchmarks without being detected under high IU. Therefore, IU could influence the opportunistic purpose of managers to mislead investors when managers of firms meet or beat earnings benchmarks.

1.2 Motivation of the thesis

According to the Company Act (2006), one of the UK financial reporting regulations is that financial statements of firms must provide a true and fair view of financial reporting. Accordingly, accounting numbers should credibly convey private information on firm performance. However, accounting standards allow firm managers to exercise flexibility in the estimates of accounting choice when preparing financial reports. This results in information asymmetry between managers and outside investors and other stakeholders that gives opportunities for managers to implement opportunistic discretion when preparing financial reports. Therefore, there has been significant interest in examining this discretion, which is termed earnings management, from academics, regulators as well as practitioners. "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 and Wahlen, 1999, p. 368). Clearly, earnings management can influence the reliability of financial reports that will affect economic consequences for market participants. Consequently, studies of earnings management are important for regulators as well as market participants.

Recent studies have increased interest in real earnings management (Graham et al., 2005; Kothari et al., 2016). I refer to real earnings management as managers' actions that deviate from normal business activities of firms for the purpose of altering the financials of the firm (Roychowdhury, 2006). Although previous research indicates that real earnings management is more difficult to be detected than accrual earnings management (e.g., Cohen et al., 2008; Jiang et al., 2018), as far as I am aware there has been no research to investigate this. The purpose of this study is first to close this gap by focusing on comparing the abilities of commonly used earnings management models to detect accrual earnings management and real earnings management. Moreover, despite the widespread use of the real earnings management models suggested by Roychowdhury (2006) in academic accounting research, there has been limited evidence about the evaluation of the ability of this model to uncover real earnings management. This study evaluates the power of the test of this model to uncover real earnings management.

Although accounting standards allow managers to exercise accounting judgement to make financial reporting more informative for users, firm managers can use discretion in financial

statements to manage earnings. Previous studies show that earnings management can occur when outside stakeholders are not able to uncover it (Healy and Wahlen, 1999). Jiang et al. (2005) show that high level of IU can result in less available public information for market participants. Accordingly, in the lower public information environment such as high IU, investors find it difficult to disentangle underlying firm performance from earnings information managed by managers (Dye, 1988; Trueman and Titman, 1988). However, there has not been empirical evidence on whether IU affects or not accrual earnings management. This thesis aims to investigate this research question.

Moreover, there is recent research interest in the trade-off between accrual earnings management and real earnings management (see Cohen and Zarowin, 2010; Zang, 2012; Owusu et al., 2020). These studies indicate that when firms are constrained by increasing professional scrutiny and reducing accounting flexibility, they are likely to increase the use of real earnings management to avoid the detection of accrual earnings management. As previously noted, when both types of earnings managements are difficult to be detected in the high IU environment, managers of firms are likely to make choices of the method that gives the higher benefit. Previous studies provide evidence that real earnings management has a more negative effect on firm performance than accrual earnings management in the long-run (see Graham et al., 2005; Cohen and Zarowin, 2010; Kothari et al., 2016). Therefore, it is considered that firms are likely to prefer using accrual earnings management to real earnings management under high IU. Nevertheless, until now, to my knowledge there has not been any research to investigate whether IU can influence the trade-off between accrual earnings management and real earnings management. This study investigates this research question, as well.

As documented in prior literature, firm managers have the largest incentive to manage earnings when moving firms from a relative or absolute loss to gains (Burgstahler and Dichev, 1997; Degeorge et al., 1999; Coulton et al., 2015). As documented in these studies, there is significant increase in benefits for firms beating/meeting earnings benchmarks (i.e., immediately above zero level of earnings and zero changes in earnings) that reflect earnings management behaviour. The subsequent economic consequences of firms managing earnings to beat/meet earnings benchmarks are not conclusive. Some studies document that benchmark beating through delaying the recording of R&D expenditures can help to signal private information about future firm performance (e.g., Dinh et al., 2016; Al-Shattarat et al., 2018). This can be beneficial for market participants. In contrast, other studies indicate

that managers of firms manage earnings through using discretionary accruals to beat earnings benchmarks and mislead investors about subsequent firm performance (see Dechow et al., 2000; Coulton et al., 2015). In this case, investors are not able to see through the implications of benchmark-beating through managing earnings; hence, benchmark-beaters can experience long-run underperformance. Clearly, under certain conditions, market participants can detect, hence, react to benchmark-beating. However, under other circumstances, they may fail to detect it. As illustrated above, when IU is high, market participants find it difficult to detect earnings management. Moreover, previous studies show that under high IU, investors experience biased behaviour such as overconfidence (Jiang et al., 2005; Zhang, 2006b). Therefore, firm mangers have opportunities for practicing opportunistic earnings management. As far as I am aware, until now there have not been any studies that examine whether IU can affect the subsequent performance of firms beating earnings benchmarks. Thus, this thesis aims to fill this gap.

1.3 Objectives of the thesis

As illustrated above, although there is recent interest in research on real earnings management but there is limited evidence about evaluating the ability of models to detect real earnings management. Moreover, market participants face uncertainty about reported earnings in financial reporting. Accordingly, under high IU, when managerial behaviour is not observable, managers of firms are likely to engage in earnings management to mislead investors about their underlying firm performance. Therefore, this thesis aims at contributing to earnings management literature by comparing the ability to detect accrual earnings management and real earnings management as well as investigating the effect of IU on managerial behaviour. The research objectives of this thesis are the following:

i. Investigate the power of models of accrual and real manipulation to determine issues in detecting both
ii. Examine the effect of IU on accrual earnings management
iii. Compare the trade-off between accrual and real manipulation under IU
iv. Investigate long-term market effect of manipulation under IU

1.4 Methodology and data

This thesis uses financial data from the Datastream database to evaluate the abilities to detect earnings management as well as investigate the effect of IU on managerial behaviour. The sample of this study includes all “dead” and “live” firms listed on London Stock Exchange

from 1992-2018. The data analysis in this thesis applies both univariate and multivariate approaches. Firstly, this thesis uses a similar approach to that suggested by McNichols and Wilson (1988) and. Following Brown and Warner (1985), managed earnings are artificially added to accruals and real accounts to evaluate the frequencies of relative accrual earnings management models and real earnings management models generate type II errors when the null hypothesis is false. Furthermore, to test the trade-off between accrual earnings management and real earnings management in the high IU condition, I use a sample of firm-year observations that are likely to manage earnings. I follow the same approach by Burgstahler and Dichev (1997), where there is high frequency of firms having small increases in earnings and small positive income. I also use an ordinary least square regression in the main test. To control for the potential differences in firms beating earnings benchmarks and firms missing earnings benchmarks. Finally, I adopt the propensity score matching analysis (hereafter, PSM) and the Heckman two-step approach.

1.5 Main empirical findings

The findings of the first study show that real earnings management is more difficult to be detected than accrual earnings management. In particular, there are no effective ways to uncover real earnings management activities in practice, and the widely-applied models by Roychowdhury (2006) experience high mis-specifications and low power of the test to detect real earnings management. The results of this thesis indicate that 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. Moreover, the findings of this study show that accrual earnings management models such as the modified-Jones model, the Kothari et al., (2005) model, and the modified Dechow-Dichev model by Francis et al. (2005) are better specified and have higher power to detect accrual manipulation than the Roychowdhury (2006) model to uncover real manipulation activities. Furthermore, the models to detect overproduction and sales manipulation (i.e., discount price) have high misspecification, resulting in artificially inflating the power of the model.

In addition, the findings in the second study suggest that under the high IU environment, managers of firms are likely to use more accrual earnings management than real earnings management. The results are robust to different methods (i.e., using propensity score matching or Heckman two step methods). Moreover, using different methodologies, such as

applying ordinary least square models and sorting firms by IU to test for differences between low IU group and high IU group, provide consistent results.

The subsequent analysis reveals that firms that manage earnings to beat earnings benchmarks face lower stock price performance than other firms, which implies that they manipulate earnings to mislead investors. The findings demonstrate that the IU plays a vital role in explaining opportunistic earnings management. Empirical analyses using different methods such as propensity score matching, and Heckman two step procedures are consistent with opportunistic benchmark-beating firms misleading investors about future firm performance under high IU.

1.6 Structure of the thesis

Chapter 2 provides the definition and classification of earnings management as well as the theoretical perspective on earnings management. It discusses the agency theory and theoretical predictions in the earnings management literature.

Chapter 3 presents the findings of the first hypothesis testing. It compares the ability of models detecting accrual earnings management and real earnings management.

Chapter 4 presents the findings of the second, third, fourth and fifth hypotheses testing. It mainly investigates the role of IU in the choice of accrual versus real earnings management.

The following chapter 5 presents the findings of the sixth and seventh hypotheses testing. This chapter mainly focuses on examining the effect of subsequent performance of firms managing earnings to beat earnings benchmarks.

Chapter 6 provides the conclusion of this thesis by summarizing the main findings and implications of the study. The final section of this chapter presents the research limitations and provides suggestions for future research.

CHAPTER 2: DEFINITION, CLASSIFICATION, THEOREITCAL PERSEPCTIVE AND INCENTIVES OF EARNINGS MANAGEMENT

2.1 Introduction

This chapter presents the definition of earnings management. Moreover, the difference between accrual earnings management and real earnings management is presented in this chapter. Furthermore, the agency theory is illustrated as theoretical perspective of earnings management. In addition, based on previous literature, this chapter summarizes motivations of earnings management such as earnings benchmarks, equity offering, executive compensation, debt covenants and import relief and political costs.

The remainder of this chapter is organised as follows. Section 2.2 presents the definitions of accrual-based earnings management and real earnings management. Section 2.3 shows the differences between accrual earnings management and real earnings management. Section 2.4 discusses theoretical perspective of earnings management. Section 2.5 presents incentives of earnings management. Section 2.6 concludes.

2.2 Definition of earnings management

Over the decades, numerous researchers have tried to provide definition of earnings management; however, until now there has not been an accepted definition of earnings management that fit all cases. There are different terms that are interchangeably applied with earnings management such as aggressive accounting, cooking the books, and income smoothing (Akpanuko and Umoren, 2018).

Healy and Wahlen (1999) provide a comprehensive definition of earnings management by presenting that it constitutes the use of managerial judgement in accounting choices or operating activities to alter financial reports to mislead investors about underlying economic performance of the firm. Clearly, accounting standards allow managers to exercise their professional judgement to intervene in the financial reporting process. For instance, managers must exercise judgement to estimate future economic events such as amortization of long-term assets. Or managers need to choose among acceptable accounting methods (e.g., depreciation method or inventory accounting method such as LIFO, FIFO). In addition, managers of firms also influence contractual outcomes by engaging in business operating

activities to overcome limitations of current accounting standards. The illustration is that managers of firms might capitalize research and development (hereafter R&D) expenditures to avoid recording R&D expenditures. Such activities are defined as earnings management when managers of firms exercise discretion in the accounting choices or real operating activities aiming at influencing contractual outcomes or earnings information to mislead stakeholders about underlying firm performance.

Similarly, Fields et al. (2001) document that earnings management occurs when managers of firms use their discretion to alter reported earnings. This discretion is opportunistic to serve the own interest of the manager, or to maximize values of firms.

Earnings management is presented by Davidson et al. (1987) as "the process of taking deliberate steps within the constraints of generally accepted accounting policies to bring about a desired of reported earnings". The emphasis of this definition is on the deliberate process. Moreover, the early study by Schipper (1989, p.92) defines earnings management as "a purposeful intervention in the external financial reporting process, with the intent of obtaining some private gain (as opposed to, say, merely facilitating the neutral operation of the process)". Schipper's (1989)'s definition assumes that earnings management only occurs for private gains and is limited to the manipulation through purposeful intervention in the financial reporting process within or outside Generally Accepted Accounting Principles (hereafter GAAP).

In addition, another tool for earnings management is classification shifting that refers to "the deliberate misclassification of items within the income statement" (McVay, 2006). Based on this definition, classification shifting is the opportunistic practice of misclassifying income statement items. Accordingly, the net reporting earnings will not be influenced, and thus accruals will not be reversed in the following period. In fact, accounting standards allow managers of firms to exercise judgment and discretion to determine how to classify items in financial reporting. Table 2.1 below summarises alternative terms and definitions of earnings management.

Table 2.1 Alternative terms and definition of earnings management

Term	Definition(s)	Used in literature
Earnings management	*"is a purposeful intervention in the external financial reporting process, with the intent of obtaining some private gain" (Schipper, 1989)*	Xu et al. (2007); Gunny (2010)
	"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 and Wahlen, 1999)	Dechow et al. (1995); Roychowdhury (2006)
	"is the choice by a manager of accounting policies so as to achieve specific objective" (Scott and O'Brien, 2003)	Nichols and Wahlen (2004)
	"is the choice of a manager of accounting policies or other actions - including voluntary earnings forecasting, voluntary disclosure, and estimation of accruals - to affect earnings intentionally" (Man, 2013)	Wilbanks et al. (2015)
Classification shifting	*"is the deliberate misclassification of items within the income statement" (McVay, 2006)*	Athanasakou et al. (2009); Haw et al. (2011)
Earnings smoothing	*"is the deliberate dampening of fluctuations about some level of earnings which is considered to be normal for the firm"(Barnea et al., 1976)*	Belkaoui and Picur (1984); Baik et al. (2020)
	"is a deliberate attempt by management to signal information to financial users"(Ronen and Sadan, 1981)	Tucker and Zarowin (2006)

2.3 Classification of earnings management

2.3.1 Accrual earnings management

Earnings management strategies are classified as two categories which are accrual-based earnings management and real earnings management. As mentioned by Dechow and Skinner

(2000), earnings management can be implemented by exercising accounting choice or real cash-flow choices. The first technique is based on estimates and accounting policies. Specifically, the Generally Accepted Accounting Principles (GAAP) allow managers to exercise their judgement about accounting choices that can influence contractual outcomes relying on reporting accounting information. For instance, to enhance earnings of financial reports, managers of firms might engage in a modification of abnormal loan provisions (e.g., Beaver et al., 1989, Wahlen, 1994, Beaver and Engel, 1996 and Liu et al., 1997).

2.3.2 Real earnings management

Recent studies have examined another method of earnings management, namely real earnings management, which is defined as operating activities deviating from normal business practice with the aim of meeting certain earnings benchmarks (Roychowdhury, 2006). Indeed, the practice of real earnings management aims at improving short-term earnings at the potential expenses of long-run firm performance (e.g., Graham et al., 2005; Cohen et al., 2010). In the survey of executives, Graham et al. (2005) show that nearly 80 percent of executives are willing to reduce research and development expenditure (R&D), advertising and maintenance expenses to meet expectations of short-term earnings.

While accrual earnings management implies discretionary accruals that are constrained by General Accepted Accounting Principles (GAAP) without any effect on cash flows, real earnings management involves deviations from normal operating activities of firms that directly affect current and future cash flows in financial reporting. Since real earnings management is not constrained by external scrutiny and monitoring such as regulators, auditors, compared to accrual earnings management, real earnings management is more opaque for capital markets (see Dichev et al., 2013; Abad et al., 2018). Roychowdhury (2006) introduces a methodology to detect real earnings management by using three models to measure three types of real earnings management activities, namely reduction in discretionary expenditure, sales manipulation, and overproduction. In detail, abnormal low spending on discretionary expenditures (i.e., R&D, administrative and advertising expenses) is used as the proxy for the reduction in discretionary expenses. Abnormal low level of cash flows is used as the proxy for sale manipulation by accelerating sales or offering price discounts that generate unsustainable sales in the adjacent periods. Abnormal high production of inventory is the proxy for the overproduction of inventory.

2.3.3 Income smoothing

Another tool of earnings management is income smoothing. Copeland (1968) provides a definition of income smoothing stating that "it involves the repetitive selection of accounting measurement or reporting rules in a particular pattern, the effect of which is to report a stream of income with a smaller variation from trend than would otherwise have appeared" (Copeland, 1968, p. 102). Similarly, Beidleman (1973) presents the definition of income smoothing as "it is may be defined as the intentional dampening of fluctuations about some level of earnings that is currently considered to be normal for a firm. In this sense smoothing represents an attempt on the part of the firm's management to reduce abnormal variations in earnings to the extent allowed under sound accounting and management principles." (Beidleman, 1973, p. 653).

Based on above definitions, income smoothing can be viewed as the tool for managers of firms reduce earnings variability over time, or within a single period by shifting towards the expected earnings. As shown in the survey by Graham et al. (2005), managers of firms have preference to smooth earnings since smoother earnings are perceived as more predictable earnings for investors.

2.4 Theoretical perspective of earnings management

2.4.1 Agency theory

2.4.1.1 Agency problem

Prior to the 1960s, firms were viewed as a black box whose role is transferring outputs to the market to maximize profits (e.g., Williamson, 2002). Indeed, under the classic theory of the firm, individual behaviour in a firm is driven by profit or wealth maximizing criterion (see Alchian, 1965). During this period, the assumption under the theory of the firm was the notion of free will and rational behaviour (i.e., agents are moral models and able to make best decisions to maximize their utilities). In subsequent periods, with the separation of ownership and control (e.g., between owners and managers), there was an increase in controversy over the limitation of the classic theory of the firm. Ross (1973) introduced the concept of 'agency problems. Later, Jensen and Meckling (1976) made a huge contribution to agency theory to provide more adequate explanation for managerial behaviour.

Under agency theory, the separation of ownership and control, between principals and agents (i.e., shareholders and managers), creates conflicts of interests. Jensen and Meckling (1976)

indicate that the contractual arrangement between the principals and agents will not come at zero costs. In detail, the agency theory is concerned about incomplete contracts caused by the conflicting agency relationship in which a principal will delegate assignments to an agent. The problem is that the principal finds it difficult or expensive to confirm the actual activities of the agent. Therefore, the central idea of the agency theory is that it is impossible to establish contracts that perfectly diminish conflicts of interest between principals and agents.

The two sources of agency problems are information asymmetry through moral hazard and adverse selection. The moral hazard problem occurs when agents' acts are based on their self-interests but without being revealed by principals. Indeed, the condition of the moral hazard problem is that the principals are not able to observe agents' actions. Therefore, the agents can implement actions that are not in line with the principals' interests. The adverse selection problem exists due to the presence of hidden information for the principals. In fact, Walker (1989) indicates that under the agency relationship, there is valuable information that is not available for the principals. Indeed, due to information asymmetry between the agents and principals, the adverse selection problem arises before the creation of the contract between the agents and principals.

2.4.1.2 Human assumption

Simon (1955) was the first to introduce bounded rationality meaning that people are intentionally rational, but only limitedly. The assumption of bounded rationality under the agency theory replaced the rationality assumption under the classical theory of the firms and both are widely accepted among researchers. Some authors such as Alchian and Demsetz (1972) and Williamson (1979) use bounded rational assumption to view a firm as a nexus of incomplete contracts in which people are only partly rational (i.e., bounded rationality) in decision-making (Simon, 1955). For example, in an employment contract, owners are not certain whether agents always keep promises and behave in a way that maximizes their wealth or not. Due to bounded rationality, people might not make optimal decisions in each situation.

Another assumption of behaviour is self-interest. The modern agency theory assumes that human behaviour is self-interested. Accordingly, the agents and principals might have conflicts of interests to maximize their own utilities (Jensen, 1994).

2.4.1.3 Agency theory and earnings management

There are several theories that have been proposed to explain earnings management behaviour, the most popular being the agency theory by Jensen and Meckling (1976). Under the agency theory, there are conflicts of interests between shareholders (principals) and managers (agents). Indeed, managers possess more private information compared to outside shareholders, and pursue their own interests (i.e., to maximize their compensation) that does not necessarily suit shareholders' wealth (Goergen and Renneboog, 2011). In contrast, the target of shareholders is to improve the firms' profits. Therefore, this creates a moral hazard problem, in which managers of firms might distort earnings information to maximize their own interest in the way that deteriorates shareholders' wealth. However, previous literature provides inconsistent results for the purpose of earnings management (e.g., Archibald, 1967; DeAngelo, 1986; Bartov, 1993; DeAngelo et al., 1994; Dechow et al., 1995).

Prior studies argue that earnings management is not always bad for outside stakeholders. In fact, General Accepted Accounting Principles (GAAP) permit managers of firms to exercise accounting choices through exercising judgement about recognizing accruals in financial statements. Dechow (1994) documents that accruals enhance the ability that earnings reflect firm performance by mitigating the matching problems of cash flows. The positive accounting theory shows the beneficial earnings management on optimizing the contracts between firms and various stakeholders (Watts and Zimmerman, 1986). Moreover, Jiraporn et al. (2008) examine the relationship between earnings management and agency theory in which, earnings management can be seen as beneficial. Indeed, managers of firms might engage in earnings management to communicate private information of firms that can help reduce the gap of information between shareholders and managers of firms. Accordingly, earnings management brings more informativeness of components of earnings about firms' future performance (e.g., Holthausen and Leftwich, 1983; Healy and Palepu, 1993; Guay et al., 1996; Subramanyam, 1996; Demski, 1998; Arya et al., 2003).

On the one hand, managers' accounting choice in recording accruals disseminate managers' withheld private information to capital markets that can help reduce information asymmetry between managers and uninformed investors (see Jensen and Meckling, 1976; Smith Jr and Warner, 1979; Watts and Zimmerman, 1986). On the other hand, Fields et al. (2001) indicate that flexibilities of accounting choices are likely to result in managers selecting accounting methods to maximize their self-interest instead of conveying fully and credibly private

information to the market. Therefore, there are two perspectives on earnings management, namely, beneficial earnings management and opportunistic earnings management.

However, the dominant view in the literature is the opportunistic perspective, in which managers use earnings management as opportunism (e.g., Healy and Palepu, 1993). The mismatch of incentives between managers and shareholders would induce managers to manage earnings opportunistically, hence, create distortion of financial reporting. A number of academic studies are favourable to view earnings management as opportunism, which is positively related to the agency conflicts (see Jiraporn et al., 2008; Hao and Yao, 2010). Indeed, several empirical research investigates the relationship between earnings management and executives' compensation. Healy (1985), Holthausen et al. (1995) find that managers of firms manage earnings downwards once their compensation is at the maximum level. Moreover, managers engage in managing earnings due to market capital incentives. Teoh et al. (1998a) show that prior to initial public offerings when there is high information asymmetry between managers and the issuers, managers use income-increasing discretionary accrual. Similarly, in seasoned equity offerings, there are consistent results that Seasoned equity offerings manage earnings upwards in attempt to maximize share prices (e.g., Rangan, 1998; Teoh et al., 1998a; Kothari et al., 2016).

2.4.2 Stakeholder theory

Stakeholder theory was originally introduced by Freeman (1984) who defined stakeholders as "any group or individual who can affect or is affected by the achievement of the organisation's objectives" (Freeman, 1984, p. 46). Whereas the agency theory by Meckling and Jensen (1976) mainly focuses on the relationship between an agent (manager) and principal (shareholders), stakeholder theory extends the agency theory by including other stakeholders (Donaldson and Preston, 1995). Indeed, stakeholders are important for the success of the business, and should be considered for management decisions. Stakeholders include internal and external stakeholders. In which, internal stakeholders are employees, managers, and shareholders. External shareholders consist of customers, suppliers, and governments.

The stakeholder theory moved from traditional views that firms mainly aim at making profits for one group of shareholders to another view of capitalism that creates value for stakeholders rather than shareholders (Ibrahim et al., 2020). According to the stakeholder theory, in addition to financial measures such as firm efficiency, there are other measures to

assess firms' effectiveness by measuring that the interests of non-shareholders are protected (McWilliams and Siegel, 2001).

As previously mentioned in the agency theory, the practice of earnings management is caused by the agency problem when there are conflicts of interest between an agent (manager) and the principal (shareholders). In this situation, earnings management is considered to cause agency costs since managers of firms pursue their own interests and do not present accurately underlying firm performance. In recent accounting studies, earnings management not only influences shareholders but also other stakeholders such as suppliers, customers, communities and regulators (Sun et al., 2010; Waweru and Riro, 2013). Indeed, Prior et al. (2008) investigate the association between earnings management and corporate social responsibility. They provide evidence that managers of firms manage earnings to obtain private interests that destroy the interests of other stakeholders.

2.4.3 Prospect theory

Prospect theory originated from the study by Tversky and Kahneman (1979). According to the prospect theory, individuals are more sensitive to losses with the same magnitude as gains. Indeed, the central concept of the prospect theory is loss aversion, implying a convex cost function that losses loom greater than gains. Furthermore, under the prospect theory, people measure the deviation of gain and losses from a reference point, rather than an absolute value of wealth. Moreover, Kahneman and Tversky (2013) show that under uncertainty, individuals' preferences are risk seeking in choices between gains and losses. In which, people prefer sure gains rather than uncertain larger gains. In contrast, people seek preference for uncertain losses rather than sure smaller losses.

The prospect theory is applied to explain why firms wish to avoid earnings decreases and losses (Burgstahler and Dichev, 1997). Based on the prospect theory, there is the largest gains in utilities when earnings of firms move from a relative or absolute loss to gains. Accordingly, managers of firms have a high motivation to manage earnings around both zero changes in earnings and zero levels of earnings.

2.5 Incentives of earnings management

The widespread use of accounting information in written contracts is widely documented in empirical studies (see Holthausen and Watts, 2001). There are different motivations for earnings management. Healy and Wahlen (1999) indicate that earnings management aiming at altering accounting numbers are not only to maximize the value of firms but also to gain

private benefits. As presented by previous literature, there is evidence of the association between different factors and earnings management e.g. meeting earnings benchmarks (Burgstahler and Dichev, 1997; Degeorge et al., 1999; Dechow and Dichev, 2002), inflating stock price around equity offerings e.g. initial public offerings (IPOs) and secondary equity offerings (SEOs) (Teoh et al., 1998a), avoiding debt covenant violations (DeFond and Jiambalvo, 1994), and achieving performance-based compensation (Bergstresser and Philippon, 2006). These are explained in the following sub-sections.

2.5.1 Earnings benchmarks

Earnings benchmarks play a vital role for capital market participants in evaluating financial performance. Accordingly, managers attempt to reach earnings benchmarks when expected earnings fall below these desired thresholds. Hayn (1995) documents that there are a few firms reporting small losses, and many firms that have small profits. Indeed, one way to meet or beat such earnings benchmarks is to engage in earnings management. For instance, Hansen (2010) provides evidence that firms just above earnings benchmarks have significantly higher discretionary accruals.

Previous studies indicate three important benchmarks that managers aim at beating or meeting which are: (1) avoid reporting losses (Burgstahler and Dichev, 1997; Osma and Young, 2009); (2) avoid reporting earnings decreases (Burgstahler and Dichev, 1997); and (3) meeting analysts' forecasts (Degeorge et al., 1999; Dechow and Dichev, 2002). One of the two important benchmarks in the capital market is to avoid reporting losses and earnings decreases (Burgstahler and Dichev, 1997). There is evidence that managers of firms report earnings upward through using discretionary accruals to avoid reporting losses and earnings decreases. Their findings show that there is an unexpectedly large number of firms reporting positive earnings and small earnings increases.

Moreover, Roychowdhury (2006) finds that firms use real earnings management (i.e., offering discounts, overproduction, reducing discretionary expenditures) to avoid reporting losses and meeting analysts' forecasts. Similarly, Cohen and Zarowin (2010) show that managers of firms decrease advertising expenditures to avoid losses and improve earnings. Similarly, Osma and Young (2009) examine 3,866 firm-year observations from 1989 to 2002 and provide evidence that firms report abnormal reduction in current research and development expenses to meet current year earnings benchmarks. Furthermore, Hinkel and Hoffman (2020) find that firms use abnormal stock purchase to beat earnings per share.

Prior studies indicate that firms enjoy market rewards when exceeding earnings benchmarks. For example, Barth et al. (1999) prove that firms exceeding previous year's earnings have higher price-earnings multiples than that of firms that do not. Moreover, Brown and Caylor (2005) find that firms reporting positive earnings and earnings increases experience positive abnormal returns. In the same vein, Lento and Yeung (2017) using a sample of Standard & Poor's (S&P) 500 firms for the period from 1998 to 2007 present that firms engaging in accrual-based earnings management to meet or beat expectations for signalling purposes enjoy larger abnormal returns. In contrast, using abnormal accruals opportunistically to meet or beat expectations receives market penalties with smaller abnormal returns.

Shin (2019) shows that managers of firms take actions of avoiding small negative earnings per share to meet expectations of market participants. Especially, this study suggests that the number of firms beating earnings benchmarks is only prominent in the high macro-economic uncertainty but low in the usual period. Her study also extends previous research suggesting that managers take actions to avoid negative earnings surprise in order to avoid negative market penalties (e.g., Degeorge et al., 1999; Burgstahler and Eames, 2006). In this study, she provides evidence of an essential factor (i.e., macro-economic uncertainty) that influences asymmetric market response to earnings news around meeting earnings expectations.

2.5.2 Equity offerings

Empirical evidence shows that managers of firms engage in opportunistic earnings management prior to or during stock market events such as an initial public offering (hereafter, IPOs) or seasoned equity offerings (hereafter, SEOs). Prior studies find that firms manage earnings upwards by applying either accrual-based earnings management or real-earnings management before IPOs to inflate stock prices. For example, Ritter (1991); Friedlan (1994); Teoh et al. (1998a); Roosenboom et al. (2003); Morsfield and Tan (2006) find that IPO firms opportunistically engage in earnings management through using income-increasing accrual-based earnings management. Accordingly, opportunistic earnings management during IPO years is negatively associated with long-term firm-performance. The reason for this phenomenon is that while managers temporarily improve earnings by using abnormal discretionary accruals, investors are not able to undo the reversal of the abnormal discretionary accruals in the future.

A large body of studies provides evidence that firms also engage in income-increasing earnings management to enhance firm performance before SEOs (Yoon and Miller, 2002; Lee and Masulis, 2009). Indeed, Rangan (1998); Teoh et al. (1998b); Ibrahim et al. (2011) find that there is significantly higher discretionary accruals prior to SEO years which reverses afterwards. Moreover, they show that firms with high levels of discretionary accruals experience negative long-run stock market performance. Furthermore, Cohen and Zarowin (2010); Kothari et al. (2016) document that managers of SEO firms use both accrual-based earnings management and real-based earnings management to inflate earnings during the year of the SEO. Accordingly, SEO firms applying earnings management experience subsequent operating performance drops.

2.5.3 Executive compensation

Healy (1984) indicates that under the compensation-maximization hypothesis, managers of firms engage in earnings management to maximize their bonus awards shown in firms' compensation plans. Following the bonus-maximization hypothesis, other studies corroborate that these managers' incentives to inflate earnings by using earnings management (e.g., Cheng and Warfield, 2005; Bergstresser and Philippon, 2006; Efendi et al., 2007).

Moreover, other studies examine executives' compensation on earnings management to meet/beat earnings benchmarks. For example, Cheng and Warfield (2005) provide evidence that CEO's equity compensation incentives (i.e., option grants) are associated with earnings management. Indeed, they document that US firms in the period from 1993 to 2000 with high equity compensation incentives manage earnings upwards by using accruals-based earnings management to meet or beat analysts' forecasts. Their results imply that CEOs engage in increasing-earnings management to inflate stock prices through meeting or beating analysts' expectations when share prices could be affected by disappointing capital markets' expectations of firm performance. Similarly, Bergstresser and Philippon (2006) find that CEOs of US firms utilise accrual-based earnings management driven from stock-based compensation contracts. In particular, they show that managers of firms engage in more accrual-based earnings management in the year that they sell more shares. Ibrahim and Lloyd (2011) prove that firms employing financial performance measures in bonus contracts have higher discretionary accruals.

In addition to accrual-based earnings management, Dechow and Sloan (1991) examine the relation between real earnings management and CEOs' performance-based compensation. They provide evidence that CEOs of firms reduce abnormal amounts of research and development expenses (R&D) to improve short-term earnings performance. Moreover, Tahir et al. (2019) using a sample of FTSE350 Index firms for the period from 2005-2014 find that once non-financial performance is used in bonus contracts, firms use less income-increasing manipulation through discretionary accruals or real earnings managements.

2.5.4 Debt covenants

Debt covenants are defined as terms or conditions with debt contracts that are based on accounting information. These provide incentives for managers of firms to engage in earnings management when a firm is near to violating a debt covenant, and accordingly they might reduce the probability of a default (Watts and Zimmerman (1986). Due to written contracts based on accounting numbers, several studies examine how to avoid the violation of debt through using earnings management. Indeed, DeFond and Jiambalvo (1994); Sweeney (1994); Dichev and Skinner (2002) prove that firms use accrual-based earnings management to avoid the violation of debt covenants.

DeFond and Jiambalvo (1994) examine the association between accrual-based earnings management and the violation of debt covenants. They use a sample of 94 listed firms in US from 1985 to 1988 and find that in the year of violation of debt covenants, there is significantly positive abnormal working capital accruals and total accruals. Similarly, Sweeney (1994) proves that US firms engage in income-increasing earnings management in the year of covenant violations to reduce default costs.

In addition to accrual-based earnings management, other studies indicate that firms use real earnings management aiming at improving earnings to avoid debt covenant violations. For instance, Bartov (1993) finds evidence that managers of firms use their sales of long-term assets as the method of real earnings management to increase earnings and thus avoid covenant violation. Moreover, Roychowdhury (2006) shows that firms report increasing earnings through engaging in real earnings management to avoid debt covenants' violation.

2.5.5 Import relief and political costs

Prior studies show that managers of firms have motivations to alter firms' earnings to avoid governmental intervention. As presented in Watts and Zimmerman (1986), the political-cost hypothesis highlights that during the period of enhanced political cost, firms engage in

income-decreasing earnings management if they might experience potential industry deregulation.

Moreover, there is evidence that firms have income-decreasing abnormal accruals during the period of investigation under US International Trade Commission (ITC) or the US Federal Trade Commission (FTC) (Cahan, 1992). Indeed, during import relief investigation, Jones (1991) proves that firms use income-decreasing earnings management to obtain favourable regulation such as tariff increases and quota reductions.

In addition, Han and Wang (1998) examine oil and gas firms during the 1990s. They prove that oil and gas firms apply income-decreasing earnings management around the third and fourth quarter of the fiscal year end to avoid political costs such as anti-trust and government regulation. Similarly, Monem (2003) finds that gold-mining firms in Australia in the period from 1985 to 1988 use income-decreasing abnormal accruals to avoid political costs imposed on firms having high earnings.

2.6 Conclusion

This chapter presents the literature on earnings management, including definitions, theoretical underpinnings, and incentives that lead to both accrual and real manipulation. Recent studies show that firm managers use multiple ways to manage earnings. Hence, this chapter also presents the difference between accrual earnings management and real earnings management. Furthermore, several theories including the agency theory are presented. This is the underlying theory to explain earnings management. Different incentives of earnings management are presented in this chapter also, including meeting or beating specific thresholds, which is the focus of the study. In the next chapter, the first empirical chapter is presented. It compares the ability of models to detect earnings management through both real earnings management and accrual earnings management methods.

CHAPTER 3. DETECTING ACCRUAL EARNINGS MANAGEMENT AND REAL EARNINGS MANAGEMENT

3.1 Introduction

The objectives of this chapter are to compare the abilities of detecting earnings management through accrual earnings management and real earnings management. In which, this chapter will compare the power of tests between accrual earnings management models and real earnings management models. Furthermore, the practical detection between different types of accrual earnings management activities and real earnings management will be compared. This chapter contributes to evaluating the specification and power of common measures of accrual earnings management and real earnings management. Previous literature mainly focuses on the evaluation of the specification and power of tests across measures of discretionary accruals that is the proxy of accrual earnings management. This study extends prior studies by providing insight into the performance of models detecting real earnings management. Indeed, the findings of this chapter contribute to literature about real earnings management by showing that Roychowdhury (2006)'s models to detect real earnings management exposes misspecifications and low power of tests. The evidence suggests that real earnings management is more difficult to be detected than accrual earnings management.

Earnings management by firms can be conducted by using accrual or real manipulation (e.g., Dechow et al., 1995; Cohen et al., 2008). Some studies investigating the trade-off between accrual and real manipulation find that there is a tendency to substitute real manipulation for accrual manipulation when monitoring and scrutinizing firms increases (e.g., Cohen et al., 2008; Cohen et al., 2010; Gao et al., 2017; Ipino and Parbonetti, 2017) or when costs of accrual manipulation increase (Zang, 2012). Other studies find that both manipulation strategies are complementary (e.g., Li, 2019). 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 earnings management) 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). However, limited evidence exists on the detection abilities of the real manipulation models. To close this gap, this study compares the abilities of relative models for detecting accrual-based and real earnings management 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 management. I artificially apply different levels and types of manipulation using accrual earnings management and real earnings. Specifically, I artificially include revenue recognition manipulation, as well as manipulation of expenses using either accruals or real accounts (e.g., discretionary expenses and overproduction). I 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, I 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 management models have lower power than accrual earnings management models. The real earnings management model to detect overproduction also experiences high misspecification of tests, resulting in artificially inflating the power of the model. I 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.

The current study contributes to the literature in the following ways. First, it extends the literature examining specification of earnings management models (e.g., Dechow et al., 1995; Kothari et al., 2005) by investigating real earnings management models. Furthermore, whereas prior research relies on US samples, this study extends the tests to a UK context.

Second, it contributes to the literature on the substitution between accrual and real manipulation (e.g., Cohen et al., 2008; Cohen et al., 2010; Zang, 2012; Gao et al., 2017;

Ipino and Parbonetti, 2017; Owusu et al., 2020) by comparing the effectiveness of the current models of accrual and real earnings management as proxies of earnings management.

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.

The study proceeds as follows. Section 3.2 reviews related literature and presents hypothesis development. Section 3.3 discusses data and research methods. Section 3.4 discusses empirical results. Section 3.5 presents a discussion and Section 3.6 concludes.

3.2 Literature review: Earnings management detection models

3.2.1 Existing literature on accrual earnings management

Accounting standards allow managers of firms to exercise judgement in preparing financial reports. Under an informational perspective, it is assumed that managers of firms select sets of reporting rules to convey all private information that they have. Accordingly, empirical evidence indicates the informativeness of accruals in financial reporting for valuing shares (e.g. Beaver, 1968a; Ball and Brown, 1968). With increasing accounting number-based performance contracts, accounting choices are considered as a source of opportunities for earnings management, in which managers select accounting estimates in such a way that managers withhold private information about financial performance of their firms (Schipper, 1989).

Healy (1985) and Healy and Wahlen (1999) define earnings management as managerial discretion in exercising judgement in accounting choices or structuring operating activities to mislead investors about firm performance or to affect contractual outcomes that rely on accounting information. The definition of earnings management indicates that managers of a firm could manipulate earnings through accrual manipulation or real operating activities. Under accrual-based earnings management, managers use their accounting judgment for their private purposes. Indeed, managers also structure the timing of operating activities (i.e., business activities deviating from normal business activities of a firm) with the purpose of improving earnings information.

The first paper to examine earnings management by Healy (1985) introduces the use of discretionary accruals. In his paper, he defines discretionary accruals as the difference between total accrual and non-discretionary accrual. Under the bonus-maximisation

hypothesis, managers select discretionary accruals that deviate from generally accepted accounting principles to modify payments from their bonus plan. Total accruals are used as a proxy for discretionary accruals because non-discretionary accruals cannot be observable; therefore, he assumes that non-discretionary accruals are equal to zero.

In DeAngelo (1986)'s paper, she applies discretionary accruals to examine whether managers use decreasing-income discretionary accrual prior to buyouts. The discretionary accrual proxy is used by a change in total accruals. However, McNichols and Wilson (1988) indicate that the proxy of discretionary accrual contains measurement error when a firm experiences a higher expected non-discretionary accruals. Accordingly, they only examine a specific discretionary accrual (i.e., bad debt provision). Their findings document that firms with unusually high or low earnings have discretionary accruals for bad debts.

Later research develops more comprehensive measures of discretionary accruals. Jones (1991) proves that during import relief investigations by the U.S. International Trade Commission (ITC), firms engage in more income-decreasing discretionary accruals. She assumes that non-discretionary accruals reflect differences in economic conditions. Indeed, non-discretionary accruals are estimated through a regression of total accruals on changes in revenues and property, plant, and equipment. All variables are scaled by beginning year assets. Discretionary accruals are the difference between total accruals and non-discretionary accruals. However, she mentions the limitations of the non-discretionary measure about managed accrual revenues.

Dechow et al. (1995) overcome this weakness through excluding accrual revenues in estimating non-discretionary accruals. They provide evidence that all models are well specified when a sample is random. Moreover, they prove that compared to previous models, their Modified Jones model has the least misspecification and the highest power test of earnings management. However, as for firms with extreme financial performance, all models generate type I errors.

In the UK context, Peasnell et al. (2000) propose the margin model to estimate non-discretionary accrual. In which, the measure of non-discretionary accruals is different from the Jones Model (Jones, 1991) and Modified Jones Model (Dechow et al., 1995) in substituting cash receipt in a current year for previous year sales. Although they prove that the margin model generates better estimates of abnormal accruals when cash flow

performance is extreme, the power test of the margin model is lower than previous earnings models at detecting sales-based manipulation and bad debt expense manipulation activities.

Kothari et al. (2005) further improve the Jones model and Modified Jones model by including matching-firm year financial performance based on firms with the closest return on assets (hereafter ROA) to control for the influence of extreme performance. However, Dechow et al. (2010) indicate that matching by closest level of ROA could induce estimation errors of discretionary accruals. Therefore, this approach could reduce the power of the test.

Dechow and Dichev (2002) suggest another model to estimate nondiscretionary accrual by using working capital accruals. In which, non-discretionary accruals are estimated by regressing past, current, and future cash flows on working capital accruals. Discretionary accruals are residuals between real working capital accruals and non-discretionary accruals. Nevertheless, Dechow et al. (2010) argue that the model has biased estimation errors since they ignore long-term accruals in estimating non-discretionary accruals.

Francis et al. (2005) extend the model of Dechow and Dichev (2002) by including firm performance (i.e., adding sales growth) and depreciation expense that are long-term accruals to overcome the weakness mentioned in McNichols (2002)'s paper. Moreover, they also propose another way to extend Dechow and Dichev (2002) by separating standard deviation of the residual into innate errors and discretionary errors. However, Dechow et al. (2010) indicate that the innate characteristics might affect estimation errors that could lower the power of the and can introduce bias into the proxy for discretionary accruals.

Furthermore, Dechow et al. (2012) introduce a new way to detect earnings management relying on the idea that any discretionary accruals in one period will be reversed in the next period. They prove that including reversal of accrual-based earnings management could enhance the power test of the model. However, Gerakos (2012) argues that there is uncertainty about an expected period in which discretionary accruals are reversed. He indicates that the improvement in estimating discretionary accruals since Dechow and Dichev (2002) is questionable.

While substantial literature has been developing and improving the power and specification of estimating discretionary accruals, there are no other models outperforming the Modified Jones Model (Dechow et al., 1995). Consequently, this study will apply the Modified Jones Model to estimate discretionary accruals as a proxy for accrual-based earnings management.

In addition to the Modified Jones model, I also use the Kothari et al. (2005) and the Modified Dechow and Dichev (2002) model to measure accrual earnings management.

3.2.2 Existing literature on real earnings management

The above definition of earnings management by Healy and Wahlen (1999) indicates that accrual earnings management is employed by exercising accounting judgment in preparing financial reports to alter impressions of some stakeholders about business performance. Alternatively, managers of firms can manipulate earnings through structuring actual operations (e.g., structuring timing of capital expenditures or asset sales).

In Graham et al. (2005)'s survey, financial executives reveal that they prefer using real manipulation activities such as reducing discretionary expenses (e.g., research and development costs – hereafter R&D) to meet or beat earnings targets because these activities are more difficult to be scrutinized by regulators or auditors. Indeed, several papers focus on examining opportunistic reduction of R&D expenses to enhance bottom line numbers of financial reports or to achieve important earnings benchmarks (see Dechow and Sloan, 1991; Baber et al., 1991; Bushee, 1998).

In addition to a decrease in R&D expenditures, other studies provide evidence that firms having negative earnings report higher earnings from asset sales (e.g., Bartov, 1993). Furthermore, prior studies document that to meet earnings targets, firms engage in overproduction of inventory (see Thomas and Zhang, 2002). Furthermore, Jackson and Wilcox (2000) indicate that firms with small positive earnings report sales price reductions. In addition, Bartov (1993) shows that firms with decreasing earnings have high income from asset sales.

Nevertheless, there is no systematic evidence about real earnings management except from Roychowdhury (2006). In his paper, he finds evidence consistent with managers engaging in real earnings management to avoid reporting losses. Real earnings management is defined as structuring operating activities that deviate from normal operational practices of a firm so that managers could mislead stakeholders about the underlying performance of a firm. There are different methods of real earnings management such as overproduction, price discounts or discretionary expense reduction. Indeed, to manipulate bottom line earnings, managers could increase production to reduce cost of goods sold. In detail, high production helps managers decrease fixed overhead costs, which reduces fixed costs per units. Therefore, cost of goods sold (COGS) is lower. Moreover, managers temporarily foster sales through

offering more lenient terms or price discounts to customers in the current year. However, customers might expect such discounts in the future. Hence, in the following periods, the increasing sales do not remain when a firm re-establishes old prices. As a result, price discounts result in lower operating cash flows.

Prior studies apply the models in Roychowdhury (2006) to examine real earnings management. For instance, Zang (2012) proves that suspect firms beating or meeting important earnings benchmarks trade-off between real earnings management and accrual earnings management based on their relative costliness. Moreover, Cohen and Zarowin (2010) show that seasoned equity offering (hereafter SEO) firms engaging in real earnings management experience more severe subsequent underperformance than when using accrual earnings management. In addition, Ibrahim et al. (2011) find evidence that SEO firms shift to real earnings management in the post-Sarbanes-Oxley years.

3.2.3 Practical ways to detect accrual earnings management and real earnings management

Prior literature mainly focuses on examining the detection of accrual manipulation and ignores misstated earnings through real earnings management (e.g., Dechow et al., 1996; Lee et al., 1999; Bentley et al., 2013). Nevertheless, the findings of a survey by Graham et al. (2005) indicate that top executives prefer real earnings management to discretionary accruals. Indeed, Lo (2008) indicates that real manipulation activities (e.g., price discounts to inflate sales) are like normal operating activities of the firm. Accordingly, real manipulation activities are opaque for the outside stakeholders. Similarly, Kothari et al. (2016) document that managers have choices of methods to inflate earnings that is more opaque to be likely to escape from scrutiny from auditors or regulators. Unlike accrual manipulation which are often guided by accounting standards, there are no regulated guidelines for real earnings management. Therefore, managers of firms select their operational or investing decisions that help them manage earnings through real activities less discernible to market participants.

On the one hand, accrual manipulation is widely examined in prior studies (e.g., Dechow et al., 1995; Peasnell et al., 2000; Francis et al., 2005; Dechow et al., 2010). Unlike misstatement of cash flows, accrual manipulation results in increasing accruals over the year. Accordingly, firms engaging in accrual manipulation tend to reverse their manipulated accruals in subsequent years. Therefore, over several periods, firms using large accruals are

probably scrutinized by investors, analysts, and auditors (Hirst, 1994; Bartov et al., 2000). For instance, firms recording premature sales or fictitious sales will result in accumulated unpaid account receivables on their balance sheets. Therefore, auditors would be able to detect suspicious sales or premature sales. Lennox and Yu (2020) indicate that manipulation by firms overstating earnings through manipulating cash flows is more difficult to be detected than when not using cash flow manipulation. In their study, they find that earnings fraud that involve misstated cash flows take a longer period to detect.

On the other hand, Harrison (2003) documents that there is the common perception about cash that it cannot be easily misstated. This perception indicates that several studies assume that operating cash flows are not able to be misstated. Nevertheless, prior studies provide evidence that several companies manipulate earnings through misreporting cash from operations (e.g., Lennox and Yu, 2020). Moreover, while accrual manipulation results in reversal of accruals in the following periods that decrease reported earnings, overstatement of operating cash flows can help firms avoid these reversals. Accordingly, Dechow et al. (2012) present that the disadvantage of accrual manipulation is that accruals will become larger in subsequent periods; hence, financial statement users might notice a red flag of misstatements of financial statements.

Under generally accepted accounting principles (GAAP), there are three types of changes in cash flows in the statement of cash flows including: (1) cash from operating activities; (2) cash from investing activities; (3) cash from financing activities. In practice, there are various ways for firms' managers to overstate cash flows. Indeed, Lee (2012) finds that firms manage cash flows through misclassifications among items between the statement of cash flows as well as wrong recognition for timing of transactions related to cash flows (i.e., delaying payments to suppliers or prepayments from customers). Similarly, Lennox and Yu (2020) provide several case studies of firms overstating cash flows. For instance, they provide one typical case of Dynegy. This firm misclassified cash from financing activities as cash from operations. The purpose is to mislead investors about the quality of overstated earnings. Another example is that of Bally whereby this company deferred recognizing the current year's expense until subsequent years.

Previous real earnings management literature shows different ways that firms apply to manage their reported cash flows within Generally Accepted Accounting Principles (hereafter, GAAP) or outside of GAAP (see Roychowdhury, 2006; Zang, 2012). For

instance, firms are allowed by GAAP to offer price discounts, which would lead to inflating current year sales. However, this type of real earnings management negatively influences cash from operations in the year of manipulation (Roychowdhury, 2006). Although this type of real manipulation is quite common in academic accounting research, in practice outside scrutiny is not able to detect such activity since it looks like normal business activities of the firm.

Furthermore, overstatement of cash flows could help firms signal to the market about the creditability of overstated earnings (e.g., Siegel, 2006). Indeed, although audit firms rely on analytical procedures to examine unusual increases or decreases in items presented on financial statements to identify risks of misstatements, auditors find it difficult to uncover misstatements by overstating cash flows (see Dyck et al., 2010). Consequently, in practice, manipulated cash flows to overstate earnings of firms are seldom detected by market participants.

3.2.4 Testable hypothesis

Prior literature mainly focuses on examining the detection of accrual manipulation and ignores misstated earnings through real earnings management (e.g., Dechow et al., 1996; Lee et al., 1999; Bentley et al., 2013). However, the findings of a survey by Graham et al. (2005) indicate that top executives prefer real earnings management to discretionary accruals. Lo (2008) indicates that real manipulation activities (e.g., price discounts to inflate sales) are like normal operating activities of the firm. Accordingly, real manipulation activities are opaque to outside stakeholders. Similarly, Kothari et al. (2016) document that managers select methods to inflate earnings that are more opaque to escape from scrutiny from auditors or regulators. Unlike accrual manipulation which are often guided by accounting standards, there are no regulated guidelines for real earnings management. Therefore, managers of firms select their operational or investing decisions that help them manage earnings through real activities less discernible to market participants.

Previous real earnings management literature shows different ways that firms apply to manage their reported cash flows within Generally Accepted Accounting Principles (hereafter, GAAP) or outside of GAAP (see Roychowdhury, 2006; Zang, 2012). For instance, firms are allowed by GAAP to offer price discounts, which would lead to inflating current year sales. However, this type of real earnings management negatively influences cash from operations in the year of manipulation (Roychowdhury, 2006). Although this type

of real manipulation is quite common in academic accounting research, in practice outside scrutiny is not able to detect such activity since it looks like normal business activities of the firm. In line with this, Lennox and Yu (2019) indicate that manipulation by firms overstating earnings through manipulating cash flows is more difficult to be detected than when not using cash flow manipulation.

Indeed, audit firms rely on analytical procedures to examine unusual increases or decreases in items presented on financial statements to identify risks of misstatements relative to abnormal accruals. However, auditors find it difficult to uncover misstatements by overstating cash flows since there is no accounting regulation for real earnings management activities (see Dyck et al., 2010). Consequently, in practice, audit firms under-detect low-quality financial reporting (e.g., DeFond and Francis, 2005; Humphrey, 2008).

The above-mentioned literature indicates that in practice, manipulated cash flows have limited success in being detected as compared to accrual manipulation. As a result, it is more likely that the ability to detect accrual-based earnings management is higher than that to uncover real earnings management. Therefore, the hypothesis to be tested is as follows:

H1: *The ability to detect real earnings management is lower than that of accrual-based earnings management.*

3.3 Research design

The purpose of the study is to compare the frequency with which accrual-based earnings management models and real earnings management models generate type II errors (i.e., incorrectly reject the null hypothesis of no earnings management when it is false).

3.3.1 Testing the hypothesis

To examine the detection ability of accrual-based and real earnings management models, I 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).

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

$$DA_t = a_0 + a_1 PART_t + \sum_{k=0}^{n} a_3 X_{kt} + \varepsilon_t \quad (3.1)$$

$$RE_t = b_0 + b_1 PART_t + \sum_{k=0}^{n} b_3 X_{kt} + e_t \quad (3.2)$$

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, are the error terms.

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 (3.1) and (3.2). Furthermore, the standard errors (SE) of $\hat{a}$ and $\hat{b}$ are:

$$\mathrm{SE}(\hat{a}) = \mathrm{S}_{\varepsilon} / \sqrt{(\mathrm{n}-1) * \mathrm{s}_{\mathrm{PART}}} \tag{3.3}$$

$$\mathrm{SE}(\hat{b}) = \mathrm{S}_{\mathrm{e}} / \sqrt{(\mathrm{n}-1) * \mathrm{s}_{\mathrm{PART}}} \tag{3.4}$$

Where:

n is the total number of observations including *PART*=0 and *PART*=1; S_{ε}, S_e are standard errors of the regressions that is the residual sum of squares divided by n-2; S_{PART} is the standard deviation of *PART*. Note that *PART* is binary variable, hence, the standard deviation of *PART* is the transformation of the proportion of *p* that is the mean of the proportion of *PART = 1*, then $\mathrm{S}_{\mathrm{PART}} = \sqrt{p(1-p)}$.

The ratio of $\hat{a}$ and $\hat{b}$ have the t test distribution with n-2 degree of freedom. Accordingly, the null hypothesis of no earnings management is rejected if $\hat{a}$ and $\hat{b}$ have t-statistics that is statistical 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_{ε}, S_{e}) 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 management. Therefore, there are measurement errors in estimating the proxy of discretionary accruals (*DAP*) or real earnings management (*REM*).

$$DAP_t = DA_t - \mu + \eta \quad (3.5)$$

$$REM_t = RE_t - \varrho + \eth \quad (3.6)$$

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 (3.5) and (3.6) (see Dechow et al., 1995; Dechow et al., 2012) are below:

3.3.1.1 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 (3.5) and (3.6), 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).

3.3.1.2 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.

3.3.1.3 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.

3.3.2 Measuring earnings management

3.3.2.1 Measuring discretionary accruals (DAP)

The cross-sectional modified Jones model (1995) is applied to estimate discretionary accruals (e.g. Subramanyam, 1996; Guidry et al., 1999; Kothari et al., 2005). 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.

$$\mathrm{NDA_t} = \alpha_1\left(\frac{1}{\mathrm{A_{t-1}}}\right) + \alpha_2\left(\frac{\Delta\mathrm{REV_t} - \Delta\mathrm{REC_t}}{\mathrm{A_{t-1}}}\right) + \alpha_3\left(\frac{\mathrm{PPE_t}}{\mathrm{A_{t-1}}}\right) \qquad (3.7)$$

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 the Eq. (3.7) 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 modified Jones model). Therefore, in this study, I also apply Kothari et al. (2005)'s model to measured discretionary accruals. To control for firm performance in estimating discretionary accruals, current year's return on assets (*ROA*) is added to Modified Jones model as an additional regressors (Kothari et al., 2005). Accordingly, return on assets for the current year is added to the equation (3.7) to estimate normal discretionary accrual as follows:

$$\mathrm{NDA_t} = \alpha_1\left(\frac{1}{\mathrm{A_{t-1}}}\right) + \alpha_2\left(\frac{\Delta\mathrm{REV_t} - \Delta\mathrm{REC_t}}{\mathrm{A_{t-1}}}\right) + \alpha_3\left(\frac{\mathrm{PPE_t}}{\mathrm{A_{t-1}}}\right) + \alpha_4\ (\mathrm{ROA_t}) \qquad (3.8)$$

where

ROA_t is equal to earnings deflated by total assets, and all other variables are as previously defined.

Third, I 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), I estimate non-discretionary accruals by using the model (hereafter the Modified DD model) as follows:

$$\mathrm{NDA_t} = \alpha_1 + \alpha_2\left(\frac{\Delta\mathrm{REV_t} - \Delta\mathrm{REC_t}}{\mathrm{A_{t-1}}}\right) + \alpha_3\left(\frac{\mathrm{PPE_t}}{\mathrm{A_{t-1}}}\right) + \alpha_4\left(\frac{\mathrm{CFO_{t-1}}}{\mathrm{A_{t-1}}}\right) + \alpha_5\left(\frac{\mathrm{CFO_t}}{\mathrm{A_{t-1}}}\right) + \alpha_6\left(\frac{\mathrm{CFO_{t+1}}}{\mathrm{A_{t-1}}}\right) \qquad (3.9)$$

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.(3.9) from total accruals (*TA*).

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

$$\mathrm{TA_t} = (\Delta\mathrm{CA_t} - \Delta\mathrm{CL_t} - \Delta\mathrm{Cash_t} + \Delta\mathrm{STD_t} - \mathrm{Dep_t}) / \mathrm{A_{t-1}} \qquad (3.10)$$

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.

3.3.2.2 Measuring real earnings management (REM)

Following previous studies (Roychowdhury, 2006; Cohen et al., 2008; Gunny, 2010; Ibrahim et al., 2011; Athanasakou et al., 2011), the measures of real earnings management are based on three types of real earnings management:

- Sales manipulation conducted by accelerating the timing of sales (i.e., offer price discounts or more lenient credit terms, which results in abnormal low cash from operations).
- Decrease in discretionary expenditures such as research and development (R&D), advertisement and selling, general and administrative expenses, which leads to abnormal low discretionary expenses.
- Overproduction which is implemented by overproducing goods to lower cost of goods sold by reducing fixed costs.

Abnormal real activities (i.e., proxy for real earnings management-REM) estimated by the Roychowdhury (2006) models are the difference between total operating activities (TOA) and estimated normal real activities (NRA). In which, REM includes abnormal cash from operating activities (REM_{CFO}), overproduction (REM_{PROD}), and reduction of discretionary expenses (REM_{DISEXP}).

$$REM_t = TOA_t - NRA_t \qquad (3.11)$$

The models to detect real earnings management decompose total real operating activities into normal real activities and abnormal real activities (i.e., proxy for real earnings management-REM). In which, the parameters of the models are estimated through a use of an estimation portfolio of firms within the same industry and year where there is no hypothesized systematic earnings management. Accordingly, the models of normal real activities (NRA) as introduced by Roychowdhury (2006) are as follows:

3.3.2.2.1 Normal cash from operations:

Following Dechow et al. (1998) and Roychowdhury (2006), normal cash from operation are relative with sales and changes in sales as below:

$$\frac{\text{Normal CFO}_t}{A_{t-1}} = \alpha_0 + \alpha_1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{REV_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) \qquad (3.12)$$

To estimate Eq. (3.12), I use the following cross-sectional Eq. (3.13) using an estimation portfolio of firms within the same industry (i.e., defined as the two-digit SIC industry group with at least 10 observations in each industry) and year to estimate the coefficients of α_0 , α_1, β_1, β_2 .

$$\frac{CFO_t}{A_{t-1}} = \alpha_0 + \alpha_1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{REV_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \varepsilon_t \qquad (3.13)$$

Where: CFO_t: operating cash flows in year t; A_{t-1}: total assets in year t-1; S_t: net sales in year t; ΔS_t: change in net sales from year t-1 to year t.

For each firm-year, abnormal cash from operation is the difference between real CFO and normal CFO obtained from equation (3.12).

Roychowdhury (2006) follows Dechow et al. (1995) to estimate cash flows. The assumption is that with the absence of fixed costs and manipulation, cash flows are estimated as the function of current-period sales and sales changes in the current year. The model to estimate normal cash flows follows the underlying assumption of the Jones model (Jones, 1991) to estimate normal accruals. Nevertheless, as noted by Dechow et al. (1995), the assumption of the Jones Model is that all sales are non-discretionary, which could lead to biased estimators. Indeed, firms can manipulate earnings through credit sales that results in extracting discretionary accruals from total accruals of firms. Hence, it leads to estimates of earnings management that could be biased toward zero.

Similarly, under the models by Roychowdhury (2006) to estimate normal cash flows from operations, when a firm engages in real earnings management such as offering price discounts, these sales manipulation activities also affect cash flows and current-period sales of a firm. Therefore, the model assuming current-period sales are normal cash from operations, which removes part of managed earnings from abnormal cash flow proxy (refer to problem 1 in section 3.3.1.1). Accordingly, the estimate of abnormal cash flows from operations is probably biased toward to zero and leads to lowering the power of the test (i.e., not rejecting the null hypothesis of no earnings management when it is false).

Another issue of the abnormal cash from operations model, as presented by Roychowdhury (2006, pp. 341), is that the reduction of discretionary expenses and overproduction have the opposite effect on abnormal cash from operations (CFO). Specifically, a decrease in discretionary expenditures has a positive effect on contemporaneous abnormal CFO; on the

contrary, overproduction has a negative effect on current-year abnormal CFO. Therefore, there is an ambiguous net effect on abnormal CFO.

In addition, in the case that a firm manipulates accrued sales, it can lead to abnormal low CFO relative to the level of contemporaneous sales. These issues could lead to problem 2 and 3 in the preceding discussion (see section 3.3.1.2 and 3.3.1.3), depending on whether the inclusion of η and ð that are relevant (correlated or uncorrelated) with PART in the models.

3.3.2.2.2 Normal discretionary expenditures:

Normal discretionary expenses by Roychowdhury (2006) is the linear function of lagged revenues. The relevant model is as below:

$$\frac{\text{Normal DISEXP}_t}{A_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{t-1}} + \beta \frac{REV_{t-1}}{A_{t-1}} \tag{3.14}$$

The estimates of $\alpha_0, \alpha_1, \beta$ in the Eq. (3.14**)** are estimated from the model by Roychowdhury (2006) using an estimation portfolio of firms within the same industry and year where there is no hypothesized systematic earnings management as follow:

$$\frac{DISEXP_t}{A_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{t-1}} + \beta \frac{REV_{t-1}}{A_{t-1}} + \varepsilon_t \tag{3.15}$$

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.

The abnormal discretionary expenses are actual DISEXP minus normal DISEXP obtained from Eq. (3.14).

Under the assumption made by Dechow et al. (1998) , discretionary expenditures are linear functions of current-period sales. However, this expression could suffer a problem that if a firm manages their earnings in a current year, there is low discretionary expenses without real earnings management (see Roychowdhury, 2006). Accordingly, to reduce this issue, Roychowdhury (2006) uses lagged sales to estimate normal discretionary expenditures. Dechow et al. (2012) state that the inclusion of too few determinants for estimating normal accruals could increase the second and the third problem. Indeed, in the model of estimating normal discretionary expenditures, the removal of contemporaneous sales Roychowdhury (2006)'s model might reduce the first problem; nevertheless, it could enhance the second and the third problem. There are other determinants that could predict normal discretionary

expenses such as change in revenues ($\Delta REV_{i,t}$) (Gunny, 2010). As a result, it is predicted that the model to estimate discretionary expenses could suffer problem 3 above mentioned in section 3.3.1.3 when the model is efficiently influenced by other uncorrelated determinants in estimating real earnings management.

3.3.2.2.3 Normal production costs:

Following Roychowdhury (2006), normal production costs are presented as the linear function of contemporaneous sales.

$$\frac{\text{Normal PROD}_t}{A_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{t-1}} + \beta_1 \frac{REV_t}{A_{t-1}} + \beta_2 \frac{\Delta REV_t}{A_{t-1}} + \beta_3 \frac{\Delta REV_{t-1}}{A_{t-1}} \qquad (3.16)$$

The coefficients of α_0 , α_1, β_1, β_2, β_3 in the Eq. (3.16**)** are estimated by below Eq. (3.17) using an estimation portfolio of firms within the same industry (i.e., defined as the two-digit SIC industry group and year (with at least 10 observations) where there is no hypothesized systematic earnings management. Production costs ($PROD_t$) is total cost of goods sold in the year t ($COGS_t$) plus the change in inventory from year t-1 to year t ($\Delta INVT_t$).

$$\frac{PROD_t}{A_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{t-1}} + \beta_1 \frac{REV_t}{A_{t-1}} + \beta_2 \frac{\Delta REV_t}{A_{t-1}} + \beta_3 \frac{\Delta REV_{t-1}}{A_{t-1}} + \varepsilon_t \qquad (3.17)$$

The abnormal production cost is actual PROD minus normal PROD obtained from Eq. (3.16).

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 a year (accrual-based earnings management). This results in abnormally low COGS. However, this does not influence production costs since lower $COGS_t$ will offset higher ΔINV_t.

3.3.3 Sample selection

The sample in the study includes all “dead” and “live” firms listed on London Stock Exchange from 1991-2018 with all available data for the computation of the cross-sectional Modified Jones Model (Dechow et al., 1995), the Performance Matched Modified Jones Model (Kothari et al., 2005) and real earnings management models (Roychowdhury, 2006). The estimation of cross-sectional model requires at least ten observations per each year-industry combination. Therefore, each industry/year group having less than ten observations is excluded from the sample. Previous studies do not remove banks and financial institutions

in calculating earnings management (e.g., Dechow et al., 1995; Kothari et al., 2015), hence, in the sample, I do not eliminate these firms. Furthermore, to avoid extreme observations causing noisy estimation, I remove observations at the top and bottom one percent of continuous variables. Table 3.1, panel A illustrates the sampling procedure of the study. The final sample includes 19,424 observations.

Moreover, Table 3.1, panels B and C show the yearly and industry distribution of the full sample. In panel B, I 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 3.1 Sample selection

Panel A. Sample selections for all live and dead firms from 1991-2018

All firm-years	34,399
Less: Firm-years with missing data for calculating discretionary accruals and real earnings management and extreme observations (trimmed at top and bottom 1%)	(14,695)
Industry-year combination less than 10 observations	(280)
Final sample	19,424

Panel B. Sample distribution by years

Year	*No. of obs.*	*%*
1991	152	0.78%
1992	506	3.61%
1993	512	3.64%
1994	521	3.68%
1995	519	3.67%
1996	476	3.45%
1997	541	3.79%
1998	859	4.42%
1999	814	4.19%
2000	757	3.90%
2001	752	3.87%
2002	741	3.81%
2003	804	4.14%
2004	848	4.37%
2005	927	4.77%
2006	980	5.05%

2007	939	4.83%
2008	887	4.57%
2009	840	4.32%
2010	792	4.08%
2011	749	3.86%
2012	722	3.72%
2013	734	3.78%
2014	720	3.71%
2015	698	3.59%
2016	677	3.49%
2017	646	3.33%
2018	311	1.60%
Total	19,424	100%

Panel C. Distribution of observations by industry

SIC code	*Industry*	*Obs.*	*Percent (%)*
01~09	Mining	1,252	6.45%
10~14	Construction	659	3.39%
15~17	Manufacturing	7,467	38.44%
20~39	Transportation and Communications	1,175	6.05%
40~48	Wholesale Trade	868	4.47%
50~51	Retail Trade	1,685	8.67%
52~59	Finance, Insurance, Real Estate	89	0.46%
70~89	Services	6,218	33.01%
91~99	Public Administration	11	0.06%
Total		19,424	100%

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

(1) Sample (1) is a random sample selected of 500 firm-years from the full sample of firm-years without replacement. I follow Brown and Warner (1985) and Dechow et al. (1995)'s approach to investigate type II errors for earnings management models. Since I 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. Accordingly, sample (1) does not include firms that have consecutive years, hence, there is no assumption of full reversal of earnings manipulation in the next fiscal

year. I assign a value of *PART = 1* to the random sample, and *PART = 0* to the remaining 18,924 observations.

(2) Sample (2) is a random sample using the same sample selection methodology as Dechow et al. (1995) whereby I 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. I therefore assume that discretionary accruals and abnormal operating accounts fully reverse in the following fiscal period. As above, I assign a value of *PART = 1* to the random sample, and *PART = 0* to the remaining 18,924 observations.

3.3.4 Types of manipulation

To evaluate the rejection frequency using one-tailed t-tests at significant levels of 5 percent between real earnings management and accrual earnings management models, I adopt a similar approach as 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 samples (1) and (2). With the given level of artificially induced earnings management into the given samples, the failure to reject the null hypothesis of no earnings management when it is false generates type II errors. The procedure is implemented by artificially introducing accrual and real account manipulation ranging from 0 percent to 10 percent of lagged assets to sample (1) and sample (2).

To compare the frequency of rejection with which real earnings management models and accrual earnings management model generate type II errors, three sets of assumptions concerning the components of accruals and real accounts that are managed are used. The three assumptions for real earnings management are based on the three types of real earnings management, namely sales manipulation, reduction of discretionary expenses and overproduction. Similarly, three assumptions regarding the components of managed accruals are equivalent with the three assumptions that real accounts are managed.

The three sets of assumptions for components of cash flows that are managed as follows:

(1) *Sales manipulation:* e.g., price discount

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 sales manipulation to cash flow from operations and revenue in the earnings management year.

(2) *Expense manipulation:* e.g., reduction of discretionary expenditure

It is assumed that all discretionary accruals are paid by cash. This approach is conducted by adding an assumed amount of expense manipulation to discretionary expenditures in the earnings management year. Since the models do not use expenses to estimate normal discretionary expense, none of 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 other variables in the model are adjusted.

To compare the power of the test of the real earnings management models and the discretionary accrual model, three types of accruals manipulation are used same as the above three sets of assumptions for components of cash flows that are managed. The equivalent three assumptions of the components of accruals are below:

(1) *Sales manipulation:* e.g., premature recognition of revenues

It is assumed that all costs are not changed. This approach is applied by adding the pre-determined amount of earnings management 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 model does not use expense to estimate non-discretionary accruals, none of other variables in the model are affected.

(3) *Overstated asset:* e.g., understated allowance for obsolete inventory

When a firm engages in overproducing goods than necessary demand, 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.

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 3.3.1, 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.

3.3.5 Practical detection of accrual earnings management and real earnings management

In academics, to detect earnings management, researchers apply statistical models that require the availability of large datasets and advanced statistical techniques for analysis. In practice, however, market participants such as auditors, regulators, and investors have limited access to huge datasets; hence, they rely on analytical procedures (i.e., traditional financial ratios) to identify fraudulent financial reporting. There are two ways to undertake financial ratio analyses including cross-sectional and time-series analyses. I use both techniques to check the effectiveness of the financial ratios in uncovering accrual-based earnings management and real earnings management. To the cross-sectional analysis, I compare the financial ratios of the random sample (1) and sample (2) with the financial ratios of related industries. Prior studies find an association between individual firm performance and industry performance averages (see Brown and Ball, 1967; Lev, 1969; Cowen and Hoffer, 1982). Another way is to apply time-series (trend) analysis to compare accounting financial ratios of the random sample (1) and sample (2) in the event years with those firms' financial ratios in the two previous years. Indeed, the trend in the financial ratios could help investors compare the percentage change of the accounting ratios over time (Beaver, 1968b).

To compare whether real earnings management is more difficult for detection than accrual earnings management in practice, sample (1) and sample (2) in section 3.3.3 are used. In which, as for sample (1) each firm is selected only once to avoid the assumption of full accrual reversals in the following year. To sample (2), it is assumed that there is full reversal of earnings manipulation in the next fiscal year. Sample (1) and sample (2) are added by earnings manipulation ranging from zero percent to 10 percent of lagged assets.

The same three types of earnings manipulations as aforementioned are applied in the analyses (i.e., sales manipulation; overvalued inventory or overproduction; aggressive reduction of discretionary expenses). The relevant accounting financial ratios are selected based on the three types of earnings manipulation activities. The firm-years in the sample (1) or (2) with added manipulation represent the event periods to be tested for earnings management. Therefore, it is hypothesised that there is systematic earnings management corresponding to the stimulus of this study in the event year. The following sub-sections explain the ratios selected with respect to each of the manipulation methods used.

3.3.5.1 Sales manipulation

3.3.5.1.1 Detecting premature revenues recognition

Timing of revenue recognition is defined under the International Financial Reporting Standard 15 (IFRS 15). In which, revenues are recognized when revenues are earned or realized. In practice, managers of firms might boost earnings by recognizing premature revenues. In which, revenue is recognized in a period prior to that a legitimate sale recorded is accepted by IFRS15. Premature recognition of sales will not be collected in cash in the current period. Accordingly, both sales and receivables increase in the period of recognized premature revenues. If revenue recognition is aggressive, this results in a build-up of accounts receivable faster than an increase in sales. This issue might raise concerns about the collectability or uncertainties about proper revenue recognition of firms.

To detect such manipulation activity, investors should watch the account receivable days (hereafter A/R days) carefully. Annual A/R days is measured as the number of days that customers' outstanding invoices are collected. This is calculated by dividing accounts receivable by daily sales (i.e., annual revenues divided by 365) (Mulford and Comiskey, 2005). This ratio can be compared with ratios of other competitors in the same industry or those of previous years. Higher ratios indicate the possibility of wrong recognition of sales or concerns about the collectability. Moreover, following Beneish (1999), Days' sales in

receivables index (hereafter DSRI) is applied to uncover revenue inflation. A large growth in DSRI can be results of sales manipulation. In addition, Fridson and Alvarez (2011) show that there is positive relation between earnings manipulation and sales growth index. In which, sales growth index (hereafter SGI) is the ratio of sales in current year to previous year. Indeed, SGI does not indicate sales manipulation; however, sales manipulation can result in unexpected increase in SGI.

Premature recognition of revenues leads to increasing both revenues and receivables. Accordingly, both accounts receivable and revenues are added to the assumed amount of sales manipulation in the earnings management year. Therefore, both sales and account receivables are added to pre-determined amounts in the manipulation year when annual A/R days, the DSRI and SGI is calculated. As for the cross-sectional analysis, the remaining non-event firm-years having the same two-digit SIC code (i.e., to be used to classify industries for firm-years) and year are matched with the sample of firm-year's event. I use the Wilcoxon test to test the null hypothesis that there is no significant difference in the average annual A/R days, the DSRI or SGI between the sample and that of other companies in the same industry with the conventional test levels of five percent and one percent, using two-tailed tests.

In conducting the time-series (trend) analysis, the financial ratio in the event firm-year with induced manipulation is compared to that in non-event firm-years in the two prior years (t-1; t-2). Accordingly, the Wilcoxon matched-pair test is applied to test the hypothesis that there is no significant difference between annual A/R days, the DSRI or SGI in a manipulation year and a previous year. As before, I use conventional test levels of five percent and one percent with two-tailed tests.

3.3.5.1.2 Detecting aggressive price discounts

As for real earnings management, managers of firms could manipulate sales to improve earnings via temporarily offering price discount. Indeed, in the period of sales manipulation, sales might temporarily increase. Accordingly, cash from operation rises as well. However, in the next period, the discount prices disappear, sales might decrease since customers expect the same discount prices as in the period of manipulation. Thus, the net cash flows will decrease.

Although Roychowdhury (2006) proposes an empirical model to detect such manipulation behaviour that are widely applied in academics, the ability of this model is questionable. Especially, in practice, there is no practical way to detect such behaviour because this manipulation improves both sales and cash in the period of manipulated sales. Thus, this manipulation is very similar to normal business activities of firms. As a result, it is difficult for investors to uncover such manipulation activities in practice.

3.3.5.2 Overvalued inventory and overproduction

3.3.5.2.1 Detecting overvalued inventory

Inventory shows the cost of unsold goods on balance sheets. According to International Accounting Standards 2 (IAS 2), inventory is stated at the lower cost and net realisable value of unsold goods on the balance sheets. In which, net realisable value (NRV) is the estimated selling price, minus essentials costs of selling. In case of damaged, obsolete, or slow-moving, a write-down to net realisable value is need. Revenue is recognized when inventory is sold and the carrying amount of sold inventory is recorded as cost of goods sold (COGS). If inventory is overvalued, there is a reduction in COGS, and correspondingly, reported income is overstated. Indeed, accounting rules allow professional judgment about whether a write-down for impaired inventory is necessary or not. Therefore, to temporarily boost reported earnings, managers could delay inventory write-down.

One useful way to detect the postponement of an inventory write-down is to examine inventory days. Inventory days is calculated by dividing inventory by cost of goods sold per day where annual COGS per day is annual COGS divided by 365 (Mulford, 2005). When managers aggressively postpone inventory write-down, inventory is overstated, and cost of goods sold is understated. Correspondingly, there is an unexpected growth in inventory that outsizes growing revenues. Therefore, the inventory days of the firm will increase and reach the level that is higher than that of other firms in the same industry or that of the firm-years in previous years. Another way is to use total accruals to total assets (hereafter TATA) to uncover overstated inventory (Beneish, 1999). Indeed, the TATA is calculated as the change in total accruals divided by total assets. The higher TATA indicates less cash underlying reported earnings, which is associated with higher likelihood of earnings manipulation.

I add artificially induced manipulation with the magnitude ranging from zero percent to 10 percent of lagged asset to annual inventory days and the TATA of the random sample. In detail, the assumed amount is added to inventory and the same amount is subtracted from

costs of goods sold (COGS) in the earnings manipulation year. As for cross-sectional analysis, the median inventory days and the TATA of the sample is compared with other firm-years in the industry. The Wilcoxon test is applied to test the null hypothesis that there is no significant difference in average inventory days between the random sample and that of other companies in the same industry. With respect to the trend analysis, the Wilcoxon matched-pair test is applied to test the hypothesis that there is no significantly different average inventory days and the TATA in the earnings manipulation year and previous years.

3.3.5.2.2 Detecting overproduction

To boost reported earnings, in addition to overvaluation of assets, managers of firms might engage in overproduction. Indeed, overproducing more goods than demand might lower fixed overhead costs that spread over larger units of goods. Thus, fixed costs per unit reduce, which lowers reported costs of goods sold (COGS). In practice, market participants are not aware of overproduction as earnings manipulation, hence, there is no way to detect overproduction.

3.3.5.3 Aggressive reduction in discretionary expense

3.3.5.3.1 Detecting aggressive reduction in accrued discretionary expenses

Expenses are recognized with unpaid and paid amounts. As for accrued expenses, expenses are recorded but not paid. Thus, unpaid amounts are shown as liabilities on the balance sheet. In terms of accrual-based earnings management, managers of firms might boost earnings by undervaluing liabilities. One way is to understate unpaid discretionary expenses (i.e., research and development expense or administrative expenses). This type of accrual manipulation leads to decreases in accrued expenses payable and discretionary expenses. A test is to compare discretionary expenses as a percentage of sales with that of previous years (Mulford and Comiskey, 2005). An unexpected reduction in this ratio can be result of delaying recognizing accrued operating expenses.

A reduction in accrued discretionary expense will reduce both operating expenses as well as accrued liabilities. Accordingly, the predetermined amount of accrual-based earnings management ranging from zero percent to 10 percent of lagged asset will be deducted from discretionary expenses and accrual liabilities in the year of manipulation. To evaluate the ability of investors or financial professionals to detect the two types of earnings manipulation activities, I compare the difference in the expense ratio (hereafter SGI) of the random sample of firms-year with the benchmark of industries as well as the ratios of the firms in the

previous years. A Wilcoxon test for the null hypothesis that there is no difference in median SGI between the sample and that of other companies in the same industry. Moreover, the Wilcoxon matched-pair test is applied to test the hypothesis that there is no significant difference in SGI between in the manipulation year t and previous year t-1.

3.3.5.3.2 Detecting aggressive reduction in paid discretionary expense

In case of a reduction in operating expenses paid in the manipulation period, accrued liabilities are not affected on the balance sheet. A delay in paid discretionary expenses influences both operating expenses and cash on the balance sheet. In detail, operating expenses reduce, and operating cash flows increase in the year when real activities manipulation occurs. There is a similar means for detecting such manipulation activities with accrual manipulation. Although the real activity manipulation affects the balance of cash on the balance sheet, there is an ambiguous amount of improvement in the cash balance on the balance sheet. This is because other types of real earnings management (i.e., overproduction or price discounts) still directly influence the balance of cash on the balance sheet. As a result, in comparison with accrued operating expenses, this type of real earnings management is more difficult to be detected.

Since it is assumed that discretionary expenses will be paid in the manipulation year, there is a decrease in operating expenditures and cash. In detail, both cash and discretionary expenses will reduce with the assumed amount of real earnings management from zero percent to 10 percent of lagged asset in the earnings management year.

3.4 Empirical results

3.4.1 Descriptive statistics

Panel A, table 3.2 presents the descriptive statistics for the full sample of 19,424 firm-years from 1991-2018. From the table, I 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 about £140M, compared to £432M in Ball and Shivakumar (2005). Mean cash from operations is approximately £14M compared to £13.5M 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 3.2 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.

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 3.2, as for the Modified Jones model, 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). To the Kothari et al. (2005) model, the results are similar to the Modified Jones model. Moreover, the average coefficient on return on asset *(ROA)* 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 3.2 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 of table 3.2 are statistically significant and comparable with those presented by Roychowdhury (2006), Gunny (2010), and Zang (2012). The adjusted R^2

of normal cash from operations, discretionary expenses and production costs is 33.4%, 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 3.2 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 $(REM_{CFO}, REM_{PROD}, REM_{DISEXP})$ 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 3.2, the standard deviations (hereafter SD) 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 SD of the RM_{DISEXP} model is highest (0.542), and the lowest SD is for the REM_{CFO} with 0.299. As shown in Cohen et al. (2020), the SD of REM_{CFO} and REM_{DISEXP} are 0.520 and 0.400, respectively. The SD of the REM_{PROD} model is 0.409 that is similar to the result shown in Cohen et al. (2020). The descriptive statistics provide consistent results with Cohen et al. (2020), in which REM_{DISEXP} exhibit the highest variation.

Table 3.2 Descriptive Statistics

Panel A: Descriptive Statistics of Firm Characteristics (N=19,424)

Variable	*Mean*	*Median*	*Std. Dev.*	*25%*	*75%*
Total assets (A) (£ million)	134.594	43.741	249.432	13.927	136.608
Sales (£ million)	139.835	44.755	233.602	10.089	155.343
CFO (£ million)	13.979	3.958	31.639	(0.033)	13.902
Accruals (£ million)	(5.510)	(1.046)	17.436	(5.550)	0.099
Sales/A	1.219	1.047	1.335	0.565	1.590
CFO/A (%)	3.000	7.700	0.290	(0.200)	14.000
Accruals/A (%)	(4.600)	(3.500)	0.254	(8.400)	0.600
Production costs/A (%)	74.900	53.400	1.217	18.700	100.300
Discretionary expenses/A (%)	37.300	27.300	42.900	12.000	48.500

Panel B: Estimation of the Normal Levels of Accruals, Cash from Operations, Discretionary Expenses and Production Costs

	DAP						**REM**					
	Modified Jones model[i]		Kothari et al. (2005) model[ii]		Modified DD model[iii]		CFO_t[iv]		$DISEXP_t$[v]		$PROD_t$[vi]	
	Mean	SD	Mean	SD	Mean	Std. Dev.	Mean	SD	Mean	SD	Mean	SD
Intercept	(0.033)	0.116	(0.030)***	0.107	0.025***	0.032	0.019	0.087	0.185	0.125	(0.197)	0.161
$1/A_{t-1}$	0.006	0.576	0.043***	0.579			(0.518)***	0.677	0.958***	0.822	(0.194)***	0.999
REV_t/A_{t-1}							0.070***	0.068			0.757***	0.13
REV_{t-1}/A_{t-1}									0.112***	0.078		
$\Delta REV_t/A_{t-1}$	(0.010)***	0.247	(0.017)***	0.248	0.008***	0.191	0.004***	0.156			(0.050)***	0.293
$\Delta REV_{t-1}/A_{t-1}$											(0.024)***	0.265
PPE_{t-1}/A_{t-1}	(0.016)***	0.314	(0.021)***	0.307	(0.034)***	0.051						
ROA_t			0.104***	0.186								
CFO_{t-1}					0.145***	0.245						
CFO_t					(0.319)***	0.323						
CFO_{t+1}					0.098***	0.235						
Adjusted R^2	0.20		0.10		0.32		0.32		0.29		0.77	

Panel C: Summary Statistics for Accrual and Real Activities Manipulation

Variable	*Mean*	*Median*	*SD*	*25%*	*75%*
DAP					
Modified Jones model	0.000	0.003	0.324	-0.050	0.053
Kothari et al., (2005) model	0.000	0.001	0.317	-0.052	0.052
Modified DD model	0.000	0.003	0.123	-0.042	0.045
REM					
$\mathrm{REM_{CFO}}$	0.000	0.012	0.299	-0.060	0.090
$\mathrm{REM_{DISEXP}}$	0.000	-0.046	0.542	-0.180	0.123
$\mathrm{REM_{PROD}}$	0.000	0.040	0.409	-0.130	0.197

All variables are defined within the body of the paper. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent level, respectively. The regressions in panel B are estimated cross-sectionally within the combination of each industry (two-digit SIC) and year from 1991 to 2018 with at least 10 observations in the year-industry combination. The above presented coefficients are the mean values of the coefficients across industry-years. Numbers in brackets represent negative numbers. The t-statistics are used to estimate significance and are calculated by using standard errors of the coefficients across industry-years. The adjusted R^2 is the mean adjusted R^2 across industry-years.

i. $\frac{Accrual_t}{A_{t-1}} = \alpha_0 + \beta_1\left(\frac{1}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \beta_3\left(\frac{PPE_t}{A_{t-1}}\right) + \varepsilon_t$

ii. $\frac{Accrual_t}{A_{t-1}} = \alpha_0 + \beta_1\left(\frac{1}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \beta_3\left(\frac{PPE_t}{A_{t-1}}\right) + \beta_4 ROA_t + \varepsilon_t$

iii. $\frac{Accrual_t}{A_{t-1}} = \alpha_1 + \alpha_2\left(\frac{\Delta REV_t - \Delta REC_t}{A_{t-1}}\right) + \alpha_3\left(\frac{PPE_t}{A_{t-1}}\right) + \alpha_4\left(\frac{CFO_{t-1}}{A_{t-1}}\right) + \alpha_5\left(\frac{CFO_t}{A_{t-1}}\right) + \alpha_6\left(\frac{CFO_{t+1}}{A_{t-1}}\right) + \varepsilon_t$

iv. $\frac{CFO_t}{A_{t-1}} = \alpha_0 + \beta_1\left(\frac{1}{A_{t-1}}\right) + \beta_2\left(\frac{REV_t}{A_{i,t-1}}\right) + \beta_3\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \varepsilon_t$

v. $\frac{DISEXP_t}{A_{t-1}} = \alpha_0 + \alpha 1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{REV_{t-1}}{A_{t-1}}\right) + \varepsilon_t$

vi. $\frac{PROD_t}{A_{t-1}} = \alpha_0 + \alpha 1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{REV_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta REV_t}{A_{t-1}}\right) + \beta_3\left(\frac{\Delta REV_{t-1}}{A_{t-1}}\right) + \varepsilon_t$

DAP (Modified Jones Model), DAP (Kothari et al., (2005) Model), DAP (Modified DD Model), $\mathrm{REM_{CFO}}$, $\mathrm{REM_{DISEXP}}$, $\mathrm{REM_{PROD}}$ are estimated residuals from above equations (i), (ii), (iii), (iv), (v) and (vi), respectively.

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

3.4.2.1 Sample 1: of firms with artificially induced earnings management with no reversal

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 and real earnings management ranging from zero percent to 10 percent of lagged assets added to the sample (1). Table 3.3 presents the results of estimate of magnitude of accrual earnings management and real earnings management with artificially induced accrual manipulation to the sample (1) ranging from zero percent to 10 percent of lagged asset. As presented in the preceding discussion, the requirement for selecting sample (1) is that a firm in a particular year appears one time only in the sample of firms-year. Hence, there is no assumption of full reversal of abnormal operating activities in the following fiscal year.

3.4.2.1.1 Bias in estimates of accrual earnings management (DAP)

Table 3.3, panel A presents the results of the estimate of the coefficient on *PART* with different magnitudes of artificially induced accrual manipulation ranging from zero percent to 10 percent of lagged asset using the sample (1). As presented in the preceding discussion, there is no assumption of full reversal of discretionary accruals 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; hence, I 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)'s 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.

3.4.2.1.2 Bias in estimates of real earnings management

Table 3.3, panel B presents the results of the estimate of the coefficient on *PART* with different magnitudes of artificially induced real earnings management ranging from zero percent to 10 percent of lagged asset using the sample (1). As presented in the preceding discussion, there is no assumption of full reversal of abnormal operating activities in the following fiscal year since each firm is randomly selected only once in year t.

3.4.2.1.2.1 Abnormal cash flows from operations (REM_{CFO})

The first column of Table 3.3, panel B provides results of coefficient estimate on *PART* with including artificially induced sales manipulation from zero percent to 10 percent of lagged asset using sample (1). In particular, 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 revenue manipulations 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 expenditure). 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 (0% of lagged assets). It indicates that abnormal CFOs are affected by the average of these real earnings management. Accordingly, the mean REM_{CFO} are nearly underestimated by about -0.057 at an induced level of 0% of lagged asset.

3.4.2.1.2.2 Reduction of discretionary expense (REM_{DISEXP})

The second column of Table 3.3, panel B shows results of coefficient estimate on *PART* with artificially induced expense manipulation ranging from zero percent to 10 percent of lagged asset. In detail, the estimates of REM_{DISEXP} are underestimated by around 3.5% for the induced amount from 0% to 10% of lagged assets. Accordingly, the mean abnormal discretionary expenditures are statistically different from zero when the induced manipulation is between 8% to 10% of lagged assets. Additionally, the discretionary expense model experiences the highest value of standard error (hereafter SE) (0.020). This indicates that it is probable that this model suffers misspecification from omitting determinants of normal level of discretionary expenditures (problem 2 shown in section 3.3.1.2).

3.4.2.1.2.3 Overproduction (REM_{PROD})

The third column in Table 3.3, panel B documents the results of coefficient estimate on *PART* including artificially induced overproduction ranging from 0 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 3.3 indicate that compared to real earnings management models, the discretionary accruals model has lower SE (0.012), suggesting that this model is more effective in generating normal accruals and suffer less bias caused by omitting determinants of normal accruals.

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

Table 3.4 illustrates the results of coefficient estimates on *PART* using 500 random sample of firm-year (sample 2) with artificially induced earnings manipulation from 0 percent to 10 percent of lagged assets. Since the random sample includes firm-year with consecutive years, the assumption of the tests is that accruals or real operating manipulation activities are fully reversed in the next year. The approaches are implemented by adding induced earnings manipulation from 0 percent to 10 percent of lag assets to the random sample. Accruals and real manipulation account of firm-years in the sample having consecutive years are reversed in the next year.

3.4.2.2.1 Bias in estimates of discretionary accruals

Table 3.4, panel A presents the results of the estimate of the coefficient on *PART* with different magnitudes of artificially induced accrual manipulation ranging from zero percent to 10 percent of lagged asset using the sample (2). Since the random sample includes firm-years with consecutive years, the assumption of the tests is that accruals are fully reversed in the next year. The approach is implemented by adding induced earnings manipulation ranging 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 3.4, Panel A presents the results of the estimates of the coefficients on *PART* with different magnitudes of artificially induced accrual manipulation ranging from 0 percent to 10 percent of lagged assets by using sample (2). 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 results shown in panel A, table 3.3. 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 (year t).

3.4.2.2.2 Bias in estimates of earnings management for measuring real earnings management

3.4.2.2.2.1 Abnormal cash flows from operations (REM_{CFO})

The first column of Table 3.4, panel B provides results of coefficient estimate on *PART* with including artificially induced sales manipulation from zero percent to 10 percent of lagged asset using sample (2). Since the random sample of firm-year includes firm-years with consecutive years, the assumption of the tests is that real manipulation accounts are fully reversed in the next year. The estimator of abnormal cash from operations is underestimated about one percent and the coefficients on *PART* are statistically different from zero when induced manipulation is between 3 percent to 10 percent 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 estimate 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 sales manipulation have abnormal low cash from operations compared to other firms in the same industry. This ambiguous 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, as noted in section 3.3.2.2.1, once firms engage in sales manipulation such as price discounts or channel stuffing, the model removes part of earnings management from abnormal cash from operations

proxy. As a result, the model for detecting sales manipulations provides ambiguous signs of the estimators.

3.4.2.2.2.2 Reduction of discretionary expense (REM_{DISEXP})

Compared to sample (1), the estimate of REM_{DISEXP} of sample (2) 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} are 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).

3.4.2.2.2.3 Overproduction (REM_{PROD})

The estimate of REM_{PROD} is underestimated by around 2% at all levels of induced real earnings management when using sample (2). This is contrary to the results using sample (1) in the previous section, which are overestimated by 3% for all rates of artificially induced overproduction. This is because in this stimulation, the full amount of REM_{PROD} is reversed in the next fiscal year. Therefore, omitted variables in measuring REM_{PROD} are not correlated with *PART* (see problem 3, section 3.3.1.3). This is explained by the higher SE in this sample (0.019) in comparison with the previous sample with the standard error (0.017). As a result, while the estimates of REM_{PROD} of 500 firms at random from year t is statistically significant for all levels, the estimate of REM_{PROD} of random sample of firm-years is statistically different from zero only when manipulation is between 6% to 10%.

Table 3.3 Bias in estimates of earnings management using sample 1

Panel A: Biases in estimates of accrual earnings management

Simulations are conducted for artificially induced amounts of earnings management from 0% to 10% of lagged assets. The simulation uses 500 firms (sample 1) selected at random in year t to test for biases in estimates of discretionary accruals (*DAP*).

	Revenue manipulation (DAP)											
	Modified Jones Model				Kothari et al., (2005) Model				Modified DD Model			
Percentage of manipulation	**Coefficient on PART**	**SE**	**t-statistics**	**p-value**	**Coefficient on PART**	**SE**	**t-statistics**	**p-value**	**Coefficient on PART**	**SE**	**t-statistics**	**p-value**
0%	-0.002	0.012	-0.138	0.890	0.003	0.011	0.237	0.406	0.003	0.010	0.314	0.754
1%	0.008	0.012	0.731	0.465	0.013	0.011	1.139	0.128	0.013	0.010	1.361	0.175
2%	0.018	0.012	1.601	0.110	0.023	0.011	3.041	0.0209**	0.023	0.010	3.409	0.017**
3%	0.028	0.012	3.470	0.014**	0.033	0.011	3.943	0.002***	0.033	0.010	3.456	0.000***
4%	0.038	0.012	3.340	0.001***	0.043	0.011	3.845	0.000***	0.043	0.010	4.503	0.000***
5%	0.048	0.012	4.209	0.000***	0.053	0.011	4.747	0.000***	0.053	0.010	5.551	0.000***
6%	0.058	0.012	5.079	0.000***	0.063	0.011	5.649	0.000***	0.063	0.010	6.598	0.000***
7%	0.068	0.012	5.948	0.000***	0.073	0.011	6.551	0.000***	0.073	0.010	7.646	0.000***
8%	0.078	0.012	6.818	0.000***	0.083	0.011	7.453	0.000***	0.083	0.010	8.693	0.000***
9%	0.088	0.012	7.687	0.000***	0.093	0.011	8.355	0.000***	0.093	0.010	9.741	0.000***
10%	0.098	0.012	8.557	0.000***	0.103	0.011	9.257	0.000***	0.103	0.010	10.788	0.000***

The results under the three alternative assumptions of the components of accruals being managed provide similar results. Therefore, I present only results for revenue manipulation. The accrual earnings management results above represent the estimated coefficient on PART from regression of the form:

$$DAP_t = \hat{a}_0 + \hat{a}_1 PART_t + \varepsilon_t$$

PART is set as equal one in the year of accrual earnings management that is hypothesized in response to the stimulus, 0 otherwise. The coefficients on PART, $\hat{a}_1$, show the estimate of the magnitude of earnings management attribute to artificially adding pre-determined accrual manipulation to the sample 1. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero.

*, **, *** indicate significance at 10 percent, 5 percent, and 1 percent level, respectively.

Panel B: Biases in estimates of real earnings management

Simulations are conducted for artificially induced amounts of real earnings management from 0% to 10% of lagged assets. The simulation includes artificially induced amounts in 500 firms selected at random in year t (sample 1) to test for biases in estimates of real earnings management.

Percentage of manipulation	Sales manipulation (REM_{CFO})				Reduction of discretionary expense (REM_{DISEXP})				Overproduction (REM_{PROD})			
	Coefficient on PART	SE	t-statistic	p-value	Coefficient on PART	SE	t-statistic	p-value	Coefficient on PART	SE	t-statistic	p-value
0%	-0.057	0.016	-3.669	0.000***	0.035	0.020	1.732	0.084*	0.034	0.017	3.005	0.046***
1%	-0.048	0.016	-3.081	0.002***	0.025	0.020	1.231	0.219	0.044	0.017	3.589	0.010***
2%	-0.039	0.016	-3.493	0.013**	0.015	0.020	0.730	0.466	0.054	0.017	3.174	0.002***
3%	-0.030	0.016	-1.905	0.057*	0.005	0.020	0.230	0.819	0.064	0.017	3.758	0.000***
4%	-0.021	0.016	-1.318	0.188	-0.005	0.020	-0.271	0.786	0.074	0.017	4.342	0.000***
5%	-0.011	0.016	-0.730	0.466	-0.015	0.020	-0.772	0.441	0.084	0.017	4.927	0.000***
6%	-0.002	0.016	-0.143	0.886	-0.025	0.020	-1.273	0.204	0.094	0.017	5.511	0.000***
7%	0.007	0.016	0.444	0.657	-0.035	0.020	-1.774	0.077*	0.104	0.017	6.096	0.000***
8%	0.016	0.016	1.031	0.303	-0.045	0.020	-3.274	0.023**	0.114	0.017	6.680	0.000***
9%	0.025	0.016	1.617	0.107	-0.055	0.020	-3.775	0.006***	0.124	0.017	6.680	0.000***
10%	0.035	0.016	3.203	0.028**	-0.065	0.020	-3.276	0.001***	0.134	0.017	7.849	0.000***

The results of the estimates of real earnings management results represent the estimated coefficient on PART from the equation below:

$REM_t = \hat{b}_0 + \hat{b}_1 PART_t + \delta_t$

In the stimulus, there are three sets of assumptions regarding three types of real earnings management (i.e., REM_{CFO}, REM_{DISEXP}, REM_{PROD}). *PART* is set as equal one in the year of real earnings management that is hypothesized in response to the stimulus, 0 otherwise. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero.

*, **, *** indicate significance at 10 percent, 5 percent, and 1 percent level, respectively.

Table 3.4 Bias in estimates of earnings management using sample 2

Panel A: Biases in estimate of accrual earnings management

Simulations are conducted for artificially induced amounts of earnings management from 0% to 10% of lagged assets. Simulations use random 500 firms-years (sample 2) to test for biases in estimates of discretionary accruals (DAP)

	Revenue manipulation (DAP)											
	Modified Jones Model				Kothari et al., (2005) Model				Modified DD Model			
Percentage of manipulation	**Coefficient on PART**	**SE**	**t-statistic**	**p-value**	**Coefficient on PART**	**SE**	**t-statistic**	**p-value**	**Coefficient on PART**	**SE**	**t-statistic**	**p-value**
0%	0.000	0.011	0.007	0.994	-0.003	0.011	-0.265	0.605	-0.001	0.008	-0.173	0.863
1%	0.010	0.011	0.875	0.382	0.007	0.011	0.625	0.266	0.008	0.008	0.975	0.330
2%	0.020	0.011	1.743	0.082	0.017	0.011	1.514	0.065*	0.018	0.008	3.124	0.034**
3%	0.029	0.011	3.611	0.009***	0.026	0.011	3.404	0.008***	0.028	0.008	3.272	0.000***
4%	0.039	0.011	3.478	0.001***	0.036	0.011	3.293	0.000***	0.037	0.008	4.419	0.000***
5%	0.049	0.011	4.345	0.000***	0.046	0.011	4.182	0.000***	0.047	0.008	5.565	0.000***
6%	0.059	0.011	5.211	0.000***	0.056	0.011	5.070	0.000***	0.057	0.008	6.710	0.000***
7%	0.068	0.011	6.077	0.000***	0.065	0.011	5.958	0.000***	0.067	0.008	7.852	0.000***
8%	0.078	0.011	6.942	0.000***	0.075	0.011	6.845	0.000***	0.076	0.008	8.993	0.000***
9%	0.088	0.011	7.806	0.000***	0.085	0.011	7.731	0.000***	0.086	0.008	10.130	0.000***
10%	0.098	0.011	8.669	0.000***	0.095	0.011	8.616	0.000***	0.096	0.008	11.265	0.000***

The results under the three alternative assumptions of the components of accruals being managed provide similar results. Therefore, I present only results for revenue manipulation. The accrual earnings management results above represent the estimated coefficient on PART from regression of the form:

$$DAP_t = \hat{a}_0 + \hat{a}_1 PART_t + \varepsilon_t$$

PART is set as equal one in the year of accrual earnings management that is hypothesized in response to the stimulus, 0 otherwise. The coefficients on PART, $\hat{a}_1$, show the estimate of the magnitude of earnings management attribute to artificially adding pre-determined accrual manipulation to the sample 2. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent level, respectively.

Panel B: Biases in estimate of real earnings management

Percentage of manipulation	Sales manipulation (REM_{CFO})				Reduction of discretionary expense (REM_{DISEXP})				Overproduction (REM_{PROD})			
	Coefficient on PART	SE	t-statistic	p-value	Coefficient on PART	SE	t-statistic	p-value	Coefficient on PART	SE	t-statistic	p-value
0%	0.005	0.012	0.397	0.692	0.005	0.022	0.234	0.815	-0.021	0.019	-1.076	0.283
1%	0.014	0.012	1.136	0.257	-0.005	0.022	-0.205	0.837	-0.011	0.019	-0.564	0.573
2%	0.023	0.012	1.875	0.061*	-0.014	0.022	-0.645	0.519	-0.001	0.019	-0.054	0.957
3%	0.032	0.012	3.613	0.009***	-0.024	0.022	-1.084	0.279	0.009	0.019	0.455	0.650
4%	0.041	0.012	3.350	0.001***	-0.034	0.022	-1.523	0.128	0.018	0.019	0.962	0.337
5%	0.050	0.012	4.087	0.000***	-0.044	0.022	-1.963	0.050*	0.028	0.019	1.467	0.143
6%	0.059	0.012	4.822	0.000***	-0.053	0.022	-3.402	0.017***	0.038	0.019	1.971	0.049**
7%	0.068	0.012	5.556	0.000***	-0.063	0.022	-3.841	0.005***	0.048	0.019	3.474	0.014**
8%	0.077	0.012	6.289	0.000***	-0.073	0.022	-3.280	0.001***	0.058	0.019	3.975	0.003***
9%	0.086	0.012	7.021	0.000***	-0.083	0.022	-3.719	0.000***	0.067	0.019	3.474	0.001***
10%	0.095	0.012	7.751	0.000***	-0.092	0.022	-4.158	0.000***	0.077	0.019	3.972	0.000***

Simulations are conducted for artificially induced amounts of real earnings management from 0% to 10% of lagged assets. Simulations use random 500 firms-years (sample 2) to test for biases in estimates of REM.

The results of the estimates of real earnings management results represent the estimated coefficient on PART from the equation (3.16):

$$REM = \hat{b}_0 + \hat{b}_1 PART_t + \delta_t$$

In the stimulus, there are three sets of assumptions regarding three types of real earnings management (i.e., REM_{CFO}, REM_{DISEXP}, REM_{PROD}). *PART* is set as equal one in the year of real earnings management that is hypothesized in response to the stimulus, 0 otherwise. The t-statistic test is applied to test the null hypothesis that the coefficients of PART are equal to zero. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent level, respectively.

3.4.3 Power of tests for detecting artificially induced earnings management

3.4.3.1 Sample 1: firms with artificially induced earnings management

3.4.3.1.1 Accrual earnings management (DAP)

Table 3.5 and Table 3.6 provide further evidence on the ability of the relative models to detect accrual earnings management and real earnings management by using the sample (1) and sample (2), respectively. The results are the power of relative models for uncovering accrual earnings management and real earnings management that are the frequency with which the null hypothesis of no earnings management is rejected with the induced earnings management ranging from zero to 10 percent of lagged asset. 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.

In particular, the first column in Table 3.5 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, I only present results using revenue manipulation. 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 3.3, 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 SE as shown in panel A, Table 3.3.

3.4.3.1.2 Real earnings management (REM)

The second column of Table 3.5 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 98% to 80%). 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 biased coefficient estimates of earnings management as shown in Table 3.3, Panel B.

The third column in Table 3.5 gives the results of the power function for detecting discretionary expense manipulation (REM_{DISEXP}). At 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 3.3, 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 SE as shown in Table 3.3, Panel B.

The last column in Table 3.5 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 3.3, 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, when 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.

3.4.3.2 Sample 2: firm-years with artificially induced earnings management

3.4.3.2.1 Accrual earnings management (DAP)

Table 3.6 provides the power of the test of accrual earnings management model and real earnings management 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 3.6 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 SE shown in panel A, table 3.4. 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) is 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

3.5, 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.

3.4.3.2.2 Real earnings management (REM)

The remaining columns of Table 3.6 provide the relative power of real earnings management models for the random sample of firm-years (sample 2). The second column of Table 3.6 shows the results of the power of REM_{PROD} model for detecting real earnings management. In comparison with the power of REM_{PROD} model of the sample (1), the power of REM_{PROD} model of sample (2) is lower. This may be because of the downwardly biased estimate of earnings management (see Table 3.4, 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.

As shown in the third and last column of Table 3.6, both REM_{SALES} 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 due to less biased estimates of earnings management as shown in Table 3.4, panel B. Moreover, REM_{SALES} 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 sales manipulation for sample (2) significantly improves due to unbiased coefficient estimate of earnings management in Table 3.4, panel B.

Table 3.5 Power for test of accrual and real earnings management conducted for artificially induced amount of earnings management from 0% to 10% of lagged assets. The simulation uses a random sample of 500 firms (sample 1)

Percentage of manipulation	DAP			REM		
	Modified Jones Model	Kothari et al. (2005) Model	Modified DD Model	REM_{CFO}	REM_{DISEXP}	REM_{PROD}
0%	7%	6%	9%	98%	53%	64%
1%	18%	21%	39%	92%	34%	83%
2%	48%	53%	78%	80%	18%	94%
3%	80%	84%	96%	60%	8%	98%
4%	96%	97%	100%	37%	8%	100%
5%	99%	100%	100%	18%	19%	100%
6%	100%	100%	100%	7%	35%	100%
7%	100%	100%	100%	11%	55%	100%
8%	100%	100%	100%	27%	74%	100%
9%	100%	100%	100%	49%	87%	100%
10%	100%	100%	100%	71%	95%	100%

The earnings management results above represent the frequency with which the null hypothesis of no earnings management is rejected in regressions of the form:

$DAP_t = \hat{a}_0 + \hat{a}_1 PART_t + \varepsilon_t$

$REM_t = \hat{b}_0 + \hat{b}_1 PART_t + \delta_t$

PART is set as equal one in the year of earnings management that is hypothesized in response to the stimulus, 0 otherwise. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero.

Table 3.6 Power for test of accrual and real earnings management conducted for artificially induced amount of earnings management from 0% to 10% of lagged assets. Simulation uses random sample of 500 firms-years (sample 2)

Percentage of manipulation	DAP			REM		
	Modified Jones Model	Kothari et al. (2005) Model	Modified DD Model	REM_{CFO}	REM_{DISEXP}	REM_{PROD}
0%	5%	8%	7%	11%	8%	28%
1%	22%	15%	25%	31%	8%	14%
2%	54%	45%	68%	59%	16%	6%
3%	83%	78%	95%	83%	29%	12%
4%	97%	95%	100%	96%	45%	25%
5%	100%	100%	100%	99%	62%	43%
6%	100%	100%	100%	100%	78%	63%
7%	100%	100%	100%	100%	88%	80%
8%	100%	100%	100%	100%	95%	91%
9%	100%	100%	100%	100%	98%	97%
10%	100%	100%	100%	100%	99%	99%

The earnings management results above represent the frequency with which the null hypothesis of no earnings management is rejected in regressions of the form:

$DAP_t = \hat{a}_0 + \hat{a}_1 PART_t + \varepsilon_t$

$REM_t = \hat{b}_0 + \hat{b}_1 PART_t + \delta_t$

PART is set as equal one in the year of earnings management that is hypothesized in response to the stimulus, 0 otherwise. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero.

3.4.4 Financial ratio analysis

3.4.4.1 Detecting sales manipulation

3.4.4.1.1 Detecting premature revenues recognition

3.4.4.1.1.1 Sample 1: firms with artificially induced earnings management

a. Account receivable days (A/R days)

Table 3.7 presents cross-sectional and time-series ratio analysis for average account receivable days (A/R days) using sample (1). The Wilcoxon test is applied to compare the difference in average account receivable days (A/R days) between the sample of firms-year and other firms-years in the same industry or previous years.

Panel A, Table 3.7 reports results for average difference in account receivable days (A/R days) between sample (1) and other firm-years in the same industry. Without manipulation (i.e., percentage of manipulation is 0%), average A/R days of the sample of firm-years in the event year is not significantly different from that of a control sample in the non-event years. From induced manipulation of 1% of lagged asset above, there is a significant difference in average A/R days of the sample (1) with that of industry matched firm-years. A/R days of the random sample of firm-years increase on average by about three days when the induced earnings management rises to 1% of lagged assets compared to that of other firm-years in the same industry. With the manipulation of 10% of lagged assets the average A/R days of manipulators are higher 30 days than that of non-manipulators.

Panel B of Table 3.7 presents results of trend analysis of average A/R days using the sample (1). There are significantly lower average A/R days of the sample in year t than in previous year (year t-1) without artificially induced discretionary accruals (0%) (p-value<1%). However, from 1% of artificially induced sales manipulation and above, average A/R days of the sample in the manipulation year (year t) are significantly higher than in the previous year (year t-1). The results for cross-sectional and time-series A/R days indicate that when managers of firms manipulate sales, there is a large increase in A/R days.

b. Days' sales in receivables index (DSRI)

Table 3.9 reports cross-sectional analysis and time-series of average days' sales in receivable index (DSRI) using sample (1). The Wilcoxon test is applied to compare the difference in average days' sales in receivable index (DSRI) between the sample of firms-years and other firms-years in the same industry or previous year.

Panel A of Table 3.9 applies the Wilcoxon test to compare the difference in average days' sales in receivables index (DSRI) between the random sample (1) and other firm-years in the same industry or between the random sample (1) in the manipulation year (year t) and previous year (year t-1). Without manipulation, DSRI of the sample (1) is not significantly different from that of control group. Similarly, at 1% of artificially induced earnings manipulation, there is no significant difference in DSRI between manipulators and non-manipulators. From 2% or greater of induced sales manipulation, DSRI of the sample of firm-years is significantly different from that of other firms in the same industry (p<1%).

Panel B, Table 3.9 presents results for time-series analysis for average DSRI. Indeed, average DSRI of the sample in the year of manipulation (year t) is significantly lower than that in the previous year (year t-1) (p<5%). From artificially induced earnings manipulation from 1% to 2% of lagged asset, average DSRI of the sample in the manipulation year (year t) is not significantly different from in the earlier year (year t-1). From the magnitudes of artificially induced earnings management between 3% and 10% of lagged assets, there is significant difference in average DSRI between the manipulation year (year t) and previous year (year t-1) at the test level of 1 percent.

c. Percentage of sales growth index (SGI)

Table 3.11 shows cross-sectional and time-series analysis of average percentage of sales growth index (SGI) using sample (1). The Wilcoxon test is applied to compare the difference in the average percentage of SGI between the sample of firms-years and other firms-years in the same industry or previous year.

Panel A of Table 3.11 presents the average percentage of SGI using cross-sectional analysis. As presented in panel A, without sales manipulation (i.e., percentage of manipulation is 0%), average SGI of the sample firm-years is significantly higher than control group (difference about 0.5%, significant at 10 percent level). Indeed, SGI does not imply manipulation. However, if there is large increase in SGI, professionals might consider as more likely to have financial statement manipulation. At the artificially induced sales manipulation at 1 percent of lagged asset, the average percentage of SGI of manipulators is significantly higher than that of non-manipulators with the difference of 5.7%, significant at 1 percent level. With the artificially induced earnings manipulation at 10% of lagged asset, average SGI of manipulators is significantly higher than non-manipulators to 18% (significant at 1 percent level).

Panel B of Table 3.11 shows the results for the average percentage of SGI using time-series analysis. From 0 percent to 2 percent of artificially induced sales manipulation, there is no significant difference between SGI of the sample in the manipulation year (year t) and in previous year (year t-1). With the induced manipulation level of 3 percent of lagged asset, there is a statistically significant difference between SGI of the random sample in the event year and previous year (difference of 7.565%, significant at 5 percent level). At the artificially induced manipulation of 10 percent of lagged asset, SGI of the sample in the manipulation year (year t) is higher than in earlier year (year t-1) (difference of 16.5%, significant at 1 percent level).

The results indicate that with premature revenue recognition, account receivables of the random sample (1) witness the significant build-up, which results in account receivables growing more quickly than sales. Therefore, A/R days show a dramatic bulge and is significantly higher than other companies in the industry. Moreover, DSRI of manipulators is significantly higher than non-manipulators in the same industry with artificially induced 2 percent of lagged asset. Similarly, DSRI of the sample in the manipulation year is significantly greater than in the previous year at the artificially induced sales manipulation of 3 percent of lagged asset.

3.4.4.1.1.2 Sample 2: of firms with artificially induced earnings management

a. Account receivable days (A/R days)

Table 3.8 uses the Wilcoxon test to compare the difference in average account receivable days (A/R days) between the random sample (2) and other firm-years in the same industry or between the random sample (2) in the manipulation year (year t) and previous year (year t-1). It is assumed that accrual manipulation is fully reversed in the next fiscal year.

Panel A of Table 3.8 shows the result of cross-sectional analysis for average A/R days. Without manipulation (0 percent of artificially induced earnings management), there is no significant difference in average A/R days between the random sample (2) and other firm-years in the same industry. Similarly, Panel B presents the consistent results that average A/R days of the random sample in event year (year t) is not significantly different from previous (year t-1). At the artificially added earnings manipulation of 1 percent of lagged asset, average A/R days of the sample (2) is significantly higher about 1 day than that of the control group (significant at 1 percent level).

Panel B of Table 3.8 presents the result of time-series analysis for average A/R days. The result of Panel B, Table 3.8 is similar to Panel A, Table 3.8, which average A/R days of the sample

(2) in the manipulation year (year t) are significantly greater by 3.498 days than in prior year (year t-1). With the added manipulation of 10 percent of lagged asset, average A/R days of the sample (2) is greater by 25.753 days than other firm-years in the same industry (Panel A, Table 3.8). Comparison with previous year, average A/R days of the sample (2) in the manipulation year are significantly greater by 27.334 days at the artificially induced earnings manipulation of 10 percent of lagged asset.

b. Days' sales in receivables index (DSRI)

Table 3.10 applies the Wilcoxon test to compare the difference in average days' sales in receivables index (DSRI) between the random sample (2) and other firm-years in the same industry or between the random sample (2) in the manipulation year (year t) and previous year (year t-1).

As shown in Panel A, Panel B of Table 3.10, without earnings manipulation, there is no significant difference in average DSRI between the sample (2) and other firm-years in the same industry, or between the manipulation year (year t) and previous year (year t-1), respectively. Average DSRI of the sample (2) in a manipulation year (year t) is significantly higher than other firm-years in the same industry and previous year (year t-1) (significant at 1 percent level) for the artificially added earnings manipulation of 1 percent of lagged asset or greater. The difference in average DSRI between the sample (2) and the control group or between the manipulation year (year t) and prior year (year t-1) is 0.038 and 0.067, respectively at 1 percent of lagged asset of earnings manipulation. At 10 percent of lagged asset of artificially induced earnings management, average DSRI of the sample (2) is significantly higher by 0.325 than the control group (significant at 1 percent level) (Panel A, Table 3.10). Similarly, average DSRI of the sample (2) in the manipulation year is greater by 0.354 than previous year (year t-1) (significant at 1 percent level) with the manipulation of 10 percent of lagged asset.

c. Percentage of sales growth index (SGI)

Table 3.12 applies the Wilcoxon test to compare the difference in the average percentage of sales growth index (SGI) between the random sample (2) and other firm-years in the same industry or between the random sample (2) in the manipulation year (year t) and previous year (year t-1).

The average percentage of SGI of the sample (2) in the manipulation year (year t) is higher than other firm-years or previous year (year t-1) (significant at 5 percent level) without induced sales manipulation. For all levels of induced earnings management, average SGI of the sample (2) is

significantly greater than the control group or prior year. At the level of 10 percent of lagged asset of added sales manipulation, the average SGI of sample (2) is higher by 13.857% and 11.982% than the control group and previous year (year t-1), respectively.

The results using the sample (2) of firm-years are consistent with previous results using the sample (1) of firm-years. When managers of firms engage in revenue manipulation, both A/R and DSRI of manipulators in the manipulation year are higher than non-manipulators and previous year for all levels of induced sales manipulation. Moreover, there is a significant increase in SGI when artificially induced sales manipulation exceeds 1 percent of lagged asset.

3.4.4.1.2 Detecting aggressive price discounts

As for real earnings management, managers of firms try to accelerate next year's sales into current-year sales through temporarily offering price discounts. This type of real earnings management affects both cash from operations and revenues of a firm. This earnings management activity could help a firm improve earnings. There are no financial ratios or ways to detect such type of real earnings management. Consequently, it is very difficult for investors to detect such abnormal behaviour in practice.

Table 3.7 Account receivable days (A/R days) using sample 1[1]

Panel A. Average A/R days of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	73.627	71.971	0.656	0.943	-0.071
1%	75.494	71.971	3.523	0.000	-5.682
2%	79.811	71.971	7.840	0.000	-8.052
3%	83.419	71.971	11.448	0.000	-10.127
4%	86.308	71.971	14.337	0.000	-11.953
5%	88.487	71.971	16.516	0.000	-13.644
6%	91.277	71.971	19.307	0.000	-15.244
7%	94.641	71.971	23.670	0.000	-16.702
8%	97.297	71.971	25.326	0.000	-18.014
9%	100.279	71.971	28.308	0.000	-19.231
10%	103.063	71.971	30.092	0.000	-20.351

* n=number of firms

Note: The Wilcoxon test compares the difference in A/R days between the sample 1 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

[1] $\text{A/R days} = \frac{\text{Receivables}_t}{\text{Sales}_t} \text{ x } 365 \text{ days}$

Table 3.7. (Cont.)

Panel B. Average A/R days of 500 randomly selected firm-years (sample 1) in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-value	z-statistic
0%	70.405	73.685	73.312	-3.280	0.001	-3.379
1%	75.494	73.685	73.312	1.809	0.000	9.629
2%	79.811	73.685	73.312	6.126	0.098	1.657
3%	83.419	73.685	73.312	9.734	0.000	3.776
4%	86.308	73.685	73.312	13.623	0.000	5.374
5%	88.487	73.685	73.312	14.802	0.000	6.555
6%	91.277	73.685	73.312	17.593	0.000	7.462
7%	94.641	73.685	73.312	20.956	0.000	8.151
8%	97.297	73.685	73.312	23.613	0.000	8.726
9%	100.279	73.685	73.312	26.594	0.000	9.193
10%	103.063	73.685	73.312	28.378	0.000	9.629

* n=number of firms

Note: The Wilcoxon test compares the difference in A/R days between the sample 1 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.8 Account receivable days (A/R days) using sample 2

Panel A. Average A/R days of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	97.724	71.971	25.753	0.657	-0.444
1%	73.887	71.971	0.916	0.000	-4.059
2%	76.897	71.971	4.926	0.000	-6.499
3%	79.530	71.971	7.559	0.000	-8.657
4%	81.935	71.971	9.964	0.000	-10.668
5%	84.878	71.971	13.907	0.000	-13.511
6%	87.424	71.971	15.453	0.000	-14.187
7%	89.466	71.971	17.495	0.000	-15.706
8%	93.133	71.971	20.162	0.000	-17.103
9%	95.195	71.971	23.224	0.000	-18.396
10%	97.724	71.971	25.753	0.000	-19.540

* n=number of firms

Note: The Wilcoxon test compares the difference in A/R days between the sample 2 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.8. (Cont.)

Panel B. Average A/R days of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference days between year t and t-1	Matched-pair Wilcoxon test	
					p-value	z-statistic
0%	68.850	70.389	73.379	-1.539	0.133	-1.504
1%	73.887	70.389	73.379	3.498	0.051	1.952
2%	76.897	70.389	73.379	6.507	0.000	4.560
3%	79.530	70.389	73.379	9.141	0.000	6.555
4%	81.935	70.389	73.379	11.546	0.000	8.145
5%	84.878	70.389	73.379	14.489	0.000	9.394
6%	87.424	70.389	73.379	17.034	0.000	10.314
7%	89.466	70.389	73.379	19.077	0.000	11.058
8%	93.133	70.389	73.379	21.744	0.000	11.678
9%	95.195	70.389	73.379	24.805	0.000	13.184
10%	97.724	70.389	73.379	27.334	0.000	13.631

* n=number of firms

Note: The Wilcoxon test compares the difference in A/R days between the sample 2 in year of manipulation (Year t) and earlier manipulation year (Year t-1). The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.9 Days' sales in receivables index (DSRI) using sample 1[2]

Panel A. Average days' sales in receivables index (DSRI) of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-value	z-statistics
0%	0.990	1.002	-0.012	0.119	1.560
1%	0.996	1.002	-0.006	0.524	-0.637
2%	1.039	1.002	0.037	0.000	-4.383
3%	1.073	1.002	0.071	0.000	-7.764
4%	1.108	1.002	0.106	0.000	-10.568
5%	1.141	1.002	0.139	0.000	-13.103
6%	1.167	1.002	0.165	0.000	-15.007
7%	1.204	1.002	0.203	0.000	-16.469
8%	1.242	1.002	0.241	0.000	-17.638
9%	1.269	1.002	0.268	0.000	-18.659
10%	1.299	1.002	0.297	0.000	-19.634

* n=number of firms

Note: The Wilcoxon test compares the difference in DSRI between the sample 1 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

[2] $\text{DSRI} = \frac{\text{Receivables}_t/\text{Sales}_t}{\text{Receivables}_{t-1}/\text{Sales}_{t-1}}$

Table 3.9. (Cont.)

Panel B. Average days' sales in receivables index (DSRI) of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-value	z-statistic
0%	0.952	0.985	1.005	-0.033	0.021	-3.306
1%	0.996	0.985	1.005	0.011	0.581	-0.552
2%	1.039	0.985	1.005	0.054	0.239	1.178
3%	1.073	0.985	1.005	0.088	0.013	3.474
4%	1.108	0.985	1.005	0.123	0.000	3.479
5%	1.141	0.985	1.005	0.156	0.000	4.435
6%	1.167	0.985	1.005	0.182	0.000	5.278
7%	1.204	0.985	1.005	0.219	0.000	5.930
8%	1.242	0.985	1.005	0.257	0.000	6.565
9%	1.269	0.985	1.005	0.284	0.000	7.132
10%	1.299	0.985	1.005	0.313	0.000	7.635

* n=number of firms

Note: The Wilcoxon test compares the difference in DSRI between the sample 1 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.10 Days' sales in receivables index (DSRI) using sample 2

Panel A. Average days' sales in receivables index (DSRI) of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	0.993	1.002	-0.009	0.481	0.705
1%	1.039	1.002	0.038	0.000	-5.278
2%	1.073	1.002	0.071	0.000	-8.941
3%	1.105	1.002	0.103	0.000	-13.160
4%	1.139	1.002	0.138	0.000	-14.827
5%	1.172	1.002	0.170	0.000	-17.048
6%	1.199	1.002	0.198	0.000	-18.869
7%	1.237	1.002	0.235	0.000	-20.349
8%	1.268	1.002	0.266	0.000	-21.525
9%	1.294	1.002	0.292	0.000	-23.441
10%	1.326	1.002	0.325	0.000	-23.156

* n=number of firms

Note: The Wilcoxon test compares the difference in DSRI between the sample 2 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.10. (Cont.)
Panel B. Average days' sales in receivables index (DSRI) of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-value	z-statistic
0%	0.993	0.972	1.024	0.021	0.651	-0.453
1%	1.039	0.972	1.024	0.067	0.096	1.666
2%	1.073	0.972	1.024	0.101	0.001	3.403
3%	1.105	0.972	1.024	0.132	0.000	4.865
4%	1.139	0.972	1.024	0.167	0.000	6.008
5%	1.172	0.972	1.024	0.200	0.000	6.926
6%	1.199	0.972	1.024	0.227	0.000	7.697
7%	1.237	0.972	1.024	0.265	0.000	8.357
8%	1.268	0.972	1.024	0.296	0.000	8.917
9%	1.294	0.972	1.024	0.321	0.000	9.392
10%	1.326	0.972	1.024	0.354	0.000	9.828

* n=number of firms

Note: The Wilcoxon test compares the difference in DSRI between the sample 2 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.11 Sales growth index (SGI) [3] using sample 1

Panel A. Average sales growth index (SGI) of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500) (%)	Other Firm-Years (n=18,919) (%)	Difference (Sample-Other) (%)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	8.478	8.012	0.467	0.062	-1.864
1%	13.735	8.012	5.723	0.000	-8.437
2%	15.792	8.012	7.780	0.000	-10.078
3%	17.037	8.012	9.026	0.000	-11.547
4%	18.519	8.012	10.508	0.000	-13.911
5%	19.863	8.012	11.852	0.000	-14.190
6%	21.015	8.012	13.004	0.000	-15.444
7%	23.111	8.012	14.100	0.000	-16.513
8%	23.524	8.012	15.513	0.000	-17.452
9%	24.664	8.012	16.653	0.000	-18.373
10%	25.978	8.012	17.967	0.000	-19.229

* n=number of firms

Note: The Wilcoxon test compares the difference in sales growth index between the sample 1 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

[3] $\mathrm{SGI} = \frac{\mathrm{Sales}_t - \mathrm{Sales}_{t-1}}{\mathrm{Sales}_{t-1}} \mathrm{x}100$

Table 3.11. (Cont.)
Panel B. Average sales growth index (SGI) of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t) (%)	Earlier manipulation year (Year t-1) (%)	Earlier manipulation year (Year t-2) (%)	Difference between year t and t-1 (%)	Matched-pair Wilcoxon test	
					p-value	z-statistic
0%	13.431	9.472	10.075	3.959	0.245	-1.162
1%	13.735	9.472	10.075	4.263	0.533	0.624
2%	15.792	9.472	10.075	6.320	0.136	1.490
3%	17.037	9.472	10.075	7.565	0.024	3.254
4%	18.519	9.472	10.075	9.047	0.003	3.997
5%	19.863	9.472	10.075	10.391	0.000	3.677
6%	21.015	9.472	10.075	11.543	0.000	4.264
7%	23.111	9.472	10.075	13.639	0.000	4.801
8%	23.524	9.472	10.075	14.052	0.000	5.293
9%	24.664	9.472	10.075	15.192	0.000	5.774
10%	25.978	9.472	10.075	16.506	0.000	6.235

* n=number of firms

Note: The Wilcoxon test compares the difference in sales growth index between the sample 1 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.12 Sales growth index (SGI) using sample 2

Panel A. Average sales growth index (SGI) of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500) (%)	Other Firm-Years (n=18,919) (%)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	10.393	8.011	3.382	0.021	-3.306
1%	11.583	8.011	3.572	0.000	-4.369
2%	13.784	8.011	4.773	0.000	-6.073
3%	14.140	8.011	6.129	0.000	-7.586
4%	15.005	8.011	6.995	0.000	-9.037
5%	15.906	8.011	7.895	0.000	-10.425
6%	17.399	8.011	9.388	0.000	-11.778
7%	17.914	8.011	9.903	0.000	-13.959
8%	18.951	8.011	10.941	0.000	-14.028
9%	19.979	8.011	11.968	0.000	-15.041
10%	20.868	8.011	13.857	0.000	-16.032

* n=number of firms

Note: The Wilcoxon test compares the difference in sales growth index between the sample 2 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.12. (Cont.)

Panel B. Average sales growth index (SGI) of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t) (%)	Earlier manipulation year (Year t-1) (%)	Earlier manipulation year (Year t-2) (%)	Difference between year t and t-1 (%)	Matched-pair Wilcoxon test	
					p-value	z-statistic
0%	10.393	8.886	9.311	1.507	0.048	-1.975
1%	11.583	8.886	9.311	3.697	0.365	-0.906
2%	13.784	8.886	9.311	3.898	0.978	-0.028
3%	14.140	8.886	9.311	5.254	0.441	0.771
4%	15.005	8.886	9.311	6.119	0.117	1.569
5%	15.906	8.886	9.311	7.020	0.019	3.352
6%	17.399	8.886	9.311	8.512	3.097	3.097
7%	17.914	8.886	9.311	9.027	0.000	3.831
8%	18.951	8.886	9.311	10.065	0.000	4.524
9%	19.979	8.886	9.311	11.093	0.000	5.170
10%	20.868	8.886	9.311	11.982	0.000	5.753

* n=number of firms

Note: The Wilcoxon test compares the difference in sales growth index between the sample 2 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

3.4.4.2 Detecting overvalued assets and overproduction

3.4.4.2.1 Detecting overvalued inventory

3.4.4.2.1.1 Sample 1: firms with artificially induced earnings management

Table 3.13 applies the Wilcoxon test to compare the difference in average inventory days between the random sample (1) and other firm-years in the same industry or between the random sample (1) in the manipulation year (year t) and previous year (year t-1). Panel A of Table 3.13 shows the results for cross-sectional analysis of average inventory days. Without delaying a write-down of inventory (i.e., the percentage of manipulation is 0%), there is no significant difference in average inventory days between the sample and industry-matched firm-years. With the increasing level of induced level of manipulation, inventory days of manipulators are significantly higher than those of other firms in the same industry. At 1 percent of artificially induced earnings manipulation, average inventory days of the sample of firm years are significantly higher than the control group (i.e., difference of 13.915 days, significant at 1 percent level). With the artificially induced earnings manipulation of 10 percent, average inventory days of manipulators are higher than non-manipulators (i.e., difference of 63.516, significant at 1 percent level).

Panel B of Table 3.13 illustrates the trend for average inventory days. In particular, average inventory days of the random sample significantly increases with the increasing magnitude of artificially induced earnings manipulation. Without accrual earnings manipulation (e.g., manipulation of 0 percent), there is no significant difference between average inventory days of the event year (year t) and previous year (year t-1). However, average inventory days of manipulators in the event year are significantly different from the previous year with the induced manipulation of 1 percent of lagged assets or greater (difference of 6.224 days, significant at 1 percent level). The overstatement of inventory results in the difference in inventory days ratio between the event year t and previous year (t-1) jumping dramatically to reach the level of 54.825 days at the manipulation level of 10% of lagged assets. Consequently, there is a significant difference between average inventory days of the random sample in the event year and that of previous year ($p<1\%$). Moreover, there is a surprising trend on increases in inventory days for surrounding the event year. Therefore, higher value of inventory days can be taken as a warning sign for overvalued inventory.

Panel A and Panel B of Table 3.15 show the cross-sectional and time-series analysis for total accrual to total assets (TATA) using the sample (1), respectively. Indeed, without manipulation,

average TATA of the sample of firm years are not significant different from that of other firm-years in the same industry for cross-sectional and time-series analysis. Nevertheless, for both cross-sectional and time-series analyses, with the increasing level of artificially induced earning management, the difference in average TATA of manipulators and non-manipulators significantly increases. Indeed, at 1 percent of manipulation, average TATA of manipulators is different from that of non-manipulators (i.e., difference of 0.019 and 0.012 for cross-sectional analysis and time-series analyses, respectively, significant at 1 percent level). There is significantly higher TATA of manipulators and non-manipulators (with difference of 0.1, and 0.093 for cross-sectional analysis and time-series analyses, respectively, significant at 1 percent level) with the artificially induced earnings manipulation of 10 percent of lagged asset.

The results indicate that when managers of firms engage in overstating value of inventory through delaying recording write-up of inventory, inventory days and TATA significantly increase with the manipulation of 1 percent of lagged assets. Moreover, inventory days of manipulators in the manipulation year are higher than control group or earlier year with the difference of 63.516 and 54.825, respectively.

3.4.4.2.1.2 Sample 2: firms with artificially induced earnings management

Table 3.14 applies the Wilcoxon test to compare the difference in average inventory days between the random sample (2) and other firm-years in the same industry or between the random sample (2) in the manipulation year (year t) and previous year (year t-1). It is assumed that discretionary accruals are full reversed in the following fiscal year. Panel A and Panel B of Table 3.14 show the results of average inventory days using cross-sectional and time-series analyses, respectively. Average inventory days significantly increase for all level of added earnings manipulation for both cross-sectional and time-series analyses. In detail, as shown in Panel A, Table 3.14, average inventory days of the sample (2) are significantly higher by 16.047 days than the control group for artificially induced earnings manipulation of 2 percent of lagged asset. This difference reaches 56.251 days when artificially induced earnings manipulation exceeds 10 percent of lagged assets. As shown in Panel B, Table 3.14, the difference in average inventory days of the sample (2) in the manipulation year (year t) and previous year (year t-1) is 3.912 days and 51.121 days for artificially added discretionary accruals of 1 percent and 10 percent of assets, respectively.

Panel A and Panel B of Table 3.16 shows the cross-sectional and time-series analysis for average total accrual to total assets (TATA) using the sample (2), respectively. As shown in Panel A of

Table 3.16, average TATA of the sample (2) and other firm-years in the same industry is not significantly different without induced earnings manipulation. Moreover, average TATA of the sample (2) is higher by 0.016 than other firm-years in the related industry (significant at 1 percent level) for the added manipulation of 1 percent of lagged asset. Average TATA of the sample (2) significantly increase with the increasing level of artificially induced earnings management. With 10 percent of lagged asset of induced earnings management, TATA is significantly greater by 0.092 than the control group (significant at 1 percent level). As for Panel B, Table 3.16, average TATA of the sample (2) in the manipulation year (year t) and previous year (year t-1) is not significantly different with the level of induced earnings management lower than 1 percent of lagged asset. Furthermore, average TATA of the sample in the manipulation year (year t) significantly increase when artificially added earnings management exceeds 2 percent of lagged asset. In detail, at 2 percent of added earnings management, average TATA of the sample (2) in the manipulation year (year t) is significantly higher by 0.028 than previous year (year t-1), significant at 1 percent level. For earnings manipulation equal to 10 percent of lagged asset, the difference in average TATA of the sample (2) between the manipulation year (year t) and prior year (year t-1) is 0.096, significant at 1 percent level.

The results indicate that in case that managers of firms overstate assets (i.e., delaying an inventory write-down), inventory days of manipulators significantly increase with the induced earnings manipulation of 1 percent of lagged asset or greater. Moreover, TATA of manipulators faces unexpected growth of inventory days when artificially added earnings management exceed 1 percent of lagged asset or greater.

3.4.4.2.2 Detecting overproduction

Earnings can be boosted by overproduction. Indeed, managers of firms might produce more goods than expected to lower COGS. This is because with the excessive inventory, this activity will reduce the average unit COGS. With the higher production, fixed costs are spread over a larger number of units. Accordingly, the higher level of inventory might be caused by overproduction. In contrast to overvalued inventory by accrual earnings management, overproduction does not mean that inventory of firms is misstated. However, this type of real earnings management leads to higher levels of inventory at the end of the fiscal year. Therefore, overproduction can cause higher inventory days. In this scenario, it is assumed that the higher level of inventory increases with the same level of reduction in COGS. As a result, the analysis would be like those discussed above related to overvalued.

Table 3.13 Inventory days[4] using sample 1

Panel A. Average inventory days of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	33.729	33.924	-1.195	0.913	-0.109
1%	47.838	33.924	13.915	0.000	-5.342
2%	83.253	33.924	49.330	0.000	-7.288
3%	63.420	33.924	28.496	0.000	-8.138
4%	70.825	33.924	36.901	0.000	-8.892
5%	83.253	33.924	49.330	0.000	-9.174
6%	83.253	33.924	49.330	0.000	-10.024
7%	87.615	33.924	53.692	0.000	-10.323
8%	90.122	33.924	56.198	0.000	-10.290
9%	90.122	33.924	56.198	0.000	-10.038
10%	96.439	33.924	63.516	0.000	-10.286

* n=number of firms

Note: The Wilcoxon test compares the difference in inventory days between the sample 1 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

[4] $\text{Inventory days} = \frac{\text{Inventory}_t}{\text{Cost of goods sold}_t} \text{ x } 365 \text{ days}$

Table 3.13. (Cont.)
Panel B. Average Inventory days of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-values	z-statistics
0%	40.220	40.712	41.615	-1.395	0.397	-0.847
1%	47.838	40.712	41.615	6.224	0.000	5.501
2%	56.465	40.712	41.615	14.850	0.000	7.135
3%	63.420	40.712	41.615	20.805	0.000	7.934
4%	70.825	40.712	41.615	29.210	0.000	7.581
5%	76.414	40.712	41.615	34.799	0.000	7.923
6%	83.253	40.712	41.615	41.639	0.000	8.497
7%	87.615	40.712	41.615	46.001	0.000	7.891
8%	90.122	40.712	41.615	48.507	0.000	7.402
9%	91.768	40.712	41.615	50.153	0.000	6.889
10%	96.439	40.712	41.615	54.825	0.000	6.758

* n=number of firms

Note: The Wilcoxon test compares the difference in inventory days between the sample 1 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.14 Inventory days using sample 2

Panel A. Average Inventory days of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	37.782	34.479	3.303	0.645	-0.461
1%	34.479	34.479	0.000	0.000	-3.759
2%	50.526	34.479	16.047	0.000	-6.129
3%	57.853	34.479	23.374	0.000	-7.528
4%	66.413	34.479	31.934	0.000	-9.232
5%	71.030	34.479	36.552	0.000	-9.885
6%	75.279	34.479	40.800	0.000	-10.301
7%	78.820	34.479	44.342	0.000	-10.745
8%	84.033	34.479	49.555	0.000	-10.818
9%	85.137	34.479	50.659	0.000	-10.751
10%	90.730	34.479	56.251	0.000	-11.389

* n=number of firms

Note: The Wilcoxon test compares the difference in inventory days between the sample 2 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.14. (Cont.)
Panel B. Average Inventory days of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-values	z-statistics
0%	37.782	39.440	39.609	-1.827	0.821	0.226
1%	43.521	39.440	39.609	3.912	0.000	8.425
2%	50.526	39.440	39.609	10.917	0.000	10.169
3%	57.853	39.440	39.609	18.244	0.000	10.765
4%	66.413	39.440	39.609	26.803	0.000	11.565
5%	71.030	39.440	39.609	31.421	0.000	11.484
6%	75.279	39.440	39.609	35.670	0.000	11.156
7%	78.820	39.440	39.609	39.211	0.000	10.760
8%	84.033	39.440	39.609	44.424	0.000	10.141
9%	85.137	39.440	39.609	45.528	0.000	9.651
10%	90.730	39.440	39.609	51.121	0.000	9.470

* n=number of firms

Note: The Wilcoxon test compares the difference in inventory days between the sample 2 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.15 Total accrual to total assets (TATA)[5] using sample 1

Panel A. Average total accrual to total assets (TATA) of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	-0.037	-0.038	0.001	0.502	-0.672
1%	-0.019	-0.038	0.019	0.000	-4.891
2%	-0.009	-0.038	0.029	0.000	-7.211
3%	0.000	-0.038	0.038	0.000	-9.285
4%	0.009	-0.038	0.047	0.000	-11.263
5%	0.018	-0.038	0.057	0.000	-13.007
6%	0.029	-0.038	0.067	0.000	-14.530
7%	0.037	-0.038	0.075	0.000	-15.864
8%	0.045	-0.038	0.083	0.000	-17.030
9%	0.053	-0.038	0.092	0.000	-18.088
10%	0.062	-0.038	0.100	0.000	-19.116

* n=number of firms

Note: The Wilcoxon test compares the difference in total accrual to total assets (TATA) between the sample 1 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

[5] $$\text{TATA} = \frac{\Delta\text{Current asset}_t - \Delta\text{Cash}_t - \Delta\text{Current liabilities}_t - \Delta\text{Current maturities of LTD}_t - \Delta\text{Income tax payable}_t - \text{Depreciation and amortization}_t}{\text{Total asset}_t}$$

Table 3.15 (Cont.)

Panel B. Average TATA of 500 randomly selected firm-years (sample 1) in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-values	z-statistics
0%	-0.031	-0.031	-0.026	0.000	0.121	1.552
1%	-0.019	-0.031	-0.026	0.012	0.630	-0.482
2%	-0.009	-0.031	-0.026	0.022	0.490	0.691
3%	0.000	-0.031	-0.026	0.031	0.072	1.802
4%	0.009	-0.031	-0.026	0.040	0.004	3.916
5%	0.018	-0.031	-0.026	0.050	0.000	3.946
6%	0.029	-0.031	-0.026	0.060	0.000	4.846
7%	0.037	-0.031	-0.026	0.068	0.000	5.686
8%	0.045	-0.031	-0.026	0.077	0.000	6.407
9%	0.053	-0.031	-0.026	0.085	0.000	7.053
10%	0.062	-0.031	-0.026	0.093	0.000	7.637

* n=number of firms

Note: The Wilcoxon test compares the difference in total accrual to total assets (TATA) between the sample 1 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.16 Total accrual to total assets (TATA) using sample 2

Panel A. Average total accrual to total assets (TATA) of 500 randomly selected firm-years (sample 2) and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	-0.033	-0.038	0.005	0.689	-0.400
1%	-0.022	-0.038	0.016	0.000	-4.672
2%	-0.013	-0.038	0.025	0.000	-7.391
3%	-0.006	-0.038	0.033	0.000	-9.922
4%	0.003	-0.038	0.041	0.000	-13.242
5%	0.012	-0.038	0.050	0.000	-14.329
6%	0.021	-0.038	0.059	0.000	-16.226
7%	0.030	-0.038	0.068	0.000	-17.900
8%	0.038	-0.038	0.076	0.000	-19.471
9%	0.047	-0.038	0.085	0.000	-20.865
10%	0.054	-0.038	0.092	0.000	-23.129

* n=number of firms

Note: The Wilcoxon test compares the difference in total accrual to total assets (TATA) between the sample 2 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.16. (Cont.)

Panel B. Average total accrual to total assets (TATA) of 500 randomly selected firm-years (sample 2) in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-values	z-statistics
0%	-0.033	-0.041	-0.032	0.008	0.619	-0.497
1%	-0.022	-0.041	-0.032	0.019	0.382	0.874
2%	-0.013	-0.041	-0.032	0.028	0.028	3.199
3%	-0.006	-0.041	-0.032	0.036	0.000	3.546
4%	0.003	-0.041	-0.032	0.044	0.000	4.799
5%	0.012	-0.041	-0.032	0.054	0.000	5.925
6%	0.021	-0.041	-0.032	0.063	0.000	6.994
7%	0.031	-0.041	-0.032	0.072	0.000	7.928
8%	0.039	-0.041	-0.032	0.080	0.000	8.743
9%	0.047	-0.041	-0.032	0.089	0.000	9.465
10%	0.054	-0.041	-0.032	0.096	0.000	10.130

* n=number of firms

Note: The Wilcoxon test compares the difference in sales growth index between the sample 2 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

3.4.4.3 Detecting aggressive reduction in discretionary expenditures

3.4.4.3.1 Detecting aggressive reduction in accrued discretionary expenditures

3.4.4.3.1.1 Sample 1: firms with artificially induced earnings management

Panel A and Panel B of Table 3.17 show the Wilcoxon test to compare the difference in sales, general, and administrative expenses (SGAI) between the sample (1) and other firms matched by related industry or between the event year (year t) and previous year (year t-1), respectively. Without artificially added manipulation, average SGAI using cross-sectional and time-series analyses is not significantly different between the sample (1) in the manipulation year and control group or in previous year. At 1 percent of artificially induced earnings manipulation, while in Panel A, average SGAI of the sample (1) is significantly lower by -0.027 than the control group (significant at 10 percent level), average SGAI of the sample in the manipulation year and previous year is significantly higher by 0.006 (significant at 1 percent level).

For artificially induced earnings management of 2 percent of lagged asset or greater, both SGAI using cross-sectional, and time-series analyses significantly decrease. For earnings management equal to 2 percent of lagged asset, average SGAI of the sample (1) is lower than other firm-years in the same industry by -0.039 (significant at 1 percent level). Similarly, at 2 percent of lagged asset of induced earnings manipulation, average SGAI of the sample in the manipulation year (year t) is significantly lower than in earlier year (year t-1) by -0.007 (significant at 1 percent level). For artificially added earnings management of 10 percent of lagged asset, there is significant difference in average SGAI between the sample (1) and control group (i.e., difference of -0.121, significant at 1 percent level) (Panel A, Table 3.17). As shown in Panel B, Table 3.17, average SGAI of the sample in manipulation year is significantly greater than in previous year (i.e., difference of -0.088, significant at 1 percent level).

3.4.4.3.1.2 Sample 2: firms with artificially induced earnings management

Panel A and Panel B of Table 3.18 show the Wilcoxon test to compare the difference in sales, general, and administrative expenses (SGAI) between the sample (2) and other firms matched by related industry or between the event year (year t) and previous year (year t-1), respectively. For artificially induced earnings management of 0 percent of lagged asset, average SGAI of the sample (2) in the manipulation year (year t) and the control group or previous year (year t-1) is not significantly different. However, average SGAI of the sample in the manipulation year is lower by -0.047 and -0.007 than the control group and previous year, respectively (significant

at 1 percent level). Moreover, average SGAI of the sample (2) in the manipulation year (year t) significantly decline with the increasing manipulation amount. Indeed, when artificially induced earnings manipulation is at 10 percent of lagged asset, the difference in average SGAI between the sample in the manipulation year (year t) and control group or prior year (year t-1) is -0.134 and -0.095, respectively (significant at 1 percent level). As a result, firms delaying recording accrued discretionary expenses experience unexpected decline in sales, general, and administrative expenses (SGAI).

3.4.4.3.2 Detecting aggressive reduction in paid discretionary expenditures

Detecting an abnormal reduction in discretionary expenses is similar whether the reduction is achieved through real earnings management or accrual earnings management. The only difference between reduction of discretionary expense by using accrual-based earnings management and real earnings management is the effect on cash instead of other accrued payables when using real earnings management. In detail, the decrease in paid discretionary expenses will increase cash from operations in the year of manipulation. However, it is difficult for investors to examine the percentage change of cash compared to that of other firms in relative industries or that of previous years. This is because other types of real earnings management activities also directly influence cash with an overall ambiguous net effect. As a result, the expense ratio and net income ratios would be used to investigate real earnings management as above. The improvement of the net income ratio might be interpreted by investors as manipulators improving their firm performance through reducing their expense ratio.

Table 3.17 Sales, general, and administrative expenses index (SGAI)[6] using sample 1

Panel A. Average sales, general, and administrative expenses index (SGAI) of 500 randomly selected firm-years and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	0.296	0.294	0.002	0.905	-0.119
1%	0.267	0.294	-0.027	0.076	1.777
2%	0.255	0.294	-0.039	0.005	3.843
3%	0.243	0.294	-0.052	0.000	3.819
4%	0.235	0.294	-0.059	0.000	4.766
5%	0.221	0.294	-0.073	0.000	5.660
6%	0.210	0.294	-0.084	0.000	6.604
7%	0.199	0.294	-0.095	0.000	7.753
8%	0.192	0.294	-0.103	0.000	8.695
9%	0.180	0.294	-0.114	0.000	9.681
10%	0.173	0.294	-0.121	0.000	10.575

* n=number of firms

Note: The Wilcoxon test compares the difference in sales, general, and administrative expenses index (SGAI) between the sample 1 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.17. (Cont.)

[6] $\text{SGAI} = \frac{\text{Selling,general and administrative expense}_t}{\text{Sales}_t} \text{x}100$

Panel B. Average sales, general, and administrative expenses index (SGAI) of 500 randomly selected firm-years in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-values	z-statistics
0%	0.276	0.262	0.247	0.014	0.157	-1.414
1%	0.267	0.262	0.247	0.006	0.000	-5.388
2%	0.255	0.262	0.247	-0.007	0.000	-7.953
3%	0.243	0.262	0.247	-0.019	0.000	-9.641
4%	0.235	0.262	0.247	-0.027	0.000	-10.49
5%	0.221	0.262	0.247	-0.040	0.000	-11.08
6%	0.210	0.262	0.247	-0.052	0.000	-11.52
7%	0.199	0.262	0.247	-0.062	0.000	-11.84
8%	0.192	0.262	0.247	-0.070	0.000	-13.11
9%	0.180	0.262	0.247	-0.082	0.000	-13.36
10%	0.173	0.262	0.247	-0.088	0.000	-13.57

* n=number of firms

Note: The Wilcoxon test compares the difference in sales, general, and administrative expenses index (SGAI) between the sample 1 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.18 Sales, general, and administrative expenses index (SGAI) using sample 2

Panel A. Average sales, general, and administrative expenses index (SGAI) of 500 randomly selected firm-years (sample 2) and all firms-years matched by two-digit SIC code for the 1992-2017 period

Percentage of manipulation	Sample of Firm-Years (n=500)	Other Firm-Years (n=18,919)	Difference (Sample-Other)	Wilcoxon signed-rank test	
				p-values	z-statistics
0%	0.283	0.295	-0.011	0.606	0.516
1%	0.248	0.295	-0.047	0.000	4.000
2%	0.237	0.295	-0.057	0.000	5.226
3%	0.225	0.295	-0.070	0.000	6.363
4%	0.220	0.295	-0.074	0.000	7.477
5%	0.215	0.295	-0.080	0.000	8.438
6%	0.200	0.295	-0.095	0.000	9.363
7%	0.189	0.295	-0.106	0.000	10.529
8%	0.178	0.295	-0.117	0.000	11.466
9%	0.167	0.295	-0.128	0.000	13.399
10%	0.161	0.295	-0.134	0.000	13.151

* n=number of firms

Note: The Wilcoxon test compares the difference in sales, general, and administrative expenses index (SGAI) between the sample 2 and other firms matched by two-digit SIC numbers for the 1992-2017 period.

The reported p-values indicate the rejections of the null hypothesis of no difference.

Table 3.18. (Cont.)

Panel B. Average sales, general, and administrative expenses index (SGAI) of 500 randomly selected firm-years (sample 2) in year of manipulation (Year t), earlier manipulation years (Year t-1 and Year t-2)

Percentage of manipulation	Year of manipulation (Year t)	Earlier manipulation year (Year t-1)	Earlier manipulation year (Year t-2)	Difference between year t and t-1	Matched-pair Wilcoxon test	
					p-values	z-statistics
0%	0.255	0.256	0.259	0.000	0.162	-1.400
1%	0.248	0.256	0.259	-0.007	0.000	-6.353
2%	0.237	0.256	0.259	-0.018	0.000	-9.179
3%	0.225	0.256	0.259	-0.031	0.000	-11.039
4%	0.220	0.256	0.259	-0.035	0.000	-13.275
5%	0.215	0.256	0.259	-0.041	0.000	-13.341
6%	0.200	0.256	0.259	-0.056	0.000	-14.013
7%	0.189	0.256	0.259	-0.067	0.000	-14.628
8%	0.178	0.256	0.259	-0.078	0.000	-14.962
9%	0.167	0.256	0.259	-0.089	0.000	-15.200
10%	0.161	0.256	0.259	-0.095	0.000	-15.386

* n=number of firms

Note: The Wilcoxon test compares the difference in sales, general, and administrative expenses index (SGAI) between the sample 2 in year of manipulation (Year t) and earlier manipulation year (Year t-1).

The reported p-values indicate the rejections of the null hypothesis of no difference.

3.4.5 New model to detect abnormal research and development expenses (R&D)

3.4.5.1 Model to detect abnormal R&D expenditures

3.4.5.1.1 Modelling abnormal R&D expenditures

Graham et al., (2005) indicate that a reduction in investment of R&D expenditures or selling, general and administrative (SG&A) expenditures is one of the most preferred techniques to overstate earnings. The modelling of discretionary expenditures including advertising, R&D and SG&A expenses by Roychowdhury (2006) as a function of lagged sales exposes limitations of omitted variables. In which, 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., 2015). 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) (section 3.3.1.2) 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 expenditures. In this section, I modify Roychowdhury (2006) model for estimating discretionary expenditures by including lagged R&D expenses in the model. As a result, the model to estimate the normal level of R&D expense as below:

$$\frac{\mathrm{R\&D_t}}{\mathrm{A_{t-1}}} = \alpha_0 + \alpha_1 \frac{1}{\mathrm{A_{t-1}}} + \beta_1 \frac{\mathrm{REV_{t-1}}}{\mathrm{A_{t-1}}} + \beta_2 \frac{\mathrm{R\&D_{t-1}}}{\mathrm{A_{t-1}}} + \varepsilon_t \qquad (3.18)$$

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

3.4.5.1.2 Normal R&D expenditures

Table 3.19 below presents the average coefficients of normal levels of R&D expenditures based on the new model to estimate R&D expenditures. Compared to the adjusted R-squared of normal level $REM_{DIEXP,}$ the adjusted R-squared in the new model is higher. It indicates that the inclusion of lagged R&D improves the ability of the model to explain the variation in the normal level of R&D expenses.

Table 3.19 Estimation of normal R&D expenditure

	$R\&D_t/A_{t-1}$ [c]	
	Mean of coefficients	Std. Dev.
Intercept	0.007***	0.010
$1/A_{t-1}$	0.011***	0.046
S_{t-1}/A_{t-1}	-0.003***	0.006
$R\&D_{t-1}/A_{t-1}$[1]	0.927***	0.489
Adjusted R^2	0.754	

**** indicates significance at 1% level.*

[c] The following regression is estimated cross-sectionally within the combination of each industry (two-digit SIC) and year from 1991 to 2018 with at least 10 observations within the year-industry combination. The presented above coefficients are the mean values of the coefficients across industry-years. The t-statistics are calculated by using standard errors of the coefficients across industry-years. The adjusted R^2 is the mean adjusted R^2 across industry-years. The descriptive statistics above are shown for the estimation of Eq. (3.18**)**.

3.4.5.1.3 Simulation of artificially induced abnormal R&D expense

I use samples (1) and (2) with artificially added real earnings management from 0 percent to 10 percent of lagged assets. In sample (1), there is no assumption of full reversal of induced earnings manipulation but in sample (2), it is assumed that full reversal is made in the next year. The assumption of a concerning reduce in recognition of R&D expense is used in the simulation. In which, the approach is implemented by subtracting the assumed amount of real earnings management 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 the sample (2).

3.4.5.2 Bias in estimate of $REM_{R\&D}$

3.4.5.2.1 Sample 1: firms with artificially induced manipulation

This section presents results of testing for biased estimates of real earnings management for sample (1). In detail, there is no assumption of reversal of R&D expenditure in next following year. Table 3.20 below provides results for mean coefficients on *PART* when is set as equal one in the year of real earnings management that is hypothesized in response to the stimulus, 0 otherwise.

With the induced earnings management ranging from 0 percent to 10 percent of lagged assets, the mean estimators are equal to artificially induced amount added to the new model. In compared to the model to estimate discretionary expenses by Roychowdhury (2006), the new model to measure abnormal R&D expenses does not experience the bias of estimate of coefficient on *PART*.

Table 3.20 Biases in estimates of real earnings management using Sample 1

Simulations are conducted for artificially induced amounts of real earnings management from 0% to 10% of lagged assets. Simulations use random 500 firms-years (sample 1) to test for biases in estimates of $REM_{R\&D}$.

Percentage of manipulation	$REM_{R\&D}$			
	Coefficient on PART	SE	t-statistics	p-values
0%	-0.001	0.004	-0.201	0.841
1%	-0.011	0.004	-3.470	0.014
2%	-0.021	0.004	-4.739	0.000
3%	-0.031	0.004	-7.008	0.000
4%	-0.041	0.004	-9.277	0.000
5%	-0.051	0.004	-11.546	0.000
6%	-0.061	0.004	-13.815	0.000
7%	-0.071	0.004	-16.084	0.000
8%	-0.081	0.004	-18.353	0.000
9%	-0.091	0.004	-20.622	0.000
10%	-0.101	0.004	-23.891	0.000

Notes:

The results of the estimates of real earnings management results represent the estimated coefficient on PART from Eq. (3.18)

$REM_{R\&D} = \hat{b}_0 + \hat{b}_1 PART_t + \delta_t$

PART is set as equal one in the year of real earnings management that is hypothesized in response to the stimulus, 0 otherwise. The coefficient on PART, $\hat{b}_1$, show the estimate of the magnitude of $REM_{R\&D}$ to artificially adding pre-determined accrual manipulation to the sample 1. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero.

3.4.5.2.2 Sample 2: firms with artificially induced manipulation

Table 3.21 presents results for testing biases in the estimates of abnormal levels of R&D expenses. The results for the new model to detect abnormal R&D expenses applied for sample (2) are indistinguishable to those sample (1). In detail, the mean coefficients of abnormal R&D are nearly equal to the induced amount of earnings management. The findings provide evidence that estimates of abnormal R&D expenditures provided by the new model are unbiased.

Table 3.21 Biases in estimates of real earnings management using sample 2

Simulations are conducted for artificially induced amounts of real earnings management from 0% to 10% of lagged assets. Simulations use random 500 firms-years (sample 2) to test for biases in estimates of $REM_{R\&D}$.

Percentage of manipulation	$REM_{R\&D}$			
	Coefficient on PART	SE	t-value	p-value
0%	-0.002	0.002	-0.885	0.377
1%	-0.012	0.002	-4.769	0.000
2%	-0.022	0.003	-8.636	0.000
3%	-0.031	0.003	-13.475	0.000
4%	-0.041	0.003	-16.272	0.000
5%	-0.051	0.003	-20.017	0.000
6%	-0.051	0.003	-23.699	0.000
7%	-0.070	0.003	-27.308	0.000
8%	-0.080	0.003	-30.836	0.000
9%	-0.090	0.003	-34.275	0.000
10%	-0.099	0.003	-37.618	0.000

The results of the estimates of real earnings management results represent the estimated coefficient on PART from the equation (3.17):

$REM_{R\&D} = \hat{b}_0 + \hat{b}_1 PART_t + \delta_t$

PART is set as equal one in the year of real earnings management that is hypothesized in response to the stimulus, 0 otherwise. The coefficient on PART, $\hat{b}_1$, show the estimate of the magnitude of $REM_{R\&D}$ to artificially adding pre-determined accrual manipulation to the sample 2. The t-statistic test is applied to test the null hypothesis that the coefficient of PART is equal to zero.

3.4.5.3 Power to detect abnormal R&D expenditures

3.4.5.3.1 Sample 1: firms with artificially induced manipulation

Table 3.22 provides results concerning the power of the new model to detect abnormal R&D expenses in the simulation applied for sample (1). The table shows the rejection rates against the magnitude of induced earnings management. All rejection rates are calculated at five percent significance level by using one-tailed tests. Due to unbiased estimates of real earnings management and low standard errors, the new model generates very 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 two percent and greater of lagged assets, the power of the test reaches 100%. In comparison with the previous results of the power test for REM_{DISEXP} in Table 3.5, the rejection rates for the new model to detect abnormal level of R&D expenditures are higher.

Table 3.22 Power for tests of $REM_{R\&D}$ using sample 1

Simulations are conducted for artificially induced amounts of earnings management from 0% to 10% of lagged assets. Simulations use a random sample of 500 firms-years (sample 1).

Percentage of manipulation	$REM_{R\&D}$
0%	7%
1%	80%
2%	100%
3%	100%
4%	100%
5%	100%
6%	100%
7%	100%
8%	100%
9%	100%
10%	100%

3.4.5.3.2 Sample 2: firms with artificially induced earnings management

Table 3.23 provides the rejection frequency with which the null hypothesis of no real earnings management is rejected applied for sample (2). The new model generates rejection rates for rejecting no real earnings management close to 100% for artificially induced earnings management around one percent of lagged assets or greater. The results are quite high compared to the power of the test of $REM_{R\&D}$ by Roychowdhury (2006) to detect abnormal discretionary expenses shown in Table 3.6.

Table 3.23 Power for tests of $REM_{R\&D}$ using sample 2

Simulations are conducted for artificially induced amounts of earnings management from 0% to 10% of lagged assets. Simulations use a random sample of 500 firms-years (sample 2).

Percentage of manipulation	Power of test
0%	22%
1%	100%
2%	100%
3%	100%
4%	100%
5%	100%
6%	100%
7%	100%
8%	100%
9%	100%
10%	100%

3.5 Discussion

The findings of this study indicate that the power of the cross-sectional Modified Jones Model (Dechow et al., 1995) are much higher than those of the time-series Modified Jones Model. Indeed, while the rejection rate in Dechow et al. (1995)'s paper is close to 100% when artificially induced earnings management reaches 50 percent of total assets, the rejection frequency of the cross-sectional Modified Jones Model in this study is close to 100% when the induced earnings management is about 5 percent of lagged assets. The results of this study are nearly the same as the reported findings by Peasnell et al. (2000). The high power of the cross-sectional Modified Jones Model is likely since the model generates unbiased tests of accrual earnings management. Furthermore, the standard errors of the estimates of earnings management are low. Accordingly, the model increases the power of the test for detecting accrual-based earnings management.

The lower power of the Roychowdhury Model for detecting three types of real earnings management activities is likely because there are biased estimates of the three types of real earnings management. To the sample (1) of 500 firms without the assumption of reversal, there is upward bias in estimates of abnormal production costs which results in high power for real earnings management to detect overproduction activities. In contrast, downward estimates of abnormal discretionary expense result in low power test for detecting aggressive reduction in discretionary expenditures. Similarly, as for sales manipulation, there is large bias in the estimates of abnormal cash from operations. Roychowdhury (2006); Zang (2012) indicate that real earnings management activities impact on cash from operation in different directions. Hence, using abnormal cash from operations as a proxy for sales manipulation can have ambiguous net effects.

However, when the sample (2) (i.e., randomly selected firms-year assuming full reversal in the adjacent fiscal year period) is applied, the bias in estimates of the two types of real earnings management, such as sales manipulation and abnormal reduction in discretionary expenditures is lower than that of sample (1). Therefore, the two models have higher power to uncover sales manipulation and abnormal reduction in discretionary expenditures than that of sample (1). Although there is an improvement in the power of the Roychowdhury Model for detecting sales manipulation and abnormal reduction in discretionary expenditures, I realize that the external validity of the results depends on how the assumption of this study are of real cases of real earnings management. For instance, research and development (R&D) expenditure is for long-

term projects. Hence, it is difficult for researchers to know about the settings where the timing of reversal and magnitudes of reversal are. Accordingly, in this study, it is assumed that full reversal of abnormal real manipulation will occur in the next fiscal year.

In general, the power of the tests based on the Roychowdhury Model for detecting the three types of real activities manipulation are lower than those of the cross-sectional Modified Jones Model for detecting accrual earnings management when the sample (1) of 500 firms without full reversal of earnings management in the next fiscal year is designed that each firm is selected in a particular year, and there are no consecutive years of each firm. As for the sample (2) including the 500 randomly selected firm-years, and if any firm-years have more consecutive fiscal years, I assume that earnings management is fully reversed in the next fiscal year. The power of the cross-sectional Modified Jones Model for detecting accrual earnings management still dominates that of the Roychowdhury Model for uncovering real earnings management. Allen et al. (2013) prove that the assumption of full reversal of accruals in the subsequent year is reasonable since there is pervasive evidence that firm-level accruals are fully reversed in the following fiscal year. In contrast, it is uncertain about the timing and magnitude of reversal of abnormal real manipulation in the literature. Hence, there is question about the validity of the full reversal of real earnings management in the next fiscal year in the study. As a result, the findings indicate that in theory, real earnings management is harder to be uncovered than accrual earnings management.

The new proposed model for detecting abnormal R&D expenditures adding lagged R&D expenses to the model estimating normal R&D expenditures Model 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 sales manipulation.

As for practical detection of earnings management, cross-sectional or time-series financial ratio analysis is applied to detect the three types of accrual earnings management and real earnings management (i.e., premature revenue recognition, overvalued inventory, and aggressive reduction in accrued discretionary expenditures). The findings show that with useful ratios (e.g., annual A/R days, DSRI ratio, TATA ratio, inventory days, and SGAI), accrual earnings management could be detected in practice.

In terms of real earnings management activities, the three types of assumptions about real manipulation also affect directly cash from operations. Accordingly, two types of real earnings management such as sales manipulation (i.e., price discount) and aggressive reduction in paid discretionary expenditures are difficult to be detected by applying accounting financial ratios. This is because there is ambiguity about the net effect of these manipulation activities on cash from operations of firms. Especially, sales manipulation (i.e., price discounts) behaves similarly to normal business activities of the firms. Therefore, there is no effective practical way to detect such real manipulation activities. In comparison to reduction of discretionary expenditures, accrual earnings management is easier to be detected since investors could understand the percentage of changes in other accrued payables on the balance sheet. In contrast, real earnings management cannot be uncovered by this way.

3.6 Summary and conclusion

This empirical chapter compares the abilities to detect earnings management between accrual earnings management and real earnings management. Table 3.24 below shows the findings' summary of the analysis conducted in the empirical chapter 3.

Table 3.24 Summary of main findings of chapter 3

Hypothesis	Expected signs	Result
H1: The ability to detect real earnings management is lower than that of accrual-based earnings management.	(+)	Confirmed (+)

With respect to accrual earnings management, I 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 chapter 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 detecting 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 assets, 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 chapter 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 chapter has the power of the test of about 53 percent, compared to nearly 30 percent for the performance-matched discretionary accrual model by Kothari et al. (2005) using the US sample.

Compared to real earnings management, 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 management. 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 management 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 chapter 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 management.

The findings of this chapter 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 management activities. The findings of this chapter imply that although prior studies widely apply the Roychowdhury (2006) model to detect real earnings management (e.g., Cohen et al., 2010; Zang, 2012; Achleitner et al., 2014; Abad et al., 2018; Alhadab and Clacher, 2018), the specification and the ability of the models to detect real earnings management is

questionable. I 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. However, further research should focus on developing better models to uncover the remaining two types of real earnings management such as overproduction and revenue manipulation.

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 mis-specified, especially for firms with extreme performance. I do not investigate this issue.

CHAPTER 4. ACCRUAL EARNINGS MANAGEMENT, REAL EARNINGS MANAGEMENT, AND INFORMATION UNCERTAINTY

4.1 Introduction

This chapter aims at investigating the role of IU on managerial choice between accrual earnings management and real earnings management. Moreover, this chapter provides evidence about a circumstance where earnings management is likely to occur. The evidence of this chapter contributes to extending previous studies by showing that under high IU where both types of earnings managements are difficult to be detected, managers of firms are likely to use more accrual earnings management than real earnings management. The reason for this is that real earnings management is more costly than accrual earnings management, hence, firm managers choose accrual earnings management which may not be uncovered under high information uncertainty to gain higher benefits. Furthermore, the findings of this chapter indicate that high IU is the condition for managerial opportunism through using accrual earnings management as well as smoothing earnings.

Accrual accounting can be used for alternative reasons including enhancing the informativeness of earnings information through signalling managers' private information to market participants (e.g., Watts and Zimmerman, 1986; Subramanyam, 1996; Guay et al., 1996; Demski, 1998; Arya et al., 2003) or to manipulate earnings opportunistically (see Dechow et al., 1996; Erickson and Wang, 1999; Teoh et al., 1998a; Shivakumar, 2000; Louis, 2004). The agency theory indicates that information asymmetry between managers and stakeholders is the condition for earnings management where managers exercise discretion in the recognition of accruals. When firms face high IU, this increases information asymmetry between managers and shareholders. I extend Healy and Wahlen (1999) to examine the condition that managers engage in accrual earnings management. In which, the findings of this thesis provide evidence that managers of firms use more accrual earnings management in the high IU condition. By IU, I mean the ambiguity of stakeholders about fundamental values of firms. Accordingly, in the high IU, investors find it harder to reasonably estimate firm values at reasonable costs (Jiang et al., 2005; Zhang, 2006b).

Previous research suggests that small-sized firms engage more in earnings management than medium and large-sized firms. For example, Kim et al. (2003) prove that small-sized firms use more earnings management than medium and large-sized firms. This is because smaller size of firms has less scrutiny than larger size of firms. Indeed, Zhang (2006b) indicates that small-sized firms have higher IU than large-sized firms. It is probable that small firms have less available information to stakeholders as well as less verified information than large firms. Accordingly, managers' discretion adapts to the condition imposed by IU. For firms having high IU, investors find it harder to see through the underlying firm performance that are manipulated by managers (Dye, 1988; Trueman and Titman, 1988).

Earnings of firms can be managed by two ways, accrual earnings management and real earnings management. For accrual-based earnings management, managers use discretion and judgment regarding accounting choice to adjust earnings in financial reporting. More specifically, accrual earnings management mispresents the underlying firm performance but does not alter operational activities of firms. In contrast, real earnings management entails deviation from normal business activities with the purpose of misleading investors into believing firm performance is at a certain level, and this is accomplished in the normal course of business (Roychowdhury, 2006). Real earnings management activities include reduction of investing in research and development (R&D) expenditures, overproducing inventory and offering price discounts, all for the purpose of meeting short-term goals (Graham et al., 2005; Roychowdhury, 2006). The essential difference between accrual earnings management and real earnings management is that while generally accepted accounting principles (GAAP) play a role as a framework for managers' judgment about recognition of accrual information in financial reporting, there does not exist a framework for real earnings management.

In the condition of high IU where investors find it harder to see through the underlying firm performance (Dye, 1988; Trueman and Titman, 1988), managers probably make decisions about choosing alternative ways to manage earnings that are perceived as less costly for the firms in the long-run. Prior research suggests that real earnings management potentially incurs higher long-run costs on stakeholders since real earnings management activities might have negative consequences on cash from operations and deteriorate long-term firm values (Roychowdhury, 2006; Cohen and Zarowin, 2010; Lennox and Yu, 2019). Therefore, in the greater IU environment, when there is more opacity of managed earnings for outside investors, managers of firms are likely to use accrual earnings management rather than real earnings management, which is perceived as less costly for firms. Although the IU condition is a critical

factor affecting managerial choices of two alternative ways to manage earnings, previous research does not consider the role of IU on examining the preference of managers for using accrual earnings management versus real earnings management. This study suggests that firms having high incentives to inflate earnings are likely to use accrual earnings management rather than real earnings management in the high IU condition. The finding implies that at the time of less observable managerial intent, managers exhibit more preference of using discretion over accruals than real earnings management when firms have high incentives to inflate earnings.

Firms with high earnings volatility are perceived as higher risk (Gul et al., 2003). In the high IU environment, there is an increase in the volatility of a firm's underlying fundamentals (see Zhang, 2006b). It is expected that firms attempt to smooth earnings to reduce the perception of risk in the high IU. This research also extends previous research in examining the association between income smoothing and IU once firms have high incentives to manage earnings. I find that firms with greater IU smooth earnings to reduce volatility of earnings when faced with high incentives to manage earnings.

Previous studies document that managers of firms are reluctant to disclose private information when there is high uncertainty about investors' response (Suijs, 2007). Accordingly, Dutta and Trueman (2002) indicate that managers of firms are likely to disclose private information by the way investors will interpret private information of firms. Moreover, some researchers find that in the condition of difficulty of detection, manager of firms use opportunistic accrual earnings management (Healy and Wahlen, 1999; Lo, 2008; Cormier et al., 2013).

In this chapter, I examine how IU can influence earnings management. I find that all listed firms in London Stock Exchange from 1992 to 2018 meeting or beating earnings benchmarks use more accrual-based earnings management under high IU. In contrast, there is no evidence that in the high IU, managers of firms engage more in real earnings management when having high incentives to manage earnings. I also show that with the increasing IU, managers of firms use more discretionary accruals than real earnings management. In additional tests, I find that managers of firms reduce the variability in reported earnings through smoothing earnings when faced with a high IU environment. The findings of this study indicate that the condition of IU plays a vital role in managerial choices of earnings management strategies.

The reminder of the chapter is organized as follows. Section 4.2 reviews the literature on motivations and perspectives on earnings management and presents the hypotheses development about the role of IU on earnings management. Section 4.3 describes the research

design. Section 4.4 presents and discusses the results of the main tests. Section 4.5 provides the results of some robustness checks, and section 4.6 presents conclusion.

4.2 Literature and hypothesis development

4.2.1 Literature review

4.2.1.1 Earnings management

The flexibility of Generally Accepted Accounting Principles (GAAP) allows managers to exercise judgment in accrual accounting that brings the information asymmetry. This is because managers' intention about discretionary behaviour is not observable to stakeholders (Dechow and Skinner, 2000). Healy and Wahlen (1999) indicate that financial reports permit managers to provide private information to market participants; therefore, managers of firms are allowed to exercise judgment in financial reporting. In according, GAAP give the flexibility for manager to engage in discretionary accruals in reporting earnings.

Prior studies show that managers use discretionary accruals to signal their private information to outside stakeholders (see Arya et al., 2003; Louis and Robinson, 2005; Subramanyam, 1996). For example, Beaver and Engel (1996) prove that managers of firms use loan loss provisions to inform investors of future firm performance. Thus, in this case, earnings management provides informativeness to users. Indeed, Goel and Thakor (2003) show that uninformed investors can benefit from earnings management through the communication of private information by managers. Similarly, Wang and Williams (1994) suggest that managers of firms manage earnings to reduce variability of earnings that can signal future firm performance.

The flexibility of accounting standards also gives avenues for managers to engage in opportunistic discretionary accruals (e.g., Healy and Wahlen, 1999). Accordingly, managers of firms can use discretionary accruals to manipulate earnings opportunistically (Christie and Zimmerman, 1994). Information asymmetry between managers and outside stakeholders means that managers' discretionary behaviour is unobservable; hence, managers' intention cannot be assessed. Therefore, previous empirical evidence shows that investors are misled by discretionary accruals and overestimate earnings that have been managed through discretionary accruals (e.g., Sloan, 1996; Teoh et al., 1998a; Xie, 2001).

4.2.1.2 Information uncertainty

Information uncertainty is defined as the ambiguity of investors about fundamental values of firms (Zhang, 2006b). Indeed, Jiang et al. (2005) provide define IU as the extent to which a

company is valued at a reasonable estimate by the most knowledgeable investors at reasonable costs. There are two sources causing IU: poor quality of information and volatility of firms' fundamental values. Theoretically, a firm's fundamental value (v) is characterized by an observed signal (s), which includes future cash flows or dividend and a noise term (ε). Hence, the variance of fundamental value of firm measures IU as follows: var(s)=var(v) + var(ε). In which, var(v) is the volatility of firms' fundamental value and var(ε) indicates information quality. Previous empirical studies do not distinguish between underlying fundamental volatility of firm value and information quality (e.g., Hirshleifer, 2001; Jiang et al., 2005; Zhang, 2006b). Therefore, in this study, I do not separate a firm's fundamental volatility and information quality since both reflect uncertainty of firm value. Moreover, it is difficult to disentangle these two dimensions of IU empirically (e.g., Hirshleifer, 2001).

Following prior studies, I use three proxies to measure IU. In which, as shown in Zhang (2006b) and Jiang et al. (2005), I apply the two proxies for IU including average daily turnover (i.e., average daily turnover in percentage) and total stock volatility (i.e., standard deviation of daily returns). Moreover, following Amin and Lee (1997) and Clinch et al. (2012), effective bid-ask spread is applied to measure IU. For all analyses, the three proxies are constructed in such a way that a greater value of the three proxies indicates higher IU. Indeed, greater IU firms are companies whose underlying fundamental values are less known because of the nature of their operating business or environment.

4.2.2 Hypotheses development

4.2.2.1 Earnings management and information uncertainty

Previous studies show that earnings management occurs if firm managers have access to private information that is not publicly available to market participants (see Healy and Wahlen, 1999; Lo, 2008). Indeed, under high IU, there is limited information from other sources such as analysts. Accordingly, market participants find it harder to uncover the implications of earnings management in high IU condition (e.g., Dye, 1988; Trueman and Titman, 1988). Similarly, Hirst and Hopkins (1998) indicate that in the less transparent reporting environment, there are lower abilities of investors to undo the effect of earnings management. Moreover, Hunton et al. (2006) indicate that in the less transparent setting, investors are less clear about earnings management behaviour. Accordingly, managers have more opportunities to engage in opportunistic accrual earnings management without losing their reputation about reporting integrity.

Under the condition of high IU, managers of firms are not likely to eliminate all accounting discretion since they have more competitive advantage of possessing private information while outside stakeholders do not have other sufficient resources to evaluate withheld private information. Hence, market participants do not find it easy to disentangle true firm performance from managed earnings information (e.g., Rangan, 1998; Bartov and Mohanram, 2004). For instance, Indjejikian (1991) indicates that financial statement data is considered as information after being analysed. However, managers of firms might be reluctant to disclose more private information. In contrast, they prefer using opportunistic accrual-based earnings management to provide more favourable information about firm values.

In addition, Fernando et al. (2018) prove that under high information asymmetry, disclosure might increase the differential precision of investors' opinions about firm valuation. Accordingly, they might prefer withholding more private information in the high IU environment (Suijs, 2007). Furthermore, with limited available public information about firm valuation in the high IU, investors may not be able to perceive that managers of firms withhold private information of firms (Jung and Kwon, 1988). Moreover, Dutta and Trueman (2002) provide evidence that firms disclose private information that is affected by the way that investors would interpret such information. As a result, in such high IU condition, managers of firms probably withhold unfavourable information about firms through engaging in managing discretionary accruals to influence investors' valuation about firms.

The second hypothesis of the thesis is as below:

H2. *There is positive relationship between the level of information uncertainty and accrual-based earnings management when firms have incentives to manage earnings.*

In addition to accrual earnings management, firms managers manage earnings via using real earnings management by engaging in operational activities that deviate from normal business activities of firms (Roychowdhury, 2006). However, previous studies show that real earnings management is more costly for firms than accrual earnings management. For instance, Cohen and Zarowin (2010) show that SEO firms using real earnings management experience more severe underperformance than using accrual earnings manipulation. Similarly, Kothari et al. (2015) document that SEO firms using real earnings management have more subsequent underperformance than applying accrual earnings manipulation. Given the cost of engaging in real manipulation and the difficulty in detecting this manipulation, I expect that firms that face

high IU will not engage in more or less real manipulation than when faced with low IU. Therefore, I formulate the third hypothesis as a null hypothesis as below:

H3. *There is no association between the level of information uncertainty and real earnings management when firms have incentives to manage earnings.*

4.2.2.2 The choice of earnings management strategies and information uncertainty

Earnings can be managed in two ways through accrual-based earnings management and real-based earnings management. The first is implemented by using discretionary accruals through using accounting estimates and methods to alter financial performance of firms. The latter is applied by changing the timing and structuring of real transactions that directly affect operating cash flows as the component of earnings. Dechow and Skinner (2000), and Roychowdhury (2006) provide examples of real earnings management activities such as delaying research and development (R&D) expenditures, offering price discounts, and overproduction.

Previous studies show that managers of firms use multiple earnings management methods such as accrual earnings management and real earnings management (Cohen et al., 2008; Ibrahim et al., 2011; Owusu et al., 2020). Graham et al. (2005)'s survey documents that managers of firms prefer using real earnings management when facing high scrutiny. Moreover, Ipino and Parbonetti (2017) prove that after adopting the mandatory international financial reporting standards, firms substitute real earnings management for accrual earnings management. In addition, Cohen and Zarowin (2010) and Zang (2012) indicate that managers of firms trade-off between accrual earnings management and real earnings management as the relative costs of doing so as well as the abilities to apply accrual earnings management.

As previously documented, the high IU provides condition where both earnings management methods such as accrual earnings management and real earnings management are difficult to be detected by outside market participants. Therefore, it is considered that in the high IU environment, managers of firms make choices of selecting earnings management strategies (i.e., either accrual discretionary activities or real earnings management) to inflate earnings, which are perceived as less costly for firms. Indeed, Roychowdhury (2006) documents that real earnings management helps firms enhance short-run earnings but negatively influences long-term operating performance. For instance, overproduction leads to excessive inventories in the future that impose higher holding costs for a company. In contrast, accrual earnings management does not come at these costs. This is because real earnings management directly affects operating cash flows and operating activities of firms, whereas the nature of accrual

earnings management is to exercise the timing recognition of accruals among periods. Accordingly, in the subsequent periods, abnormal accruals will be reversed.

The empirical results indicate that real earnings management might be more costly for firms than accrual-based earnings management. For instance, Cohen and Zarowin (2010) show that Secondary Equity Offering (SEO) firms engaging in real earnings management have a more severe decline in their subsequent operating performance than SEO firms using accrual-based earnings management. Similarly, Kothari et al. (2016) provide evidence that SEO firms engage in opportunistic reduction of R&D expenditures as well as selling, general, and administrative expenditures. Accordingly, these activities are more costly in the long run for firms than accrual manipulation. Furthermore, Lennox and Yu (2019) indicate that market reactions are more negative when managers of firms use real earnings managements rather than accrual manipulation.

Moreover, Zang (2012) proves that accrual-based earnings management is made after a fiscal year end when there is the most certain need for earnings management. In contrast, real earnings management takes place during the fiscal year and there is uncertainty about the effect of real earnings management until the abnormal operating activities are realized at the end of the fiscal year (Zang, 2012). Consequently, in the high IU, managers of firms might prefer to use discretionary accruals to real earnings management to avoid the real effects of real manipulation. Based on the discussion above, I state the fourth hypothesis as below:

H4. *There is a higher likelihood that managers use accrual versus real manipulation when firms have incentives to manage earnings under high information uncertainty than under low information uncertainty.*

4.2.2.3 Income smoothing and information uncertainty

Earnings smoothing is widely documented in previous literature (e.g., Beidleman, 1973; Ronen and Sadan, 1981 ; Schipper, 1989; Subramanyam, 1996; Healy and Wahlen, 1999; Baik et al., 2020). In the survey implemented by Graham et al. (2005), 96.9% of survey respondents reveal that they would like to smooth earnings. Trueman and Titman (1988) provide a definition of earnings smoothing as the intentional decrease in the fluctuations of firms' earnings realizations. The purpose of earnings smoothing is to counteract the influence of transitory changes in profitability. Accordingly, earnings smoothing makes earnings less variable over time (Goel and Thakor, 2003).

Extant literature suggests that IU might reflect the volatility of a firm's underlying earnings (e.g., Hirshleifer, 2001; Zhang, 2006a). In according, when faced with ambiguity of the precision about earnings information, investors discount stock price to compensate for the volatility of reported earnings (Epstein and Schneider, 2008). Therefore, Hansen (2010) indicates that IU can lead to reducing firm value. More importantly, under the condition of high IU, investors tend to apply the worst case to evaluate the value of firms.

Goel and Thakor (2003) suggest that income smoothing affects investors' perception about reported earnings through reducing the variability of reported earnings. Similarly, Subramanyam (1996) indicates that managers smooth earnings to decrease the variance of reported earnings as well as to enhance the predictability of earnings information. Based on the above, I formulate the fifth hypothesis as follows:

H5. *There is a positive relation between smoothing earnings and the level of information uncertainty when firms have incentives to manage earnings.*

4.3 Research design

4.3.1 Sample selection

To test the hypotheses presented, I begin with the sample that includes all "alive" and "dead" listed firms in London Stock Exchange (LSE hereafter) for the period 1991-2018 to avoid survivorship bias. Datastream is used to collect the data. Moreover, further requirements of data availability to calculate all variables needed results in a final sample of 16,811 firm-year observations. In detail, to calculate accruals and real manipulation, all essential data requires at least 10 observations in each two-digit SIC grouping per year. Furthermore, to avoid extreme observations influencing noisy estimation, I remove observations at the top and bottom one percent of the distribution for all continuous variables.

To test the relation between earnings management and IU, I use a sample of firms that are likely to have managed earnings. Previous studies prove that firms are likely to use discretionary accruals to meet or beat earnings benchmarks (see Burgstahler and Dichev, 1997; Degeorge et al., 1999; Bartov et al., 2002). As shown in survey by Graham et al. (2005), incentives for earnings management, namely, meeting/beating last's year earnings and avoiding reporting losses are important for managing earnings. Accordingly, earnings management suspects are defined as firm-years just meeting or beating previous year earnings and zero earnings. Earnings benchmarks are explained in detail in section 2.5.1.

In detail, following Roychowdhury (2006) and Zang (2012), a sample of suspect firms has high incentives to engage in earnings management and this includes firms-years with earnings before extraordinary items over total assets between 0 and 0.005. Moreover, in terms of meeting/beating prior year earnings, suspects are defined as those where the change in earnings before extraordinary items per share (EPS) from last year is between 0 and 0.0025. During the sample period, there are 1,105 earnings management suspect firm-years and 15,706 non-suspects over the period 1992-2018.

4.3.2 Methodologies

4.3.2.1 Propensity score matching (PSM)

Previous studies indicate that suspect firms (hereafter, suspects) that just meet or beat earnings benchmarks have inherently different characteristics from non-suspect firms (hereafter, non-suspects) that are not closed to meeting their earnings benchmarks. To eliminate endogeneity concerns, I match suspects and non-suspects with the same characteristics; specifically, I use a Propensity Score Matching (hereafter, PSM) method to control for the effect of growth opportunity and firm performance (Shipman et al., 2016). Therefore, following Rosenbaum and Rubin (1983), Li and Prabhala (2007); and Francis et al. (2010), propensity score matching (PSM) is applied to create a sample of treated and untreated observations that have similar characteristics. This matching method is considered effective for estimating average treatment effects. Indeed, Tucker (2010) documents that PSM method addresses observable selection biases through matching control firms from the untreated group that is closest to the treated group to minimize different characteristics between treated and untreated groups. The selection model is as below:

$$\mathrm{PROB}(\mathrm{SUSPECT}_{it} = 1) = \mathrm{PROB}(\alpha_0 + \alpha_1 \mathrm{M/B}_{it} + \alpha_2 \mathrm{SHARE}_{it} + \alpha_3 \mathrm{SIZE}_{it} + \alpha_4 \mathrm{ROA}_{it} \sum_j \alpha_j \mathrm{INDUSTRY}_{\mathrm{DUMMY}_{it}} + \sum_k \alpha_k \mathrm{YEAR}_{\mathrm{DUMMY}_{it}} + \varepsilon_{it}) \quad (4.1)$$

Variables in Eq. (4.1) are presented in the Appendix. A selection model pertaining to appropriate variables based on previous literature is conducted in step 1. Indeed, Roychowdhury (2006) shows that suspects have higher firm performance (return on assets - *ROA*) than non-suspects. Moreover, Bartov et al. (2002), and Kasznik and McNichols (2002) indicate that firms with more growth opportunities are more likely to meet/beat earnings benchmarks. Similarly, Matsumoto (2002) shows that firms with growth prospects are concerned about missing earnings benchmark. Accordingly, I include market to book (*M/B*) as growth prospects. In addition, I follow including the number of shares outstanding (*SHARE*) in

the selection model to control for incentives for suspects to manipulate in the current period. Furthermore, I also include firm size (*SIZE*) in the selection model. Models are estimated by using probit regression with standard errors that are robust to heteroscedasticity.

4.3.2.2 The inverse mills ratio (IMR) method

As an alternative to test for differences in characteristics between suspects and non-suspects, I apply the Heckman (1979) procedure. Heckman (1979) proposes the inverse mills ratio (hereafter, IMR) method to correct for unobservable variables. Accordingly, Heckman (1979) provides the IMR[7] approach to control for selection biases through estimating a bias correction error term in the first stage. Then, the IMR obtained from the selection model in the first stage is added to the second stage outcome regression.

In detail, following Zang (2012), in the first stage of the Heckman procedure, the *IMR* is obtained by estimating the probit model that explains the likelihood of firms beating earnings benchmarks. The below selection model is applied in the first stage:

$$\begin{aligned}&\mathrm{PROB}(\mathrm{SUSPECT}_{it}=1)=\mathrm{PROB}(\alpha_0+\alpha_1\mathrm{M/B}_{it}+\ \alpha_2\mathrm{SHARE}_{it}+\alpha_3\mathrm{SIZE}_{it}+\alpha_4\mathrm{ROA}_{it}\\&\textstyle\sum_j\alpha_j\,\mathrm{INDUSTRY}_{\mathrm{DUMMY}_{it}}+\sum_k\alpha_k\,\mathrm{YEAR}_{\mathrm{DUMMY}_{it}}+\ \varepsilon_{it})\end{aligned}\qquad(4.2)$$

In the second stage, the *IMR* obtained from the first stage is added to the main regression as an independent variable.

4.3.2.3 Variable construction

4.3.2.3.1 Measuring information uncertainty

IU refers to investors' ambiguity about fundamental valuation of firms. In this study, I apply three different proxies for measuring IU that are commonly used in the literature: stock return volatility (*VOLATILITY*), trading volume (*VOLUME*) and bid-ask spread (*SPREAD*).

The first proxy is stock return volatility (*VOLATILITY*). Following previous studies (e.g., Lim, 2001; Jiang et al., 2005; Zhang, 2006b), return volatility is defined as the standard deviation of daily returns over the past 25 trading days.[8]

---

[7] The inverse mill ratio is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

[8] Alternatively, I use different time horizons in measuring returns (e.g., weekly returns over the year). The results are similar using alternative measures.

The second proxy is trading volume (*VOLUME*) that is defined as the average daily turnover in percentage over the past six months, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day (Jiang et al., 2005).

The third proxy is the bid-ask spread at the end of year (*SPREAD*). Prior studies find that the percentage of spread is positively related with price volatility (e.g., Stoll, 1978; Chiang and Venkatesh, 1988; Glosten and Harris, 1988). Accordingly, following Welker (1995) and Leuz (2003), I use the bid-ask spread to capture IU. Greater bid-ask spread indicates higher levels of IU.

4.3.2.3.2 Measuring earnings management

In this chapter, discretionary accrual (hereafter *DAP*), the proxy of accrual earnings management, is measured through the modified-Jones model (Jones, 1991; Dechow et al., 1995). In the robustness testing, Kothari et al. (2005)'s model and the Modified DD model are applied to estimate *DAP*. These measures are illustrated in section 3.3.2.1.

To estimate real earnings management (hereafter *REM*), the three measures of real earnings management proposed by Roychowdhury (2006) are applied as described in section 3.3.2.2. Following Cohen et al. (2008), Cohen and Zarowin (2010), Ibrahim and Lloyd (2011), I combine the three individual type of real earnings management activities into a single variable. However, since three individual variables have different effects on reported earnings. I first multiply REM_{CFO} and REM_{DISEXP} by minus one so that higher REM_{CFO} and REM_{DISEXP} indicating that managers manage earnings upwards. Therefore, total manipulation through real accounts (*AREAL*) is the sum of three types of REM.

4.3.2.3.3 Measuring income smoothing

The first way to measure income smoothing (*SMOOTHING*) is to use the correlation between changes in total accruals and changes in cash flows from operations (both deflated by the beginning-of-year total assets), over a five-year period (see Leuz, 2003; Yu et al., 2018; Monjed and Ibrahim, 2020). I multiply *SMOOTHING* by minus one indicating higher values correspond to a greater level of income smoothing.

Following Leuz (2003), in the robustness testing, I also use an alternative way to measure income smoothing by using the ratio of a firm's standard deviation of net income divided by the standard deviation of its cash from operations (both deflated by the beginning-of-year total

assets) using annual data for the period of five years. I multiply income smoothing by minus one indicating higher values correspond to a greater level of income smoothing.

4.3.2.4 Association of accrual-based earnings management and information uncertainty of suspects

To test hypothesis 2 investigating the relationship between accrual-based earnings management and IU of suspects, the following regression equation is applied:

$$\begin{aligned} \mathrm{DAP_{it}} = \beta_0 \; + \; & \beta_1 \mathrm{SUSPECT_{it}} + \beta_2 \mathrm{HIU_{it}} + \beta_3 \, \mathrm{SUSPECT_{it}} \mathrm{x} \, \mathrm{HIU_{it}} + \beta_4 \, \mathrm{SIZE_{it}} + \beta_5 \mathrm{BIG_{8_{it}}} \\ & + \; \beta_6 \, \mathrm{ROA_{it}} + \beta_7 \, \mathrm{LEV_{it}} + \beta_8 \, \mathrm{M/B_{it}} + \sum\nolimits_{\mathrm{j}} \beta_{\mathrm{j}} \, \mathrm{INDUSTRY_{DUMMY_{it}}} \\ & + \sum\nolimits_{\mathrm{k}} \beta_{\mathrm{k}} \, \mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{\mathrm{it}} \end{aligned} \tag{4.3}$$

where *i* refers to the firm and *t* to the year. When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise. The coefficient of interest is β_3 in Eq. (4.3), which represents the coefficient of the interaction between *HIU* and firms meeting or beating the earnings benchmark. Hypothesis 2 predicts that there is a positive relation between high IU and accrual-based earnings management of suspects. When IU is high, suspects use more accrual-based earnings management. Accordingly, β_3 in Eq. (4.3) is expected to be significantly positive. All variables are defined in the Appendix.

To control for the potential difference in firm characteristics between firms beating earnings benchmarks and firms missing earnings benchmarks, the propensity score matching (PSM) method and the Heckman two steps are applied. As for the PSM method, the propensity-matched sample is obtained from Eq. (4.1). Using the propensity score, I match each firm beating earnings benchmarks to a control firm missing earnings benchmarks. With the propensity-matched sample, the main regression Eq. (4.3) is estimated. To the Heckman procedure, the Inverse mill ratio (*IMR*) is estimated by a selection model from Eq. (4.2) using the full sample of firm-years. In the second step, I include *IMR* as a control variable in the main regression Eq. (4.3).

Based on previous literature, I control for different incentives for earnings management as well as the discretionary accrual measure (Bartov et al., 2000). Indeed, earnings performance, firm size, growth prospects and litigation risks are essential control variables for studying discretionary accruals. In detail, I control for leverage through including *LEV* as a control

variable for the impact of financial risk on accrual-based earnings management. Previous studies prove that leverage is associated with discretionary accruals (e.g., Butler et al., 2004; Lawrence et al., 2011). Indeed, Press and Weintrop (1990) and DeFond and Jiambalvo (1994) indicate that firms close to debt covenant violation are likely to manage earnings. Beneish and Press (1995) document that high leverage is also related with financial distress. Moreover, Barth et al. (1999) and Skinner and Sloan (2002) show that firms have high incentives to manage earnings increasing with higher firms' growth opportunities. I control for firms with growth prospects by including market-to-book ratio (*M/B*) since firms have incentives to manage earnings to have higher growth prospects (with higher market-to-book values). Furthermore, I also control for firm performance (*ROA*) since firms have incentives to manage earnings so as to improve firm performance (e.g., Dechow, 1994). Following Becker et al. (1998), I include the log of market value of equity to control for the potential effects of size on the choice of discretionary accruals. Indeed, Kim et al. (2003) indicate that large firms might experience higher reputation costs when engaging in earnings management. Specifically, large firms have better control over their business relative to small firms. Accordingly, Lev and Nissim (2006) show the negative relation between the size of the firm and earnings management. Finally, to control for changes in microeconomic factors across time and year, I include industry and year fixed effects as dummy variables. I also apply robust standard errors clustered at firm level to control for heteroscedasticity and serial correlation problems.

4.3.2.5 Association of real earnings management and information uncertainty of suspects

To test hypothesis 3 which investigates the relationship between real earnings management and IU of suspects, the following regression equation is applied:

$$\begin{aligned} \mathrm{AREAL_{it}} = \beta_0 &+ \beta_1\,\mathrm{SUSPECT_{it}} + \beta_2\mathrm{HIU_{it}} + \beta_3\,\mathrm{SUSPECT_{it}}\ \mathrm{x}\ \mathrm{HIU_{it}} + \beta_4\,\mathrm{SIZE_{it}} \\ &+ \beta_5\mathrm{BIG_{8_{it}}} + \beta_6\,\mathrm{ROA_{it}} + \beta_7\,\mathrm{LEV_{it}} + \beta_8\,\mathrm{M/B_{it}} \\ &+ \sum\nolimits_j \beta_j\,\mathrm{INDUSTRY_{DUMMY_{it}}} + \sum\nolimits_k \beta_k\,\mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it} \end{aligned} \tag{4.4}$$

where *i* refers to the firm and *t* to the year. When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise. *SUSPECT x HIU* is the interaction term, where β_3 in Eq. (4.3) represents the coefficient of interaction between high IU and firms meeting or beating the earnings benchmark. Hypothesis 3 predicts that there is no relation

between high IU and real earnings management of suspects. Accordingly, β_3 in Eq. (4.3) is expected to be insignificant. All variables are defined in the Appendix.

To control for the potential difference in firm characteristics between firms beating earnings benchmarks and firms missing earnings benchmarks, the propensity score matching (PSM) method and the Heckman two steps are applied as illustrated above in section 4.3.2.4. All control variables in Eq. (4.3) are mentioned in section 4.3.2.4. I also include industry and year fixed effects as dummy variables. I apply robust standard errors clustered at firm level to control for heteroscedasticity and serial correlation problems.

4.3.2.6 Accrual earnings management versus real earnings management and information uncertainty

To examine hypothesis 4, whereby the likelihood that managers of firms use accrual earnings management rather than real earnings management in the high IU when these firms meet/beat earnings benchmarks, the following probit regression is applied:

$$\begin{aligned}\mathrm{PROB}(\mathrm{DTR_{it}} = 1) \\ &= \beta_0 + \beta_1 \mathrm{SUSPECT_{it}} + \beta_2 \mathrm{HIU_{it}} + \beta_3\, \mathrm{SUSPECT_{it}} \text{ x } \mathrm{HIU_{it}} + \beta_4\, \mathrm{SIZE_{it}} \\ &+ \beta_5\, \mathrm{BIG\_8_{it}} + \beta_6\, \mathrm{ROA_{it}} + \beta_7\, \mathrm{LEV_{it}} + \beta_8\, \mathrm{M/B_{it}} + \beta_9\, \mathrm{Z\_SCORE_{it-1}} \\ &+ \beta_{10}\, \mathrm{CYCLE_{it-1}} + \sum_j \beta_j\, \mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \beta_k\, \mathrm{YEAR_{DUMMY_{it}}} + \varepsilon\end{aligned} \tag{4.5}$$

where *i* refers to the firm and *t* to the year. Variables used in Eq. (4.5) are presented in detail in the Appendix. The dependent variable in the Eq. (4.5) is defined as 1 if a firm-year's accrual earnings management proxy is higher than the firm-year's real earnings management proxy, and 0 otherwise. When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise. I examine the difference in *DTR* between firms beating earnings benchmarks (*SUSPECT=1)* and the propensity-score matched control group (*SUSPECT=0)* in the condition of *HIU.* The *SUSPECT x HIU* is the interaction term, where the proxy for IU is above (below) the sample median. β_3 in Eq. (4.5) represents the coefficient of the interaction between high IU and firms beating earnings benchmarks. Hypothesis 4 predicts that there is a higher likelihood that managers prefer to use accrual earnings management over real earnings management in the high IU when firms beat earnings benchmarks. Accordingly, the coefficient on *SUSPECT x HIU* (β_3) in Eq. (4.5) is expected to be significantly positive.

I also apply the propensity-matching score method (PSM) and the Heckman two-step procedure to control for potential difference in firm characteristics between firms beating earnings benchmarks and firms missing earnings benchmarks. As for the PSM method, given that firms have high incentives to manipulate earnings by either accrual or real earnings management (i.e., firms beating earnings benchmarks), I examine the role of IU on the choice of accrual versus real earnings management. The above annual cross-sectional Probit model is estimated by using the propensity-matched sample obtained from Eq. (4.1). To the Heckman Procedure, in the first step, the Inverse mill ratio (*IMR*) is estimated by a selection model from the Eq. (4.2) using the full sample of firm-years. In the second step, I include *IMR* as an independent variable in the main regression in the Eq. (4.5).

Following Zang (2012); Cohen et al. (2010), I control for the relative costs of accrual earnings management and real earnings management. In particular, the costs related to accrual earnings management concern the scrutiny of auditors and regulators and the abilities of doing accrual earnings management. In which, following previous research, higher scrutiny increases with the presence of a big 8 auditors and the auditor's experience in the client. I include big 8 audit firms (*BIG_8*) as a dummy variable to control for the cost of accrual earnings management, which can constrain accrual earnings management (e.g., Becker et al., 1998; Francis et al., 1999). This is because big 8 firms have a higher reputation and audit quality than smaller audit firms. To the cost of real earnings management, I follow Zang (2012) to use modified version of Altman's Z-score (Altman, 2000) as a proxy for the firm's financial health. I apply the beginning of the year (Z_SCORE_{t-1}) to capture the cost of real earnings management. The higher score indicates healthier financial condition of firms, and lower cost of real earnings management. Dechow (1994) and Zang (2012) show that firms' length of their operating cycle determines firms' accounting flexibility. Firms having longer operating cycles have more flexibility in their accrual accounts. Therefore, these firms have larger accruals and longer periods for accruals to be reversed. The operating cycle is defined as the days receivable plus the days inventory less the days payable at the beginning of the year (Dechow, 1994). I apply $CYCLE_{t-1}$ at the beginning of the year to capture operating cycle as a constraint for accrual earnings management.

I also include the same variables as in Eq. (4.5) including firm size (*SIZE)*, big 4 firms (*BIG_4)*, firm performance (*ROA)*, leverage (*LEV)*, and firm growth (*M/B)*. To control for changes in microeconomic factors across time and years, I include industry and year fixed effects as dummy variables. I also apply robust standard errors clustered at firm level to control for

heteroscedasticity and serial correlation problems. All other variables are defined in the Appendix.

Moreover, following Zang (2012), I include cost of real earnings management in the empirical model. In which, a modified version of Altman's Z-score (Zang, 2012; Altman, 2013) is used to proxy for firms' financial health.

$$\text{Z\_SCORE}_t = 0.3\frac{\text{NI}_t}{\text{ASSET}_t} + 1.4\frac{\text{RETAINED EARNINGS}_t}{\text{ASSET}_t} + 1.2\frac{\text{WORKING CAPITAL}_t}{\text{ASSET}_t} + 0.6\frac{\text{STOCK PRICE}_t\ x\ \text{SHARE OUTSTANDING}_t}{\text{TOTAL LIABILITIES}_t}$$

I apply Z_SCORE_{t-1} at the beginning of the year to capture the cost of real earnings management where the higher value of Z_SCORE_{t-1} indicate better firms' financial health resulting lower costs of real earnings management.

4.3.2.7 Income smoothing and information uncertainty

To test hypothesis 5 investigating the relationship between income smoothing and IU of suspects, the following OLS regression is applied by using the full sample.

$$\begin{aligned}\text{SMOOTHING}_{it} = {} & \beta_0 + \beta_1\,\text{SUSPECT}_{it} + \beta_2\text{HIU}_{it} + \beta_3\text{SUSPECT}_{it}\ \text{x}\ \text{HIU}_{it} + \\ & + \beta_4\,\text{SIZE}_{it} + \beta_5\,\text{ROA}_{it} + \beta_6\,\text{LEV}_{it} + \beta_7\,\text{M/B}_{it} + \beta_8\,\text{SIG\_CFO}_{it} \\ & + \sum_j \beta_j\,\text{INDUSTRY}_{\text{DUMMY}_{it}} + \sum_k \beta_k\,\text{YEAR}_{\text{DUMMY}_{it}} + \varepsilon_{it}\end{aligned} \tag{4.6}$$

where *i* refers to the firm and *t* to the year. Variables used in Eq. (4.6) are presented in detail in the Appendix. The variable of interest is the interaction between just beating earnings benchmarks (*SUSPECT)* and high information uncertainty (*HIU),* which equals 1 for high information uncertainty, and 0 otherwise. H5 predicts that firms beating earnings benchmarks use more income smoothing under high IU. Therefore, it is expected that the coefficient on *SUSPECT x HIU* (β_3) is positively significant.

Moreover, I also apply the propensity-score matching method (PSM) and the Heckman procedure methodology to control for potential differences in firm characteristics between firms beating earnings benchmarks and firms missing earnings benchmarks. As for the PSM, the propensity-matched sample obtained from Eq. (4.1). In addition, to the Heckman procedure, in the first step, the Inverse mill ratio (*IMR*) is estimated by a selection model from the Eq. (4.2) using the full sample of firm-years. In the second step, I include IMR in the main test as an independent variable.

Following prior literature, I use control variables based on determinants of earnings quality including firm size (*SIZE)*, leverage (*LEV)*, firm performance (*ROA)* and firm growth (*M/B)* (see Dechow and Dichev, 2002; Hribar and Craig Nichols, 2007). These control variables included in the Eq. (4.6) are the same as in Eq. (4.5). In addition, firm-specific risk arising from changes in the firm's operating cash flows (*SIG_CFO*) (Markarian and Gill-de-Albornoz, 2010; Monjed and Ibrahim, 2020) is used as another control variable. To control for changes in microeconomic factors across time and year, I include industry and year fixed effects as dummy variables. White's heteroskedasticity-corrected standard errors is used to calculate t-statistics in the regressions. All variables are defined in Appendix.

4.3.3 Descriptive statistics

Table 4.1, panel A presents the descriptive statistics of relevant variables for the full sample, which includes 16,811 firm-year observations for the period from 1992 to 2018. To reduce the effect of outliers, all continuous variables are trimmed at the top and bottom one percent of their distributions. The mean residual abnormal accruals from the modified Jones model (Dechow et al., 1995) (*DAP*) is close to zero in the sample firms. It is consistent with results reported by Dechow et al. (1995), which represents that there is no systematic evidence of accrual-based earnings management in the sample firm-years.

Moreover, the mean residuals from reduction of discretionary expenses (REM_{DISEXP}) model, overproduction (REM_{PROD}) costs model, and sales manipulation (REM_{CFO}) model are equal to zero. I multiply the residuals of discretionary expenses (REM_{DISEXP}) model and sales manipulation (REM_{CFO}) model by -1, which indicates greater extent of real earnings management activities by cutting discretionary expenses and offering more discount prices. The total manipulation measure (*AREAL*) is the sum of REM_{DISEXP}, REM_{PROD} and REM_{CFO}. Indeed, the mean residual of *AREAL* is nearly equal to zero. With respect to income smoothing (*IS)*, the mean value is -1.405 presenting that firms on average have higher volatility in operating net income as compared to operating cash flows.

Panel B of table 4.1 reports Pearson correlation coefficients among variables shown in panel A of table 4.1. There is positive correlation between accrual-based earnings management (*DAP*) and firm performance (*ROA*) (Pearson correlation of 0.122). In contrast, there is negative correlation between *DAP* and firm growth (*M/B*) (Pearson correlation of -0.017). Furthermore, three proxies of high information uncertainty *(HIU)* such as *HIU(VOLUME)*,

HIU(VOLATILITY) and HIU(SPREAD) are positively correlated with each other, suggesting that these proxies capture the same phenomenon.

Table 4.1 Descriptive statistics

Panel A. Summary statistics for full sample[9](n=16,811)

Variable	Mean	Std. Dev.	25 percent	Median	75 percent
DAP_t	-0.001	0.297	-0.050	0.004	0.052
REM_{DISEXP_t}	0.005	0.541	-0.180	-0.042	0.125
REM_{PROD_t}	-0.001	0.407	-0.136	0.039	0.196
REM_{CFO_t}	-0.002	0.282	-0.064	0.012	0.088
$AREAL_t$	0.066	0.248	0.000	0.000	0.000
IS_t	-1.405	3.835	-1.506	-0.872	-0.493
DTR_t	0.081	0.185	0.021	0.043	0.081
$SUSPECT_t$	0.481	0.500	0.000	0.000	1.000
$HIU(VOLATILITY_t)$	0.491	0.500	0.000	0.000	1.000
$HIU(VOLUME_t)$ a	0.258	0.438	0.000	0.000	1.000
$HIU(SPREAD_t)$ b	0.258	0.438	0.000	0.000	1.000
M/B_t	1.310	1.825	0.038	1.295	3.630
$SIZE_t$	-0.024	0.225	-0.042	0.039	0.084
ROA_t	0.037	0.400	0.001	0.084	0.155
BIG_8_t	0.174	0.330	0.009	0.124	0.254
LEV_t	3.439	5.769	1.028	1.444	3.156
$ZSCORE_{t-1}$	63.416	191.215	14.380	59.207	110.578
$CYCLE_{t-1}$	1.405	3.835	0.493	0.872	1.506
SIG_CFO_t	-0.001	0.297	-0.050	0.004	0.052

a n = 13,815
b n = 14,938

Table 4.2, Panel A shows the descriptive statistics for the full sample and propensity-score matched sample. In which, Panel A presents 16,811 firms-years that include 1,105 suspects and 15,706 non-suspects. In detail, the descriptive statistics for the full sample indicate that there are significantly different characteristics in terms of *SHARE, M/B, ROA* and S*IZE* between suspects and non-suspects. Suspects are approximately 0.8 times the size of non-suspect firms (*SIZE*). Moreover, suspect firms have significantly higher growth opportunities than non-suspects. Similarly, earnings performance (*ROA*) of suspects is significantly higher than non-suspects.

[9] All variables are defined in the Appendix.

Panel B. Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) $SUSPECT_t$	1.000																	
(2) $HIU(VOLATILITY_t)$	0.053*	1.000																
(3) $HIU(VOLUME_t)$	0.092*	0.200*	1.000															
(4) $HIU(SPREAD_t)$	0.101*	0.079*	0.259*	1.000														
(5) DAP_t	-0.002	-0.010	-0.025*	-0.017*	1.000													
(6) REM_{DISEXP_t}	-0.019*	0.027*	0.019*	-0.007	-0.460*	1.000												
(7) REM_{PROD_t}	0.001	0.023*	0.023*	0.042*	-0.037*	-0.120*	1.000											
(8) REM_{CFO_t}	0.009	-0.064*	-0.070*	-0.073*	0.181*	-0.478*	-0.312*	1.000										
(9) M/B_t	0.078*	0.085*	-0.032*	0.077*	-0.017*	0.022*	0.027*	-0.077*	1.000									
(10) $SIZE_t$	-0.117*	-0.066*	-0.395*	-0.627*	0.014*	0.036*	-0.048*	0.068*	-0.083*	1.000								
(11) ROA_t	-0.052*	-0.180*	-0.245*	-0.287*	0.122*	-0.142*	-0.150*	0.423*	-0.216*	0.371*	1.000							
(12) BIG_8_t	-0.092*	0.005	-0.158*	-0.319*	-0.004	-0.004	-0.033*	0.017*	-0.075*	0.463*	0.196*	1.000						
(13) LEV_t	0.002	0.036*	0.029*	0.045*	-0.008	0.003	0.027*	-0.126*	-0.015*	-0.034*	-0.175*	0.035*	1.000					
(14) $ZSCORE_{t-1}$	0.035*	0.017*	0.014	0.016*	-0.002	-0.004	-0.002	0.017*	0.069*	0.031*	-0.014*	-0.034*	-0.045*	1.000				
(15) $CYCLE_{t-1}$	-0.027*	-0.025*	-0.022*	-0.015*	0.011	-0.070*	0.074*	0.007	-0.015*	0.024*	0.051*	0.014*	-0.023*	-0.032*	1.000			
(16) DTR_t	0.008	-0.028*	-0.024*	-0.060*	0.074*	0.285*	-0.584*	0.160*	-0.020*	0.065*	0.133*	0.008	-0.046*	0.015*	-0.051*	1.000		
(17) IS_t	0.003	-0.054*	-0.081*	-0.053*	0.017*	0.021*	-0.025*	0.012	-0.043*	0.095*	0.124*	0.024*	-0.020*	-0.002	0.018*	0.036*	1.000	
(18) SIG_CFO_t	0.058*	0.090*	0.129*	0.122*	-0.022*	0.128*	0.056*	-0.270*	0.114*	-0.147*	-0.306*	-0.129*	0.133*	-0.005	-0.049*	0.005	0.046*	1.000

* represents significance at the 10 percent level.

Table 4.2 Descriptive statistics full sample and propensity-score matched samples

Panel A. Full sample (n=16,811)

	$SUSPECT_t$	$NON\_SUSPECT_t$	
	Mean	**Mean**	**Difference in mean**
$\mathrm{SHARE_t}$	4.096	3.802	0.294***
$\mathrm{ROA_t}$	-0.066	-0.023	-0.044***
$\mathrm{M/B}_t$	4.035	1.390	3.645***
SIZE_t	0.506	1.353	-0.848***
Obs.	1,105	15,706	

Panel B. Propensity-score matched sample

	$SUSPECT_t$	$NON\_SUSPECT_t$	
	Mean	**Mean**	**Difference in mean**
$\mathrm{SHARE_t}$	4.112	3.991	0.120
$\mathrm{ROA_t}$	-0.069	-0.084	0.015
$\mathrm{M/B}_t$	3.949	4.668	-0.719
SIZE_t	0.508	0.399	0.109
Obs.	1,105	1,105	

*, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed t-tests of differences in means.
This table presents the descriptive statistics for our full and propensity-score matched samples. The propensity matching score is run from the probit selection model (4.1). All variables are defined in the Appendix.

Panel C. Propensity score matching model (selection model (1)) for volatility sample [10]

$\mathrm{SHARE_t}$	0.191
	(14.90)
$\mathrm{M/B}_t$	0.024
	(13.90)
$\mathrm{SIZE_t}$	-0.207
	(-18.71)
$\mathrm{ROA_t}$	0.468
	(5.94)
Obs.	16,811
Pseudo R2	0.101
Year/Industry fixed effect included	YES

*, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels.

[10] The results are run from the probit selection model (4.1). All variables are defined in the Appendix.

In Table 4.2, Panel B, the matching is done by using the above Eq. (4.1) to calculate the propensity score. In which, using one of the most common methods is one-to-one matching, where each suspect is matched to non-suspect observation. Following Shipman et al. (2016), the quality of matching is that there is covariate balance between suspects and non-suspects. The result shown in Panel B, Table 4.2 shows that after matching, the propensity-score model is effective to form a balanced sample, as all variables such as S*HARE, M/B, ROA*, and *SIZE* in the propensity-score matched sample are insignificantly different between suspects and non-suspects.

Table 4.2, Panel C reports the results for the probit model based on the PSM method. In detail, the summary statistics indicate that the coefficients on *SHARE, M/B, ROA* are positive and significant at 0.01 level. The results are consistent with previous research that indicate that firms meeting or beating earnings benchmarks have stronger incentives to manage earnings in the current period (e.g., Bartov et al., 2002; Kasznik and McNichols, 2002; Zang, 2012).

4.4 Main results

4.4.1 The relation between accrual-based earnings management and information uncertainty of firms beating/meeting earnings benchmarks

Table 4.3 shows the results for testing H2 regarding the influence of high IU (*HIU*) on accrual-based earnings management (*DAP*) for firms meeting or beating earnings benchmarks (*SUSPECT*) by using the full sample, the propensity-score matched sample and Heckman procedure. The t-statistics are calculated from White's heteroskedasticity-consistent standard errors to adjust for heteroscedasticity (i.e., possible correlation among the residuals) (see White, 1980; Behn et al., 2008). I use the Modified Jones model to measure accrual-based earnings management (*DAP)*. Moreover, I use three proxies for IU such as *VOLATILITY*, *VOLUME* and *SPREAD*. When the proxy for IU is above (below) the sample median, I define firm as a firm facing high (low) information uncertainty. *HIU* equals 1 for high IU, and 0 otherwise.

With the first regression, I use the full sample to examine the relation between discretionary accruals of suspect firms and IU. All the coefficients of the interaction between firms beating earnings benchmarks and HIU (*SUSPECT x HIU) (β_3)* are statistically positively significant at conventional levels for the three measures of IU (the coefficients of 0.031 and 0.049 where the measures of *HIU* are *HIU(VOLATILITY)* and *HIU(VOLUME),* respectively, significant at 10 percent and 5 percent levels, respectively). In the second regression of Table 4.3, the results using the PSM are generally similar to that in the full sample. The coefficients on two proxies

of *HIU*: *HIU(VOLATILITY)*, and *HIU(VOLUME)* are 0.086 and 0.067, respectively, significantly positive at 10 percent and 1 percent levels, respectively. In addition to the PSM method, the study also applies the Heckman procedure to reduce the effect of sample selection biases. The last column of Table 4.3 provides results using the Heckman procedure. The coefficients on *SUSPECT x HIU* are 0.031 and 0.052 for the two measures of *HIU* such as *HIU(VOLATILITY)*, and *HIU(VOLUME)*, respectively (significant at 10 percent and 5 percent levels, respectively). The results are consistent with those shown in the first and second columns of Table 4.3. The results suggest that greater IU produce higher accrual-based earnings management to meet or beat earnings benchmarks.

Moreover, some coefficients on the control variable are statistically significant. In detail, for all proxies of high IU, the coefficients on the size of firm (*SIZE*) are significantly negative (p-value<0.1 or greater). This directional effect of firm size on discretionary accrual is the same as that in previous studies (Zang, 2012; Lawrence et al., 2011). Furthermore, the coefficients on firm performance (*ROA*) are significantly positive at the significance of 10 percent level or greater. This result is consistent with previous studies documenting that discretionary accruals are positively related with firm-specific performance (Dechow et al., 1995; Cassell et al., 2015).

Table 4.3 The association between discretionary accrual and information uncertainty of firms beating/meeting earnings benchmarks

DAP_t	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	-0.021	-0.032	0.002	-0.034	-0.037	0.006	-0.020	-0.033	0.003
	[-1.371]	[-1.390]	[0.126]	[-1.115]	[-1.606]	[0.336]	[-1.303]	[-1.454]	[0.208]
HIU_t	0.005	-0.005	-0.002	-0.043	-0.022	0.004	0.005	-0.007	-0.001
	[1.037]	[-0.607]	[-0.227]	[-0.971]	[-1.600]	[0.236]	[1.157]	[-0.999]	[-0.168]
$SUSPECT_t$x HIU_t	0.031*	0.049**	-0.009	0.086*	0.067***	-0.011	0.031*	0.052**	-0.009
	[1.739]	[1.968]	[-0.547]	[1.673]	[3.595]	[-0.454]	[1.764]	[3.040]	[-0.516]
$SIZE_t$	-0.005*	-0.005*	-0.006	-0.031*	-0.003	-0.002	-0.007**	-0.003	-0.008*
	[-1.768]	[-1.743]	[-1.529]	[-1.659]	[-0.737]	[-0.304]	[-3.233]	[-1.553]	[-1.923]
BIG_8_t	-0.008	-0.001	-0.006	0.038	-0.002	-0.010	-0.008	-0.002	-0.006
	[-1.122]	[-0.124]	[-0.813]	[1.021]	[-0.129]	[-0.622]	[-1.121]	[-0.303]	[-0.812]
ROA_t	0.204***	0.192***	0.204***	0.410	0.135***	0.156***	0.207***	0.179***	0.207***
	[5.165]	[3.887]	[4.724]	[1.559]	[4.184]	[5.006]	[5.639]	[3.988]	[5.156]
LEV_t	0.018	0.010	0.015	0.045	0.003	-0.001	0.018	0.007	0.015
	[1.339]	[0.749]	[0.996]	[0.806]	[0.137]	[-0.081]	[1.339]	[0.574]	[1.006]
M/B_t	0.000	-0.001	0.000	0.001	-0.001	0.000	0.000	-0.001	0.001
	[0.835]	[-1.394]	[1.016]	[0.417]	[-1.400]	[0.316]	[1.151]	[-1.579]	[1.336]
IMR							0.013	-0.012	0.012
							[0.724]	[-0.803]	[0.616]
Constant	0.015	0.023	0.024*	0.003	-0.031	-0.024	-0.010	0.027	0.000
	[1.299]	[1.608]	[1.698]	[0.065]	[-0.631]	[-0.726]	[-0.257]	[0.862]	[0.003]

Observations	16,811	13,815	14,800	2,210	1,802	2,036	16,811	13,815	14,800
Adjusted R-squared	0.014	0.017	0.014	0.035	0.057	0.010	0.014	0.018	0.014
Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes:

This table shows the results of association between accrual earnings management and IU when firms beat/meet earnings benchmarks using the full, propensity-score matched sample and Heckman two-step. I use three variables to proxy for information uncertainty such as *VOLATILITY*, *VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define firm as a firm facing high (low) information uncertainty. HIU equals 1 for high information uncertainty, and 0 otherwise. The multivariate estimates are based on the main regression equation (4.3) below:

$$\mathrm{DAP_{it}} = \beta_0 + \beta_1\,\mathrm{SUSPECT_{it}} + \beta_2\mathrm{HIU_{it}} + \beta_3\,\mathrm{SUSPECT_{it}xHIU_t} + \beta_8\,\mathrm{SIZE_{it}} + \beta_4\,\mathrm{BIG_{8_{it}}} + \beta_6\,\mathrm{ROA_{it}} + + \beta_9\,\mathrm{LEV_{it}} + \beta_5\,\mathrm{M/B_{it}} + \sum_j \beta_j\,\mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \beta_k\,\mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Significance tests are two-tailed. See Appendix for variable definitions and calculations.

4.4.2 The relation between real earnings management and information uncertainty of firms beating/meeting earnings benchmarks

Table 4.4 shows the results for testing H3 investigating the relationship between real earnings management (*AREAL*) and high IU for firms meeting and beating earnings benchmarks (*SUSPECT)* by using the full sample, the propensity-score matched sample and the Heckman procedure. The t-statistics are calculated from White's heteroskedasticity-consistent standard errors to adjust for heteroscedasticity (i.e., possible correlation among the residuals) (see White, 1980; Behn et al., 2008). I use the Modified Jones model to measure accrual-based earnings management (*DAP)*. Moreover, I use three proxies for IU such as *VOLATILITY, VOLUME* and *SPREAD*. When the proxy for IU is above (below) the sample median, I define firm as a firm facing high (low) information uncertainty. *HIU* equals 1 for high IU, and 0 otherwise.

For all regressions, all the coefficients of the interaction between firms beating earnings benchmarks and high IU (*SUSPECT x HIU) (β_3)* are not statistically positively significant at conventional levels for the three measures of *HIU*. The results cannot reject the null hypothesis that there is no relation between real earnings management and high IU when firms meet and beat earnings benchmarks. The results indicate that when firms have high incentives to manage earnings (i.e., meet/beat earnings benchmarks), managers of firms do not engage in more real earnings management in the high IU, compared to in the low IU environment.

As for the control variables, with the full sample, the coefficients on *SIZE* are -0.022, -0.025, -0.016 for the three measures of *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD),* significant at conventional levels. Similarly, the results are consistent using the Heckman two-step approach (the coefficients on *SIZE* are -0.021, -0.017 for the two proxies of *HIU* such as *HIU(VOLATILITY), HIU(SPREAD),* significant at 1 percent and 5 percent levels, respectively). As for the effect of the audit firm, when using the full sample and the Heckman two-step approach, the results are nearly the same. Hence, I only present the results using the full sample. The coefficients on *BIG_4* for the three measures of *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD)* are *0.033, 0.047, 0.039,* respectively, significant at 5 percent, 10 percent, and 1 percent levels, respectively. Coefficients on *ROA* for three proxies of IU (*VOLATILITY, VOLUME* and *SPREAD)* are -0.443, -0.379, -0.443, respectively, significant at the 1 percent level. The results are consistent using the PSM approach (coefficients on *ROA* for measures of *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD) are* -0.494, -0.395, -0.494, respectively, significant at 1

percent, 10 percent, and 1 percent levels, respectively. The results are the same for the Heckman two-step approach. The results for the control variables are consistent with previous literature (see Zang, 2012; Owusu et al., 2020).

Table 4.4 The association between real earnings management and information uncertainty of firms beating/meeting earnings benchmarks

	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
AREAL	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	0.036	0.012	0.010	-0.019	-0.127	-0.018	0.036	0.011	0.010
	[1.140]	[0.469]	[0.279]	[-0.317]	[-1.592]	[-0.347]	[1.129]	[0.437]	[0.295]
HIU_t	0.009	-0.022	0.009	-0.035	-0.114	0.064	0.009	-0.018	0.009
	[0.845]	[-1.572]	[0.559]	[-0.518]	[-1.335]	[1.057]	[0.819]	[-1.382]	[0.571]
$SUSPECT_t$ x HIU_t	-0.054	-0.025	-0.002	-0.028	0.068	-0.037	-0.054	-0.022	-0.001
	[-1.319]	[-0.712]	[-0.036]	[-0.356]	[0.763]	[-0.527]	[-1.320]	[-0.627]	[-0.029]
$SIZE_t$	-0.022***	-0.025**	-0.016**	-0.022	-0.025	-0.006	-0.021***	-0.045	-0.017**
	[-4.357]	[-2.386]	[-2.472]	[-1.220]	[-0.657]	[-0.269]	[-3.620]	[-1.381]	[-2.325]
BIG_8_t	0.033**	0.047*	0.039***	0.033	0.078	0.035	0.033**	0.048*	0.039***
	[2.494]	[1.673]	[2.740]	[0.976]	[0.934]	[0.976]	[2.495]	[1.712]	[2.744]
ROA_t	-0.443***	-0.379***	-0.443***	-0.494***	-0.395*	-0.494***	-0.444***	-0.326***	-0.441***
	[-7.281]	[-5.625]	[-6.708]	[-4.124]	[-1.903]	[-4.130]	[-7.525]	[-3.534]	[-6.924]
LEV_t	0.054	-0.131***	0.069	0.193	-0.140*	0.202*	0.054	-0.130***	0.069
	[1.344]	[-3.029]	[1.597]	[1.630]	[-1.726]	[1.668]	[1.344]	[-3.021]	[1.599]
M/B_t	0.000	0.002	0.000	0.004**	0.001	0.003*	0.000	0.004	0.001
	[0.352]	[1.099]	[0.452]	[2.129]	[0.513]	[1.905]	[0.327]	[1.109]	[0.522]
IMR							-0.004	0.132	0.007
							[-0.118]	[0.724]	[0.187]
Constant	-0.062	-0.133***	-0.064	0.108	-0.492**	0.080	-0.054	-0.423	-0.077
	[-1.406]	[-3.240]	[-1.339]	[0.617]	[-2.252]	[0.450]	[-0.659]	[-1.070]	[-0.869]
Observations	16,811	13,815	14,800	2,210	1,802	2,036	16,811	13,815	14,800
Adjusted R-squared	0.066	0.027	0.062	0.073	0.048	0.070	0.066	0.027	0.062

Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes:

This table shows the results of association between accrual earnings management and IU when firms beat/meet earnings benchmarks using the full, propensity-score matched sample and Heckman two-step. I use three variables to proxy for information uncertainty such as *VOLATILITY*, *VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define firm as a firm facing high (low) information uncertainty. HIU equals 1 for high information uncertainty, and 0 otherwise. The multivariate estimates are based on the main regression equation (4.3) below:

$$\mathrm{AREAL_{it}} = \beta_0 + \beta_1\,\mathrm{SUSPECT_{it}} + \beta_2\mathrm{HIU_{it}} + \beta_3\,\mathrm{SUSPECT_{it}}\mathrm{x}\,\mathrm{HIU_t} + \beta_8\,\mathrm{SIZE_{it}} + \beta_4\,\mathrm{BIG_{8_{it}}} + \beta_6\,\mathrm{ROA_{it}} + + \beta_9\,\mathrm{LEV_{it}} + \beta_5\,\mathrm{M/B_{it}} + \sum_j \beta_j\,\mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \beta_k\,\mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Significance tests are two-tailed. See Appendix for variable definitions and calculations.

4.4.3 Real earnings management versus discretionary accruals and information uncertainty

Hypothesis 4 predicts that managers of firms are more likely to use accrual-based earnings management compared to real earnings management in the high IU when firms meet or beat earnings benchmarks. Table 4.5 presents average absolute value of *DAP* and *AREAL* sorted on three IU proxies (i.e., *VOLATILITY, VOLUME, SPREAD*). In which, I compute the absolute value of *DAP* for accrual earnings management, the absolute value of *AREAL* for total of three types of real earnings management activities and refer to them as *ABS_DAP*, *ABS_AREAL*, respectively. As shown in Panel A, Table 4.5, each year I evenly sort *ABS_DAP*, *ABS_AREAL* into ten deciles using three proxies for IU shown in three separate columns (i.e., *VOLATILITY, VOLUME, SPREAD*). *IU1* represents the lowest deciles of IU and *IU10* represents the highest deciles of IU.

I find that with the increasing level of IU for all IU proxies, there is no significant increase in real earnings management. Indeed, the average value of total real manipulation for high-IU firms are not different from that of low-IU firms. For instance, there is no significant difference between average *ABS_AREAL* of decile 1 representing low IU *(IU1)* and that of decile 10 representing high IU *(IU10)* for the two proxies of IU (*VOLATALITY* and *VOLUME*). In contrast, with greater IU, the level of discretionary accruals significantly increases. In detail, for *VOLATILITY*, the mean *ABS_DAP* for lowest IU (*IU1)* is 0.098 and this rises to 0.15 in highest IU (*IU10*). The *IU10-IU1* yields the significant difference in mean *ABS_DAP* of 0.052, significant at the one percent level. Similarly, with *VOLUME* and *SPREAD*, there are significant differences between *IU10* and *IU1 (IU10-IU1)* with mean differences for *ABS_DAP* of 0.049 and 0.06, respectively, significant at one percent level. The results suggest that managers of firms tend to use more discretionary accruals versus real earnings management with greater IU.

Panel B, Table 4.5 presents average *ABS_DAP* and *ABS_AREAL* sorted on median values of IU (*IU*) proxies: *VOLATILITY, VOLUME, SPREAD.* In which, *HIU* represents high IU (above median value of IU*),* and *LIU* represents low IU (below median value of IU). As for real earnings management (*AREAL),* three IU proxies show no significant difference in mean *ABS_AREAL* between *HIU* and *LIU*. In contrast, there are significantly different means of *ABS_DAP* between high IU (*HIU*) and low IU (LIU) groups. In detail, the significant difference in mean *ABS_DAP* between *HIU* and *LIU* of *VOLATALITY* and *VOLUME* are 0.025 and 0.023

(t=-5.8 and -5.05), respectively. The results suggest that there are differences in the pattern of average *ABS_DAP* across high-IU and low-IU portfolios.

Figure 4.1 and Figure 4.2 present a graphical summary of the results shown in Table 4.5. These figures show average yearly real earnings management and discretionary accruals sorted on deciles of the IU for three IU proxies (i.e., *VOLATILITY, VOLUME, SPREAD)*. *IU1* represents the lowest decile of IU and *IU10* shows the highest decile of IU. As shown in Figure 4.1, the mean *ABS_AREAL* approximately is unchanged with the increasing level of IU. In contrast, as presented in Figure 4.2, mean *ABS_DAP* for the three IU proxies such as *VOLATILITY, VOLUME, SPREAD* experience an increase with the greater IU.

Table 4.6 provides results of the probability of firms using accrual earnings management versus real earnings management in the condition of high IU. In which, *DTR* is the proxy of firms using higher accrual earnings management than real earnings management (i.e., indicator variable taking the value of 1 when *DAP* is higher than *AREAL*). In which, *DAP* is accrual earnings management measured by modified Jones model and *AREAL* is total three types of real earnings management measured by Roychowdhury (2006). When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise.

As shown in Panel A, with the full sample, the coefficients of *DTR* on *SUSPECT x HIU* are 0.157, 0.281, 0.152 for three proxies of *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD),* significant at the 10 percent, 1 percent, and 10 percent levels, respectively. The results are consistent when using the Propensity Score Matching method and Heckman procedure. In detail, in the PSM method, the coefficients of *DTR* on *HIU x SUSPECT* (with the proxy of *HIU*: *HIU(VOLATILITY), HIU(VOLUME)*) are 0.270, 0.239 at the significance level of 10 percent and 5 percent. Similarly, with the Heckman procedure, the significant coefficients of *DTR* on *HIU* and *SUSPECT* are 0.160, 0.307, 0.151 for measures of *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD),* significant at 10 percent, 1 percent, and 10 percent levels, respectively. The results support hypothesis 4 that managers of suspect firms (i.e., firms meeting or beating earnings benchmarks) prefer to apply accrual earnings management rather than real earnings management under the greater level of IU.

Table 4.5 Average absolute value of DAP and AREAL sorted by information uncertainty level

Panel A. 10-Decile average absolute value of DAP and AREAL sorted by information uncertainty level

	Mean of ABS_AREAL			Mean of ABS_DAP		
	(1) Sorted by VOLATILITY	**(2) Sorted by VOLUME**	**(3) Sorted by SPREAD**	**(1) Sorted by VOLATILITY**	**(2) Sorted by VOLUME**	**(3) Sorted by SPREAD**
IU1 (low IU)	0.485	0.44	-0.002	0.098	0.086	0.077
IU2	0.461	0.452	0.019	0.086	0.089	0.07
IU3	0.449	0.438	0.017	0.088	0.082	0.086
IU4	0.429	0.424	0.016	0.08	0.078	0.092
IU5	0.426	0.422	0.019	0.086	0.098	0.094
IU6	0.443	0.453	-0.012	0.098	0.087	0.11
IU7	0.446	0.472	0.025	0.091	0.095	0.115
IU8	0.441	0.462	0.001	0.106	0.109	0.113
IU9	0.46	0.471	-0.011	0.117	0.114	0.111
IU10 (high IU)	0.473	0.464	-0.043	0.15	0.135	0.138
IU10 - IU1	-0.012	0.024	-0.041*	0.052***	0.049***	0.06***
	(-0.55)	(-1.15)	(-3.489)	(-3.4)	(-5.9)	(-6.9)
Obs.	16,811	13,815	14,938	16,811	13,815	14,938

***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

The significances of the differences in the means in *ABS_AREAL*, *ABS_DAP* between *IU10* (high IU) firms and *IU1* (low IU) firms are based on t-statistics from t-tests.

Panel B. Average absolute value of DAP and AREAL sorted by median of information uncertainty level

	Mean of ABS_AREAL			Mean of ABS_DAP		
	(1) Sorted by VOLATILITY	**(2) Sorted by VOLUME**	**(3) Sorted by SPREAD**	**(1) Sorted by VOLATILITY**	**(2) Sorted by VOLUME**	**(3) Sorted by SPREAD**
HighIU	0.454	0.008	0.447	0.113	0.109	0.002
LowIU	0.45	0.009	0.452	0.088	0.086	-0.003
HighIU-LowIU	0.004	-0.001	-0.004	0.025***	0.023***	0.004
	(-0.45)	(0.1)	(0.4)	(-5.8)	(-5.05)	(-0.75)
Obs.	16,811	13,815	14,938	16,811	13,815	14,938

***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

The significances of the differences in the means in *ABS_REAL*, *ABS_DAP* between HighIU (high IU) firms and LowIU (low IU) firms are based on t-statistics from t-tests.

Figure 4.1 Average ABS_AREAL formed using information uncertainty sorted by deciles

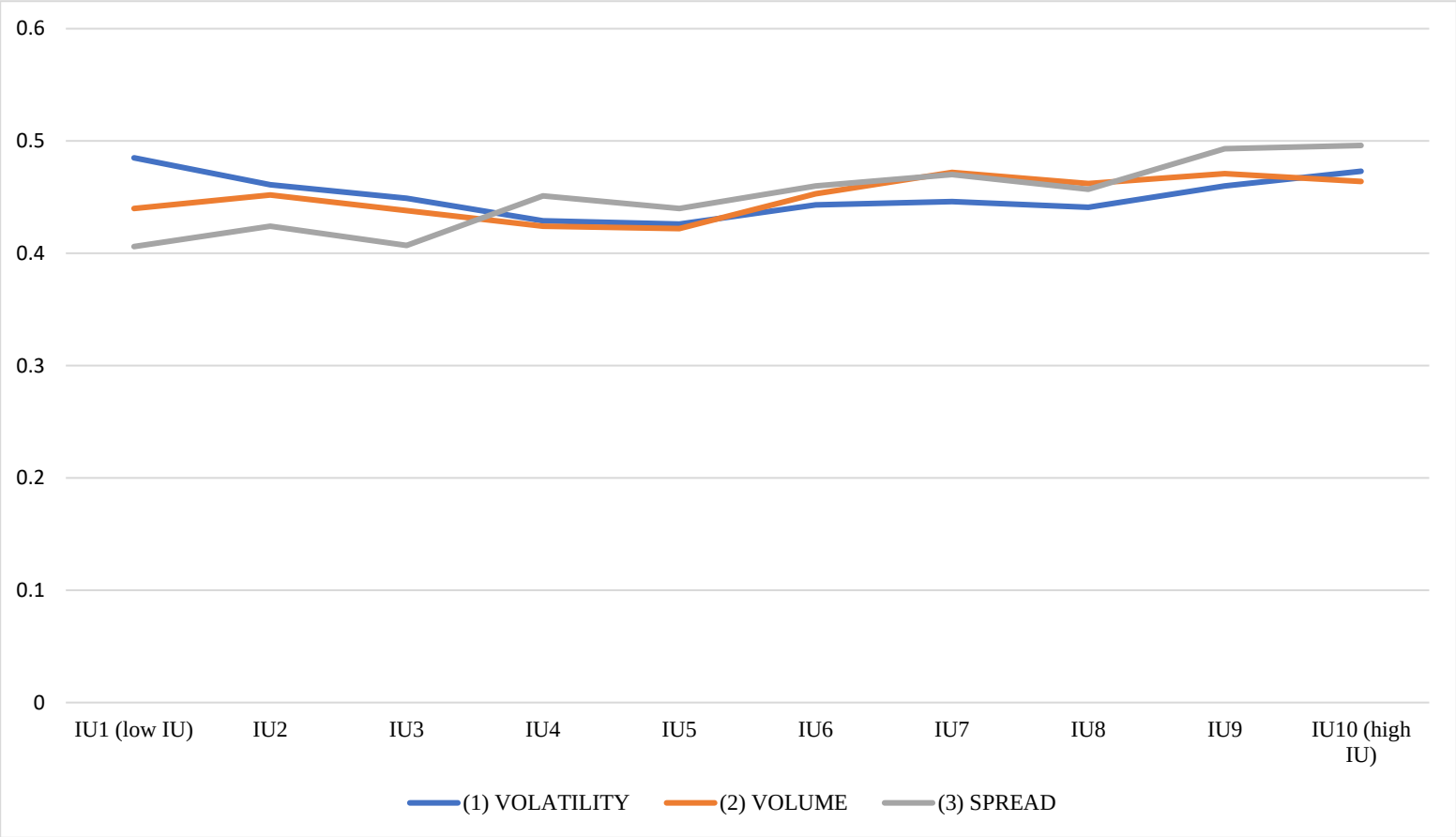


Figure 4.2 Average ABS_DAP formed using information uncertainty sorted by deciles

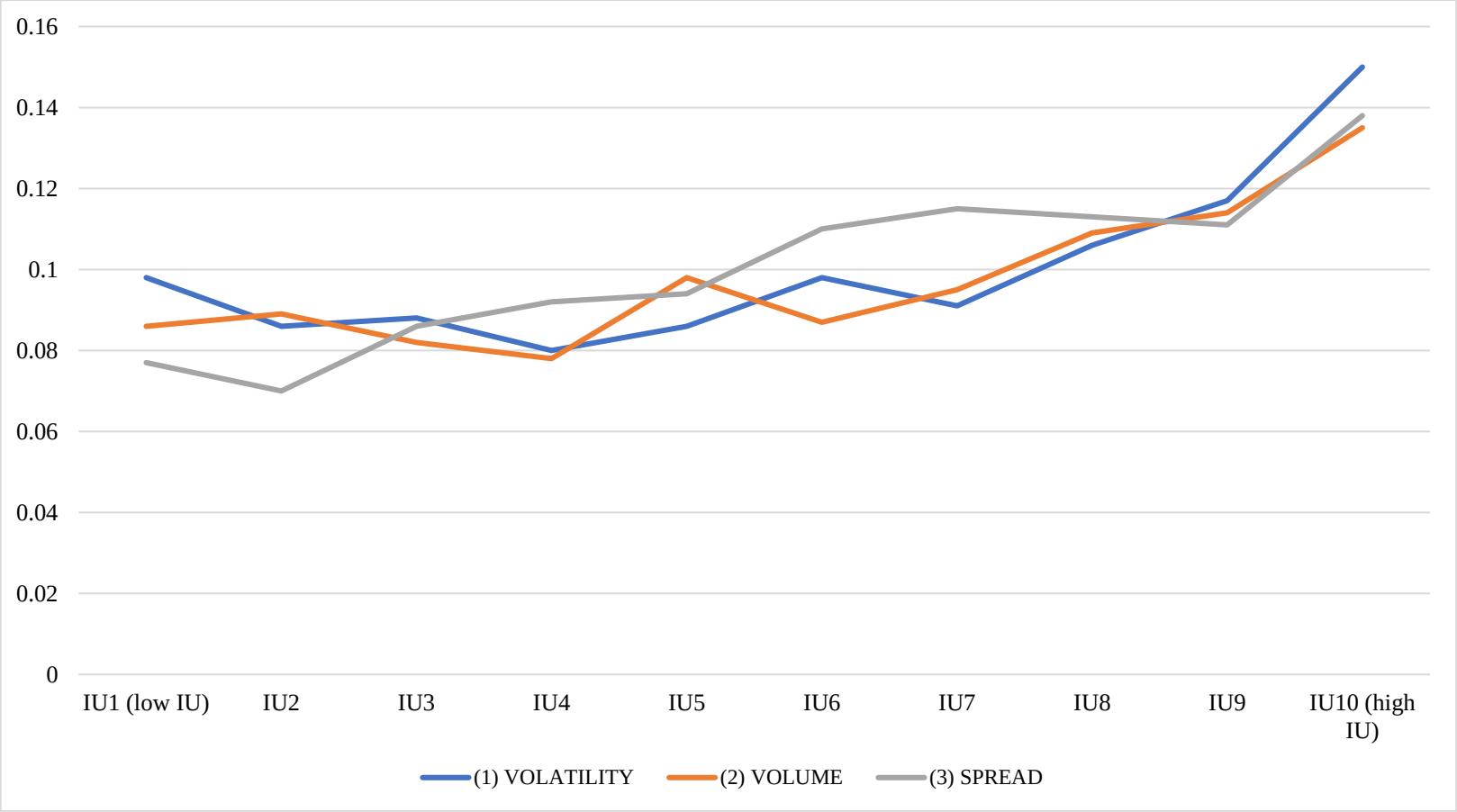


Table 4.6 The probability of using accrual earnings management than real earnings management with the level of information uncertainty

	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
DTR_t[11]	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	-0.048	-0.142*	-0.041	-0.067	-0.148	-0.149	-0.041	-0.137*	-0.044
	[-0.783]	[-1.801]	[-0.591]	[-0.762]	[-1.308]	[-1.576]	[-0.656]	[-1.731]	[-0.642]
HIU_t	-0.075***	0.007	-0.084***	-0.051	0.044	-0.192**	-0.070***	0.043	-0.085***
	[-3.476]	[0.265]	[-2.964]	[-0.595]	[0.421]	[-1.964]	[-3.235]	[1.477]	[-2.990]
$SUSPECT_t$ x HIU_t	0.157*	0.281***	0.152*	0.142	0.270*	0.239**	0.160*	0.307***	0.151*
	[1.906]	[2.893]	[1.759]	[1.196]	[1.928]	[1.987]	[1.940]	[3.162]	[1.742]
$SIZE_t$	0.033***	0.043***	0.016*	0.049**	0.072***	0.001	0.024***	0.029***	0.019**
	[4.695]	[5.112]	[1.879]	[2.541]	[2.982]	[0.048]	[2.676]	[2.626]	[1.966]
BIG_8_t	-0.071***	-0.122***	-0.068***	-0.031	-0.059	-0.057	-0.071***	-0.126***	-0.068***
	[-2.904]	[-4.475]	[-2.739]	[-0.443]	[-0.755]	[-0.841]	[-2.896]	[-4.602]	[-2.731]
ROA_t	0.987***	0.992***	0.547***	0.863***	0.988***	0.541***	1.010***	0.801***	0.544***
	[15.604]	[14.118]	[8.468]	[5.657]	[5.670]	[3.694]	[15.638]	[10.105]	[8.371]
LEV_t	-0.051	-0.019	-0.265***	-0.118	-0.166	-0.357**	-0.051	-0.004	-0.264***
	[-1.176]	[-0.431]	[-3.733]	[-1.069]	[-1.204]	[-2.233]	[-1.174]	[-0.066]	[-3.727]
M/B_t	0.000	0.000	0.000	-0.004*	-0.001	-0.006**	0.001	0.003	0.000
	[0.312]	[0.081]	[0.191]	[-1.901]	[-0.301]	[-2.361]	[0.822]	[1.162]	[0.034]
$ZSCORE_{t-1}$	0.000	0.000	0.002*	-0.001	-0.001	0.001	0.000	-0.000	0.002*
	[0.096]	[0.102]	[1.727]	[-0.317]	[-0.637]	[0.666]	[0.079]	[-0.066]	[1.716]
$CYCLE_{t-1}$	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***
	[-8.429]	[-7.530]	[-6.569]	[-3.486]	[-3.147]	[-3.549]	[-8.450]	[-7.560]	[-6.505]

[11] Alternatively, DTR = 1 if DAP above median and AREAL below median of all firm/year observations and the results provide qualitatively similar results.

IMR_t							0.092*	0.271***	-0.028
							[1.664]	[3.419]	[-0.626]
Constant	0.381***	0.272**	-0.057	0.630**	0.027	0.283	0.202	-0.289	0.005
	[4.227]	[2.153]	[-0.830]	[2.107]	[0.055]	[1.102]	[1.454]	[-1.410]	[0.043]
Observations	16,474	13,533	14,502	2,089	1,685	1,977	16,474	13,533	14,502
Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R-squared									

Notes:

This table shows the results of the likelihood that managers of firms use accrual earnings management rather than real earnings management when firms beat/meet earnings benchmarks by using the full, propensity-score matched sample and Heckman two-step. I use three variables to proxy for information uncertainty: *VOLATILITY*, *VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define the firm facing high (low) information uncertainty. *HIU* equals 1 for high information uncertainty, and 0 otherwise.

The main regression equation (4.5) is as below:

$$\mathrm{PROB}(\mathrm{DTR}_{it} = 1) = \beta_0 + \beta_1 \mathrm{HIU}_{it} + \beta_2\, \mathrm{SUSPECT}_{it} + \beta_3\, \mathrm{SUSPECT}_{it} \times \mathrm{HIU}_{it} + \beta_4\, \mathrm{SIZE}_{it} + \beta_5\, \mathrm{BIG\_8}_{it} + \beta_6\, \mathrm{ROA}_{it} + \beta_7\, \mathrm{LEV}_{it} + \beta_8\, \mathrm{M/B}_{it} + \beta_9\, \mathrm{Z\_SCORE}_{it-1} + \beta_{10}\, \mathrm{CYCLE}_{it-1} + \sum_j \beta_j\, \mathrm{INDUSTRY}_{\mathrm{DUMMY}_{it}} + \sum_k \beta_k\, \mathrm{YEAR}_{\mathrm{DUMMY}_{it}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported z-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. See appendix for variable definitions and calculations.

4.4.4 Income smoothing and information uncertainty

Table 4.7 provides results for testing the fifth hypothesis on the association between income smoothing of firms beating earnings benchmarks and IU. When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise. The variable of interest is the interaction between meeting earnings benchmarks (*SUSPECT)* and high IU (*SUSPECT x HIU).* The White's heteroskedasticity-corrected standard errors is applied to calculate all t-statistics.

As shown in Table 4.7, with the full sample, the first regression presents the results using income smoothing as a proxy of *SMOOTHING. (IU x SUSPECT)* is positively related with *IS* (the coefficients on *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)*are 0.090 and 0.114, respectively, significant at the 5 percent and 1 percent levels, respectively). Moreover, with the propensity matching method, the results show that there is positive relation between *SMOOTHING* and (*IU x SUSPECT)* (with the coefficients of 0.126, 0.149, 0.181 for *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD),* respectively, significant at the 5 percent level). Similarly, with the Heckman procedure, there is the positive association between *IU x SUSPECT* and *SMOOTHING (*with the coefficients of 0.099 and 0.116 for *HIU* such as *HIU(VOLATILITY), HIU(VOLUME),* respectively, significant at the 5 percent level and 1 percent level, respectively). The results support the hypothesis testing indicating that income smoothing is positively associated with IU when firms meet/beat earnings benchmarks. Consequently, in the high IU, managers of firms attempt to smooth earnings through beating/meeting earnings benchmarks.

As for control variables, firm size is negatively related with income smoothing with the Heckman two-step method (coefficients on *SIZE* = -0.024 and -0.017 for the two proxies of *HIU* such as *HIU(VOLATILITY),* and *HIU(SPREAD),* respectively, significant at 5 percent and 10 percent levels, respectively). This is consistent with the results by prior studies (Baik et al., 2020, Demerjian et al., 2020). Moreover, all coefficients on *ROA* are positively significant. With the full sample, the coefficients on *ROA* are 0.358, 0.340, 0.365 for the three measures of *HIU* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD),* respectively, significant at the 1 percent level. The results of the coefficients on *ROA* when using the Heckman two-step approach are similar to those using the full sample. Similarly, with the PSM, the coefficients on *ROA* are 0.274, 0.271, 0.271 for three measures of *HIU* such as *HIU(VOLATILITY),*

HIU(VOLUME) and *HIU(SPREAD)*, respectively, significant at the 5 percent level. This directional effect of firm performance on income smoothing is the same as that in previous studies (e.g., Grant et al., 2009).

Table 4.7 Income smoothing of firms beating earnings benchmarks and information uncertainty

	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
SMOOTHING[12]	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	-0.042	-0.065*	-0.053	-0.084**	-0.113**	-0.121***	-0.038	-0.064*	-0.046
	[-1.406]	[-1.856]	[-1.579]	[-2.423]	[-2.605]	[-2.712]	[-1.327]	[-1.730]	[-1.387]
HIU_t	-0.031	-0.045***	0.009	-0.078	-0.060	-0.058	-0.021	-0.036	0.017
	[-1.655]	[-3.700]	[0.393]	[-1.524]	[-1.022]	[-1.475]	[-1.199]	[-1.528]	[0.805]
$SUSPECT_t$ x HIU_t	0.090**	0.114***	0.107	0.126**	0.149**	0.181**	0.099**	0.116***	0.108
	[3.111]	[3.757]	[1.646]	[2.178]	[2.141]	[2.111]	[3.311]	[3.840]	[1.629]
$SIZE_t$	-0.014	-0.015	-0.011	-0.007	-0.006	-0.006	-0.024**	-0.019	-0.017*
	[-1.230]	[-1.227]	[-1.046]	[-0.405]	[-0.269]	[-0.264]	[-3.132]	[-1.656]	[-1.709]
ROA_t	0.358***	0.340***	0.365***	0.274**	0.271***	0.271**	0.387***	0.351***	0.378***
	[5.345]	[7.570]	[5.401]	[2.250]	[2.702]	[2.177]	[6.195]	[7.621]	[5.515]
LEV_t	-0.032	-0.030	-0.033	-0.130	0.013	-0.050	-0.027	-0.031	-0.034
	[-1.265]	[-0.947]	[-1.199]	[-1.429]	[0.126]	[-0.421]	[-1.057]	[-0.956]	[-1.222]
M/B_t	-0.003	-0.002	-0.003	-0.001	-0.000	-0.001	-0.004**	-0.001	-0.003
	[-1.438]	[-0.843]	[-1.378]	[-0.304]	[-0.139]	[-0.361]	[-3.453]	[-0.632]	[-1.155]
$sigma\_CFO_t$	-0.008	-0.022	-0.013	0.050	-0.005	0.047	-0.038	-0.019	-0.008
	[-0.142]	[-0.428]	[-0.233]	[0.677]	[-0.064]	[0.627]	[-0.618]	[-0.363]	[-0.153]
IMR							0.075*	0.039	0.072
							[1.676]	[0.580]	[1.530]
Constant	0.595***	0.574***	0.562***	0.644***	0.616**	0.604***	0.470***	0.495***	0.428***
	[11.846]	[9.322]	[11.784]	[3.712]	[2.493]	[3.066]	[4.133]	[3.925]	[3.640]
Observations	9,274	8,163	8,458	1,379	1,210	1,298	9,274	8,163	8,458
Adjusted R-squared	0.022	0.017	0.022	0.0377	0.0335	0.0377	0.024	0.017	0.023
Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES

[12] I also apply another measure of income smoothing that is calculated by the ratio of a firm's standard deviation of net income divided by the standard deviation of its cash from operations (both deflated by the beginning-of-year total asset). The results are qualitatively unchanged.

Notes:

This table shows the results of association between income smoothing and IU when firms beat/meet earnings benchmarks using the full, propensity-score matched sample and Heckman two-step. I use three variables to proxy for information uncertainty such as *VOLATILITY, VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define the firm facing high (low) information uncertainty. HIU equals 1 for high information uncertainty, and 0 otherwise. The regression equation (4.6) is as below:

$$\mathrm{SMOOTHING_{it}} = \beta_0 + \beta_1\,\mathrm{SUSPECT_{it}} + \beta_2\mathrm{HIU_{it}} + \beta_3\,\mathrm{SUSPECT_{it}}\,\mathrm{x}\,\mathrm{HIU_t} + +\beta_4\,\mathrm{SIZE_{it}} + \beta_5\,\mathrm{ROA_{it}} + \beta_6\,\mathrm{LEV_{it}} + \beta_7\,\mathrm{M/B_{it}} + \beta_8\,\mathrm{SIG\_CFO_{it}} + \sum_j \beta_j\,\mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \beta_k\,\mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. See Appendix for variable definitions and calculations.

4.5 Sensitivity analysis

The results reported in this chapter relied on the cross-sectional Modified Jones Model (Dechow et al., 1995). As a robustness check, I apply the alternative measure of discretionary accruals by Kothari et al. (2005). In which, as suggested by Kothari et al. (2005), I match each firm-year observation with one having the same two-digit SIC code, with the closest level of return on assets. The results using this alternative measure of accruals are consistent with those results reported in the study.

I also repeat the analysis by choosing alternative benchmarks for firms meeting or beating earnings benchmarks. In detail, following Cohen et al. (2008) and Zang (2012), I select earnings-management firm-years suspects having changes in earnings before extraordinary items scaled by total assets in the interval [0, 0.0025). My main results are qualitatively unchanged.

As an additional robustness test, to test the relation between earnings management of firms meet or beating earnings benchmarks and IU, I use the highest decile of the three proxies of IU (i.e., *VOLUME, VOLATALITY, SPREAD*) to classify them as the high IU instead of using median value as in the main tests. The results are qualitatively similar to the above-mentioned results. Furthermore, in the main tests, I use the three proxies of IU (i.e., *VOLUME, VOLATALITY, SPREAD*) instead of using dummy variable (*HIU)* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD)*. Using these alternative measures of IU, I find a significant positive relationship only when using the variable, *VOLATILITY* for testing hypothesis 2. Moreover, the results are qualitatively similar for testing hypothesis 3, hypothesis 4 and hypothesis 5 when I use these alternative measures of IU.

In further robustness testing, I use the alternative sample for the period from 2005 to 2018. The chosen start year of 2006 is to address the major regulatory change in accounting in 2004 and 2005. In detail, on 1 January 2005, all listed firms on London Stock Exchange are required to adopt International Financial Reporting Standards (IFRSs) to prepare their financial reporting. All results presented in previous tables are unchanged.

4.6 Summary and conclusion

Table 4.8 below presents the main findings of the analyses shown in the empirical chapter 4.

Table 4.8 Summary of main findings of chapter 4

Hypotheses	Expected signs	Results
H2: There is a positive relationship between the level of information uncertainty and accrual-based earnings management when firms have incentives to manage earnings.	(+)	Confirmed (+)
H3: There is no association between the level of information uncertainty and real earnings management when firms have incentives to manage earnings.	(+)	Confirmed (+)
H4: There is a higher likelihood that managers use accrual versus real manipulation when firms have incentives to manage earnings under high information uncertainty than under low information uncertainty.	(+)	Confirmed (+)
H5: There is a positive relation between smoothing earnings and the level of information uncertainty when firms have incentives to manage earnings.	(+)	Confirmed (+)

The findings of the study contribute to the existing literature by providing empirical evidence that IU is an important condition which managers consider in decisions to use discretionary accruals but not real earnings management when firms have high incentives for managing earnings. Indeed, this study provides insight into concerns about conditions in which discretionary accruals in financial reporting is applied, which is raised by Healy and Wahlen (1999, p. 380), Dechow et al. (2000), and Burgstahler and Chuk (2017). Indeed, Arya et al. (2003) show that under high IU, there is diffused private information about firm performance. Accordingly, in the high IU, managed earnings convey more information than unmanaged earnings for market participants. Moreover, the findings extend the study by Dechow (1994) providing further insight into the association between uncertainty and accruals. Furthermore, this study extends previous studies about examining factors affecting managerial discretionary accruals (e.g., Zang, 2012; Cohen et al., 2010) in exploring the condition of IU influencing managerial choice of using accrual-based earnings management. Moreover, the study suggests that managers of firms attempt to reduce variability of reported earnings through smoothing earnings under high IU. Moreover, this study contributes to explaining the managers' strategies

for using accrual-based earnings management versus real earnings management when faced with IU. The empirical evidence of this study suggests that under the condition of high IU, managers of firms use more accrual earnings management than real earnings management since real manipulation activities cause higher subsequent costs for firms (e.g., Lennox and Yu, 2020). This study contributes to enhancing our understanding of how and why managers of firms use discretionary accruals.

The findings of the study provide several implications. In detail, the findings imply that the managerial intention of using discretionary accruals are not observable due to information asymmetry between managers and market participants. IU accentuates information asymmetry, which provides more opportunities for managers to use discretionary accruals without being detected. Moreover, the overall results indicate that under high IU, firms with high incentives to manage earnings engage more in accrual-based earnings management than real earnings management. However, since real earnings management might cause economically long-run costs for firms, there is no additional real manipulation under low and high IU. Instead, managers of firms use more accrual-based earnings management versus real earnings management to inflate earnings during the period of high IU. Our findings extend previous studies examining firms' choice to use accrual earnings management and real earnings management and the costs of doing so (e.g., Zang, 2012; Cohen et al., 2010) through explaining the role of IU on managerial preferences between accrual earnings management and real manipulation. The evidence implies that in the settings where managers' intentions are unobservable and verified (i.e., high IU), managers use alternative ways to manage earnings that are perceived as less costly for firms.

The findings have practical implications that in the high IU environment, using accounting information can be more costly for investors since managers of firms are likely to opportunistically engage in earnings management. For regulators and auditors, the findings of this study imply that firms having high IU should consider higher scrutiny since they probably use more opportunistic accrual earnings management. However, the limitation of the study is that the sample of firm-years has high incentives to use income-increasing manipulation. Future research should consider different contexts where managers of firms have different incentives for earnings management.

CHAPTER 5. FUTURE PERFORMANCE FOLLOWING BENCHMARK BEATING UNDER INFORMATION UNCERTAINTY

5.1 Introduction

The objectives of this chapter are to examine the subsequent performance of firms beating/meeting earnings benchmarks using accrual and real manipulation when faced with IU. In prior literature, economic consequences of firms managing earnings is not conclusive. This chapter contributes to providing evidence that firms that manage earnings to beat earnings benchmarks will experience long-run underperformance, especially when faced with high IU. The findings of this chapter show that under high IU, managers of firms beat earnings benchmarks through managing earnings to mislead investors about the fundamental value of firms. In the high IU condition, investors are not able to see through the implications of managed earnings when firms meet/beat important earnings benchmarks.

Degeorge et al. (1999) present that under the psychological effect, people differentiate between positive and negative numbers. In which, there is a tendency for individuals to prefer non-negative numbers. Accordingly, this might drive managers' choice of selecting a threshold of absolute earnings. When earnings fall below this threshold, executives of firms might perceive this as unfavourable. Therefore, the benchmarks of earnings are considered as the target for executives to achieve. Prior literature provide evidence that to avoid negative earnings surprises, managers of firms manage earnings (see Degeorge et al., 1999). For example, Burgstahler and Dichev (1997), Kasznik (1999) and Payne and Robb (2000) find firms engaging in managing earnings to meet investors' earnings expectations. In the survey by Graham et al. (2005), most executives prefer beating earnings benchmarks to avoid negative surprises for investors.

Whether the market fully understands the economic consequences of earnings management through meeting/beating earnings benchmarks has two competing viewpoints. On the one hand, some authors provide empirical evidence that market participants cannot uncover earnings beating through managing earnings in financial reporting. Accordingly, there is negative relation between long-run abnormal returns and firms beating earnings expectations (Bhojraj et

al., 2009). Therefore, managers of firms meet/beat earnings benchmarks as opportunism to distort earnings.

On the other hand, some argue that earnings beating could enhance the informativeness of earnings that allow managers to communicate private information of firms (e.g., Bartov et al., 2002; Athanasakou et al., 2011). With this stream of study, beating earnings benchmarks improves the ability of earnings to signal future firm performance. For example, Koh et al. (2008) indicate that earnings beating conveys private information about future profitability of firms. The empirical evidence suggests that the market can value components of managed earnings to reflect fundamental values of firms.

The opposing views and evidence about the pricing of earnings beating implies that there may be other variables at play. Indeed, IU might influence investors' valuation about firm performance. Clearly, investors face uncertainty when interpreting managed earnings to estimate a firm's value. As shown in prior studies, IU is defined as the ambiguity of investors about firm value. Higher IU causes less knowledgeable estimates of expected cash flows (see Jiang et al., 2005; Kim, 2006; Zhang, 2006b).

Furthermore, under the condition of IU, investors face more difficulty in detecting managed earnings (Lo, 2008). Indeed, Healy and Wahlen (1999) document that the difficulty in detection of earnings management is evidence of opportunism. This is because under high IU, investors are not able to see through the managerial opportunism (see Dye, 1988; Trueman and Titman, 1988; DeFond and Park, 2001; Burgstahler and Chuk, 2017). Accordingly, investors can face greater mis-valuation of firms under high IU.

Other researchers present that investor experience psychological biases in the high IU environment. In which, investors witness over-confidence in their interpretation of the accuracy of financial reporting. For example, Jiang et al. (2005) show that under greater IU, investors rely on less reliable information and can be over-confident about the withheld private information of managers. Hence, higher IU can result in investors being more misled by reported earnings that are applied to value firms.

This study provides evidence that UK listed firms manage earnings to report positive earnings and sustain previous year's firm performance. Moreover, the study also focuses on evaluating the long-term operating performance as well as abnormal returns of firms meeting/beating earnings benchmarks in the condition of high IU. This study contributes to examining the condition of the high IU where managers of firms beat earnings benchmarks to mislead

investors about subsequent performance of firms. Indeed, under low IU, market participants can disentangle earnings information from other sources to evaluate underlying performance of firms when managers of firms meet/beat earnings benchmarks. Therefore, managers of firms are more likely to beat earnings benchmarks to communicate private information of firms. In contrast, in the high IU, market participants find it difficult to uncover managed earnings to meet/beat earnings benchmarks. Accordingly, the study finds that managers of firms opportunistically manage earnings to meet/beat earnings benchmarks to mislead investors about future firm performance.

The rest of this chapter is structured as follows. Section 5.2 presents related literature and section 5.3 shows testable hypotheses. Section 5.4 explains the research design. Section 5.5 presents and discusses the main results. Section 5.6 presents the robustness tests and section 5.7 presents the conclusion of this chapter.

5.2 Literature review

This chapter examines whether the long-run performance of firms meeting/beating earnings benchmarks is different under high IU. Accordingly, this chapter contributes to the literature review on the test of market efficiency. This section comprises efficient market hypothesis as well as behavioural finance as the background for the main contribution of this chapter.

5.2.1 The efficient market hypothesis

Prior studies indicate that the capital market is efficient, in which, the market price is always accurate and reflects all available information (see Fama, 1998). Under the efficient market hypothesis, new information spreads very quickly, therefore, is completely reflected in stock prices. Accordingly, there is no opportunity for investors to make excessive profits. According to Fama (1970), there are three levels of market efficiency, namely weak, semi-strong and strong forms. In which, the weak form indicates that the stock price already reflects all historical information that leaves no chance for investors to make abnormal returns. Furthermore, with the semi-strong form, stock prices instantly reflect all publicly available information. In the strong form of market efficiency, private information will instantly be reflected in stock price. Therefore, trading activities that rely on private information of insiders will not yield abnormal returns. The market efficiency hypothesis indicates that the market is efficient (Ball and Brown, 1968; Fama et al., 1969).

5.2.2 The market anomalies and the emergence of behavioural finance

Under the traditional paradigm of market efficiency, the market is efficient; however, later empirical studies find evidence that there are abnormal returns known as the 'anomaly' literature. Indeed, abnormal returns are defined as returns not explained by risks. For example, De Bondt and Thaler (1985) show that some investors can earn abnormal profits through buying stocks with lower returns and later selling those with higher returns. Furthermore, Banz (1981) proves that smaller firms experience higher abnormal returns than those of larger firms. In addition, in some specific periods such as around public offerings, Ritter (1991); Loughran and Ritter (1995) find that seasoned equity offerings (SEO) tend to have poorer abnormal returns after issuing stocks. Moreover, Sloan (1996) and Xie (2001) contribute to showing that the market is misled by the component of discretionary accruals in earnings, which results in negative future returns.

As for the market efficiency hypothesis, the assumption is that market participants are rational. In which, the market participants have perfect knowledge and can make unbiased decisions relying on related information. Nevertheless, other authors criticize the assumption of rationality of market participants. The explanation for the market efficiency hypothesis is based on behavioural finance. Tversky and Kahneman (1974) indicate that human beings are not rational and are systematically biased. In fact, they present three forms of heuristics that influence people's judgement such as representativeness, availability, and adjustment and anchoring. The representativeness heuristic prevents people from considering all relevant information to make their judgements. Another heuristic is 'availability' whereby people over-rely on information which is retrievable or available. The last heuristic is 'adjustment and anchoring' whereby humans make mistakes in estimating adjustments from an initial value.

Behavioural finance has emerged over the last decades, helping to explain market anomalies such as abnormal returns. Some studies also indicate that human beings are systematically biased (e.g., through over-confidence) (e.g., Fischhoff et al., 1977; Kahneman and Tversky, 1982). Indeed, De Bondt and Thaler (1990) show that people are over-optimistic. Accordingly, people have the tendency to make biased decisions since they do not have sufficient time for their tasks. In detail, Daniel et al. (1998) show that over-confident investors over-estimate the precision of their own ability to generate information.

5.2.3 Earnings-based benchmarks

Prior studies indicate that investors rely on using simple earning benchmarks to make firm valuations (e.g., Burgstahler and Dichev, 1997). Accordingly, as shown in the survey by Graham et al., (2005), executives focus on earnings benchmarks since they are aware that market participants focus on these. For instance, Habib and Hansen (2008) present that investors apply earnings benchmarks to evaluate firm performance. Empirical evidence shows discontinuity around earnings benchmarks. For example, these earnings benchmarks include earnings change (i.e., avoid earnings decline), earnings level around zero (i.e., avoid earnings losses) or analysts' earnings forecasts (i.e., report positive earnings surprise) (see review by Dichev et al., 2013). An explanation for these studies are based on the prospect theory by Kahneman and Tversky (1979). According to the prospect theory, individuals' value function is concave in gains and convex in losses. It means that people are more sensitive to losses than gains with the same magnitude. Thus, Burgstahler and Dichev (1997) indicate that individuals have the largest gains when wealth moves from losses to gains, relative to a reference point. Accordingly, the prospect theory indicates that investors' value functions are concave above benchmarks, however, convex below the same benchmarks. Therefore, managers of firms have great incentives to manage earnings when earnings numbers are below a reference point.

To influence the perception of investors about firm performance, managers of firms might manipulate earnings when firms earnings are just below the benchmarks such as zero changes in earnings or zero levels of earnings (Burgstahler and Dichev, 1997; Degeorge et al., 1999). Since firms meet earnings benchmark by borrowing future earnings to sustain recent earnings performance, these firms underperform in the future. However, other studies provide opposite evidence that firms beating earnings benchmark signal private information about future firm performance. For example, Bartov et al. (2002) prove that meeting earnings expectations is informative of subsequent firm performance. These firms enjoy higher future returns than firms failing to meet earnings expectations.

5.3 Hypotheses development

5.3.1 Subsequent operating performance following firms meeting/beating earnings benchmarks under high information uncertainty

Prior studies find strong evidence to suggest that managers of firms attempt to manage earnings to avoid earnings losses or earnings decreases (e.g., Hayn, 1995; Burgstahler and Dichev, 1997; Holland and Ramsay, 2003; Wilson and Wu, 2011; Burgstahler and Chuk, 2017). Indeed,

empirical evidence shows that the distribution of earnings and earnings changes has discontinuities around zero (see Burgstahler and Dichev, 1997; Degeorge et al., 1999). Benchmark beating is considered an important aim for managers to achieve (see Graham et al., 2005; Dichev et al., 2016).

The accounting literature documents that firms' managers exercising discretion to meet simple benchmarks is driven by opportunistic incentives (e.g., Cheng et al., 2005; Coulton et al., 2015). In the survey by Graham et al. (2005), chief financial officers (CFOs) are willing to engage in real operating activities to meet short-run benchmarks that would reduce long-term firm values. Similarly, prior studies provide evidence that firms' managers use myopic behaviour to meet/beat earnings benchmarks that can be harmful for future operating performance of firms (see Baber et al., 1991; Bhojraj et al., 2009).

The effect of IU is unclear. Previous studies show that with the greater IU, managers of firms are not clear about investors' interpretation about firms' information. Accordingly, firms' managers are likely to withhold private information (e.g., Dutta and Trueman, 2002; Fishman and Hagerty, 2003; Suijs, 2007). Similarly, Burgstahler and Chuk (2017) document that the low quality information environment provides higher incentives for managers to meet/beat earnings benchmarks such as zero earnings. In such environment, market participants find it harder to unravel managed earnings to meet/beat earnings benchmarks. Therefore, managers of firms can engage in opportunistic earnings management to meet/beat earnings benchmarks (Healy and Wahlen, 1999; Lo, 2008). As a result, managers of firms have more incentives to manage earnings to beat/meet earnings benchmarks in the high IU since it is difficult for market participants to unravel the false information.

From the above literature, with the greater IU, managers of firms having high IU have higher incentives to meet/beat earnings benchmarks opportunistically. Thus, in the high IU, when firms' managers manage earnings through using discretionary accruals in this current year to beat/meet earnings benchmarks, there will be a reversal of accruals in the future periods. In accordance, I expect that high IU firms beating/meeting earnings benchmarks will have subsequent operating or accounting underperformance. Hence, the sixth hypothesis in this study is as below:

H6. *Ceteris paribus, firms meeting or beating earnings benchmarks experience more negative long-run accounting performance under high information uncertainty than under low information uncertainty.*

5.3.2 Subsequent stock performance following firms meeting/beating earnings benchmarks under high information uncertainty

In the survey by Dichev et al. (2016), managers of firms emphasize the importance of beating earnings benchmarks. One of main incentives for benchmark-beating is capital market incentives (see Athanasakou et al., 2011). Indeed, Graham et al. (2005)'s survey shows that managers of firms would like to meet earnings benchmarks to avoid negative reactions of the market. This is because if firms miss earnings benchmarks, there is negative reaction of the market about the prospects of firms. Therefore, firms' stock prices can be reduced. Ronen and Sadan (1981) indicate that beating earnings benchmarks might help firms signal to market participants the future firms' prospects. Barth et al. (1999) find a relationship between share prices and the length of time with increasing earnings. In fact, after controlling for the level of earnings, firms having consistent increases in earnings experience higher stock price changes. Similarly, Bartov et al. (2002) document that firms meeting or beating earnings expectations enjoy higher premium returns than those firms missing earnings expectation. Similarly, Schrand and Walther (2000) prove that meeting earnings benchmarks avoids negative earnings change or surprises and influences equity investors' perception about favourable relative current-year performance. Accordingly, Krische (2005) shows that meeting/beating earnings benchmarks can influence investors' valuation of firm performance. Specifically, investors rely on prior-period earnings as a benchmark to evaluate company performance. Hence, firms whose current earnings perform better than previous year's earnings enjoy higher stock prices. In addition, Tan et al. (2002) show that firms overstate earnings to decrease the possibility of negative earnings surprises or changes when earnings are announced.

Although benchmark beating is likely to help managers of firms enjoy capital market benefits in the short term, prior literature shows mixed evidence about the future stock performance of beating earnings benchmarks. On the one hand, investors are naively over-optimistic about the implications of managed earnings to exceed the benchmarks of earnings level or earnings change (e.g., Coulton et al., 2015), which would lead to future negative price consequences. On the other hand, investors are aware of the manipulation and discount the price when the firms meet/beat earnings expectations and so there is no future negative price consequences (see Bartov et al., 2002).

Under the first view, managers of benchmark-beaters may manage earnings to inflate reported earnings in an effort to mislead investors about subsequent firms' performance (e.g., Dichev et

al., 2016). As shown in the survey by Graham et al. (2005), managers of firms are willing to sacrifice long-term economic benefits to meet or beat short-term earnings benchmarks. Some empirical evidence presents that firms slightly meeting or beating an earnings benchmark have opportunistic incentives for inflating stock prices on a temporary basis, which experiences a decline in subsequent years (see Dechow et al., 2000). Similarly, Bhojraj et al. (2009) show that although benchmark-beaters might enjoy short-term benefits from valuation premia, there is a reversal in the 3-year horizon stock returns. Skinner and Sloan (2002) provide evidence that investors are naively optimistic about the prospects of earnings beating. This is because market participants are not able to fully understand the implications of earnings guidance through managing earnings. Moreover, Coulton et al. (2015) show that firms beating earnings benchmarks have overvalued equity. Therefore, prices in the future would decline when the earnings manipulation reverses and is revealed.

In the second view, market participants are rational and can understand where earnings are likely to be managed to meet or beat earnings expectations. Therefore, investors will not reward firms whose earnings are managed to meet or beat earnings benchmarks (see Bartov et al., 2002). For example, Osma and Young (2009) prove that investors have an equity valuation discount when they perceive that firms cut research and development (R&D) expenditures opportunistically to meet earnings benchmarks. Similarly, Xue (2003) proves that market participants are able to recognize the information of managed earnings to beat earnings benchmarks, hence, rationally incorporate it into stock prices. Further, Keung et al. (2010) indicate that market participants are more sceptical about firms just meeting zero earnings benchmarks. Accordingly, investors discount firms that manage earnings to meet analysts' expectations.

The role that IU plays in the future price consequences of firms meeting/beating earnings is unclear. Burgstahler and Chuk (2017) document that there are weaker incentives for firm managers to manage earnings to meet simple earnings benchmarks such as zero earnings when there is a high-quality information environment. As a result, managers of firms only engage in opportunistic benchmark-beating to temporarily inflate reported earnings, once market participants are not able to uncover the opportunistic behaviour. As previously mentioned, managerial behaviour is not observable, and investors face uncertainty when using accounting information to estimate firm values. Under the condition of high IU, it is more difficult for investors to understand managers' behaviour of withholding private information. This is because they face limited sources of public information about firm performance. For example,

Hobson and Stirnkorb (2020) provide evidence that with low public scrutiny, firms managers are likely to manage earnings to meet earnings benchmarks. Further, under high IU, managers are not certain about investors' response to additional disclosed information (Dye, 1998; Dutta, 2003). Dutta and Trueman (2002) show that firms disclose private information that is affected by the way that investors would interpret such information of firms. Therefore, managers of firms aim at beating earnings benchmark in the condition of high IU as the favourable signal to investors.

In addition, under high IU where there is a lack of available information about firm values, investors may make biased decisions (e.g., Daniel et al., 1998; Hirshleifer, 2001). Investors are over-optimistic about meeting earnings benchmarks by adjusting earnings in financial reporting subject to the high IU environment. As mentioned in Odean (1998), under high IU, investors experience more biased psychological effects such as over-confidence. Accordingly, over-confident investors might overreact to irrelevant information and are misled by earnings management. Under the condition of high IU, while some market participants are ambiguous about the information about firms, over-confident investors are over-optimistic about their abilities to interpret firm performance (Odean, 1998). Accordingly, the trading of over-confident investors could influence the behaviour of other investors about the precision of earnings information. Hence, other investors could follow the estimate of over-confident investors resulting in the mis-valuation in the short run in the high IU environment. From previous literature, managers of firms subject to high IU can manipulate earnings to meet/beat earnings benchmarks to inflate stock prices. Consequently, firms meeting/beating earnings benchmarks are expected to have long-run stock underperformance under high IU. This leads to the following hypothesis:

H7. *Ceteris paribus, firms meeting or beating earnings benchmarks experience more negative long-run stock market performance under high information uncertainty than under low information uncertainty.*

5.4 Research design

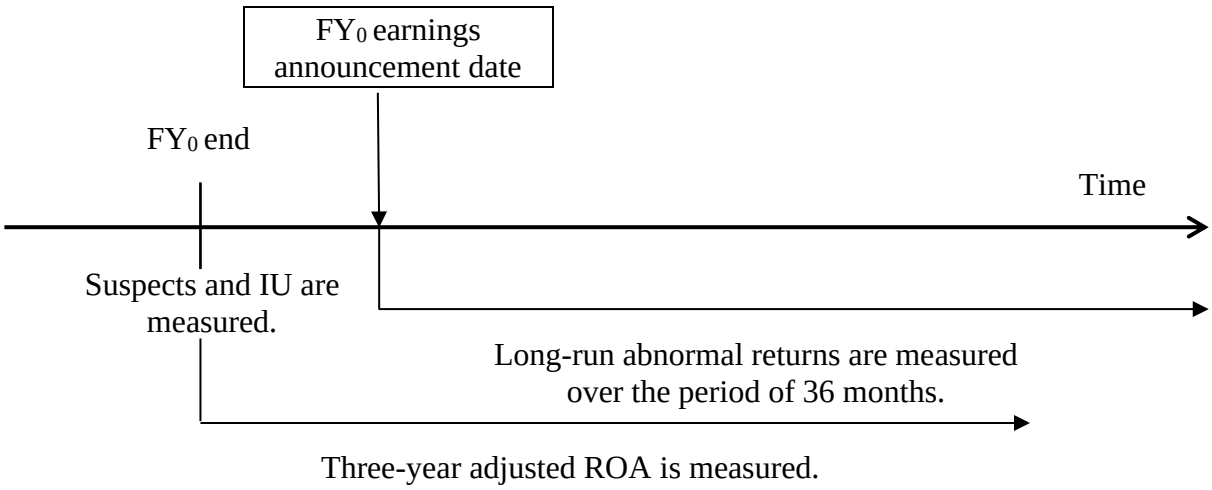
5.4.1 Sample

Because this chapter employs the same sample as that in Chapter 4, the descriptive procedures for selecting the sample have been presented in Chapter 4 (Section 4.3.1). To select firms meeting/beating earnings benchmarks, I follow prior studies such as Roychowdhury (2006) and Cohen et al. (2008) including firm-years with earnings before extraordinary items over total

assets between 0 and 0.005. Moreover, following Hayn (1995) and Zang (2012) in terms of meeting/beating prior year earnings, suspects are defined as those where the change in earnings before extraordinary items per share (EPS) from last year is between 0 and 0.0025. During the sample period, there are 1,778 earnings management suspect firm-years and 15,033 non-suspect firm-years over the period 1992-2018. Moreover, the cumulation of stock return starts three months after the fiscal year end (Figure 5.1). If a stock delists during the holding period, the stock will be removed from the sample when calculating stock returns.

I define year 0 (FY_0) as the fiscal year-end in which firms manage earnings to beat earnings benchmarks and where IU is measured. Moreover, to examine subsequent performance of firms managing earnings to beat earnings benchmarks, post abnormal returns is calculated over a 36-month period following the annual earnings announcement of the fiscal year 0. I alternatively use a three-year adjusted return on assets (ROA) to measure operating performance. See Figure 5.1 for a depiction of the timeline.

Figure 5.1 Timeline



5.4.2 Empirical methodology

5.4.2.1 Variable construction

5.4.2.1.1 Measure of long-run stock price performance

5.4.2.1.1.1 Buy-and-hold returns

For each firm observation, buy-and-hold returns are calculated on a monthly basis with the assumption of dividend reinvestment as follows:

$$BHRR_{i,j}^{m} = \frac{RI_{i,j}}{RI_{i,j-1}} - 1$$

In which: $BHRR_{i,j}^{m}$ is buy-and-hold returns of stock i in the month j; $RI_{i,j}$ is Return index from Datastream at the end of month j; $RI_{i,j-1}$ is Return index from Datastream at the end of month j-1.

5.4.2.1.1.2 Abnormal buy-and-hold returns

As shown in the study by Barber and Lyon (1997), buy-and-hold abnormal returns are favoured when compared to cumulative returns (summed monthly abnormal returns) to measure long-term abnormal returns. This is because cumulative abnormal returns ignore the effect of monthly compounding. Accordingly, cumulative abnormal returns can be a biased measure of long-run abnormal returns. Therefore, in this study, to detect long-run abnormal returns, I use long-run buy-and-hold abnormal returns. There are two ways to measure abnormal returns such as buy-and-hold size-adjusted returns and four-factor buy-and-hold abnormal returns.

a. Fama-French four-factor model (BHAR4F)

The first method to calculate long-term stock performance is to apply the Fama-French four-factor model. Carhart (1997) extends the three-factor model by Fama and French (1992). Traditional Capital Asset Pricing Model (CAPM) measures abnormal returns using only risk factors (see Sharpe, 1964; Lintner, 1965; Black, 1972). Later, Fama and French (1992) added size and market-to-book as additional risk factors in the CAPM model. Later, Carhart (1997) included another factor into the three-factor model known as the fourth risk factor. To estimate four-factor abnormal returns, the following equation is used for each stock by using time-series regressions as follows:

$$\mathrm{BHRR}_{\mathrm{p,j}}^{\mathrm{m}} - \mathrm{Rf_j} = \alpha + \beta_1(\mathrm{Rm_j} - \mathrm{Rf_j}) + \beta_2\mathrm{SMB_j} + \beta_3\mathrm{HML_j} + \beta_4\mathrm{UMD_j} \qquad (5.1)$$

Where

- $BHRR_{p,j}^{m}$: the weighted portfolio returns of portfolio p in month j.
- $Rf_j - Rm_j$: monthly risk-free rate
- SMB_j: return on value-weighted portfolio of small stocks less value-weighted portfolio of big stocks
- HML_j: return on value-weighted portfolio of high book-to-market stocks less return on value-weighted portfolio of low book-to-market stocks
- UMD_j: momentum factors. This is downloaded from the database provided by Gregory et al., (2016).

To estimate coefficients on equation (5.1), I need at least 36 observations, hence, a stock with less than 36 observations is removed from the main sample. Then, the expected returns for each stock are estimated using these coefficients as follows:

$$E(R4F_{i,j}^{m}) = Rf_j + \beta_1(Rm_j - Rf_j) + \beta_2 SMB_j + \beta_3 HML_j + \beta_4 UMD_j \quad (5.2)$$

Annual four-factor abnormal returns are estimated for each stock by converting the above monthly four-factor abnormal returns into annual four-factor abnormal returns. The long-run abnormal returns are compounded over a 36-month window as follows:

$$BHAR4F_{i,j}^{a} = \prod_{i=1}^{36}(1 + BHRR_{i,j}^{m}) - \prod_{i=1}^{36}(1 + E(R4F_{i,j}^{m})) \quad (5.3)$$

(j= announcement month 1 in year t to month 36 in year t+3)

- $BHRR_{i,j}^{m}$: weighted portfolio returns of portfolio p in month j.
- $E(R4F_{i,j}^{m})$: expected returns estimated by using the Eq. (5.2)

b. Long-run buy-and-hold size-adjusted returns ($BHSAR$)

Firm-specific monthly buy-and-hold size-adjusted returns are used as previous studies indicate that size is applied to predict future returns (e.g., Ou and Penman, 1989; Bernard and Thomas, 1989; Sloan, 1996). Following Barber and Lyon (1997), monthly buy-and-hold size-adjusted returns are calculated by using reference portfolios. In which returns of portfolios are sorted into ten deciles based on market capitalization at the end of each fiscal year. The returns on each size decile portfolio d (d=1…10) is measured separately. Specifically, $BHER_{i,j}^{m}$, is calculated by monthly average returns of all stocks belonging to decile d. The buy-and-hold abnormal return of stock i in month j is calculated as below:

$$BHSAR_{i,j}^{m} = BHRR_{i,j}^{m} - BHER_{i,j}^{m}$$

In which:

$BHRR_{i,j}^{m}$: monthly buy-and-hold return of stock i in month j

$BHER_{i,j}^{m}$: mean monthly buy-and-hold returns of portfolio d

In the main regression, the annual abnormal returns are applied, hence, the above monthly buy-and-hold size-adjusted returns are converted into annual buy-and-hold size-adjusted returns. Following Sloan (1996); Rangan (1998); Teoh et al. (1998a), for each firm, the firm-specific annual buy-and-hold size-adjusted return is calculated as the difference between the compound annual return and adjusted return averages into three-year cumulative return.

$$\mathrm{BHSAR}^{a}_{i,j} = j\prod_{j=1}^{36}\left(1+\mathrm{BHRR}^{m}_{i,j}\right) - \prod_{j=1}^{36}\left(1+\mathrm{BHER}^{m}_{i,j}\right)$$

(*j*= announcement month 1 in year t to month 36 in year t+3)

5.4.2.1.2 Measure of post-announcement earnings underperformance

5.4.2.1.2.1 Adjusted changes in earnings

Following Barber and Lyon (1996), operating performance is measured by using accounting numbers, and expected performance is generally evaluated relative to firms in the same industry. Previous studies widely use return on assets (hereafter ROA) to measure performance of firms, which is calculated by dividing net income before extraordinary items by the book value of total assets. Moreover, prior studies indicate that there is mean reversion in operating performance. Accordingly, to control for the normal amount of reversion in ROA, the changes in ROA of a firm is matched with other firms having the same two-digit SIC codes and total assets as of the end of the fiscal year within 70%-130% of the firm's total assets in years 1 to 3 following the announcement date of financial statements.

Expected operating performance is specified by comparing ROA of each firm with other firms. Operating performance of a firm is compared with a benchmark of other firms in the same industry. It is considered that sample firms in related industries experience a similar pattern in ROA. For example, if the industry has growth in ROA, it is expected that sample firms in those industries will experience similar growth in ROA. Following Barber and Lyon (1996), a benchmark applied to measure expected operating performance is performance in the comparison group using the two-digit SIC code. Indeed, matching by industry assumes that the cross-sectional difference in ROA can be explained by an industry benchmark. Accordingly, in this study, expected operating performance is calculated by using median ROA of all firms in the same two-digit SIC code with similar size (70%-130% of total assets at end of fiscal year). The reason for using the median instead of mean ROA is that previous literature presents the skewness of financial ratios (see Frecka and Hopwood, 1983; Krishnan et al., 2004). Hence, using median ROA rather than mean ROA can avoid the effect of outliers in the results. Moreover, Fama and French (1996) prove that small firms have lower earnings scaled by book value of equity than large firms. Accordingly, beside the industry benchmark, firms with similar size are matched. Previous studies of operating performance match sample firms to similar-size firms in the same industry (see Kaplan and Kaplan, 1989; Denis and Denis, 1993; Dann et al., 1991; Degeorge and Zeckhauser, 1993). As a result, in this study, expected operating

performance is measured by using ROA of all firms in the same two-digit SIC code with similar sizes.

Adjusted changes in operating performance is defined as the difference between changes in real operating performance and changes in expected operating performance. Indeed, adjusted changes in operating performance is the difference between changes in ROA of each firm and changes in expected ROA for all firms in the same two-digit SIC code with similar size.

$$\Delta A\_ROA_t = \Delta ROA_t - \Delta E(ROA)_t \qquad (5.4)$$

Where ΔA_ROA_t is adjusted changes in ROA from year t-1 to year t; ΔROA_t is actual changes in ROA from year t-1 to year t; $\Delta E(ROA)_t$ is expected *ROA* measured as the median changes in ROA for all firms in the same two-digit SIC code and similar size from year t-1 to year t. Book value of total assets is used to measure size. Following previous studies (e.g., Degeorge and Zeckhauser, 1993; Barber and Lyon, 1997; Cohen and Zarowin, 2010), matched firms include all firms in the same two-digit SIC code and those whose total assets are between 70 and 130 percent of the sample firm.

5.4.2.1.2.2 Post-announcement adjusted change in earnings

Following Teoh et al., 1998b, Rangan (1998), and Loughran and Ritter, 1997), the post-announcement adjusted change in ROA is the mean value of adjusted change in ROA from year 1 to year 3 following the announcement date of year 0.

5.4.2.2 Suspect firms just beating/meeting important earnings benchmarks

In this chapter, I use the sample of firm-years that just meet/beat important earnings benchmarks where earnings management are likely to occur. As previously illustrated in section 5.4.1, there are 1,778 earnings management suspect firm-years over the period 1992-2018. I begin by comparing the differences in firm characteristics between firms beating/meeting earnings benchmarks (*SUSPECT*) and firms missing earnings benchmarks (*NON_SUSPECT*). I follow Roychowdhury (2006) and Zang (2012) to estimate the following regression model:

$$EM = \alpha_0 + \alpha_1 M/B_{it} + \alpha_2 SIZE_t + \alpha_3 ROA_{it} + \alpha_4\, SUSPECT_{it} + \sum_k \alpha_k\, YEAR_{DUMMY_{it}} + \varepsilon_{it} \qquad (5.5)$$

Where: EM represents measures of earnings management which are accrual earnings management (*DAP*) and real earnings management (*REM*). The proxies of *DAP* and *REM* are based on the Modified Jones Model and Roychowdhury (2006)'s models. *SUSPECT* is a dummy variable that is equal to 1 if firm-year beets/meets earnings benchmarks, and 0 if it misses all benchmarks.

Following prior literature (e.g., Roychowdhury, 2006; Zang, 2012), earnings management is related to firm size (*SIZE)*, firm growth (*M/B*) and firm performance (*ROA).* Indeed, previous studies show that there is a link between firm growth and earnings manipulation. Collins et al. (2017) indicate that firms with high growth are expected to have higher working capital and are likely to engage in earnings management. Similarly, Dechow et al. (1998) document that firm growth should have high capital working accruals as a response to increasing sales. Therefore, to control for firm growth, market to book ratio (*M/B)* is included in the regression model. Moreover, McNichols (2000) show that firm performance has a positive relation with earnings management. Accordingly, return on asset (*ROA)* is used as proxy for firm performance. I also follow Zang (2012) to include firm size (*SIZE)* as an independent variable in the regression model.

5.4.2.3 Empirical model for hypothesis testing for long-run accounting performance of firms meeting or beating earnings benchmarks and information uncertainty

To examine the association between long-term accounting performance of firms meeting/beating earnings benchmarks and IU, the following regression model is applied to test.

$$\Delta A\_ROA_t = \beta_0 + \beta_1 SUSPECT_{it} + \beta_2 HIU_t + \beta_3\, SUSPECT_{it} x HIU_t + \beta_4\, M/B_{it} + \beta_5\, SIZE_{it} + \beta_6\, \Delta CAPEX_{it} + \beta_7\, \Delta SALES_{it} + \sum_j \alpha_j\, INDUSTRY_{DUMMY_{it}} + \sum_k \alpha_k\, YEAR_{DUMMY_{it}} + \varepsilon_{it} \quad (5.6)$$

where *i* refers to the firm and *t* to the year. White's heteroskedasticity-corrected standard errors is used to calculate t-statistics in the regressions. The dependent variable in model (5.6) is adjusted return on asset (*ΔA_ROA)* that is illustrated in section 5.4.2.1.1.

I examine the association between firm accounting performance and firms beating earnings benchmarks (*SUSPECT=1)* in the condition of high IU (*HIU)*, where the proxy for IU is above (below) the sample median. I define firm as a firm facing high (low) IU. HIU equals 1 for firm-year observations that face high information uncertainty, and 0 otherwise. When there is high IU, managers of firms manage earnings by using discretionary accruals to meet/beat earnings benchmarks. Therefore, in the subsequent periods, there is reversal of accruals that results in future operating underperformance, more so under high IU. As a result, when managers of firms attempt to meet or beat earnings benchmarks through managing earnings in the high IU, post accounting performance is negative. In this case, I expect that β_3 is negative. Accordingly, there is a negative relationship between suspect firms and long-run firm accounting performance in the high IU environment.

Moreover, there are two ways to control for the potential difference in firm characteristics between firms meeting/beating earnings benchmarks and firms missing earnings benchmarks. The first way is to apply the propensity score matching (PSM) method. In particular, firms meeting earnings benchmarks (*SUSPECT*) are matched with firms missing earnings benchmarks (*NON_SUSPECT*) with the closest propensity score obtained from the probit model equation (4.1).

The second way is to use Heckman (1979)'s two-step procedure. In the first step, I estimate a selection model using all the sample firms and obtain the inverse Mills ratio (IMR). In the second step, the inverse Mills ratio (IMR) that is estimated by Eq. (4.2) is included in the regression model on the suspect sample as a control variable to correct for endogeneity problems.

$$\Delta A\_ROA_t = \beta_0 + \beta_1 SUSPECT_{it} + \beta_2 HIU_t + \beta_3\, SUSPECT_{it} \text{ x } HIU_t + \beta_4\, M/B_{it} + \beta_5\, SIZE_{it} + \beta_6\, \Delta CAPEX_{it} + \beta_7\, \Delta SALES_{it} + \beta_8\, IMR_{it} + \sum_j \alpha_j\, INDUSTRY_{DUMMY_{it}} + \sum_k \alpha_k\, YEAR_{DUMMY_{it}} + \varepsilon_{it} \quad (5.7)$$

The control variables in the main regression are based on prior studies. Indeed, previous literature indicates that the effect of firm size and growth opportunities might predict future firm performance (e.g., Rangan, 1998; Barber and Lyon, 1997; Loughran and Ritter, 1997). Therefore, I include the log of market capitalization ($SIZE_t$) and market to book ratio (M/B_t) as control variables in the main regression model. In addition to the size of firm and firm growth, prior studies show that sales growth ($\Delta SALES_t$), and capital expenditures ($\Delta CAPEX_t$) predict future firm performance. In detail, firms with high sales growth and capital expenditures have deteriorating operating performance in subsequent periods (e.g., Loughran and Ritter, 1997; Teoh et al., 1998a; Rangan, 1998). All variables are defined in the appendix.

5.4.2.4 Empirical model for hypothesis testing about subsequent stock performance of firms meeting or beating earnings benchmarks and information uncertainty

To examine the association between subsequent stock performance of firms meeting/beating earnings benchmarks and IU, the following regression model is applied to test.

$$BHSAR_{it}(BHAR4F_{it}) = \beta_0 + \beta_1 SUSPECT_{it} + \beta_2 HIU_t + \beta_3\, SUSPECT_{it} \text{ x } HIU_t \quad (5.8)$$

$$+\beta_4\ \mathrm{M/B_{it}} + \beta_5\ \mathrm{SIZE_{it}} + \beta_6\ \Delta\mathrm{CAPEX_{it}} + \beta_7\ \Delta\mathrm{SALES_{it}} + \sum_{\mathrm{j}} \alpha_{\mathrm{j}}\ \mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_{\mathrm{k}} \alpha_{\mathrm{k}}\ \mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it}$$

where *i* refers to the firm and *t* to the year. White's heteroskedasticity-corrected standard errors is used to calculate t-statistics in the regressions. The dependent variables in model (5.6) are buy-and-hold four-factor abnormal returns (*BHAR4F)*, and buy-and-hold abnormal returns (*BHSAR)*, that are illustrated in section 5.4.2.1.1.

I examine the association between subsequent stock and firms beating earnings benchmarks (*SUSPECT=1)* in the condition of high IU (*HIU)*, where the proxy for IU is above (below) the sample median. I define firm as a firm facing high (low) information uncertainty. HIU equals 1 for firm-year observations that face high IU, and 0 otherwise. When there is high IU, managers of firms attempt to meet/beat earnings benchmarks through managing earnings to mislead investors about firm profitability. Therefore, in the subsequent periods, investors will be disappointed about future earnings. As a result, when managers of firms attempt to meet or beat earnings benchmarks through managing earnings in the high IU, post stock performance is negative. In this case, I expect that β_3 is negative. Indeed, under high IU, firms meeting or beating earnings benchmarks are more likely to mislead investors about future performance of firms. Accordingly, there is negative relationship between suspect firms and long-run abnormal returns in the high IU environment.

To control for the potential difference in firm characteristics between firms beating earnings benchmarks and firms missing earnings benchmarks, the propensity score matching (PSM) method and the Heckman two steps are applied as illustrated above in section 5.3.1. All control variables in Eq. (5.8) are mentioned in section 5.3.1. I also include industry and year fixed effects as dummy variables. I apply robust standard errors clustered at firm level to control for heteroscedasticity and serial correlation problems.

5.5 Results

5.5.1 Descriptive statistics and correlations

Table 5.1 shows the summary statistics for variables in the main tests. The number of observations varies due to the availability of data. Panel A of table 5.1 provides the descriptive statistics for the full sample, which includes 16,811 firm-year observations for the period of 1992-2018. The mean adjusted change in *ROA (ΔA_ROA)* is -0.26% and the median for *ΔA_ROA* is -0.24%. Moreover, the mean and median of adjusted-size buy-and-hold abnormal return (*BHSAR*) are -31.9%and -38.2%, respectively. The sample mean (median) of market to book (*M/B*) is 1.562 (0.160). The sample mean (median) of firm size (*SIZE)* representing the log of total assets is 1.310 (1.295). The mean (median) change in sales (*ΔSALES*) is 16.3% (6.9%). The mean (median) change in capital expenditure (*ΔCAPEX*) is 1% (0.1%).

Panel B of table 5.1 presents the Pearson correlation matrix for the variables used in the multivariate analyses. The dummy representing firms meeting/beating earnings benchmarks (*SUSPECT*) has a significantly negative correlation (-0.064) with subsequent accounting performance (*ΔA_ROA*). Furthermore, subsequent accounting performance (*ΔA_ROA*) is negatively correlated (-0.034) with changes in capital expenditures (*ΔCAPEX*).

Table 5.2 shows the difference in firm characteristics such as log of share (*SHARE*), return on asset (*ROA*), market to book (*M/B*), firm size (*SIZE*) between suspects (i.e., firms meeting/beating earnings benchmarks) and non-suspects (i.e., firms missing earnings benchmarks) using the full sample and propensity-score matched sample. Indeed, with the full sample, there are statistically significant differences in *SHARE, ROA, M/B* and *SIZE* between suspects and non-suspect at the 1 percent level. The results show that suspect firms have significantly higher *SHARE* and *M/B* than non-suspect firms. In contrast, *ROA* and *SIZE* of suspect firms are significantly lower than those of non-suspect firms. However, after using propensity-score matching, there are insignificant differences in all variables between suspect firms and non-suspect firms. Therefore, the propensity-score matched sample successfully removes the potential difference in firms' characteristics between suspect firms and non-suspect firms.

In addition, panel C of Table 5.2 reports the estimation results obtained from the probit model equation (4.1). The coefficients on *SHARE, ROA, M/B* are positively significant at the 1 percent level. The results are consistent with previous studies such as Bartov et al. (2002) and Kasznik

and McNichols (2002) indicating that suspect firms with higher firm performance (*ROA*) are likely to engage in managing earnings to beat earnings benchmarks. The results also support that firms having more growth opportunities (*M/B*) probably beat earnings threshold (e.g., Barth et al., 1999). Similar to Zang (2012), firms having higher shares (*SHARE*) are likely to meet/beat earnings benchmarks. Additionally, firms meeting earnings benchmarks are negatively associated with the size of firms (*SIZE*). Table 5.3 shows the results of the coefficients on the dummy variable, *SUSPECT*, and earnings management models. Consistent with Roychowdhury (2006) and Zang (2012), when firms meet or beat earnings benchmarks, the coefficient on *SUSPECT* for accrual earnings management (*DAP)* is significant at the 5 percent level. It suggests that firms use accrual-based earnings management to meet/beat earnings benchmarks. Moreover, the coefficient on *SUSPECT* for the abnormal cash flow models (REM_{CFO}) is 0.015, significant at the 10 percent level, which suggests that suspect firms offer price discount to report favourable income. In addition, the coefficient on *SUSPECT* for the discretionary expense model is 0.050, significant at the 1 percent level, which suggests that firms meeting earnings benchmarks report reduction in discretionary expenditures to report favourable earnings.

Table 5.1 Descriptive statistics

Panel A. Summary statistics

Variable	Obs.	Mean	Std. Dev.	25 percent	Median	75 percent
$\mathrm{SUSPECT_t}$	16,811	0.066	0.248	0.000	0.000	0.000
$\mathrm{\Delta A\_ROA_t}$	9,053	-0.003	0.129	-0.044	-0.002	0.031
$\mathrm{BHSAR_t}$	15,025	-0.243	1.640	-0.919	-0.328	0.164
$\mathrm{HIU(VOLATILITY_t)}$	16,811	0.481	0.500	0.000	0.000	1.000
$\mathrm{HIU(VOLUME_t)}$ [a]	13,815	0.491	0.500	0.000	0.000	1.000
$\mathrm{HIU(SPREAD_t)}$	14,800	0.473	0.499	0.000	0.000	1.000
$\mathrm{SHARE_t}$	16,811	1.310	1.825	0.038	1.295	3.630
$\mathrm{SIZE_t}$	16,811	-0.024	0.225	-0.042	0.039	0.084
$\mathrm{ROA_t}$	16,811	1.562	8.068	0.081	0.160	0.344
$\mathrm{M/B_t}$	16,811	0.011	0.064	-0.011	0.002	0.021
$\mathrm{\Delta CAPEX_t}$	15,608	0.004	0.050	-0.010	0.002	0.018
$\mathrm{\Delta SALES_t}$	16,811	-0.122	1.099	-0.173	-0.030	0.076

Table 5.1 (Cont.)

Panel B. Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) $SUSPECT_t$	1.000										
(2) ΔA_ROA_t	-0.027*	1.000									
(3) $BHSAR_t$	0.018*	-0.063*	1.000								
(4) $HIU(VOLATILITY_t)$	0.053*	0.027*	0.095*	1.000							
(5) $HIU(VOLUME_t)$ [a]	0.092*	0.052*	-0.057*	0.200*	1.000						
(6) $HIU(SPREAD_t)$	0.101*	0.045*	-0.144*	0.079*	0.259*	1.000					
(7) $SHARE_t$	-0.117*	-0.054*	0.220*	-0.066*	-0.395*	-0.627*	1.000				
(8) $SIZE_t$	-0.052*	-0.327*	-0.121*	-0.180*	-0.245*	-0.287*	0.371*	1.000			
(9) ROA_t	0.078*	-0.015	0.156*	0.085*	-0.032*	0.077*	-0.083*	-0.216*	1.000		
(10) M/B_t	0.011	-0.008	0.008	-0.001	-0.009	-0.014*	0.038*	-0.017*	0.005	1.000	
(11) $\Delta CAPEX_t$	0.000	-0.020*	0.011	0.008	0.014*	-0.004	-0.008	-0.017*	0.001	0.076*	1.000

Table 5.2 Descriptive statistics full sample and propensity-score matched samples

	Panel A. Full sample (15,025)			Panel B. Propensity-score matched sample		
	$\mathbf{SUSPECT_t}$	$\mathbf{NON\_SUSPECT_t}$		$\mathbf{SUSPECT_t}$	$\mathbf{NON\_SUSPECT_t}$	
	Mean	**Mean**	**Difference in mean**	**Mean**	**Mean**	**Difference in mean**
$\mathrm{SHARE_t}$	3.992	3.786	0.206***	3.992	3.996	-0.004
$\mathrm{ROA_t}$	-0.066	-0.018	-0.048***	-0.066	-0.075	0.009
$\mathrm{M/B}_t$	4.257	1.500	2.757***	4.257	3.884	0.373
SIZE_t	0.482	1.364	-0.881***	0.482	0.417	0.065
Obs.	987	14,038		987	987	

*, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed t-tests of differences in means.
This table presents the descriptive statistics for our full and propensity-score matched samples. The propensity matching score is run from the probit selection model (4.1). All variables are defined in the Appendix.

Panel C. Propensity score-matching model for volatility sample

$\mathrm{SHARE_t}$	0.398***
	[14.89]
$\mathrm{M/B}_t$	0.046***
	[14.17]
SIZE_t	-0.428***
	[-18.93]
$\mathrm{ROA_t}$	0.849***
	[5.24]
Observations	15,025
Pseudo R2	0.092
Year/Industry fixed effect included	YES

*, **, *** Represent significance at 10 percent, 5 percent, 1 percent, respectively.
The results are run from the probit selection model (4.1). All variables are defined in the Appendix.

$$\mathrm{PROB(SUSPECT_{it} = 1) = PROB}(\alpha_0 + \alpha_1 \mathrm{M/B_{it}} + \alpha_2 \mathrm{SHARE_{it}} + \alpha_3 \mathrm{SIZE_{it}} + \alpha_4 \mathrm{ROA_{it}} \sum_j \alpha_j \mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \alpha_k \mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it})$$

Table 5.3 Comparison of suspect firms with the rest of sample

	(1) DAP	(2) AREAL	(3) REM_{CFO}	(4) REM_{DISEXP}	(5) REM_{PROD}
M/B	-0.000	0.002*	-0.001***	-0.001	0.001*
	[-0.800]	[1.787]	[-2.842]	[-0.860]	[1.735]
SIZE	-0.004***	0.030***	-0.005*	0.008***	0.016***
	[-4.196]	[6.531]	[-1.889]	[2.850]	[6.898]
ROA	0.070***	-0.210***	0.190***	0.101***	-0.121***
	[6.240]	[-4.789]	[5.453]	[3.715]	[-4.997]
SUSPECT	0.009**	0.042**	0.015*	0.050***	0.007
	[2.162]	[2.005]	[1.779]	[3.769]	[0.593]
Constant	0.015***	-0.123***	0.020*	-0.046***	-0.057**
	[2.944]	[-3.805]	[1.804]	[-2.674]	[-2.466]
Observations	16,811	16,811	16,811	16,811	16,811
Adjusted R-squared	0.052	0.016	0.094	0.010	0.016
Year indicators	YES	YES	YES	YES	YES

Notes:

This table presents results for the coefficients obtained from the regression equation (5.5):

$$EM = \alpha_0 + \alpha_1 M/B_{it} + \alpha_2 SIZE_t + \alpha_3 ROA_{it} + \alpha_4 SUSPECT_{it} + + \sum_k \alpha_k YEAR_{DUMMY_{it}} + \varepsilon_{it}$$

The dependent variable in the above regression model includes the measures of accrual earnings management and real earnings management that are above illustrated in section 3.3.2.
SUSPECT is dummy variable set as 1 if firms beating/meeting earnings benchmarks that are previously defined, 0 otherwise.
T-statistics that reported in parentheses, are calculated by using White (1980) standard errors clustered by firm to correct for autocorrelation and heteroskedasticity.
Variables are as previously defined.

*, **, *** represent that the coefficient is significant at 10%, 5%, and 1%, respectively.

5.5.2 Main results

5.5.2.1 Evidence of earnings management to avoid earnings decreases and losses

5.5.2.1.1 Evidence of managed earnings for avoidance of earnings decreases

Figure 5.2 presents the histogram of the earnings scaled by total assets[13] for the data over the period 1992 through 2018. Consistent with Burgstahler and Dichev (1997), the distribution interval width of annual net income level of 0.005 for the range -0.25 to +0.25 is applied. The figure shows that the distribution is relatively a smooth bell shape except for around zero. Following Burgstahler and Dichev (1997), Holland and Ramsay (2003), Coulton et al. (2005), I assess the statistical significance of the discontinuity around zero through t-statistics (i.e., known as a standardized difference), which equals the difference between actual and expected frequency of each interval, where this is based on the immediate two adjacent intervals divided by the estimated standard deviation of the difference.[14] For the distribution of operating earnings scaled by total asset, Burgstahler and Dichev test statistics for the interval immediately above zero is 7.141, which is statistically significant at the 1 percent level. The result indicates that UK listed firms manage earnings to beat at the earnings level benchmark.

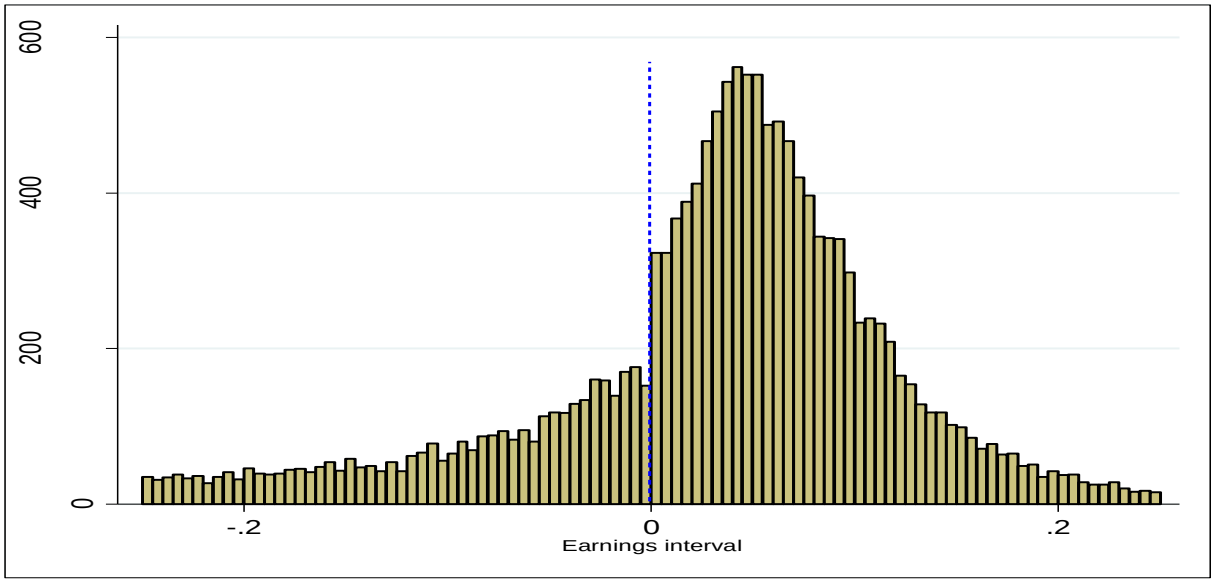


Figure 5.2 Distributions of earnings scaled by total assets

[13] In additional tests, I use alternative deflators such as market value. The results are almost identical.

[14] The expected number of observations in the interval is the average of the numbers in the two adjacent intervals. The variance of the difference between the actual and expected number of observations is approximately the sum of variance of the difference. The variance of the difference between the observed and expected number of observations for the interval is: $Np_i(1-p_i) + 1/4N(p_{i-1} + p_{i+1})(1- p_{i-1} - p_{i+1})$. In which, N is the total number of observations, p_i is the probability that an observation is belong to the interval i.

5.5.2.1.2 Evidence of managed earnings for avoidance of earnings losses

Figure 5.3 shows the results of the distribution of change in earnings per share.[15] Consistent with Burgstahler and Dichev (1997); Holland and Ramsay (2003); Coulton et al. (2005), Durtschi and Easton (2005), I examine the distribution of changes in earnings per share by using a histogram with interval widths of 0.0025 for the range from -0.25 to +0.25. The figure visually shows the highest frequency immediately above zero. Compared to using earnings level, the standardized difference for the interval immediately to the right of zero is 3.068, which is significant at the 5 percent level. The result indicates that there is the evidence of presence of managed earnings to beat earnings benchmarks using change in earnings scaled by total asset.

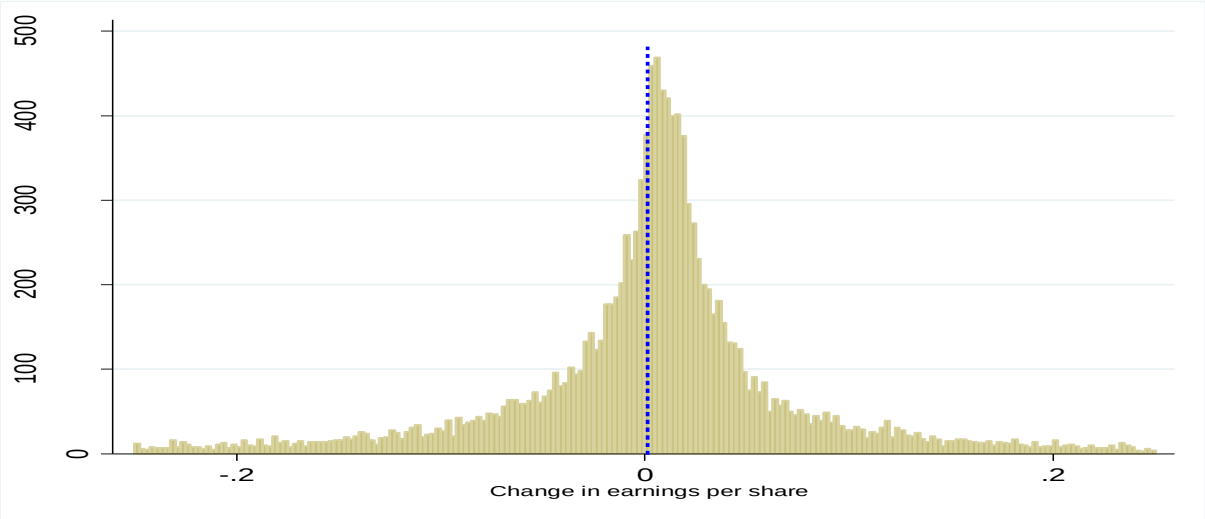


Figure 5.3 Distribution of changes in earnings per share for period 1992 to 2018

5.5.2.2 Regression analyses of suspects' long-run accounting performance and information uncertainty

Table 5.4 presents results from the cross-sectional analysis of subsequent accounting performance of suspect firms (i.e., meeting/beating earnings benchmarks) with respect to the level of IU where the adjusted change in ROA (*ΔA_ROA)* is used as a dependent variable. When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise. The t-statistics are calculated using heteroskedasticity-consistent standard errors (White, 1980).

[15] In addition to using earnings per shares, I also consider change in net income scaled by total assets. The results are almost identical.

The first regression of table 5.4 represents the results using the full sample. With the full sample, the coefficients on the interaction term between firms beating benchmarks and high IU (*SUSPECT x HIU*) are significantly negative (coefficients = -0.041, -0.027, -0.047 for *HIU(VOLATALITY), HIU(VOLUME), HIU(SPREAD)* as measures of *HIU*, respectively, significant at 1 percent, 5 percent, and 1 percent levels, respectively). In the second regression using the propensity-score matched sample, the coefficients on *SUSPECT x HIU* are -0.046, -0.031, -0.044 for the three measures of *HIU: HIU(VOLATALITY), HIU(VOLUME), HIU(SPREAD),* respectively, significant at the 1%, 10%, and 5% levels, respectively. The third regression of table 5.4 shows the results when the Heckman procedure is applied. In detail, there is a significantly negative relation between *SUSPECT x HIU* and long-run accounting performance (*ΔA_ROA*) (coefficients of -0.040, -0.023, -0.045 with three measures of *HIU* such as *HIU(VOLATALITY), HIU(VOLUME), HIU(SPREAD),* respectively, significant at 1 percent, 10 percent, and 5 percent levels, respectively). The results are generally consistent with those in the first and second regression. The overall evidence in table 5.4 supports hypothesis 6 that under high IU, suspect firms (i.e., firms meeting or beating earnings benchmarks) experience long-term underperformance, compared to those firms under low IU. It indicates that managers of firms having high IU opportunistically manage earnings to temporarily inflate short-run earnings to beat/meet earning benchmarks.

As for the control variables, in the full sample, firm size (*SIZE)* is negatively related to subsequent accounting performance for all measures of IU as *VOLATILITY, VOLUME,* and *SPREAD,* with the coefficient of -0.006, -0.005, -0.005, significant at 1 percent level. Similarly, with the Heckman two-step approach, all coefficients on *SIZE* are negative (e.g., -0.012, -0.009, -0.011 for the three measures of IU such as V*OLATILITY, VOLUME,* and *SPREAD,* respectively, significant at the 1 percent level). The signs of the coefficients on *SIZE* are the same as the results by previous studies (see Wang and Zheng, 2020).

As for sales growth (*ΔSALES*), there is a negative relation between *ΔSALES* and future accounting performance (*ΔA_ROA).* For the full sample, the coefficients on *ΔSALES* are -0.020, -0.019, -0.020 for the three proxies of IU, V*OLATILITY, VOLUME,* and *SPREAD,* respectively, significant at the 1 percent level. Similarly, with the Heckman two-step approach, the results are nearly the same. As for the PSM method, the coefficients on *ΔSALES* are -0.027, -0.027, -0.026 for the three proxies of IU, V*OLATILITY, VOLUME,* and *SPREAD,* respectively, significant at the 10 percent, 5 percent, and 10 percent levels, respectively.

As for capital expenditure growth (*ΔCAPEX),* there is negative relation between *ΔCAPEX* and future accounting performance (*ΔA_ROA)* (coefficients = -0.085, -0.060, -0.084 for the three proxies of IU, V*OLATILITY*, *VOLUME*, and *SPREAD*, respectively, significant at the 1 percent,10 percent, and 5 percent levels, respectively). Similarly, with the Heckman two-step approach, the results are nearly the same. Using the PSM method, the coefficients on *ΔSALES* are -0.198 and -0.238 for the proxies of IU such as V*OLATILITY* and *VOLUME*, respectively, significant at the 10 percent and 5 percent levels, respectively. The results are consistent with previous literature indicating that firms with high sales growth and capital expenditures growth experience a decline in subsequent operating performance (see Lakonishok et al., 1994; Loughran and Ritter, 1997; Rangan, 1998).

Table 5.4 Subsequent firm accounting performance of suspect firms in high information uncertainty

	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
ΔA_ROA	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	-0.015**	-0.017**	-0.007	-0.013	0.005	-0.012	-0.009	-0.014	-0.002
	[-2.387]	[-1.999]	[-1.069]	[-1.188]	[0.426]	[-1.002]	[-1.512]	[-1.609]	[-0.235]
HIU_t	0.008***	0.008**	0.007*	0.021	0.014	0.002	0.011***	0.021***	0.008**
	[2.931]	[2.343]	[1.687]	[1.545]	[1.058]	[0.089]	[3.661]	[5.607]	[1.992]
$SUSPECT_t$ x HIU_t	-0.041***	-0.027**	-0.047***	-0.046***	-0.031*	-0.044**	-0.040***	-0.023*	-0.045***
	[-3.823]	[-2.199]	[-4.465]	[-2.641]	[-1.741]	[-2.553]	[-3.687]	[-1.916]	[-4.236]
M/B_t	-0.000	0.001	0.000	-0.000	-0.000	-0.000	0.000	0.002***	0.001
	[-0.243]	[1.461]	[0.127]	[-0.698]	[-0.159]	[-0.473]	[1.309]	[2.965]	[1.627]
$SIZE_t$	-0.006***	-0.005***	-0.005***	-0.000	0.003	-0.005	-0.012***	-0.009***	-0.011***
	[-6.051]	[-4.558]	[-3.637]	[-0.040]	[1.101]	[-1.207]	[-8.153]	[-6.954]	[-6.086]
$\Delta CAPEX_t$	-0.085***	-0.060*	-0.084**	-0.198*	-0.238**	-0.133	-0.086***	-0.058*	-0.086**
	[-2.669]	[-1.707]	[-2.388]	[-1.814]	[-2.086]	[-1.219]	[-2.737]	[-1.679]	[-2.457]
$\Delta SALES_t$	-0.020***	-0.019***	-0.020***	-0.027*	-0.027**	-0.026*	-0.021***	-0.020***	-0.021***
	[-3.170]	[-2.832]	[-3.036]	[-1.804]	[-2.049]	[-1.686]	[-3.424]	[-2.942]	[-3.247]
IMR							0.071***	0.071***	0.072***
							[6.467]	[7.107]	[6.225]
Constant	0.010	-0.013	0.005	-0.018	0.011	0.008	-0.134***	-0.154***	-0.139***
	[0.617]	[-0.557]	[0.305]	[-0.488]	[0.272]	[0.199]	[-5.014]	[-5.728]	[-4.999]
Observations	8,477	6,742	7,524	1,024	828	948	8,477	6,742	7,524
Adjusted R-squared	0.035	0.022	0.0332	0.0907	0.084	0.0911	0.035	0.034	0.0435
Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes:

This table shows the results of association between firms beat/meet earnings benchmarks and long-run firm performance in the high IU when using the full, propensity-score matched sample and Heckman two-step. I use three variables to proxies for information uncertainty such as *VOLATILITY, VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define firm as a firm facing high (low) information uncertainty. HIU equals 1 for high information uncertainty, and 0 otherwise. The multivariate estimates are based on the regression equation (5.6) below:

$$\Delta A\_ROA_t = \beta_0 + \beta_1 SUSPECT_{it} + \beta_2 HIU_t + \beta_3\, SUSPECT_{it} \text{ x } HIU_t + \beta_4\, M/B_{it} + \beta_5\, SIZE_{it} + \beta_6\, \Delta CAPEX_{it} + \beta_7\, \Delta SALES_{it} + \sum_j \alpha_j\, INDUSTRY_{DUMMY_{it}} + \sum_k \alpha_k\, YEAR_{DUMMY_{it}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as φ(z)/Φ(z), where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm to correct for autocorrelation and heteroskedasticity.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Significance tests are two-tailed. See Appendix for variable definitions and calculations.

5.5.2.3 Regression analyses of suspects' long-run stock performance and information uncertainty

Panels A and Panel B of Table 5.5 show the results of the cross-sectional regression analyses of subsequent abnormal returns of suspects in the high IU environment, compared to the low IU in which four-factor buy-and-hold abnormal returns (*BHRR4F*) and buy-and-hold size adjusted abnormal returns *(BHSAR*) are used to measure long-run stock performance. When the proxy for IU is above (below) the sample median, I define a firm as having high (low) uncertain information. Therefore, *HIU* equals 1 for high uncertainty of information environment, and 0 otherwise. The White (1980)'s t-statistics are computed with heteroskedasticity standard errors.

Panel A of Table 5.5 presents the results using four-factor buy-and-hold abnormal returns (*BHRR4F*) to measure subsequent stock performance. The first regression of Table 5.5 represents the results using the full sample. With the full sample, the coefficients on the interaction term between firms beating benchmarks and high IU (*SUSPECT x HIU*) are significantly negative (coefficients = -0.361, -0.364, -0.595 for *HIU(VOLATALITY), HIU(VOLUME), HIU(SPREAD)* as measures of IU, respectively, significant at the 10 and 5 percent levels). In the second regression using the propensity-score matched sample, the coefficients on *SUSPECT x HIU* are -0.425, -0.537 for the two measures of *HIU* such as

HIU(VOLUME), HIU(SPREAD), respectively, significant at the 5% and 10% level, respectively. The third regression of table 5.4 shows the results when the Heckman procedure is applied. In detail, there is a significantly negative relation between *SUSPECT x HIU* and long-run operating performance (*ΔA_ROA*) (coefficients of -0.333, -0.305, -0.571 with three measures of *HIU* such as *HIU(VOLATALITY), HIU(VOLUME), HIU(SPREAD),* respectively, significant at the 10 percent, 5 percent levels, respectively). The results are generally consistent with those in the first and second regression. The overall evidence in table 5.4 supports hypothesis 7 that under high IU, suspect firms (i.e., firms meeting or beating earnings benchmarks) experience long-term underperformance, compared to firms in low IU. It indicates that managers of firms having high IU opportunistically manage earnings to temporarily inflate short-run earnings to beat/meet earning benchmarks.

As for the control variables, in the full sample, firm size (*SIZE)* is negatively related to subsequent stock performance for the measure of IU as *SPREAD* with the coefficient of -0.035, significant at 10 percent level. Similarly, with the Heckman two-step approach, all coefficients on *SIZE are* negative (-0.145, -0.075, -0.150 for three measures of IU such as V*OLATILITY, VOLUME,* and *SPREAD,* respectively, significant at the 1 percent level). Moreover, as for firm growth, there is a significantly positive relationship between firms' growth (*M/B*) and subsequent stock performance (*ΔA_ROA*). In the full sample, all coefficients on *M/B are* positive (0.084, 0.030, 0.084 for the three measures of IU such as V*OLATILITY, VOLUME,* and *SPREAD,* respectively, significant at 1 percent, 5 percent, and 1 percent levels). The results are consistent with using the Heckman two-step approach. As for the PSM method, the coefficients on *M/B* are 0.023 and 0.037 for the measures of IU such as V*OLATILITY,* and *SPREAD,* respectively, significant at 5 percent and 1 percent levels. The signs of coefficients on *SIZE* and *M/B* are the same as the results by previous studies (see Wang and Zheng, 2020).

As for sales growth (*ΔSALES*), there is negative relation between *ΔSALES* and future accounting performance (*ΔA_ROA).* For the full sample, the coefficients on *ΔSALES* are -0.227, -0.139, -0.194 for the three proxies of IU: V*OLATILITY, VOLUME,* and *SPREAD,* respectively, significant at the 1 percent, 10 percent, and 5 percent levels. Similarly, with the Heckman two-step approach, the results are nearly the same. The results are consistent with previous literature indicating that firms with high sales growth experience a decline in subsequent operating performance (see Lakonishok et al., 1994; Loughran and Ritter, 1997).

Panel B of Table 5.5 reports the results of subsequent stock performance of suspect firms in the high IU compared to low IU. The long-run abnormal return is measured by using buy-and-hold size adjusted abnormal returns *(BHSAR*). The t-statistics are computed with White's heteroskedasticity-corrected standard errors.

In the first regression of Panel B, Table 5.5 using the full sample, the coefficient on the interaction term (*SUSPECT x HIU)* is -0.190, and -0.225 for the measures of *HIU* such as *HIU(VOLATALITY)* and *HIU(VOLUME)*, respectively, significant at the 5 percent level. In the second regression using the propensity-score matched sample, there is a significantly negative relation between *SUSPECT x HIU* and *BHSAR* (coefficients of -0.255, -0.437 for the two measures of *HIU* such as *HIU(VOLATALITY)* and *HIU(VOLUME)*, respectively, significant at the 10 percent and 1 percent level, respectively). The last regression of panel B, Table 5.5 presents the results using the second step of two-step Heckman method to examine the relation between firms beating earnings benchmarks and long-run abnormal returns interacted with the level of IU. The results are the same as the first and second regression for the two measures of *HIU* such as *HIU(VOLATALITY)* and HIU*(VOLUME)*, respectively. The coefficients on *SUSPECT x HIU* are -0.181, -0.201 for the two measures of *HIU* such as *HIU(VOLATALITY)* and *HIU(VOLUME)*, respectively, significant at the 5 percent and 10 percent levels, respectively. The evidence again supports the third hypothesis that in the high IU, investors of firms beating earnings benchmarks are overoptimistic about the earnings information.

Table 5.5 Subsequent stock performance of suspect firms in high information uncertainty

Panel A. Four-factor buy-and-hold abnormal returns

	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
BHRR4F	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	-0.071	-0.011	0.100	0.092	0.173	0.359	0.054	0.010	0.235
	[-0.614]	[-0.099]	[0.464]	[0.789]	[1.143]	[1.404]	[0.458]	[0.086]	[1.094]
HIU_t	0.188***	0.206***	-0.031	0.331**	0.232	0.121	0.248***	0.352***	0.002
	[3.316]	[3.714]	[-0.373]	[2.235]	[1.345]	[0.555]	[4.263]	[5.271]	[0.028]
$SUSPECT_t$ x HIU_t	-0.361*	-0.364**	-0.595**	-0.152	-0.425**	-0.537*	-0.333*	-0.305**	-0.571**
	[-1.801]	[-2.564]	[-2.493]	[-0.634]	[-2.028]	[-1.801]	[-1.697]	[-2.125]	[-2.463]
M/B_t	0.084***	0.030**	0.084***	0.023**	0.011	0.037***	0.094***	0.039**	0.093***
	[5.614]	[2.069]	[5.558]	[2.417]	[1.434]	[2.582]	[5.979]	[2.471]	[5.829]
$SIZE_t$	-0.014	-0.008	-0.035*	-0.007	-0.055	0.019	-0.145***	-0.075***	-0.150***
	[-0.865]	[-0.507]	[-1.665]	[-0.156]	[-1.209]	[0.361]	[-5.236]	[-3.090]	[-4.902]
$\Delta CAPEX_t$	0.815	0.542	1.071	0.036	0.001	0.572	0.653	0.449	0.888
	[1.438]	[1.092]	[1.501]	[0.777]	[0.031]	[0.626]	[1.162]	[0.909]	[1.490]
$\Delta SALES_t$	-0.227***	-0.139*	-0.194**	-0.098*	-0.059	-0.313	-0.224***	-0.139*	-0.209**
	[-2.764]	[-1.653]	[-2.184]	[-1.849]	[-1.186]	[-1.431]	[-2.735]	[-1.653]	[-2.310]
IMR							1.482***	0.884***	1.380***
							[5.480]	[3.653]	[4.839]
Constant	0.728	1.452**	0.994*	0.379	0.985*	-0.148	-2.217***	-0.413	-1.754**
	[1.545]	[2.479]	[1.742]	[0.822]	[1.865]	[-0.317]	[-2.881]	[-0.515]	[-2.027]
Observations	14,639	12,184	12,846	1,806	1,506	1,664	14,639	12,184	12,874
Adjusted R-squared	0.060	0.029	0.061	0.017	0.019	0.054	0.066	0.031	0.067

Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes:

This table shows the results of association between firms beat/meet earnings benchmarks and long-run stock performance in the high IU when using the full, propensity-score matched sample and Heckman two-step. I use three variables to proxy for information uncertainty such as *VOLATILITY*, *VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define firm as a firm facing high (low) information uncertainty. HIU equals 1 for high information uncertainty, and 0 otherwise. The multivariate estimates are based on the regression equation (5.6) below:

$$\mathrm{BHAR4F_{it}} = \beta_0 + \beta_1 \mathrm{SUSPECT_{it}} + \beta_2 \mathrm{HIU_t} + \beta_3\, \mathrm{SUSPECT_{it}} \times \mathrm{HIU_t} + \beta_4\, \mathrm{M/B_{it}} + \beta_5\, \mathrm{SIZE_{it}} + \beta_6\, \Delta\mathrm{CAPEX_{it}} + \beta_7\, \Delta\mathrm{SALES_{it}} + \sum_j \alpha_j\, \mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \alpha_k\, \mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm to correct for autocorrelation and heteroskedasticity.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Significance tests are two-tailed. See Appendix for variable definitions and calculations.

Panel B. Firm adjusted sized buy-and-hold abnormal returns

	FULL SAMPLE			PROPENSITY-SCORE MATCHED SAMPLE			TWO-STAGE HECKMAN APPROACH		
BHSAR	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
$SUSPECT_t$	0.042	0.083	-0.026	0.044	0.138	-0.017	0.079	0.092	0.009
	[0.682]	[0.909]	[-0.486]	[0.505]	[1.408]	[-0.219]	[1.250]	[1.016]	[0.163]
HIU_t	0.147***	0.074***	-0.018	0.269**	0.222*	-0.086	0.166***	0.134***	-0.038
	[6.840]	[2.749]	[-0.556]	[2.525]	[1.813]	[-0.743]	[7.474]	[3.923]	[-1.149]
$SUSPECT_t$ x HIU_t	-0.190**	-0.225**	0.002	-0.255*	-0.437***	0.040	-0.181**	-0.201*	0.019
	[-2.082]	[-2.133]	[0.022]	[-1.769]	[-2.977]	[0.310]	[-2.003]	[-1.902]	[0.181]
M/B_t	0.030***	0.021***	0.026***	0.013***	0.010**	0.008**	0.033***	0.025***	0.029***
	[7.302]	[3.017]	[6.466]	[2.759]	[2.042]	[2.323]	[7.763]	[3.232]	[6.834]
$SIZE_t$	0.194***	0.188***	0.169***	0.173***	0.152***	0.147***	0.157***	0.163***	0.134***
	[24.808]	[18.488]	[20.444]	[5.943]	[3.914]	[5.680]	[15.255]	[13.434]	[12.243]
$\Delta CAPEX_t$	0.317	0.014	0.336	0.496	0.003	0.451	0.261	0.014	0.285
	[1.252]	[1.360]	[1.317]	[0.694]	[0.194]	[0.685]	[1.039]	[1.353]	[1.123]
$\Delta SALES_t$	-0.053***	-0.053**	-0.045***	-0.052	-0.077	0.007	-0.053***	-0.053**	-0.045***
	[-2.818]	[-2.546]	[-2.576]	[-0.946]	[-1.221]	[0.274]	[-2.809]	[-2.557]	[-2.584]
IMR							0.423***	0.343***	0.393***
							[5.095]	[2.833]	[4.976]
Constant	0.049	0.228	0.228*	0.076	0.052	0.173	-0.858***	-0.551*	-0.588***
	[0.399]	[1.378]	[1.688]	[0.211]	[0.110]	[0.507]	[-3.900]	[-1.646]	[-2.767]
Observations	13,932	11,384	12,313	1,702	1,375	1,548	13,932	11,384	12,313
Adjusted R-squared	0.139	0.110	0.130	0.078	0.068	0.099	0.142	0.112	0.134
Year/Industry included	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table shows the results of association between firms beat/meet earnings benchmarks and long-run stock performance in the high IU when using the full, propensity-score matched sample and Heckman two-step. The multivariate estimates are based on the regression equation (5.6) below:

$$\mathrm{BHSAR_{it}} = \beta_0 + \beta_1 \mathrm{SUSPECT_{it}} + \beta_2 \mathrm{HIU_t} + \beta_3\ \mathrm{SUSPECT_{it}}\ \mathrm{x}\ \mathrm{HIU_t} + \beta_4\ \mathrm{M/B_{it}} + \beta_5\ \mathrm{SIZE_{it}} + \beta_6\ \Delta\mathrm{CAPEX_{it}} + \beta_7\ \Delta\mathrm{SALES_{it}} + \sum_j \alpha_j\ \mathrm{INDUSTRY_{DUMMY_{it}}} + \sum_k \alpha_k\ \mathrm{YEAR_{DUMMY_{it}}} + \varepsilon_{it}$$

Propensity score matching sample is obtained from probit regression equation (4.1). The inverse mill ratio (*IMR)* is calculated as $\varphi(z)/\Phi(z)$, where z is the fitted value of probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution, respectively.

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm to correct for autocorrelation and heteroskedasticity.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Significance tests are two-tailed. See Appendix for variable definitions and calculations.

5.5.2.4 Additional analysis: Accrual earnings management and subsequent accounting performance and information uncertainty

Prior studies indicate that firms beating/meeting earnings benchmarks have significantly high discretionary accruals compared to firms just missing earnings benchmarks (e.g., Degeorge et al., 1999; Cohen et al., 2008; Fan et al., 2010; Harris et al., 2018). Therefore, in additional analysis, I examine whether firms beating/beating earnings benchmarks that engage in accrual-based earnings management experience subsequent underperformance in the high information condition compared to low information uncertainty. I use the sample of suspect firms where earnings management are likely to happen. In accordance, firm-years with earnings just beating/meeting the previous year's earnings and zero earnings are selected as the earnings management suspect firms.

Using a non-random sample can cause potential omitted variables, hence, Following Zang (2012), I apply Heckman (1979)'s two-step procedure to address non-random sample biases. In which, in the first step, I estimate a selection model similar to the equation (4.2) to obtain the inverse mill ratio (*IMR).* In the second step, the *IMR* is added to the following main regression model using earning manipulation suspect firms to examine the relationship between accrual-based earnings management and long-term firm performance in the high IU.

$$\begin{aligned}\Delta\text{A\_ROA}_t = {} & \beta_0 + \beta_1 \text{DAP}_{it} + \beta_2 \text{HIU}_t + \beta_3\, \text{DAP}_{it} \text{ x } \text{HIU}_t + \beta_4\, \text{M/B}_{it} \\ & + \beta_5\, \text{SIZE}_{it} + \beta_6\, \Delta\text{CAPEX}_{it} + \beta_7\, \Delta\text{SALES}_{it} + \beta_8\, \text{IMR}_{it} \\ & + \sum\nolimits_j \alpha_j\, \text{INDUSTRY}_{\text{DUMMY}_{it}} + \sum\nolimits_k \alpha_k\, \text{YEAR}_{\text{DUMMY}_{it}} + \varepsilon_{it}\end{aligned} \tag{5.9}$$

I use stock return volatility (*VOLATALITY)*, stock volume (*VOLUME)* and bid-ask spread (*SPREAD)* to measure IU. *HIU* is dummy variable set as 1 when IU variables are above the median, and 0 otherwise. All variables in Eq. (5.9) are defined in the Appendix. White's heteroskedasticity-corrected standard errors are used to calculate t-statistics in the regression equation (5.9). It predicts that under high IU, suspect sample using discretionary accrual experience long-run underperformance. Therefore, β_3 in Eq. (5.9) is expected to be significantly negative.

Table 5.6 presents results for testing the association between accrual-based earnings management and long-run operating performance in the high IU using earnings management suspect sample. Accrual earnings management (*DAP)* is measured by using the two models: the Modified Jones model and Kothari et al., (2005) model. The variable of interest is the

interaction between accrual earnings management and high IU (*DAP x HIU*). In detail, with the Modified Jones model, the coefficients of *DAP x HIU* are -0.048 and -0.09, for the two measures of *HIU* such as *HIU(VOLATILITY)* and *HIU(VOLUME)*, significant at the 10 percent and 1 percent level, respectively. As for the Kothari et al., (2005) model, the results are consistent with the Modified Jones model. Therefore, the results indicate that firms beating earnings benchmark using accrual earnings management have negative subsequent operating performance in the high IU. The results indicate that under high IU, investors are misled by accounting information managed by using discretionary accrual when firms beat/meet earnings benchmarks.

Table 5.6 Accrual earnings management and subsequent operating performance in the high information uncertainty

	Modified-Jones Model			Kothari et al. (2005) model		
ΔA_ROA	(1) VOLATILITY	(2) VOLUME	(3) SPREAD	(1) VOLATILITY	(2) VOLUME	(3) SPREAD
DAP_t	-0.003	0.011	-0.003	0.009	0.011	-0.014
	[-0.227]	[0.746]	[-0.227]	[0.704]	[0.781]	[-0.873]
HIU_t	-0.000	-0.002	-0.000	-0.002	-0.002	-0.006
	[-0.038]	[-0.167]	[-0.038]	[-0.271]	[-0.179]	[-0.547]
DAP_t x HIU_t	-0.048*	-0.090***	-0.048*	-0.042*	-0.069**	0.009
	[-1.735]	[-3.115]	[-1.735]	[-1.712]	[-3.531]	[0.413]
M/B_t	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	[-0.765]	[-0.117]	[-0.765]	[0.190]	[0.242]	[-0.431]
$SIZE_t$	-0.013***	-0.007	-0.013***	-0.010**	-0.007	-0.014**
	[-3.112]	[-1.402]	[-3.112]	[-3.402]	[-1.547]	[-3.448]
$\Delta CAPEX_t$	-0.003	-0.022	-0.003	-0.001	-0.030	-0.014
	[-0.055]	[-0.303]	[-0.055]	[-0.504]	[-0.404]	[-0.199]
$\Delta SALES_t$	-0.007	0.013	-0.007	-0.002	0.013	-0.005
	[-0.730]	[1.165]	[-0.730]	[-0.632]	[1.157]	[-0.297]
IMR	0.090**	0.040	0.090**	0.072**	0.049	0.080
	[3.568]	[1.012]	[3.568]	[3.025]	[1.222]	[1.508]
Constant	-0.131	-0.019	-0.131	-0.076	-0.028	-0.106
	[-1.466]	[-0.255]	[-1.466]	[-0.888]	[-0.369]	[-1.064]
Observations	609	476	609	609	476	609
Adjusted R-squared	0.06	0.096	0.06	0.066	0.107	0.073
Year/Industry included	YES	YES	YES	YES	YES	YES

Notes:

This table shows the results of association between accrual earnings management of firms meeting/beating earnings benchmarks and long-run accounting performance in the high IU when using the Heckman two-step procedure. The inverse mill ratio (*IMR)* is obtained from the selection model (4.2). The IMR is calculated as φ(z)/Φ(z), where z is the fitted value of the probit regression index function, φ and Φ are the standard normal density and standard normal cumulative distribution. I use three variables to proxy for information uncertainty such as *VOLATILITY, VOLUME* and *SPREAD*. When the proxy for information uncertainty is above (below) the sample median, I define a firm as facing high (low) information uncertainty. Therefore, *HIU* equals 1 for high information uncertainty, and 0 otherwise.

The multivariate estimates are based on the regression model below:

$$\Delta A\_ROA_t = \beta_0 + \beta_1 DAP_{it} + \beta_2 HIU_t + \beta_3\, DAP_{it} \text{ x } HIU_t + \beta_4\, M/B_{it} + \beta_5\, SIZE_{it} + \beta_6\, \Delta CAPEX_{it} + \beta_7\, \Delta SALES_{it} + \beta_8\, IMR_{it} + \sum_j \alpha_j\, INDUSTRY_{DUMMY_{it}} + \sum_k \alpha_k\, YEAR_{DUMMY_{it}} + \varepsilon_{it}$$

Reported t-statistics (shown below the coefficients) are based on White (1980) standard errors clustered by firm to correct for autocorrelation and heteroskedasticity.

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Significance tests are two-tailed. See Appendix for variable definitions and calculations.

5.6 Robustness testing

I also repeat the analysis by choosing alternative benchmarks for firms meeting or beating earnings benchmarks. In detail, following Cohen et al. (2008) and Zang (2012), I define suspect firms as those having change in earnings before extraordinary items scaled by total assets that lie in the interval [0, 0.0025). The main results are qualitatively unchanged.

To measure long-term abnormal accounting performance and abnormal returns, I also use 12-month and 24-month periods ending three months after the firm's fiscal year end. The results are qualitatively similar.

As an additional robustness test, to test the relation between firms meeting or beating earnings benchmarks and long-run firm performance in the high IU, I use the highest decile of the three proxies of IU (i.e., *VOLUME, VOLATALITY, SPREAD*) to classify them as high IU instead of using the median value as in the main tests. The results are qualitatively similar to the above-mentioned results. Furthermore, in the main tests, I use the three proxies of IU (i.e., *VOLUME, VOLATALITY, SPREAD*) instead of using dummy variable (*HIU)* such as *HIU(VOLATILITY), HIU(VOLUME)* and *HIU(SPREAD)*. The results are qualitatively similar.

In the robustness tests, I use the alternative sample for the period from 2005 to 2018. The chosen start year of 2005 is to address the major regulatory change in accounting in 2004 and 2005. In detail, on 1 January 2005, all listed firms on London Stock Exchange are mandatory to adopt International Financial Reporting Standards (IFRSs) to prepare their financial reporting. All results presented in previous tables are unchanged.

5.7 Summary and conclusion

Table 5.7 below presents the main findings of the analyses shown in the empirical chapter 5.

Table 5.7 Summary of main findings of chapter 5

Hypotheses	Expected signs	Result
H6: Ceteris paribus, firms meeting or beating earnings benchmarks experience more negative long-run accounting performance under high information uncertainty than under low information uncertainty.	(-)	Confirmed (-)
H7: Ceteris paribus, firms meeting or beating earnings benchmarks experience more negative long-run stock market performance under high information uncertainty than under low information uncertainty.	(-)	Confirmed (-)

Prior literature presents mixed evidence about subsequent firm performance for firms beating earnings benchmarks. On the one hand, Herrmann et al. (2011) find that market participants are able to uncover the opportunistic earnings managed to meet earnings benchmarks. Hence, there is no relation between beating earnings benchmarks and future firm performance. On the other hand, Skinner and Sloan (2002) prove that investors are naively overoptimistic about the prospects of growth stocks when these firms beat earnings benchmarks. The objective of this study is to examine whether the mixed evidence in the literature can be explained by the IU in the capital market at the time firms meet/beat the earnings benchmarks. Specifically, I investigate whether under the condition of high IU, managers of firms might opportunistically engage in managing earnings to beat earnings benchmarks to mislead investors about future firm performance. Therefore, the subsequent performance of suspect firms will deteriorate.

The results of the study suggest that under high IU, managers of firm have high higher incentives for beating earnings benchmark through opportunistically manipulating earnings. The results indicate that under the condition of high IU, investors find it difficult to detect opportunistic behaviour of managers through beating earnings benchmark to achieve short-term

benefits at the cost of long-run performance. Therefore, in the high IU, investors are misled by earnings information. The study contributes to providing evidence that in the condition of high IU, manager of firms beat/meet earnings benchmarks to opportunistically mislead investors about underlying firm performance.

Accordingly, the practical implication of the study is that in the high IU, investors should discount the value of benchmark beaters. Therefore, auditors should consider higher scrutiny of firms having net income immediately above zero in the condition of high information since these firms might opportunistically manage earnings. The limitation of the study is that the study assumes that firms opportunistically meet/beat earnings benchmarks through engaging in increasing-income manipulation in a current year to inflate short-run stock prices in the condition of high IU.

CHAPTER 6. THESIS CONCLUSION

The topic of earnings management has been widely researched by accounting academic researchers. Understanding of earnings management is important for market participants when using accounting information for investment decisions. This thesis aims at contributing to the area of earnings management. At the comparison of models to detect accrual earnings management versus real earnings management, investigating the conditions for practice of earnings management, and the subsequent performance of firms managing earnings to beat earnings benchmarks. Next section 6.1 summarizes the work done in this thesis and the main results and section 6.3 documents practical and theoretical implications of the study. Section 6.3 reflects on the research limitations of this thesis and suggests some avenues for future research.

6.1 Summary of key findings

This thesis is designed to examine three main topics about comparing the abilities to detect accrual earnings management and real earnings management; the role of IU on the trade-off between accrual earnings management and real earnings management; the future performance of firms meeting/beating earnings benchmarks in the high IU. To investigate these topics, the analysis is conducted by using all live and dead UK listed firms in London Stock Exchange for the period from 1992 to 2018. Each of these three topics is discussed/analysed in an empirical chapter (chapters 3, 4 and 5, respectively). In these empirical chapters a number of hypotheses are tested, which are summarized in table 6.1 below.

Table 6.1 Summary of testing hypotheses

Chapter	Hypotheses	Result
3	H1: The ability to detect real earnings management is lower than that of accrual-based earnings management.	Accepted
4	H2: There is a positive relationship between the level of information uncertainty and accrual-based earnings management when firms have incentives to manage earnings.	Accepted
4	H3: There is no association between the level of information uncertainty and real earnings manipulation when firms have incentives to manage earnings.	Accepted

4	H4: There is a higher likelihood that managers use accrual versus real manipulation when firms have incentives to manage earnings under high information uncertainty than under low information uncertainty.	Accepted
4	H5: There is a positive relation between smoothing earnings and the level of information uncertainty when firms have incentives to manage earnings.	Accepted
5	H6: Ceteris paribus, firms meeting or beating earnings benchmarks experience more negative long-run accounting performance under high information uncertainty than under low information uncertainty.	Accepted
5	H7: Ceteris paribus, firms meeting or beating earnings benchmarks experience more negative long-run stock market performance under high information uncertainty than under low information uncertainty.	Accepted

The findings of the first empirical chapter indicate that the abilities to detect real earnings management is lower than that to uncover accrual earnings management. With respect to accrual earnings management, I 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.

Furthermore, the second empirical chapter in this thesis focuses on the relationship between IU and earnings management. The analysis finds that there is positive relationship between high IU and accrual earnings management. Furthermore, managers of firms beating earnings benchmarks exhibit more preference for using accrual earnings management than real earnings manipulation with the greater level of the information uncertainty. The findings extend previous studies examining firms' choice to use accrual earnings management and real earnings management as their costs of doing so (e.g., Zang, 2012; Cohen et al., 2010) through explaining role of the information uncertainty on managerial preference between accrual earnings management and real manipulation. The evidence implies that in the settings where managers' intentions are unobservable and verified (i.e., high information uncertainty), managers use alternative ways to manage earnings that are perceived as less costly for firms.

In the third empirical chapter, I investigate whether under the condition of high IU, managers of firms might opportunistically engage in managing earnings to beat earnings benchmarks to mislead investors about future firm performance. Therefore, the subsequent performance of suspect firms will deteriorate. The results indicate that under the condition of high IU, investors find it difficult to detect opportunistic behaviour of managers through beating earnings benchmark to achieve short-term benefits at the cost of long-run performance. Therefore, in the high IU, investors are misled by earnings information. The findings of this chapter help to solve conflicting evidence about subsequent firm performance for firms beating earnings benchmark (e.g., Skinner and Sloan, 2002; Herrmann et al., 2011).

6.2 Practical and theoretical implications of the findings

From the above analyses, the findings of this thesis incorporate the following implications. First, regardless of the real earnings management models used to detect real earnings management, the power of the test is very low. 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. 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. I 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.

Second, the findings of this thesis imply that in the high IU environment, investors should discount firm value when using accounting information because managers of firms are likely to engage in accrual-based earnings management. Moreover, regulators and auditors should have higher scrutiny for accrual information in financial reporting when firms face a high IU environment.

Third, the results provide insight for investors and regulators. Specifically, in the high IU, managers of firms tend to manipulate earnings to beat earnings benchmarks aiming at misleading investors about future firm performance. The practical implication of the study is that in the high IU, investors should discount the value of earnings for benchmark-beaters. Therefore, auditors should consider higher scrutiny of firms having net income immediately above or below zero (or zero change in earnings) in the condition of high information since these firms might opportunistically manage earnings. Moreover, as for regulators, firms beating benchmarks should have higher scrutiny for their accounting recognition when firms have high IU.

6.3 Limitations of the thesis and some suggestions for future research

Although substantial work is done in this thesis, due to time and resource constraint, the thesis still is far from being perfect. In chapter 3, the study makes a contribution to showing that while the Roychowdhury (2006) models are popular for estimating abnormal real operating accounts, the models are severely mis-specified, and have low power to detect the three types of real earnings management activities such as price discount, overproduction, and reduction in discretionary expenditures. However, prior evidence indicates that the models to detect earnings management are mis-specified, especially for firms with extreme performance. The thesis does not investigate this issue. Moreover, this study only suggests the alternative model to detect abnormal research and development (R&D) expenditures. Hence, future research should focus on developing new models to uncover other types of real earnings management activities.

One of the concerns is that while the use of UK listed firms as the sample data in this thesis is well justified and contributes to the existing knowledge and literature on the research field of earnings management, the external validity of this study and whether the results of the thesis are generalisable to other markets is unclear. Previous studies mostly focus on using US sample data.

Chapter 4 concludes that under high IU, managers of firms engage in more accrual-based earnings management when having high incentives to manage earnings (i.e., beating earnings benchmarks). Moreover, in chapter 5, the results indicate that firms beating earnings benchmarks experience long-run underperformance. The assumption of chapters 4 and 5 is that managers of firms engage in income-increasing earnings manipulation to meet/beat earnings benchmarks. This thesis does not investigate other contexts where managers of firms have incentives to manage earnings downwards. Accordingly, future research could examine situations where managers of firms apply income-decreasing manipulation to meet/beat earnings benchmarks in the context of high IU.

In conclusion, some limitations of this thesis may have not been recognized by the author, even though it has been attempted to conduct this thesis with the greatest caution.

APPENDIX

Definition and Measure of Variables

HIU	VOLATILITY	indicator variable equal to 1 if firms have high volatility (above median of the sample), 0 otherwise where volatility is measured as standard deviation of daily returns for the past 25 trading days prior to fiscal year-end
	VOLUME	indicator variable equal to 1 if firms have high trading volume (above median of the sample), 0 otherwise where trading volume is defined as the average daily turnover in percentage over the past six months prior to fiscal year-end. Daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day
	SPREAD	indicator variable equal to 1 if firms have bid-ask spread (above median of the sample), 0 otherwise where bid-ask spread at the end of the year is defined as below: $SPREAD_t$=(ASK_t-BID_t)/((ASK_t+BID_t)/2) (Where: ASK_t: ask price of stock; BID: bid price of stock)
SUSPECT		set equal to 1 if BENCH1 lies in the interval [0, 0.005) or BENCH2 lies in the interval [0, 0.0025), 0 otherwise
BENCH1		earnings before extraordinary items scaled by total asset
BENCH2		change in earnings before extraordinary items per shares
DAP		discretionary accruals represented by the firm-specific error from a cross-sectional version of the modified Jones model (Jones, 1991; Dechow et al., 1995); Kothari et al., (2005) model; Modified Dechow and Dichev (2002)
ABS_DAP		absolute discretionary accruals
REM_{CFO}		level of abnormal sales manipulation (i.e., price discount)
REM_{PROD}		level of abnormal production costs, where production costs are defined as the sum of cost of goods sold and the change in inventories
REM_{DISEXP}		level of abnormal discretionary expenses, where discretionary expenses are the sum of advertising expense, SG&A expense, and R&D expense
AREAL		total manipulation measure is the sum of the three real earnings management proxies (i.e., REM_{CFO}, REM_{PROD}, REM_{DISEXP}), where abnormal cash flows from operations and abnormal discretionary expenses are multiplied by negative one
ABS_AREAL		absolute total real earnings management
DTR		set as 1 if accrual earnings management (DAP) higher than total real earnings management (AREAL) in a firm/year observation, 0 otherwise.

SMOOTHING	the ratio of a firm's standard deviation of net income divided by the standard deviation of its cash from operations (both deflated by the beginning-of-year total asset). The measure is multiplied by -1 that higher values indicate higher income smoothing.
BHSAR	size-adjusted buy-and-hold abnormal returns over a 36-month period ending three months after the fiscal year end measured as the difference between a firm's annual buy-and-hold returns and the buy-and-hold returns for the same 12-month period from a market-capitalization-based portfolio decile to which the firm belongs.
BHAR4F	buy-and-hold abnormal returns are calculated by the application of three-factor model by Fama and French (1993) as follow: $BHRR_{pj} = \alpha + \beta_1(R_{mj} - R_{fj}) + \beta_2 SMB_j + \beta_3 HML_j + \beta_4 UMD_j$ Where: • $BHRR_{pj}$ is monthly equally weighted portfolio raw returns of portfolio p of month j. The return cumulation period starts three months after the fiscal year-end of the year and continues through the three-year period • $R_{mj} - R_{fj}$ is the excess return on the market portfolio • SMB_j is the difference in returns of a value-weighted portfolio of small and large stocks • HML_j is the difference in returns of a value-weighted portfolio of high book-to-market and low book-to-market stocks • UMD_j is momentum factor All data is obtained from the database that is published by Gregory et al., (2017)
ΔA_ROA	adjusted change in ROA (change in net income divided by the average of beginning- and ending-period book value of total assets) measured as the firm specific change in ROA minus the (two-digit SIC) industry-year and size median change in ROA. Size is measured as the book value of assets. Abnormal change in ROA is the mean abnormal change in ROA for years 1 to 3 relative to year 0 (= fiscal year of firms meeting or beating earnings benchmark)
LEV	total assets divided by total liabilities
M/B	market value of equity divided by the book value of equity
SIZE	natural logarithm of total market of equity
SHARE	logarithm of total shares outstanding
ROA	return on assets, measured as net income divided by total assets
BIG_8	indicator variable equal to 1 if audit firm is one of Big-8 audit firms, and 0 otherwise
SIG_CFO	the standard deviation of operating cash flows deflated by total assets, calculated using annual data over a five-year period
Z_SCORE	$0.3\frac{NI_t}{ASSET_t} + 1.4\frac{RETAINED\ EARNINGS_t}{ASSET_t} + 1.2\frac{WORKING\ CAPITAL_t}{ASSET_t} + 0.6\frac{STOCK\ PRICE_t \times SHARE\ OUTSTANDING_t}{TOTAL\ LIABILITIES_t}$

CYCLE	$\frac{\text{RECEIVABLES}_t}{\text{REVENUES}_t}365 + \frac{\text{INVENTORY}_t}{\text{COST OF GOODS SOLD}_t}365 - \frac{\text{PAYABLESS}_t}{\text{COST OF GOODS SOLD}_t}365$
ΔCAPEX	capital expenditures are calculated as the mean capital expenditures in years 1 to 3 relative to base year 0 (= fiscal year of firms meeting or beating earnings benchmark), scaled by total assets.
ΔSALES	mean change percentage growth rate in sales in years 1 to 3 relative to base year 0 (= fiscal year of firms meeting or beating earnings benchmark)
A/R days	$\frac{\text{Receivables}_t}{\text{Sales}_t}$ x 365 days
DSRI	$\frac{\text{Receivables}_t/\text{Sales}_t}{\text{Receivables}_{t-1}/\text{Sales}_{t-1}}$
SGI	$\frac{\text{Sales}_t - \text{Sales}_{t-1}}{\text{Sales}_{t-1}}$x100
Inventory days	$\frac{\text{Inventory}_t}{\text{Cost of goods sold}_t}$ x 365 days
TATA	$\frac{\Delta\text{Current asset}_t - \Delta\text{Cash}_t - \Delta\text{Current liabilities}_t - \Delta\text{Current maturities of LTD}_t - \Delta\text{Income tax payable}_t - \text{Depreciation and amortization}_t}{\text{Total asset}_t}$

REFERENCES

Abad, D., Cutillas-Gomariz, M. F., Sánchez-Ballesta, J. P. & Yagüe, J. 2018. Real earnings management and information asymmetry in the equity market. *European Accounting Review,* 27: 209-235.

Achleitner, A.-K., Günther, N., Kaserer, C. & Siciliano, G. 2014. Real earnings management and accrual-based earnings management in family firms. *European Accounting Review,* 23: 431-461.

Akpanuko, E. E. & Umoren, N. J. 2018. The influence of creative accounting on the credibility of accounting reports. *Journal of Financial Reporting and Accounting*.

Al-Shattarat, B., Hussainey, K. & Al-Shattarat, W. 2018. The impact of abnormal real earnings management to meet earnings benchmarks on future operating performance. *International Review of Financial Analysis*.

Alchian, A. A. 1965. The basis of some recent advances in the theory of management of the firm. *The Journal of Industrial Economics*: 30-41.

Alchian, A. A. & Demsetz, H. 1972. Production, information costs, and economic organization. *The American economic review,* 62: 777-795.

Alhadab, M. & Clacher, I. 2018. The impact of audit quality on real and accrual earnings management around IPOs. *The British Accounting Review,* 50: 442-461.

Allen, E. J., Larson, C. R. & Sloan, R. G. 2013. Accrual reversals, earnings and stock returns. *Journal of accounting and economics,* 56: 113-129.

Altman, E. I. 2000. Predicting financial distress of companies. *Retrieved on September 4th, 2009 from http://pages. stern. nyu. edu/~ ealtman/Zscores. pdf*: 15-22.

Altman, E. I. 2013. Predicting financial distress of companies: revisiting the Z-score and ZETA® models. *Handbook of research methods and applications in empirical finance.* Edward Elgar Publishing.

Amin, K. I. & Lee, C. M. 1997. Option trading, price discovery, and earnings news dissemination. *Contemporary Accounting Research,* 14: 153-192.

Archibald, T. R. 1967. The return to straight-line depreciation: An analysis of a change in accounting method. *Journal of accounting Research*: 164-180.

Arya, A., Glover, J. C. & Sunder, S. 2003. Are unmanaged earnings always better for shareholders? *Accounting horizons,* 17: 111-116.

Athanasakou, V., Strong, N. C. & Walker, M. 2011. The market reward for achieving analyst earnings expectations: Does managing expectations or earnings matter? *Journal of Business Finance & Accounting,* 38: 58-94.

Athanasakou, V. E., Strong, N. C. & Walker, M. 2009. Earnings management or forecast guidance to meet analyst expectations? *Accounting and business research,* 39: 3-35.

Baber, W. R., Fairfield, P. M. & Haggard, J. A. 1991. The effect of concern about reported income on discretionary spending decisions: The case of research and development. *Accounting Review*: 818-829.

Baik, B., Choi, S. & Farber, D. B. 2020. Managerial ability and income smoothing. *The Accounting Review,* 95: 1-22.

Ball, R. & Brown, P. 1968. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research,* 6: 159-178.

Ball, R. & Shivakumar, L. 2005. Earnings quality in UK private firms: comparative loss recognition timeliness. *Journal of accounting and economics,* 39: 83-128.

Banz, R. W. 1981. The relationship between return and market value of common stocks. *Journal of financial economics,* 9: 3-18.

Barber, B. M. & Lyon, J. D. 1996. Detecting abnormal operating performance: The empirical power and specification of test statistics. *Journal of financial Economics,* 41: 359-399.

Barber, B. M. & Lyon, J. D. 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of financial economics,* 43: 341-372.

Barnea, A., Ronen, J. & Sadan, S. 1976. Classificatory smoothing of income with extraordinary items. *The Accounting Review,* 51: 110-122.

Barth, M. E., Elliott, J. A. & Finn, M. W. 1999. Market rewards associated with patterns of increasing earnings. *Journal of Accounting Research,* 37: 387-413.

Bartov, E. 1993. The timing of asset sales and earnings manipulation. *Accounting Review*: 840-855.

Bartov, E., Givoly, D. & Hayn, C. 2002. The rewards to meeting or beating earnings expectations. *Journal of accounting and economics,* 33: 173-204.

Bartov, E., Gul, F. A. & Tsui, J. S. 2000. Discretionary-accruals models and audit qualifications. *Journal of accounting and economics,* 30: 421-452.

Bartov, E. & Mohanram, P. 2004. Private information, earnings manipulations, and executive stock-option exercises. *The Accounting Review,* 79: 889-920.

Beaver, W., Eger, C., Ryan, S. & Wolfson, M. 1989. Financial reporting, supplemental disclosures, and bank share prices. *Journal of Accounting Research,* 27: 157-178.

Beaver, W. H. 1968a. The information content of annual earnings announcements. *Journal of accounting research*: 67-92.

Beaver, W. H. 1968b. Market prices, financial ratios, and the prediction of failure. *Journal of accounting research*: 179-192.

Beaver, W. H. & Engel, E. E. 1996. Discretionary behavior with respect to allowances for loan losses and the behavior of security prices. *Journal of Accounting and Economics,* 22: 177-206.

Becker, C. L., Defond, M. L., Jiambalvo, J. & Subramanyam, K. 1998. The effect of audit quality on earnings management. *Contemporary accounting research,* 15: 1-24.

Behn, B. K., Choi, J.-H. & Kang, T. 2008. Audit quality and properties of analyst earnings forecasts. *The Accounting Review,* 83: 327-349.

Beidleman, C. R. 1973. Income smoothing: The role of management. *The Accounting Review,* 48: 653-667.

Belkaoui, A. & Picur, R. D. 1984. The smoothing of income numbers: Some empirical evidence on systematic differences between core and periphery industrial sectors. *Journal of Business Finance & Accounting,* 11: 527-545.

Beneish, M. D. 1999. The detection of earnings manipulation. *Financial Analysts Journal,* 55: 24-36.

Beneish, M. D. & Press, E. 1995. Interrelation among events of default. *Contemporary Accounting Research,* 12: 57-84.

Bentley, K. A., Omer, T. C. & Sharp, N. Y. 2013. Business strategy, financial reporting irregularities, and audit effort. *Contemporary Accounting Research,* 30: 780-817.

Bergstresser, D. & Philippon, T. 2006. CEO incentives and earnings management. *Journal of financial economics,* 80: 511-529.

Bernard, V. L. & Thomas, J. K. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research,* 27: 1-36.

Bhojraj, S., Hribar, P., Picconi, M. & Mcinnis, J. 2009. Making sense of cents: An examination of firms that marginally miss or beat analyst forecasts. *The Journal of Finance,* 64: 2361-2388.

Black, F. 1972. Capital market equilibrium with restricted borrowing. *The Journal of business,* 45: 444-455.

Brown, L. D. & Caylor, M. L. 2005. A temporal analysis of quarterly earnings thresholds: Propensities and valuation consequences. *The Accounting Review,* 80: 423-440.

Brown, P. & Ball, R. 1967. Some preliminary findings on the association between the earnings of a firm, its industry, and the economy. *Journal of Accounting Research*: 55-77.

Brown, S. J. & Warner, J. B. 1985. Using daily stock returns: The case of event studies. *Journal of financial economics,* 14: 3-31.

Burgstahler, D. & Chuk, E. 2017. What have we learned about earnings management? Integrating discontinuity evidence. *Contemporary Accounting Research,* 34: 726-749.

Burgstahler, D. & Dichev, I. 1997. Earnings management to avoid earnings decreases and losses. *Journal of accounting and economics,* 24: 99-126.

Burgstahler, D. & Eames, M. 2006. Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. *Journal of Business Finance & Accounting,* 33: 633-652.

Bushee, B. J. 1998. The influence of institutional investors on myopic R&D investment behavior. *Accounting review*: 305-333.

Butler, M., Leone, A. J. & Willenborg, M. 2004. An empirical analysis of auditor reporting and its association with abnormal accruals. *Journal of Accounting and Economics,* 37: 139-165.

Cahan, S. F. 1992. The effect of antitrust investigations on discretionary accruals: A refined test of the political-cost hypothesis. *Accounting Review*: 77-95.

Capalbo, F., Frino, A., Mollica, V. & Palumbo, R. 2014. Accrual-based earnings management in state owned companies: Implications for transnational accounting regulation. *Accounting, Auditing & Accountability Journal,* 27: 1026-1040.

Carhart, M. M. 1997. On persistence in mutual fund performance. *The Journal of finance,* 52: 57-82.

Cassell, C. A., Myers, L. A. & Seidel, T. A. 2015. Disclosure transparency about activity in valuation allowance and reserve accounts and accruals-based earnings management. *Accounting, Organizations and Society,* 46: 23-38.

Cheng, M., Subramanyam, K. & Zhang, Y. 2005. Earnings guidance and managerial myopia. *Available at SSRN 851545*.

Cheng, Q. & Warfield, T. D. 2005. Equity incentives and earnings management. *The accounting review,* 80: 441-476.

Chiang, R. & Venkatesh, P. 1988. Insider holdings and perceptions of information asymmetry: A note. *The journal of finance,* 43: 1041-1048.

Christie, A. A. & Zimmerman, J. L. 1994. Efficient and opportunistic choices of accounting procedures: Corporate control contests. *Accounting review*: 539-566.

Clinch, G., Stokes, D. & Zhu, T. 2012. Audit quality and information asymmetry between traders. *Accounting & Finance,* 52: 743-765.

Cohen, D., Mashruwala, R. & Zach, T. 2010. The use of advertising activities to meet earnings benchmarks: Evidence from monthly data. *Review of Accounting Studies,* 15: 808-832.

Cohen, D., Pandit, S., Wasley, C. E. & Zach, T. 2020. Measuring real activity management. *Contemporary Accounting Research,* 37: 1172-1198.

Cohen, D. A., Dey, A. & Lys, T. Z. 2008. Real and accrual-based earnings management in the pre-and post-Sarbanes-Oxley periods. *The accounting review,* 83: 757-787.

Cohen, D. A. & Zarowin, P. 2010. Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of accounting and Economics,* 50: 2-19.

Collins, D. W., Pungaliya, R. S. & Vijh, A. M. 2017. The effects of firm growth and model specification choices on tests of earnings management in quarterly settings. *The Accounting Review,* 92: 69-100.

Copeland, R. M. 1968. Income smoothing. *Journal of accounting research*: 101-116.

Cormier, D., Houle, S. & Ledoux, M.-J. 2013. The incidence of earnings management on information asymmetry in an uncertain environment: Some Canadian evidence. *Journal of International Accounting, Auditing and Taxation,* 22: 26-38.

Coulton, J., Taylor, S. & Taylor, S. 2005. Is 'benchmark beating'by Australian firms evidence of earnings management? *Accounting & Finance,* 45: 553-576.

Coulton, J. J., Saune, N. & Taylor, S. L. 2015. Overvalued equity, benchmark beating and unexpected accruals. *Accounting & Finance,* 55: 989-1014.

Cowen, S. S. & Hoffer, J. A. 1982. Usefulness of financial ratios in a single industry. *Journal of Business Research,* 10: 103-118.

Daniel, K., Hirshleifer, D. & Subrahmanyam, A. 1998. Investor psychology and security market under-and overreactions. *the Journal of Finance,* 53: 1839-1885.

Dann, L. Y., Masulis, R. W. & Mayers, D. 1991. Repurchase tender offers and earnings information. *Journal of Accounting and Economics,* 14: 217-251.

Darrough, M. & Rangan, S. 2005. Do insiders manipulate earnings when they sell their shares in an initial public offering? *Journal of accounting research,* 43: 1-33.

Davidson, S., Stickney, C. & Weil, R. 1987. Accounting: The language of business. Thomas Horton and Daughter. *Sun Lakes Arizona*.

De Bondt, W. F. & Thaler, R. 1985. Does the stock market overreact? *The Journal of finance,* 40: 793-805.

De Bondt, W. F. & Thaler, R. H. 1990. Do security analysts overreact? *The American Economic Review*: 52-57.

Deangelo, H., Deangelo, L. & Skinner, D. J. 1994. Accounting choice in troubled companies.

Deangelo, L. E. 1986. Accounting numbers as market valuation substitutes: A study of management buyouts of public stockholders. *The accounting review,* 61: 400.

Dechow, P., Ge, W. & Schrand, C. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of accounting and economics,* 50: 344-401.

Dechow, P., Richardson, S. A. & Tuna, A. 2000. Are benchmark beaters doing anything wrong? *Available at SSRN 222552*.

Dechow, P. M. 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. *Journal of accounting and economics,* 18: 3-42.

Dechow, P. M. & Dichev, I. D. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The accounting review,* 77: 35-59.

Dechow, P. M., Hutton, A. P., Kim, J. H. & Sloan, R. G. 2012. Detecting earnings management: A new approach. *Journal of accounting research,* 50: 275-334.

Dechow, P. M., Kothari, S. P. & Watts, R. L. 1998. The relation between earnings and cash flows. *Journal of accounting and Economics,* 25: 133-168.

Dechow, P. M. & Skinner, D. J. 2000. Earnings management: Reconciling the views of accounting academics, practitioners, and regulators. *Accounting horizons,* 14: 235-250.

Dechow, P. M. & Sloan, R. G. 1991. Executive incentives and the horizon problem: An empirical investigation. *Journal of accounting and Economics,* 14: 51-89.

Dechow, P. M., Sloan, R. G. & Sweeney, A. P. 1995. Detecting earnings management. *Accounting review*: 193-225.

Dechow, P. M., Sloan, R. G. & Sweeney, A. P. 1996. Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary accounting research,* 13: 1-36.

Defond, M. L. & Francis, J. R. 2005. Audit research after sarbanes-oxley. *Auditing: A journal of practice & theory,* 24: 5-30.

Defond, M. L. & Jiambalvo, J. 1994. Debt covenant violation and manipulation of accruals. *Journal of accounting and economics,* 17: 145-176.

Defond, M. L. & Park, C. W. 2001. The reversal of abnormal accruals and the market valuation of earnings surprises. *The accounting review,* 76: 375-404.

Degeorge, F., Patel, J. & Zeckhauser, R. 1999. Earnings management to exceed thresholds. *The Journal of Business,* 72: 1-33.

Degeorge, F. & Zeckhauser, R. 1993. The reverse LBO decision and firm performance: Theory and evidence. *The Journal of Finance,* 48: 1323-1348.

Demerjian, P., Lewis-Western, M. & Mcvay, S. 2020. How does intentional earnings smoothing vary with managerial ability? *Journal of Accounting, Auditing & Finance,* 35: 406-437.

Demski, J. S. 1998. Performance measure manipulation. *Contemporary Accounting Research,* 15: 261-285.

Denis, D. J. & Denis, D. K. 1993. Managerial discretion, organizational structure, and corporate performance: A study of leveraged recapitalizations. *Journal of Accounting and Economics,* 16: 209-236.

Dichev, I., Graham, J., Harvey, C. R. & Rajgopal, S. 2016. The misrepresentation of earnings. *Financial Analysts Journal,* 72: 22-35.

Dichev, I. D., Graham, J. R., Harvey, C. R. & Rajgopal, S. 2013. Earnings quality: Evidence from the field. *Journal of Accounting and Economics,* 56: 1-33.

Dichev, I. D. & Skinner, D. J. 2002. Large–sample evidence on the debt covenant hypothesis. *Journal of accounting research,* 40: 1091-1123.

Dinh, T., Kang, H. & Schultze, W. 2016. Capitalizing research & development: Signaling or earnings management? *European Accounting Review,* 25: 373-401.

Donaldson, T. & Preston, L. E. 1995. The stakeholder theory of the corporation: Concepts, evidence, and implications. *Academy of management Review,* 20: 65-91.

Durtschi, C. & Easton, P. 2005. Earnings management? The shapes of the frequency distributions of earnings metrics are not evidence ipso facto. *Journal of Accounting Research,* 43: 557-592.

Dutta, S. 2003. Capital budgeting and managerial compensation: Incentive and retention effects. *The Accounting Review,* 78: 71-93.

Dutta, S. & Trueman, B. 2002. The Interpretation of Information and Corporate Disclosure Strategies. *Review of Accounting Studies,* 7: 75-96.

Dyck, A., Morse, A. & Zingales, L. 2010. Who blows the whistle on corporate fraud? *The journal of finance,* 65: 2213-2253.

Dye, R. A. 1988. Earnings management in an overlapping generations model. *Journal of Accounting research*: 195-235.

Dye, R. A. 1998. Investor sophistication and voluntary disclosures. *Review of accounting studies,* 3: 261-287.

Efendi, J., Srivastava, A. & Swanson, E. P. 2007. Why do corporate managers misstate financial statements? The role of option compensation and other factors. *Journal of financial economics,* 85: 667-708.

Epstein, L. G. & Schneider, M. 2008. Ambiguity, information quality, and asset pricing. *The Journal of Finance,* 63: 197-228.

Erickson, M. & Wang, S.-w. 1999. Earnings management by acquiring firms in stock for stock mergers. *Journal of Accounting and Economics,* 27: 149-176.

Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance,* 25: 383-417.

Fama, E. F. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics,* 49: 283-306.

Fama, E. F., Fisher, L., Jensen, M. C. & Roll, R. 1969. The adjustment of stock prices to new information. *International economic review,* 10: 1-21.

Fama, E. F. & French, K. R. 1992. The cross-section of expected stock returns. *the Journal of Finance,* 47: 427-465.

Fama, E. F. & French, K. R. 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance,* 51: 55-84.

Fan, Y., Barua, A., Cready, W. M. & Thomas, W. B. 2010. Managing earnings using classification shifting: Evidence from quarterly special items. *The Accounting Review,* 85: 1303-1323.

Fernando, G. D., Giboney, J. & Schneible, R. A. 2018. Voluntary disclosures and market response to earnings announcements. *Review of Accounting and Finance.*

Fields, T. D., Lys, T. Z. & Vincent, L. 2001. Empirical research on accounting choice. *Journal of Accounting and Economics,* 31: 255-307.

Fischhoff, B., Slovic, P. & Lichtenstein, S. 1977. Knowing with certainty: The appropriateness of extreme confidence. *Journal of Experimental Psychology: Human perception and performance,* 3: 552.

Fishman, M. J. & Hagerty, K. M. 2003. Mandatory versus voluntary disclosure in markets with informed and uninformed customers. *Journal of Law, Economics, and organization,* 19: 45-63.

Francis, J., Lafond, R., Olsson, P. & Schipper, K. 2005. The market pricing of accruals quality. *Journal of accounting and economics,* 39: 295-327.

Francis, J. J., Johnston, M., Robertson, C., Glidewell, L., Entwistle, V., Eccles, M. P. & Grimshaw, J. M. 2010. What is an adequate sample size? Operationalising data saturation for theory-based interview studies. *Psychology and Health,* 25: 1229-1245.

Francis, J. R., Maydew, E. L. & Sparks, H. C. 1999. The role of Big 6 auditors in the credible reporting of accruals. *Auditing: a Journal of Practice & theory,* 18: 17-34.

Frecka, T. J. & Hopwood, W. S. 1983. The effects of outliers on the cross-sectional distributional properties of financial ratios. *Accounting Review*: 115-128.

Freeman, R. E. 1984. Strategic management: a stakeholder approach.

Fridson, M. S. & Alvarez, F. 2011. *Financial statement analysis: a practitioner's guide,* John Wiley & Sons.

Friedlan, J. M. 1994. Accounting choices of issuers of initial public offerings. *Contemporary accounting research,* 11: 1-31.

Gao, J., Gao, B. & Wang, X. 2017. Trade-off between real activities earnings management and accrual-based manipulation-evidence from China. *Journal of International Accounting, Auditing and Taxation,* 29: 66-80.

Gerakos, J. 2012. Discussion of detecting earnings management: A new approach. *Journal of Accounting Research,* 50: 335-347.

Glosten, L. R. & Harris, L. E. 1988. Estimating the components of the bid/ask spread. *Journal of financial Economics,* 21: 123-142.

Goel, A. M. & Thakor, A. V. 2003. Why do firms smooth earnings? *The Journal of Business,* 76: 151-192.

Goergen, M. & Renneboog, L. 2011. Managerial compensation. *Journal of Corporate Finance,* 17: 1068-1077.

Graham, J. R., Harvey, C. R. & Rajgopal, S. 2005. The economic implications of corporate financial reporting. *Journal of accounting and economics,* 40: 3-73.

Grant, J., Markarian, G. & Parbonetti, A. 2009. CEO Risk-related incentives and income smoothing. *Contemporary Accounting Research,* 26: 1029-1065.

Guay, W. R., Kothari, S. & Watts, R. L. 1996. A market-based evaluation of discretionary accrual models. *Journal of accounting research,* 34: 83-105.

Guidry, F., Leone, A. J. & Rock, S. 1999. Earnings-based bonus plans and earnings management by business-unit managers. *Journal of accounting and economics,* 26: 113-142.

Gul, F. A., Chen, C. J. & Tsui, J. S. 2003. Discretionary accounting accruals, managers' incentives, and audit fees. *Contemporary accounting research,* 20: 441-464.

Gunny, K. A. 2010. The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research,* 27: 855-888.

Habib, A. & Hansen, J. C. 2008. Target shooting: Review of earnings management around earnings benchmarks. *Journal of Accounting Literature,* 27: 25-70.

Han, J. C. & Wang, S.-w. 1998. Political costs and earnings management of oil companies during the 1990 Persian Gulf crisis. *Accounting review*: 103-117.

Hansen, J. C. 2010. The effect of alternative goals on earnings management studies: An earnings benchmark examination. *Journal of Accounting and Public Policy,* 29: 459-480.

Hao, Q. & Yao, L. J. 2010. An explanation for earnings management: opportunistic or signaling? *Journal of Theoretical Accounting Research,* 5.

Harris, D. G., Shi, L. & Xie, H. 2018. Does benchmark-beating detect earnings management? Evidence from accounting irregularities. *Advances in accounting,* 41: 25-45.

Harrison, D. S. 2003. Business valuation made simple:. *Strategic Finance,* 84: 44.

Haw, I. M., Ho, S. S. & Li, A. Y. 2011. Corporate governance and earnings management by classification shifting. *Contemporary Accounting Research,* 28: 517-553.

Hayn, C. 1995. The information content of losses. *Journal of accounting and economics,* 20: 125-153.

Healy, P. M. 1984. The effects of bonus schemes on accounting decisions.

Healy, P. M. 1985. The effect of bonus schemes on accounting decisions. *Journal of accounting and economics,* 7: 85-107.

Healy, P. M. & Palepu, K. G. 1993. The effect of firms' financial disclosure strategies on stock prices. *Accounting horizons,* 7: 1.

Healy, P. M. & Wahlen, J. M. 1999. A review of the earnings management literature and its implications for standard setting. *Accounting horizons,* 13: 365-383.

Heckman, J. J. 1979. Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*: 153-161.

Herrmann, D., Hope, O. K., Payne, J. L. & Thomas, W. B. 2011. The market's reaction to unexpected earnings thresholds. *Journal of Business Finance & Accounting,* 38: 34-57.

Hinkel, T. P. & Hoffman, B. W. 2020. Meeting earnings benchmarks via real activities manipulation: Debt market effects. *Journal of Accounting, Auditing & Finance,* 35: 349-378.

Hirshleifer, D. 2001. Investor psychology and asset pricing. *The Journal of Finance,* 56: 1533-1597.

Hirst, D. E. 1994. Auditor sensitivity to earnings management. *Contemporary accounting research,* 11: 405-422.

Hirst, D. E. & Hopkins, P. E. 1998. Comprehensive income reporting and analysts' valuation judgments. *Journal of Accounting Research,* 36: 47-75.

Hobson, J. L. & Stirnkorb, S. 2020. Managing Earnings to Appear Truthful: The Effect of Public Scrutiny on Exactly Meeting a Threshold. *Available at SSRN 3707447*.

Holland, D. & Ramsay, A. 2003. Do Australian companies manage earnings to meet simple earnings benchmarks? *Accounting & Finance,* 43: 41-62.

Holthausen, R. W., Larcker, D. F. & Sloan, R. G. 1995. Annual bonus schemes and the manipulation of earnings. *Journal of accounting and economics,* 19: 29-74.

Holthausen, R. W. & Leftwich, R. W. 1983. The economic consequences of accounting choice implications of costly contracting and monitoring. *Journal of accounting and economics,* 5: 77-117.

Holthausen, R. W. & Watts, R. L. 2001. The relevance of the value-relevance literature for financial accounting standard setting. *Journal of accounting and economics,* 31: 3-75.

Hribar, P. & Craig Nichols, D. 2007. The use of unsigned earnings quality measures in tests of earnings management. *Journal of Accounting Research,* 45: 1017-1053.

Humphrey, C. 2008. Auditing research: a review across the disciplinary divide. *Accounting, Auditing & Accountability Journal*.

Hunton, J. E., Libby, R. & Mazza, C. L. 2006. Financial reporting transparency and earnings management (retracted). *The Accounting Review,* 81: 135-157.

Ibrahim, S. & Lloyd, C. 2011. The association between non-financial performance measures in executive compensation contracts and earnings management. *Journal of Accounting and Public Policy,* 30: 256-274.

Ibrahim, S., Tahir, M. & N'guessan, K. 2020. Earnings Management and Fraud: A Theoretical Background and Discussion. *Handbook of Research on Accounting and Financial Studies*. IGI Global.

Ibrahim, S., Xu, L. & Rogers, G. 2011. Real and accrual-based earnings management and its legal consequences: Evidence from seasoned equity offerings. *Accounting Research Journal,* 24: 50-78.

Indjejikian, R. J. 1991. The impact of costly information interpretation on firm disclosure decisions. *Journal of Accounting Research,* 29: 277-301.

Ipino, E. & Parbonetti, A. 2017. Mandatory IFRS adoption: the trade-off between accrual-based and real earnings management. *Accounting and business research,* 47: 91-121.

Jackson, S. B. & Wilcox, W. E. 2000. Do managers grant sales price reductions to avoid losses and declines in earnings and sales? *Quarterly Journal of Business and Economics*: 3-20.

Jensen, M. C. 1994. Self-interest, altruism, incentives, and agency theory. *Journal of applied corporate finance,* 7: 40-45.

Jensen, M. C. & Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics,* 3: 305-360.

Jiang, G., Lee, C. M. & Zhang, Y. 2005. Information uncertainty and expected returns. *Review of Accounting Studies,* 10: 185-221.

Jiang, H., Habib, A. & Wang, S. 2018. Real earnings management, institutional environment, and future operating performance: An international study. *The International Journal of Accounting,* 53: 33-53.

Jiraporn, P., Miller, G. A., Yoon, S. S. & Kim, Y. S. 2008. Is earnings management opportunistic or beneficial? An agency theory perspective. *International Review of Financial Analysis,* 17: 622-634.

Jones, J. J. 1991. Earnings management during import relief investigations. *Journal of accounting research,* 29: 193-228.

Jung, W.-O. & Kwon, Y. K. 1988. Disclosure when the market is unsure of information endowment of managers. *Journal of Accounting research*: 146-153.

Kahneman, D. & Tversky, A. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 47: 263-291.

Kahneman, D. & Tversky, A. 1982. Variants of uncertainty. *Cognition,* 11: 143-157.

Kaplan, R. & Kaplan, S. 1989. *The experience of nature: A psychological perspective,* CUP Archive.

Kasznik, R. 1999. On the association between voluntary disclosure and earnings management. *Journal of accounting research,* 37: 57-81.

Kasznik, R. & Mcnichols, M. F. 2002. Does meeting earnings expectations matter? Evidence from analyst forecast revisions and share prices. *Journal of Accounting research,* 40: 727-759.

Keung, E., Lin, Z. x. & Shih, M. 2010. Does the stock market see a zero or small positive earnings surprise as a red flag? *Journal of Accounting Research,* 48: 105-136.

Kim, D. 2006. On the information uncertainty risk and the January effect. *The Journal of Business,* 79: 2127-2162.

Kim, Y., Liu, C. & Rhee, S. G. 2003. The relation of earnings management to firm size. *Journal of Management Research,* 4: 81-88.

Koh, K., Matsumoto, D. A. & Rajgopal, S. 2008. Meeting or beating analyst expectations in the post-scandals world: Changes in stock market rewards and managerial actions. *Contemporary Accounting Research,* 25: 1067-1098.

Kothari, S. P., Leone, A. J. & Wasley, C. E. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics,* 39: 163-197.

Kothari, S. P., Mizik, N. & Roychowdhury, S. 2015. Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review,* 91: 559-586.

Kothari, S. P., Mizik, N. & Roychowdhury, S. 2016. Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review,* 91: 559-586.

Krische, S. D. 2005. Investors' evaluations of strategic prior-period benchmark disclosures in earnings announcements. *The Accounting Review,* 80: 243-268.

Krishnan, R. A., Joshi, S. & Krishnan, H. 2004. The influence of mergers on firms' product-mix strategies. *Strategic Management Journal,* 25: 587-611.

Lakonishok, J., Shleifer, A. & Vishny, R. W. 1994. Contrarian investment, extrapolation, and risk. *The journal of finance,* 49: 1541-1578.

Lawrence, A., Minutti-Meza, M. & Zhang, P. 2011. Can Big 4 versus non-Big 4 differences in audit-quality proxies be attributed to client characteristics? *The accounting review,* 86: 259-286.

Lee, G. & Masulis, R. W. 2009. Seasoned equity offerings: Quality of accounting information and expected flotation costs. *Journal of Financial Economics,* 92: 443-469.

Lee, L. F. 2012. Incentives to inflate reported cash from operations using classification and timing. *The Accounting Review,* 87: 1-33.

Lee, T. A., Ingram, R. W. & Howard, T. P. 1999. The difference between earnings and operating cash flow as an indicator of financial reporting fraud. *Contemporary Accounting Research,* 16: 749-786.

Lennox, C. & Yu, Y. J. 2019. Cooking the books using different ingredients: An examination of cash flow frauds.

Lennox, C. S. & Yu, Y. J. 2020. Cooking the Books Using Different Ingredients: An Examination of Earnings Frauds That Also Involve Misreported Cash Flows. *Available at SSRN 3591493*.

Lento, C. & Yeung, W. H. 2017. Earnings benchmarks, earnings management and future stock performance of Chinese listed companies reporting under ASBE-IFRS. *Asian Review of Accounting*.

Leuz, C. 2003. IAS versus US GAAP: information asymmetry–based evidence from Germany's new market. *Journal of accounting research,* 41: 445-472.

Lev, B. 1969. Industry averages as targets for financial ratios. *Journal of Accounting Research*: 290-299.

Lev, B. & Nissim, D. 2006. The persistence of the accruals anomaly. *Contemporary Accounting Research,* 23: 193-226.

Li, K. & Prabhala, N. R. 2007. Self-Selection Models in Corporate Finance. Handbook of Corporate Finance: Empirical Corporate Finance. Elsevier Science.

Li, V. 2019. The effect of real earnings management on the persistence and informativeness of earnings. *The British Accounting Review,* 51: 402-423.

Lim, T. 2001. Rationality and analysts' forecast bias. *The journal of Finance,* 56: 369-385.

Lintner, J. 1965. Security prices, risk, and maximal gains from diversification. *The journal of finance,* 20: 587-615.

Liu, C.-C., Ryan, S. G. & Wahlen, J. M. 1997. Differential valuation implications of loan loss provisions across banks and fiscal quarters. *Accounting Review*: 133-146.

Lo, K. 2008. Earnings management and earnings quality. *Journal of Accounting and Economics,* 45: 350-357.

Loughran, T. & Ritter, J. R. 1995. The new issues puzzle. *The Journal of finance,* 50: 23-51.

Loughran, T. & Ritter, J. R. 1997. The operating performance of firms conducting seasoned equity offerings. *The journal of finance,* 52: 1823-1850.

Louis, H. 2004. Earnings management and the market performance of acquiring firms. *Journal of financial economics,* 74: 121-148.

Louis, H. & Robinson, D. 2005. Do managers credibly use accruals to signal private information? Evidence from the pricing of discretionary accruals around stock splits. *Journal of Accounting and Economics,* 39: 361-380.

Man, C. K. 2013. Corporate governance and earnings management: A survey of literature. *Journal of Applied Business Research,* 29: 391-418.

Markarian, G. & Gill-De-Albornoz, B. Income smoothing and idiosyncratic volatility. 2010. AAA.

Mcnichols, M. & Wilson, G. P. 1988. Evidence of earnings management from the provision for bad debts. *Journal of accounting research*: 1-31.

Mcnichols, M. F. 2000. Research design issues in earnings management studies. *Journal of accounting and public policy,* 19: 313-345.

Mcnichols, M. F. 2002. Discussion of the quality of accruals and earnings: The role of accrual estimation errors. *The accounting review,* 77: 61-69.

Mcvay, S. E. 2006. Earnings management using classification shifting: An examination of core earnings and special items. *The Accounting Review,* 81: 501-531.

Mcwilliams, A. & Siegel, D. 2001. Corporate social responsibility: A theory of the firm perspective. *Academy of management review,* 26: 117-127.

Meckling, W. H. & Jensen, M. C. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics,* 3: 305-360.

Monem, R. M. 2003. Earnings management in response to the introduction of the Australian gold tax. *Contemporary Accounting Research,* 20: 747-774.

Monjed, H. & Ibrahim, S. 2020. Risk disclosure, income smoothing and firm risk. *Journal of Applied Accounting Research*.

Morsfield, S. G. & Tan, C. E. 2006. Do venture capitalists influence the decision to manage earnings in initial public offerings? *The Accounting Review,* 81: 1119-1150.

Mulford, C. W. & Comiskey, E. E. 2005. *The financial numbers game: detecting creative accounting practices,* John Wiley & Sons.

Nichols, D. C. & Wahlen, J. M. 2004. How do earnings numbers relate to stock returns? A review of classic accounting research with updated evidence. *Accounting Horizons,* 18: 263-286.

Odean, T. 1998. Volume, volatility, price, and profit when all traders are above average. *The journal of finance,* 53: 1887-1934.

Osma, B. G. & Young, S. 2009. R&D expenditure and earnings targets. *European Accounting Review,* 18: 7-32.

Ou, J. A. & Penman, S. H. 1989. Financial statement analysis and the prediction of stock returns. *Journal of accounting and economics,* 11: 295-329.

Owusu, A., Zalata, A. M., Omoteso, K. & Elamer, A. A. 2020. Is there a trade-off between accrual-based and real earnings management activities in the presence of (fe) male auditors? *Journal of Business Ethics*: 1-22.

Payne, J. L. & Robb, S. W. 2000. Earnings management: The effect of ex ante earnings expectations. *Journal of Accounting, Auditing & Finance,* 15: 371-392.

Peasnell, K. V., Pope, P. F. & Young, S. 2000. Detecting earnings management using cross-sectional abnormal accruals models. *Accounting and Business research,* 30: 313-326.

Press, E. G. & Weintrop, J. B. 1990. Accounting-based constraints in public and private debt agreements: Their association with leverage and impact on accounting choice. *Journal of accounting and economics,* 12: 65-95.

Prior, D., Surroca, J. & Tribó, J. A. 2008. Are socially responsible managers really ethical? Exploring the relationship between earnings management and corporate social responsibility. *Corporate governance: An international review,* 16: 160-177.

Rangan, S. 1998. Earnings management and the performance of seasoned equity offerings. *Journal of Financial economics,* 50: 101-122.

Ravenda, D., Valencia-Silva, M. M., Argiles-Bosch, J. M. & Garcia-Blandon, J. 2018. Accrual management as an indication of money laundering through legally registered Mafia firms in Italy. *Accounting, Auditing & Accountability Journal*.

Ritter, J. R. 1991. The long-run performance of initial public offerings. *The journal of finance,* 46: 3-27.

Ronen, J. & Sadan, S. 1981. Smoothing Income Numbers: Objectives and Implications (Addison Wellesley, Reading, MA).

Roosenboom, P., Van Der Goot, T. & Mertens, G. 2003. Earnings management and initial public offerings: Evidence from the Netherlands. *The International Journal of Accounting,* 38: 243-266.

Rosenbaum, P. R. & Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika,* 70: 41-55.

Ross, S. A. 1973. The economic theory of agency: The principal's problem. *The American economic review,* 63: 134-139.

Roychowdhury, S. 2006. Earnings management through real activities manipulation. *Journal of accounting and economics,* 42: 335-370.

Schipper, K. 1989. Earnings management. *Accounting horizons,* 3: 91.

Schrand, C. M. & Walther, B. R. 2000. Strategic Benchmarks in Earnings Announcements: The Selective Disclosure of Prior-Period Earnings Components. *The Accounting Review,* 75: 151-177.

Scott, W. R. & O'brien, P. C. 2003. *Financial accounting theory,* prentice hall Toronto.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance,* 19: 425-442.

Shin, J. E. 2019. Asymmetric investor reaction around earnings benchmark under economic uncertainty. *Asia-Pacific Journal of Financial Studies,* 48: 98-122.

Shipman, J. E., Swanquist, Q. T. & Whited, R. L. 2016. Propensity score matching in accounting research. *The Accounting Review,* 92: 213-244.

Shivakumar, L. 2000. Do firms mislead investors by overstating earnings before seasoned equity offerings? *Journal of Accounting and Economics,* 29: 339-371.

Siegel, M. A. 2006. Accounting shenanigans on the cash flow statement. *The CPA Journal,* 76: 38.

Simon, H. A. 1955. A behavioral model of rational choice. *The quarterly journal of economics,* 69: 99-118.

Skinner, D. J. & Sloan, R. G. 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of accounting studies,* 7: 289-312.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting review*: 289-315.

Smith Jr, C. W. & Warner, J. B. 1979. On financial contracting: An analysis of bond covenants. *Journal of financial economics,* 7: 117-161.

Stoll, H. R. 1978. The pricing of security dealer services: An empirical study of NASDAQ stocks. *The journal of finance,* 33: 1153-1172.

Subramanyam, K. 1996. The pricing of discretionary accruals. *Journal of accounting and economics,* 22: 249-281.

Suijs, J. 2007. Voluntary disclosure of information when firms are uncertain of investor response. *Journal of Accounting and Economics,* 43: 391-410.

Sun, N., Salama, A., Hussainey, K. & Habbash, M. 2010. Corporate environmental disclosure, corporate governance and earnings management. *Managerial Auditing Journal*.

Sweeney, A. P. 1994. Debt-covenant violations and managers' accounting responses. *Journal of accounting and Economics,* 17: 281-308.

Tahir, M., Ibrahim, S. & Nurullah, M. 2019. Getting compensation right-The choice of performance measures in CEO bonus contracts and earnings management. *The British Accounting Review,* 51: 148-169.

Teoh, S. H., Welch, I. & Wong, T. J. 1998a. Earnings management and the long-run market performance of initial public offerings. *The journal of finance,* 53: 1935-1974.

Teoh, S. H., Welch, I. & Wong, T. J. 1998b. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial economics,* 50: 63-99.

Thomas, J. K. & Zhang, H. 2002. Inventory changes and future returns. *Review of Accounting Studies,* 7: 163-187.

Trueman, B. & Titman, S. 1988. An explanation for accounting income smoothing. *Journal of accounting research*: 127-139.

Tucker, J. W. 2010. Selection bias and econometric remedies in accounting and finance research. *Journal of Accounting Literature, Winter*.

Tucker, J. W. & Zarowin, P. A. 2006. Does income smoothing improve earnings informativeness? *The accounting review,* 81: 251-270.

Tversky, A. & Kahneman, D. 1974. Judgment under uncertainty: Heuristics and biases. *science,* 185: 1124-1131.

Tversky, A. & Kahneman, D. 1979. Prospect Theory: An Analysis of Decision under Risk. David K. Levine.

Wahlen, J. 1994. The Nature of Information in Commercial Bank Loan Loss Disclosures. *The Accounting Review,* 69: 455.

Walker, M. 1989. Agency theory: A falsificationist perspective. *Accounting, Organizations and Society,* 14: 433-453.

Wang, W. & Zheng, K. 2020. Real earnings manipulation and future performance: A revisit using quarterly data of firms with debt covenants. *Review of Financial Economics,* 38: 76-96.

Wang, Z. & Williams, T. H. 1994. Accounting income smoothing and stockholder wealth. *Journal of Applied Business Research (JABR),* 10: 96-104.

Warfield, T. D., Wild, J. J. & Wild, K. L. 1995. Managerial ownership, accounting choices, and informativeness of earnings. *Journal of accounting and economics,* 20: 61-91.

Watts, R. L. & Zimmerman, J. L. 1986. Positive accounting theory.

Waweru, N. M. & Riro, G. K. 2013. Corporate governance, firm characteristics and earnings management in an emerging economy. *Journal of Applied Management Accounting Research,* 11: 43.

Welker, M. 1995. Disclosure policy, information asymmetry, and liquidity in equity markets. *Contemporary accounting research,* 11: 801-827.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society*: 817-838.

Wilbanks, R. M., Hermanson, D. R. & Sharma, V. D. 2015. Audit Committee Oversight of Fraud Risk: The Role of Social Ties and Governance Characteristics.

Williamson, O. E. 1979. Transaction-cost economics: the governance of contractual relations. *The journal of Law and Economics,* 22: 233-261.

Williamson, O. E. 2002. The theory of the firm as governance structure: from choice to contract. *Journal of economic perspectives,* 16: 171-195.

Wilson, M. & Wu, Y. 2011. Do publicly signalled earnings management incentives affect analyst forecast accuracy? *Abacus,* 47: 315-342.

Xie, H. 2001. The mispricing of abnormal accruals. *The accounting review,* 76: 357-373.

Xu, R. Z., Taylor, G. K. & Dugan, M. T. 2007. Review of real earnings management literature. *Journal of Accounting Literature,* 26: 195.

Xue, Y. 2003. Information content of earnings management: Evidence from managing earnings to exceed thresholds. *Available at SSRN 582601*.

Yoon, S. S. & Miller, G. 2002. Earnings management of seasoned equity offering firms in Korea. *The international journal of accounting,* 37: 57-78.

Yu, K., Hagigi, M. & Stewart, S. D. 2018. Income smoothing may result in increased perceived riskiness: Evidence from bid-ask spreads around loss announcements. *Journal of Corporate Finance,* 48: 442-459.

Zang, A. Y. 2012. Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The accounting review,* 87: 675-703.

Zhang, X. F. 2006a. Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research,* 23: 565-590.

Zhang, X. F. 2006b. Information uncertainty and stock returns. *The Journal of Finance,* 61: 105-137.