Three Essays on Accounting Fraud

by

Jae Hwan Ahn

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Declaration

I declare that any material contained in this thesis has not been submitted for a degree to any other university. Chapter 3 is a collaboration work with Zulfiqar Shah, and Chapter 4 is co-authored with Zulfiqar Shah and Shahed Imam. I contribute by developing research ideas, conducting empirical analyses, and writing up. My co-authors contribute by providing constructive comments and improving the writing.

During the preparation of this thesis a number of papers were prepared. In particular, one paper titled "The SEC as a Constrained Agency and the Reliability of AAERs as an Accounting Fraud Database", drawn from Chapter 2 of this thesis, and one paper titled "CEO Equity Incentives, Risk Tolerance, and Financial Misreporting", drawn from Chapter 3 of this thesis were presented at various seminars and conferences such as the Warwick Business School Accounting Group Seminar Series in 2016, the University of Glasgow Accounting and Finance Group Seminar Series in 2017, the British Accounting and Finance Association Annual Meeting in 2017 and 2018, the European Accounting Association Annual Congress in 2017 and 2018, and the American Accounting Association Annual Meeting in 2017 and 2018.

Abstract

This thesis consists of three empirical papers that investigate the impacts of equity incentives on accounting fraud from the perspective of the risk it presents for CEOs and controlling shareholders.

As a prerequisite for this thesis, the first paper investigates whether AAERs constitute a reliable accounting fraud database, despite their partial coverage of misreporting cases and the resource constraints of the SEC. Using comprehensive samples covering three financial misreporting databases from the U.S., I find that, compared to securities class action lawsuits and restatements, AAERs are composed of firms that are more likely to represent material accounting irregularities, which are characterised by aggressive adoption of accruals, strong financing needs, and significant market impact of misreporting cases.

The second paper investigates whether CEOs change their misreporting behaviours at higher levels of equity incentives, at which they may begin to seriously consider the risk side of incentives. Using both unmatched and matched accounting fraud samples from the U.S., I find that, contrary to misreporting patterns at average equity incentives, CEOs' option delta is negatively associated with accounting fraud propensity, whereas their stock ownership is positively related to this at respectively higher levels.

The third paper examines the extent to which, in the context of accounting fraud, controlling shareholders' control-ownership wedge interacts with their ownership concentration - a common feature of business groups - and with the additional imposition of government regulation on Korean *chaebols*. Using matched samples from Korea, I find that control-ownership wedge is positively associated with

accounting fraud propensity, whereas business group and *chaebol* affiliations are not.

Overall, the results suggest that the impacts of equity incentives on accounting fraud propensity hinge critically on how CEOs and controlling shareholders perceive the risk of accounting fraud commitment.

Chapter 1

Overview

1.1. Motivation

Investment decisions in capital markets are made based on the credibility of accounting information (see Penman 2002; Dechow et al. 2010). Governance controls within reporting firms, auditing by independent and outside auditors, and even periodic reviews by accounting regulators (e.g., the Division of Corporate Finance of the Securities and Exchange Commission (SEC)) support the investors' belief in *true and fair* accounting information. However, despite these external and internal governance systems, firms often exploit discretions in Generally Accepted Accounting Principles (GAAP), and in more rare cases deviate from their bonding mechanisms by crossing into GAAP violations (see Christie and Zimmerman 1994; Dechow et al. 1996; Core 2010). These latter aberrations have critical consequences for financial statement users, since accounting fraud seriously undermines the credibility of financial reporting systems (see also Karpoff et al. 2008a, 2008b)[1]. Therefore, the investigation of mechanisms through which accounting fraud is committed has highly significant and practical implications for both accounting regulators and financial statement users.

[1] For example, when Enron Corp.'s accounting scandal was revealed in late 2001, its share price plummeted to below $1 per share; compared to its peak price in 2000, market value of $65 billion had evaporated, which represents the GDP at market prices of the 47th ranked country in the world (http://data.worldbank.org/indicator/NY.GDP.MKTP.CD/countries?page=1).

Equity incentives [2] are one of the most widely recognised determinants of accounting fraud because they tend to induce equity holders to opportunistically misreport with the intent to benefit from stock price increases (see Core 2010). Indeed, extensive research has shown that managers' option holdings and controlling shareholders' stock ownership are positively associated with firms' accounting fraud propensity and/or aggressive earnings management (see 1.2. Review of literature). However, previous studies have mainly focused on the reward effect of equity incentives that motivates equity holders to misreport (e.g., Burns and Kedia 2006; Efendi et al. 2007; Zhang et al. 2008; Peng and Röell 2008), but they have failed to consider the potential risk effect of accounting fraud commitment that discourages them from misreporting seriously (see Armstrong et al. 2013). Contrary to earnings management strategies conducted within GAAP, accounting fraud commitment entails serious economic and legal costs (see e.g., Dechow et al. 1996; Karpoff et al. 2008a, 2008b) and thus may cause variations in firms' misreporting patterns that are known to us.

Therefore, a much more comprehensive approach would explicitly take into account the potential reactions of equity holders to the risk effect of accounting fraud. If financial statement reporters made rational decisions in consideration of the *net* benefits of accounting fraud commitment, the impact of equity incentives on accounting fraud propensity would not be simply linear or unidirectional as prior studies listed above inherently assumed. Specifically, it is not conceivable that firms would have a continuously increasing accounting fraud propensity at higher levels of CEOs' equity incentives, since excessive ill-gotten gains acquired from equity holdings not only increase the reward from accounting fraud schemes but also the risk

[2] In this thesis, equity incentives refer to both stock options and stocks as in Armstrong et al. (2010).

of detection by the SEC or incurring critical legal costs once detected. Similarly, controlling shareholders with substantial cash investment in their business groups may not be strongly incentivised to violate GAAP, even though they may be shrewd enough to manage earnings aggressively within GAAP (e.g., Kim and Yi 2006).

In this vein, CEOs' excessive equity incentives in the U.S. context and controlling shareholders' ownership structure in the non-U.S. context provide ideal settings to test whether CEOs and controlling shareholders react to the risk effect of accounting fraud. In both settings, I expect that CEOs and controlling shareholders would reverse their misreporting patterns responding to the increased risk that considerable equity incentives may create in the context of accounting fraud.

In the U.S. context, I first investigate *whether* CEOs change their misreporting behaviours at higher levels of equity incentives, where they may begin to consider the serious disadvantages of incentives. Excessive equity incentives inevitably increase the magnitude of CEOs' ill-gotten gains (see also Thevenot 2012) and this then becomes a main consideration when the SEC decides on the level of sanctions. In the non-U.S. accounting fraud context, I further examine *the extent* to which controlling shareholders' control-ownership wedge[3] interacts with ownership concentration, which inevitably increases their cash investment in business groups, and with the additional imposition of government regulation on Korean business groups called *chaebols*. The Korean institutional background provides a unique set of conditions in which to test this research question, in that *chaebols* are usually controlled by their individual ultimate owners and are regulated by government rules the like of which rarely exist in other jurisdictions.

[3] The divergence between voting rights and actual cash investment in shares.

To answer these research questions, it is a critical prerequisite to adopt a reliable accounting fraud database that is more likely to represent accounting irregularities. Crucially, it would not be relevant to investigate motivational determinants of accounting fraud using samples of financial misreporting resulting from simple errors. Among alternatives, Accounting and Auditing Enforcement Releases (AAERs) have been most widely adopted by prior studies to capture the intentional nature of accounting fraud (see Dechow et al. 2010). In particular, Dechow et al. (1996) explicitly assume that the SEC is "on average" correctly identifying "intentional" accounting fraud cases. They argue that, due to the prudent selection process of the SEC, AAERs are quite homogeneous in their intentional properties. Subsequent studies have also relied on the assumption that AAERs are an objective (Beasley et al. 2000), less biased (Erickson et al. 2006), reliable (Dechow et al. 2011) and clean (Erickson et al. 2004) proxy, whose Type I error may be lower than other databases (Dechow et al. 2011; Davidson 2011).

However, the reliability of AAERs is vigorously challenged by a recent study by Karpoff et al. (2017). Cautioning researchers as to the choices of alternative financial misreporting databases, the authors raise a serious concern by demonstrating that AAERs capture only a narrow and limited selection of misreporting cases. In fact, as a constrained agency in terms of its staffing, regional offices, and budgets, the SEC inevitably targets only a proportion of misreporting cases, even when they have been identified by other misreporting detectors (e.g., capital market investors). AAERs cover only 5-12 percent of its alternative databases analysed in this thesis.

Moreover, contrary to the widely-accepted research practice of adopting AAERs as a main proxy for accounting fraud, there has been a long-standing debate on whether government (i.e., the SEC) is indeed a superior accounting fraud detector as far as market investors themselves are concerned (see also Shleifer 2005). Since capital market investors have equally strong motivations as the SEC to identify material accounting fraud cases for their own damage compensation, we cannot *ex ante* guarantee that AAERs are more composed of accounting irregularities than securities class action lawsuits.

Unfortunately, however, most prior studies have provided only fragmented evidence on the characteristics of financial misreporting databases (e.g., Files 2012; Correia 2014), and only recently do a few papers explicitly focus on this issue (e.g., Choi and Pritchard 2016; Karpoff et al. 2017). However, prior studies have rarely investigated whether researchers may reliably employ AAERs to explore financial statement reporters' intentional motivation to misreport. Therefore, I investigate *whether* AAERs indeed constitute a relatively reliable accounting fraud database, by comparing their characteristics with those of securities class action lawsuits and restatements from these perspectives: financial reporting quality, financing needs, and market impacts of financial misreporting cases. These three criteria are main concerns of accounting research. The analysis would also provide valuable insights into the SEC's ability to detect accounting irregularities compared to capital market investors.

1.2. Review of literature

Early studies exploring determinants of accounting fraud are characterised by two distinct focuses of research: firms' motives and managerial incentives (see Dechow et al. 2010). Dechow et al. (1996) is probably the first study that focuses on the incentive mechanisms by which firms are motivated to commit accounting fraud[4]. Specifically,

[4] Prior to Dechow et al. (1996), Feroz et al. (1991) find that the market reacts negatively to accounting fraud releases by the SEC and Beasley (1996) shows that fraud firms have significantly higher percentages of outside directors than non-fraud firms.

they find that firms' financing needs and desire to avoid debt covenant violations are positively associated with accounting fraud probability. They also identify the moderating role of internal governance (e.g., outsiders on the board) on the relation between firms' financing needs and accounting fraud propensity.

An alternative perspective is adopted by Beneish (1999) who shows that managers in accounting fraud firms are more likely to be involved in rent-seeking activities regarding their personal equity incentives (see also Summers and Sweeney 1998): managers sell stocks and exercise options/warrants during manipulation periods more than managers in non-fraud firms do in the same periods. Contrary to Dechow et al. (1996), the author does not find that external financing needs significantly motivate managers to commit accounting fraud[5]. This study shifts the focus of the literature from firms' motives to managerial equity incentives and sets in motion a series of succeeding studies (e.g., Erickson et al. 2006; Armstrong et al. 2013).

The literature on managerial equity incentives is further divided into two strands. On the one hand, ever since the seminal work of Sanders (2001)[6], a considerable volume of studies has established that stock options and stocks have *distinct* impacts on firms' financial misreporting behaviours including accounting fraud[7]. Specifically, based mainly on the different payoff structures of options and stocks (i.e., convex and linear, respectively), these studies have reported that stock options increase the likelihood of restatement (e.g., Efendi et al. 2007), litigation regarding financial misreporting (e.g., Denis et al. 2006), and the combination of SEC enforcement actions

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[5] However, using more comprehensive samples, Dechow et al. (2011) later affirm their earlier findings (see also Dechow et al. 2010).

[6] The author reports diametrically opposite impacts of stock options and stock ownership on CEOs' acquisition and divestiture decisions.

[7] Financial misreporting is composed of accounting irregularities (e.g., accounting fraud) and errors (e.g., restatements resulting from clerical errors) (see Hennes et al. 2008).

and litigation (e.g., Khanna et al. 2015), whereas stocks decrease or do not have a significant impact on financial misreporting (e.g., Burns and Kedia 2006; Efendi et al. 2007; Zhang et al. 2008). Conversely, based on an opposing assumption that options and stocks have congruent effects, other studies have produced rather equivocal results on the relation between managerial equity incentives (i.e., the combination of options and stocks) and the propensity for filing AAERs by the SEC: no association (Erickson et al. 2006; Armstrong et al. 2010; Schrand and Zechman 2012) or positive association (Johnson et al. 2009; Feng et al. 2011).

In Asian and European countries, another agency conflict between controlling and minor shareholders is more acute than in the U.S. context (Bebchuk and Weisbach 2010). Using pyramiding and cross-holding of shares within a business group, controlling shareholders in these regions usually exercise more voting rights than their actual cash investments, whose divergence is called control-ownership wedge (see e.g., Lin et al. 2011). Based on its opportunistic nature[8], Kim and Yi (2006) and Gopalan and Jayaraman (Gopalan and Jayaraman 2012) argue that firms with a deeper wedge structure may produce a lower quality of earnings measured by discretionary accruals. In this case, "opportunism by controlling shareholders" matters more than "opportunism by executives" (Bebchuk and Weisbach 2010).

In sum, extant studies exploring the relations between accounting fraud propensity and equity incentives of managers and controlling shareholders have largely focused on linear and unidirectional associations, presumably due to their lack of consideration of the cost effects of accounting fraud schemes. By shifting the focus to excessive equity holdings where the cost effect would be more prevalent, my thesis attempts to

[8] Control-ownership wedge provides an ideal setting for controlling shareholders to expropriate outside investors (see e.g., Gopalan and Jayaraman 2012).

provide more dynamic and balanced predictions on the equity holders' misreporting behaviours.

1.3. Outline of research design

My three empirical studies largely stand upon a common agency theory: incentive misalignment between managers and shareholders is one of the key mechanisms of accounting fraud commitment (see Smith 1776; Berle and Means 1932; Jensen and Meckling 1976). Even though equity incentives were originally known to align the interests of managers and shareholders, they often induce managers to produce a lower quality of earnings in favour of their self-interest (see also Chen and Steiner 1999). Accounting-based contracts such as stock options, for example, motivate CEOs to exploit discretions within GAAP and, in rarer cases, to fraudulently misreport (Warfield et al. 1995; Burns and Kedia 2006). In particular, stock options fail to perfectly replicate stock ownership as an instrument for aligning the diverged interests of CEOs and outside shareholders due to their missing voting rights.

In a similar vein, I rely on the positive accounting theory (PAT) (see Ball and Brown 2014) to explain managers' opportunistic misreporting behaviours. Specifically, according to the bonus plan hypothesis (Watts and Zimmerman 1990), managers may opportunistically misreport to benefit themselves instead of maximising firms' benefits. The fundamental assumption of PAT is that managers are *rational* reporters (see Scott 2015). This assumption is important because, to maximise their own self-interest (Watts and Zimmerman 1978, 1990), they would consider not only the reward effect but also the cost side of accounting fraud commitment, which is the focus of my research questions. Thus, I expect that, in the context of accounting fraud, the costs of financial misreporting may ironically curb accounting fraud incidences because managers may reduce their opportunistic behaviours while pursing the maximisation of their self-interest. This expectation is tested by employing equity incentive data from the U.S. and Korea and would contribute to our understanding of the incentives of CEOs and controlling shareholders to commit accounting fraud.

To accommodate unique characteristics of accounting fraud samples, I establish four research designs. First, due to the non-random characteristics of accounting fraud cases (see Palepu 1986), I mainly adopt the choice-based method (Manski and Lerman 1977; Cosslett 1981; Maddala 1991), by which fraud firms are paired with an approximately equal number of non-fraud firms in the sample based on predetermined matching criteria (e.g., propensity-score). In Chapter 2, however, I do not employ matched samples because its focus is on the comparison of different financial misreporting databases, where potential endogeneity issues are less critical, and the adoption of matching methods is not feasible[9]. Second, to capture accounting irregularities rather than errors, I analyse AAERs as a main proxy for accounting fraud. However, to mitigate potential sampling bias and provide more holistic view on my findings, I present additional analysis results of alternative proxies such as securities class action lawsuits and restatements if needed and able to do so. Third, due to the binary characteristics of accounting fraud cases, I employ probit and/or the simple hazard models (Shumway 2001) after controlling for covariates that major prior studies have suggested (e.g., Dechow et al. 2011). The adoption of alternative models with different assumptions, however, does not alter my analysis results. Finally, I adopt the passage of the Sarbanes-Oxley Act (SOX) and the designation of Korean *chaebols* as two external shocks respectively to equity incentives of CEOs and controlling shareholders in the context of accounting fraud. This identification strategy provides

[9] In Chapter 2, I compare AAERs not with non-AAERs but with other misreporting databases.

ideal settings to exploit exogenous shocks to test how equity holders react to the enhanced risk of financial misreporting.

1.4. Main findings

Using comprehensive accounting fraud databases, I provide three main empirical findings. First, using both unmatched and matched accounting fraud samples from the U.S., I find that, contrary to misreporting patterns at average equity incentives, CEOs' option delta is negatively associated with accounting fraud propensity whereas their stock ownership is positively related to it at respectively higher levels. Further analyses indicate that the drastically reversing trends and their opposing directions can be explained by CEOs' distinct risk tolerance as two equity holders: CEOs as option holders are concerned about the increased risk whereas owner-CEOs underestimate it presumably due to the controlling power attached to stocks. I also document that the changes in accounting fraud decisions do not seem to be strongly associated with the decreasing marginal utility of option holdings. The findings are not susceptible to additional controls of CEO overconfidence and competence. Overall, the results suggest that CEOs' excessive equity incentives engender drastic changes in their misreporting behaviours depending on how they perceive the risk of committing accounting fraud.

Second, using matched samples from Korea, I find that control-ownership wedge is positively associated with firms' accounting fraud propensity, but business group affiliation is not. In particular, I report that *chaebol* affiliated firms are less likely to commit accounting fraud. Further analyses suggest that the distinct effects of business groups and *chaebols* from those of control-ownership wedge can be explained by controlling shareholders' substantial cash flow rights in business groups, and the tightened levels of monitoring over their expropriation in *chaebols*. I also document that the variations in firms' misreporting behaviours do not seem to be strongly associated with the political influence of large business groups. Overall, the findings suggest that the detrimental effect of control-ownership wedge on firms' accounting fraud decisions is countered by the increased costs of expropriation in business groups in general, and *chaebols*, in particular.

Finally, by comparing the characteristics of AAERs with those of securities class action lawsuits and restatements from the U.S., I find that AAERs cover cases that are more likely to represent material accounting irregularities, which are characterised by aggressive adoption of accruals, strong financing needs, and significant market impact of misreporting cases. Again, these findings cannot be *ex ante* anticipated because the SEC's declared aim to detect material accounting irregularities (see GAO 2002) does not necessarily guarantee its effective detection of those cases, and its alternative financial misreporting detectors such as capital market investors also have an equally strong motivation to detect egregious accounting fraud cases for their own damage compensation (see also Shleifer 2005). Further analyses indicate that the characteristics of AAERs can be explained by the SEC's approaches in utilizing constrained resources, in addition to AAERs' inherently egregious nature in that they involve accountants' collusion or serious defects in the financial auditing process. I specifically find that high-risk and systematically important firms are associated with a higher propensity for detection by the SEC, and states with higher firm population tend to have SEC regional offices. Through this optimisation, the SEC may mitigate inefficiencies inherent in accounting fraud investigation processes and address the potential geographic bias, which suggests that 11 regional offices are not sufficient to regulate all U.S. firms. Overall, the findings support the *relative* reliability of AAERs as an accounting fraud database and strengthen the general robustness of the arguments of this thesis.

Based on the consistent results of my analyses, I interpret the findings to imply that CEOs and controlling shareholders actively react to the risk effect of accounting fraud commitment.

1.5. Contributions

This thesis makes distinct contributions to the existing literature. First, Chapter 2 builds on research investigating characteristics of financial misreporting databases (e.g., Hennes et al. 2008; Schrand and Zechman 2012; Choi and Pritchard 2016). This is one of the limited studies explicitly investigating heterogeneities of financial misreporting databases including accounting fraud. Contrary to prior studies which have focused on information asymmetry (Choi and Pritchard 2016) or coverage (Karpoff et al. 2017) of financial misreporting cases in different databases, I compare them from the perspectives of financial reporting quality (e.g., discretionary accruals) and financing needs (e.g., debt issuance), which are main concerns of accounting research. In particular, my research contradicts Karpoff et al. (2017)'s recent finding that each financial misreporting database captures only a narrow and limited selection of cases, by contending that, despite the coverage issue, AAERs still constitute a relatively reliable accounting fraud database that is more likely to represent material accounting irregularities (see also Dechow et al. 2010). The findings should be of interest to researchers who use AAERs to proxy for accounting fraud and practitioners who are interested in heterogeneities of financial misreporting databases.

Second, Chapter 3 contributes to the literature exploring the impacts of options and stocks on financial misreporting propensity (e.g., Denis et al. 2006; Efendi et al. 2007;

Khanna et al. 2015). Based largely on their different payoff structures, these studies have reported that options and stocks have *distinct linear* impacts on CEOs' acquisition and divestiture decisions (Sanders 2001), market reactions to firms' initial public offerings (Certo et al. 2003), and financial misreporting (e.g., Burns and Kedia 2006; Efendi et al. 2007; Zhang et al. 2008; Peng and Röell 2008). This study extends the literature by demonstrating that, in the context of accounting fraud, CEOs' misreporting patterns at normal incentive levels are ultimately reversed at higher levels, presumably due to their disparate tolerance as two types of equity holders. A considerable volume of studies has already reported the non-linearity of equity incentives with various research focuses such as firm-value (e.g., Morck et al. 1988) and firm-performance (e.g., Hanlon et al. 2003). However, to my best knowledge, this is the first study to show the contrasting non-linear impacts of both stocks and options *simultaneously*, and to highlight that, in the context of accounting fraud, the non-linearity is driven by the increasing risk effect of accounting fraud commitment rather than the decreasing reward effect of equity incentives. The findings should be of interest to accounting regulators who need to focus on those with a high risk of becoming offenders around accounting fraud: CEOs with average option incentives or excessive stock incentives are more likely to misreport.

Finally, Chapter 4 adds to the literature exploring the impacts of business group and *chaebol* affiliations on firms' financial reporting quality. While prior studies have shown congruent effects of control-ownership wedge, business groups, and *chaebols* using relatively indirect proxies for financial reporting quality such as discretionary accruals (e.g., Fan and Wong 2002; Kim and Yi 2006; Gopalan and Jayaraman 2012), this study extends the literature by providing new evidence that the detrimental effect of control-ownership wedge is countered by the existence of potential exposure to economic and legal cost considerations inherent to accounting fraud. This study is the first to document the distinct impacts of control-ownership wedge and business group/*chaebol* affiliation on accounting fraud propensity. My research also provides separate analyses of unregulated business groups and regulated *chaebols* by Korean government rules and reports their incremental impacts on firms' accounting fraud propensity. In particular, the findings validate the role of government regulation in curbing firms' fraudulent misreporting and provide valuable insights into the enduring popularity of large business groups as investment targets, despite the long-held concerns over their aggressiveness in earnings management (e.g., Kim and Yi 2006).

1.6. Thesis structure

The remainder of this thesis is structured as follows. Chapter 2 examines the reliability of AAERs as an accounting fraud database. Chapter 3 examines the relation between CEOs' excessive equity incentives and accounting fraud propensity in the U.S. setting and Chapter 4 investigates the impacts of business group and *chaebol* affiliations on accounting fraud propensity in Korean context. Section 5 concludes by summarising the main findings and emphasising the contributions and practical implications of this thesis.

Chapter 2

The Reliability of Accounting Fraud Databases

2.1. Introduction

The SEC is a federal agency equipped with the legal authority and expertise to investigate accounting fraud cases. Based on its credibility, its regulatory outcomes, or AAERs, have been widely adopted by researchers as one of the major accounting fraud databases (e.g., Dechow et al. 1996; Davidson et al. 2015). However, the reliability of AAERs is vigorously challenged by Karpoff et al. (2017), who show that AAERs and other financial misreporting databases capture only a narrow and limited selection of misreporting cases and, thus, that the choice of different databases may produce disparate analysis results. In fact, the SEC's resource constraints (e.g., staffing, offices, and budgets) have consistently raised concerns over the reliability of AAERs (see e.g., Richardson et al. 2002). As a constrained agency, the SEC inevitably targets only a proportion of misreporting cases, even when they have been identified by its alternative misreporting detectors (e.g., capital market investors and firms' managers)[10]. Moreover, the long-standing debate over whether government is better at detecting material accounting irregularities than market investors (see also Shleifer 2005) seriously questions the current research practice to adopt AAERs as a main proxy for accounting fraud. Since capital market investors have equally strong motivation as the SEC to identify material accounting fraud cases for their own

[10] AAERs cover only 5-12 percent of its alternative financial misreporting databases analysed in this study.

damage compensation, we cannot *ex ante* guarantee that AAERs are more likely to be composed of accounting irregularities than securities class action lawsuits. Therefore, this study seeks to provide empirical evidence responding to these doubts on the reliability of AAERs as an accounting fraud proxy.

To do this, I compare the characteristics of AAERs with those of their alternative financial misreporting databases, i.e., securities class action lawsuits (SCALs) and restatements compiled by Audit Analytics (AA). Specifically, I test whether, compared to SCALs and AA, AAERs are composed of firms that are more likely to represent material accounting irregularities, which are a main focus of accounting studies (see Hennes et al. 2008). Despite their own biases[11], SCALs and AA constitute ideal benchmarks for the comparative analyses in terms of their significance in market impact (see Dechow et al. 2010) and a wider coverage of misreporting cases (Scholz 2008, 2014) respectively.

As characteristics of material accounting irregularities, I adopt financial reporting quality prior to the incidence of financial misreporting (see Hope et al. 2013; Ettredge et al. 2010) and firms' financing needs during manipulation periods (see Dechow et al. 2011), as well as the ultimate market impact of the accounting fraud cases (see Karpoff et al. 2008a). These are main concerns of accounting research. In particular, I adopt eight different types of accruals measures (e.g., the size, reliability, or estimation errors of accruals) to mitigate the potential bias resulting from the subjective nature of *intentionality* included in the definition of accounting irregularities[12] (see also Leuz

[11] Market investors tend to file suits for cases whose potential damage compensation is expected to exceed their legal costs. They are usually the cases that have caused significant losses in stock markets (see Dechow et al. 2010). On the other hand, firms' managers weigh the costs of their admittance and concealment of financial misreporting once it is revealed by either internal control or outside auditors. Thus, cases that are trivial, or material but less likely to be detected, may be excluded from the AA sample.

[12] From Statement on Auditing Standards (SAS) No. 82 issued in 1997, AICPA distinguishes intentional

and Wysocki 2016).

Inherently, AAERs are likely to represent egregious accounting fraud cases in that they involve accountants' collusion or serious defects in the financial auditing process (see Dechow et al. 2011). To provide additional explanations for the reliability of AAERs, I investigate how the SEC utilises its constrained resources through its accounting fraud detection process. By adopting the bivariate probit regression model (see Wang 2013), which combines an accounting fraud commitment model for firms and an accounting fraud detection model for the SEC, I examine which target firms the SEC prioritises through its accounting fraud investigation process. Using a simple office allocation model, I further test which factors the SEC considered more seriously through its office reorganisation process in 2007. These analyses help validate the SEC's ability to deal with its resource constraints.

Using comprehensive samples covering three financial misreporting databases for the fiscal years 1992-2012, I provide consistent evidence supporting the relative reliability of AAERs as an accounting fraud database. To begin, I find that, compared to SCALs and/or AA, AAERs are indeed composed of firms that are more likely to represent material accounting irregularities, which are characterised by aggressive adoption of accruals, strong financing needs, and significant market impact of misreporting cases. These findings imply that, as prior studies have correctly assumed (e.g., Dechow et al. 1996), AAERs effectively cover egregious accounting fraud cases rather than simple errors. These results also provide valuable insights into the long-standing debate on whether government is better at detecting accounting irregularities

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and unintentional financial misreporting using the terms "fraud" and "errors", instead of irregularities and errors. However, to maintain consistency with prior studies (e.g., Hennes et al. 2008) and to avoid confusion with a widely accepted usage of accounting fraud (e.g., Beasley 1996; Crutchley et al. 2007; Erickson et al. 2006; Khanna et al. 2015; Gao et al. 2017), I adopt accounting irregularities and errors to represent intentional and unintentional financial misreporting respectively.

than markets themselves, which have equivalently strong motivation to do so for their own damage compensation.

I further find that firms without unqualified audit opinion or young growth firms (see Beneish 1999), whose likelihood of misreporting is higher than other firms, are associated with a higher propensity for detection by the SEC. In addition, firms with large asset sizes or Fortune 500 firms, whose impact on the economy would be more significant once accounting fraud is committed, are also more frequently detected by the SEC. These investigation targets are high-risk and systematically important firms that may increase the SEC's chances of detecting material accounting irregularities with its limited resources (e.g., budgets). These findings indicate that the SEC may indeed have the ability to mitigate potential inefficiencies inherent in its accounting fraud detection process.

I also find that states with higher firm population and larger firms tend to have regional offices[13] of the SEC. In fact, in 2007, the SEC elevated six district offices to regional offices, most of which were in states with higher firm population and with larger firms. If SEC enforcement were indeed less effective where it is not "local" (Kedia and Rajgopal 2011), it would be a reasonable decision for the SEC to deploy its major offices in this way. The potential geographic bias then might apply mainly in states where firms are less populated and relatively small firms are located. This finding provides evidence suggesting that the SEC effectively mitigate the potential geographic bias by optimising its utilisation of limited regional offices.

Finally, two additional analyses provide supporting evidence that the SEC's focused investigation targets and office reorganisation improve the reliability of AAERs. For

[13] Until 2007, the SEC had a three-tier hierarchy structure of offices consisting of its headquarters, regional offices, and district offices in order. Offices in upper tiers have more authority in administering the SEC program.

instance, I find that the SEC's targeted firms are associated with lower financial reporting quality and greater financing needs. I further find that AAER firms in the states where the reorganisation occurred have higher levels of discretionary accruals than AAER firms in other states. These results imply that the strategic utilisation of constrained resources may enable the SEC to effectively prioritise material accounting irregularities over simple errors.

Overall, these findings together suggest that, despite evidently partial coverage of misreporting cases, AAERs are a reliable database broadly representing material accounting irregularities, and the relative reliability of AAERs can be at least partly explained by the SEC's approaches in utilising constrained resources.

The main contributions of this research are as follows. To begin, this is one of the limited studies explicitly investigating heterogeneities of financial misreporting databases including accounting fraud[14]. Most prior studies have provided fragmented evidence and, only recently, a few papers explicitly focus on this issue. First, studies have revealed some characteristics of different misreporting databases incidental to their main research focuses. For example, while investigating the political bias of SEC enforcement, Correia (2014) shows that restatement firms with higher accruals are more likely to be sanctioned by the SEC, implying that SEC enforcement cases may have higher levels of accruals than average restatement cases. In her study investigating the SEC leniency program, Files (2012) further reports that securities class action lawsuits filed against restatement cases have a positive association with

[14] Due to the lack of thorough analyses on this issue, research practices of the accounting fraud literature are divided: some studies aggregate different misreporting proxies in an effort to decrease Type II error (e.g., Dyck et al. 2013; Khanna et al. 2015), others have analysed them separately and found similar and/or different empirical findings in respective research contexts (e.g., Armstrong et al. 2010; Bentley et al. 2013; Davidson et al. 2015; Cao et al. 2015).

SEC enforcement, implying that SEC enforcement cases may have more similar characteristics to lawsuits than to restatements.

Second, more recent attention has been paid to the explicit comparison between different misreporting databases. Choi and Pritchard (2016), for example, directly compare AAERs with securities class action lawsuits using information asymmetry measures (e.g., changes in earnings response coefficients) and argue that the market perceives greater information asymmetry for lawsuits than AAERs. Most recently, Karpoff et al. (2017) investigate the *scopes* of different financial misreporting databases and argue that each misreporting database captures only a narrow and limited selection of misreporting cases. They additionally provide some preliminary analysis results of average changes in six firm characteristics (e.g., working capital accruals and ROA) between prior to misreporting year (*t-1*) and misreporting year (*t*), and argue that analyses using different databases may produce disparate results.

This study is different to these preceding examples in that I compare misreporting databases from the perspective of their reliability as accounting fraud databases using major accounting irregularity proxies (e.g., accruals and financing needs), which are main concerns of accounting research. In particular, this study complements Karpoff et al. (2017)'s recent finding by showing that, despite the partial coverage issue that they raised, AAERs still constitute a relatively reliable accounting fraud database. By mainly focusing on the comparison of AAERs and SCAL, the results further provide a valuable insight into the long-held debate on whether government (i.e., the SEC) is better at identifying accounting irregularities than markets themselves (i.e., investors) (see also Shleifer 2005). Again, since capital market investors have similarly strong motivation to the SEC as an accounting fraud detector, we cannot *ex ante* guarantee that AAERs will be more composed of accounting irregularities than SCAL.

This study further contributes to the literature exploring SEC enforcement and its potential biases (see also Leuz and Wysocki 2016). Kedia and Rajgopal (2011) document that SEC enforcement is geographically biased due to its resource constraints, and Correia (2014) argues that the SEC is captured by firms' political influence. On the contrary, Files (2012) and Kedia et al. (2015) show that the SEC' leniency program and "revolving door" for trial lawyers do not cause serious bias to SEC enforcement actions. More recently, Heese et al. (2017) contradicts Correia (2014) by reporting that firms' political connections instead increase the SEC's comment-letter reviews. This study particularly extends Kedia and Rajgopal (2011) by demonstrating that the SEC has the ability to mitigate potential geograpghic bias by locating its regional offices mainly where larger firms are more populated. Contrary to Kedia and Rajgopal (2011), I contend that the geographic bias does not seriously matter since it is prevalent mainly for smaller firms in states where firms are less populated.

The remainder of this chapter is structured as follows. Section 2.2 summarises prior research. Sections 2.3 discusses relevant theories and hypotheses. Section 2.4 describes data and research design. Sections 2.5, 2.6, and 2.7 provide empirical results, a battery of additional analyses and robustness checks respectively. Section 2.8 concludes.

2.2. Review of related literature

2.2.1. SEC enforcement[15]

This study examines the reliability of AAERs as an accounting fraud database. The efficacy of SEC enforcement is one of the main dimensions that may affect the characteristics of AAERs. From the perspective of the economics of government regulation, a number of studies have reported that the SEC's regulatory process is biased toward the inclusion of certain target firms. For instance, Kedia and Rajgopal (2011) find that the SEC has a geographic bias. Using distance measures between firms' headquarters and SEC offices, they show that SEC enforcement is not effective in deterring financial misreporting for firms located far from SEC offices. Maguire (2009) further finds that, among foreign registrants, the SEC focuses on firms that have more significant effects on U.S. markets. In particular, firms from countries whose firms are registered in the U.S. at a higher rate than other countries are more likely to be sanctioned by the SEC. Other studies show that SEC enforcement is affected by the political influence of its regulated firms. Using Political Action Committee (PAC) data, Correia (2014) reports that firms that contribute more funds to politicians are less frequently sanctioned by the SEC. In a similar vein, Blackburne (2014) finds that firms' political contributions are likely to decrease the SEC's budget allocation for staffs regulating those firms, and Yu and Yu (2011) also find that, among private civil lawsuits, lobbying firms are less likely to be detected by the SEC. More recently, Heese (2015) documents that the SEC is less likely to file cases for firms that have

[15] I do not review literature that investigates the effectiveness of specific enactments such as Statement of Financial Accounting Standard (SFAS) No. 133 and No. 158 (e.g., Zhang 2009; Choi et al. 2014), or U.S. insider trading laws (e.g., Guercio et al. 2017), because they do not directly relate to the SEC's enforcement activities that consume its constrained resources.

more employees, i.e. potential voters, and, particularly in presidential election years, the SEC is less likely to detect fraud cases in "politically important states".

Conversely, there is a strand of literature that explores the efficacy of the SEC's regulation. Kedia and Rajgopal (2011) themselves, for example, report that past-year sanctions by the SEC in a given county are likely to decrease the restatement propensity of firms in that county in subsequent years. This finding implies that SEC enforcement is effective in deterring financial misreporting at least when firms have regulation experience in their regions. Blackburne (2014) also documents that the SEC's increased oversight, measured by the budget per regulated firm allocated to each office in the Division of Corporate Finance[16], is likely to decrease firms' accruals management and restatements. In particular, Baugh et al. (2017) and Bozanic et al. (2017) find that the SEC's 10-K review process tends to improve firms' financial reporting quality as measured by follow-up restatements and their disclosure quality (proxied by a qualitative composite measure) respectively.

On the other hand, Files (2012) provides an explanation for the ambiguity in the prior literature by showing that the SEC's leniency program may not cause serious bias in the coverage of SEC enforcement. Firms that cooperated with SEC investigation are in fact more often sanctioned by the SEC; they are instead rewarded by decreased monetary penalties. Similarly, Kedia et al. (2015) show that the "revolving door" for trial lawyers in the SEC does not cause serious bias to SEC enforcement actions, and Heese et al. (2017) also document that firms' political connections rather increase the SEC's comment-letter reviews. These findings together suggest that, despite potential biases in SEC enforcement, the SEC effectively mitigates their effects.

[16] The Division of Corporate Finance of the SEC is in charge of reviewing firms' financial statements.

2.2.2. Financial misreporting firms

Ever since Dechow et al. (1996), extensive studies have explored the characteristics of financial misreporting firms. In particular, a large body of literature has provided strong empirical evidence that accruals are positively associated with firms of all financial misreporting types (see Jones et al. 2008). For example, Perols and Lougee (2011), Chalmers et al. (2012) and Ettredge et al. (2010) show that high levels of accruals in prior years are likely to lead to incidences of AAERs, securities class action lawsuits and restatements in succeeding years. Between misreporting types, slight differences are observed. While AAERs are most widely analysed in the context of accruals management, private civil lawsuits and restatements are relatively less researched. A plausible reason is that the effects of accruals on private civil lawsuit and restatement propensities would be less substantial than those of AAERs. In fact, Jones et al. (2008) show that, in their restatement sample (25 firm-years), only Dechow and Dichev (2002)'s accrual estimation errors have statistically significant associations with restatements, while a wider range of accruals (10 types) have statistically pronounced associations with AAERs. Ettredge et al. (2010) and Hayes (2014) further argue that more intentional restatement cases are likely to have higher levels of accruals than simple error restatements.

A substantial literature has further documented that firms tend to misreport to attract external financing at low costs (Dechow et al. 2010). Dechow et al. (1996), McTier and Wald (2011) and Richardson et al. (2002) all show that misreporting firms largely have higher levels of both issuance of stocks/bonds and capital expenditure across all misreporting types. However, the details of analyses differ depending on the samples adopted by each study. While Dechow et al. (1996) find that AAER firms have higher levels of financing needs using data between 1978 and 1990, Beneish (1999), using data between 1987 and 1993, does not find any statistically significant effects of firms' financing needs on AAERs. However, using a more comprehensive sample of AAERs between 1971 and 2003, Dechow et al. (2011) again show that AAER firms have higher levels of actual issuance of both stocks and bonds (see Dechow et al. 2010). On the other hand, they do not find any difference in the levels of capital expenditure between AAER and non-AAER firms. These findings imply that the funds raised in AAER firms may not be intended for use in long-term investments.

2.3. Theory and hypothesis development

2.3.1. The economics of regulation

The economics of government regulation is broadly divided into two strands of theories (see also Blackburne 2014). To begin, the *no-effect hypothesis* (see Jordan 1972) suggests that the SEC might not be an effective accounting fraud detector. Two factors support this view. A limited budget is a crucial factor that may decrease the regulatory efficacy of the SEC (see Dechow et al. 2010; Richardson et al. 2002). Given this budget constraint, the SEC may target firms for which it is likely to file cases successfully. Thus, financial misreporting cases that are a material violation of GAAP but whose chances of prosecution are likely to be low may be dropped during the investigation process. The capture theory further suggests that the SEC is a "self-interested utility maximiser" (Blackburne 2014). Becker (1983) articulates that, due to their self-interested nature, government regulations serve to maximise the "welfare of more influential pressure groups" rather than that of the general public (see also e.g., Correia 2014; Heese 2015).

On the contrary, the *optimal intervention hypothesis* (see Joskow and Rose 1989; Posner 1974) suggests that the SEC conducts its role as an accounting fraud detector effectively by properly addressing potential biases resulting from its constrained resources. This view is based on the public interest theory stating that government is both “benign” and “capable” of regulating firms (Shleifer 2005). The two potential properties are formed institutionally. First, the SEC is forced to be in good faith by the tight control of Congress and the media. Its budget, operation, and regulatory outcomes are all subject to their monitoring (see The SEC 2016). Second, the SEC’s capability as an accounting regulator is supported by its organisational and legal institutions. The SEC is staffed with skilled professionals and endowed with due authority to conduct its regulatory roles[17].

2.3.2. The reliability of AAERs

By design, AAER firms are likely to be egregious cases in that they potentially involve critical defects in the financial auditing process or accountants’ collusion. AAERs were originally a secondary designation for enforcement cases involving *mostly* accountants (see Dechow et al. 2011; Karpoff et al. 2017). Moreover, given the *optimal intervention hypothesis*, it would be also an obvious expectation that AAERs, the regulatory outcomes of the SEC, may effectively include intentional and egregious

[17] The Enforcement Division of the SEC is composed of skilled accountants and attorneys with at least two to five years of prior experience (See https://www.sec.gov/enforce/Article/enforce-about.html), and is supported by other divisions in the SEC’s headquarters in Washington DC and 11 regional offices staffed with 4,554 full-time employees as of 2016. The Corporate Finance Division, in particular, supports the Enforcement Division by reviewing the financial statements of firms (Dechow et al. 2011). Moreover, the SEC’s legal rights to investigate cases and collect official evidence from firms and witnesses (e.g., subpoenas) compensate its constraints and differentiate it from other fraud detection channels (Bremser et al. 1991; The SEC 2005).

misreporting cases. Material accounting irregularities may have three main attributes that distinguish them from simple errors or subtle cases.

First, accounting irregularity firms would have lower levels of financial reporting quality prior to the incidence of financial misreporting. Frequent and high levels of accruals are usually considered to represent managers' opportunistic intent to misreport because accruals, in and of themselves, involve managerial discretion (see Richardson et al. 2006; Ettredge et al. 2010). The mechanisms by which accruals lead to accounting irregularities are twofold. Accruals are directly used to misreport during the manipulation period (Dechow et al. 2011; Jones et al. 2008), and the reversal mechanics of accruals over time cause financial misreporting by decreasing the capacity of firms to manage their earnings within legitimate boundaries (see Dechow et al. 1996; Beneish 1997; Ettredge et al. 2010; Dechow et al. 2012). In this chapter, I focus on the effects of prior-year adoption of accruals on future financial misreporting (see Perols and Lougee 2011; Ettredge et al. 2010). If current-year financial misreporting were intentional, accounting irregularity firms would have adopted abnormal levels of accruals compared with error or subtle misreporting cases.

Additionally, accrual reliability measured by respective components of accruals can also be used as a proxy for the intentionality of financial misreporting (see Richardson et al. 2005; Richardson et al. 2006). For example, while working capital is frequently used to manage earnings for its ease of manipulation (Ettredge et al. 2010), non-current operating assets are known to be relatively difficult to manage[18] since the depreciation mechanism is rather transparent (Barton and Simko 2002; Dechow et al. 2011). In particular, the increase in less reliable current working capital accruals is a signal of

[18] According to Richardson et al. (2005), however, fixed assets also could be adopted as an aggressive earnings management strategy, as in WorldCom's case by capitalising PP&E.

intentional income-increasing activities (Richardson et al. 2005). Given these considerations, I hypothesise that, compared to SCAL and AA firms, AAER firms would have higher levels of accruals and lower levels of accrual reliability. Thus, the first two hypotheses of this study are as below.

H1: AAERs are likely to be composed of firms that have adopted accruals than SCALs and AA.

Second, accounting irregularity firms would have greater financing needs because firms tend to misreport to attract external financing at low costs (Dechow et al. 2010). Financial ratios are a key consideration of lenders through their credit screening process (see Dimitras et al. 1996). Despite some limitations[19], financial ratios have been considered to be critical in addressing information asymmetry between creditors and debtors due to their strong predictive power regarding business failures and simplicity (see Emel et al. 2003). Among various financial factors, firms' profitability and liquidity are two main considerations that credit screening models have commonly adopted (Courtis 1978). In this vein, firms with more opportunistic intentions around financial misreporting are likely to have greater financing needs.

H2: AAERs are likely to be composed of firms that have stronger financing needs than SCALs and AA.

[19] The predictive power of financial ratios is affected by non-financial attributes of firms such as managerial and industry characteristics, macroeconomic conditions, and firms' financial misreporting (Emel et al. 2003).

Third, material financial misreporting cases would have a more significant impact on stock markets once disputed misreporting is revealed to the public. Accounting fraud firms are known to experience a drastic drop in stock returns (approximately 10 percent) after their financial misreporting is revealed to the public by the media or the SEC (Feroz et al. 1991; Dechow et al. 1996; Karpoff et al. 2008a). The impact of fraud announcement on stock returns is mainly caused by the disparity between investors' outdated perception of firm value constructed by misreported earnings and their more accurate one adjusted by the new information regarding potential misreporting (see e.g., Fama et al. 1969). In this study, the market impact of financial misreporting is measured by observing whether securities class action lawsuits are filed and ultimately settled for misreporting firms (see Hennes et al. 2008)[20]. Given that securities class action lawsuits are filed based on the actual losses incurred to plaintiffs and their reasonable conclusions on defendant firms' scienter (Ramphal 2007; Poser 2008), firms with material financial misreporting are ultimately more likely to be sued by market investors. Therefore, the initiation and settlement of private civil lawsuits implies that firms' financial misreporting caused significant impact to stock markets.

H3: AAERs are likely to be composed of firms for which securities class action lawsuits are filed more than for AA firms.

[20] I do not adopt stock returns data because changes in stock returns on the official release dates of three misreporting types cannot be directly compared due to potential endogeneity issues. For example, they are released by detectors with different credibility, and disputed misreporting cases are under distinct levels of investigation. In particular, the courts' discovery process begins only after class action civil lawsuits are initiated, whereas the SEC have already investigated AAERs for 2-3 years.

2.3.3. Fraud detection process and office reorganisation decisions

To effectively cover material accounting irregularities in AAERs with its constrained resources, the SEC can be expected to utilise these resources in a strategic way. For instance, the SEC may narrow down targets through its accounting fraud investigation process to reduce potential inefficiencies in the process (see also Bremser et al. 1991). First, if the SEC cannot investigate all disputed misreporting thoroughly, it would be an inevitable and reasonable strategy for the SEC to investigate high-risk firms, whose likelihood of misreporting is higher than other firms. Indeed, the SEC is known to target, for example, young growth firms because they likely have stronger motivation to misreport due to their potentially higher levels of financing needs (Beneish 1999). Second, it would also be an optimal decision for the SEC to investigate systematically important firms, whose impact to the public would be greater once accounting fraud is committed. For one thing, the SEC is known to target for sanctions firms with higher visibility such as Fortune 500 firms (Correia 2014).

Finally, as additional evidence of the SEC's strategic utilisation of its constrained resources, the SEC may allocate its regional offices so that it can mitigate the potential geographic bias and facilitate the detection of material accounting irregularities. According to Kedia and Rajgopal (2011), firms are more likely to commit accounting fraud when they are located far from SEC offices because they believe that the resource-constrained SEC may not easily detect misreporting in their regions. They empirically demonstrate that firms' spatial distance from the SEC is positively associated with their misreporting deviations[21] (or fraud rates). However, if the

[21] The difference between a county's share of restatements from total number of restatements and its share of firms from total number of firms.

optimal intervention hypothesis holds, the SEC may have instituted remedies to mitigate this potential bias.

Based on the review of its enforcement program, the SEC has reorganised the structure of its offices - headquarters, regional offices, and district offices - by adding or closing offices, and changing their levels in the three-tier hierarchy[22]. However, the specific mechanism through which the SEC's office decisions are made has been a black box to the public. During the sample period of this study (1992-2012), there was one closure, of the Seattle district office (WA) in 1994, and two changes in office levels between regional offices and district offices in 1993 and 2007. Due to data availability, the only testable office reorganisation is the first elevation of six district offices to the upper tier of regional offices (major offices) in 2007 following the last change in 1993 (see also Kedia and Rajgopal 2011). A plausible strategy for the constrained SEC would have been to deploy its regional offices in states where regulatory demand is higher, or where regulated firms are more populated. Through this optimisation, the SEC may mitigate the geographic bias so that it is mainly observed in states where firms are relatively less populated. Taken together, the final hypotheses of this study are as below.

H4: The SEC is likely to have instituted remedies to address its resource constraints by (for example):

[22] Regional offices report directly to SEC headquarters, and district offices assist regional offices in administering SEC programs (see 17 CFR 200.11 and §200.27 2007).

H4a: having focused investigation targets, whose likelihood of misreporting is higher or whose market impact would be more significant once accounting fraud is committed.

H4b: allocating its regional offices in states with higher firm population.

2.4. Data and research design

2.4.1. Data and sample selection

The sample selection process is summarised in Table 2.1. The base sample is chosen from the Compustat database, resulting in 179,929 firm-years from 1992 to 2012 after excluding financial firms[23] and firms without 10 year-industry observations. The minimum requirement of 10 observations is set in order to obtain sufficient data to estimate accrual measures as in Jones et al. (2008). Three different types of fraud database are then merged with the base sample. The merged fraud observations are 1,237 for AAERs compiled by the Center for Financial Reporting and Management (CFRM) (Dechow et al. 2011); 1,488 for SCALs collected from Securities Class Action Clearinghouse established by the Stanford Law School; and 14,499 for AA complied by Audit Analytics. Dismissed or ongoing SCAL cases are deleted to mitigate the risk of analysing frivolous lawsuits (see Donelson et al. 2013), and SCAL cases that are not relevant to financial misreporting or disclosure issues are also not included in the sample.

The sample starts from 1992, which is the common first misreporting year of the three databases. The terminal year 2012 is determined so that each misreporting

[23] I exclude financial firms because their main accruals type (i.e., loan loss provision) is different from that of manufacturing firms.

detection channel would have had enough time to detect cases. However, I also analyse a sub-sample for the years 2000-2012 for all three categories of misreporting case in order to have a sufficient number of samples (see Panel B in Table 2.1). The analysis results do not differ by the sampling periods.

SCALs and AA in this chapter are financial misreporting cases that are *exclusively* detected by market investors and firms' managers respectively (Figure 2.1). This process ensures that we do not compare AAERs with themselves if they belong to more than one misreporting category simultaneously, and provides the chance to contrast the characteristics of AAERs with misreporting cases that are not included in AAERs. AAERs, SCALs, and AA commonly include non-misreporting firm-years for each misreporting firm. On the other hand, the duplications among different databases are analysed separately to test whether the analyses of this study are consistent with those of prior studies. Since prior research largely aimed to analyse accounting irregularities from their original samples by choosing cases that are closer to AAERs in nature (see e.g., Hennes et al. 2008; Hayes 2014), I expect that the duplications would show similar analysis results to those of AAERs.

2.4.2. Financial misreporting databases

AAERs have generally been considered to be an appropriate sample for analysing intentional violations of GAAP (Dechow et al. 2011). AAERs are the result of the SEC's official investigation process, which is supported by due organisational and legal institutions, and the standardised enforcement process of the SEC tends to ensure homogeneous misreporting cases (e.g., types of GAAP violations and their intentionality). However, its enforcement process is potentially biased due to its constrained resources. Considering its costly investigation process, the SEC is likely to focus on more overt cases when instituting regulatory processes (Dechow et al. 1996; Richardson et al. 2002). Potential interference from external influential groups including regulated firms themselves is another concern regarding this database (see Becker 1983; Correia 2014).

SCALs include most misreporting cases that generated critical damages for market investors. These cases are chosen by investors themselves in consideration of the potential monetary compensation and costs of suits. As with the definition of accounting fraud (SAS No. 99), SCALs also assume the scienter of accused firms (Ramphal 2007; Poser 2008). However, SCALs are distinguished from AAERs in that private civil lawsuits are only instituted when plaintiffs suffered significant losses regarding their purchases and sales of securities; material accounting irregularities that did not cause significant losses to investors are thus not included in this sample. The possibility that investors may file suits to extract funds from the legal process without sufficient grounds to prove the scienter of accused firms is a major concern of this sample. In fact, the majority of SCAL cases are settled based on firms' insurance policies before courts even initiate their due discovery process (see Khanna et al. 2015). Thus, despite the enactment of the Public Securities Litigation Reform Act (PSLRA) in 1995, frivolous lawsuits are still a potential bias in this sample. To mitigate this concern, dismissed cases are usually excluded from analyses (see Alexander 1991; Wang et al. 2010; Donelson et al. 2013).

Finally, AA includes "nearly" all restatement cases filed with the SEC since 2000, except some cases resulting from adopting new accounting standards (see Scholz 2008, 2014). Restatement decisions are made by managers after weighing the costs of concealment and admission. Since restatement does not consider the intentionality of misreporting, it includes virtually all GAAP violations screened by managers based on their own cost-benefit analyses. Large sample size is one of the main benefits of this database. However, the large sample size inevitably entails a potential bias. In contrast to AAERs and SCALs, which mainly target intentional misreporting cases, AA includes both accounting irregularities and simple errors (Hennes et al. 2008). Since these potential heterogeneities may decrease the power of empirical analyses, studies have paid attention to the sample selection issue of restatement databases (see Dechow et al. 2011)[24].

2.4.3. Descriptive statistics

Descriptive statistics of the total Compustat observations and each misreporting category are reported in Table 2.2. *t*-tests and Wilcoxon rank-sum (WRS) results in Columns between (1) and (6) reveal that misreporting firms are larger in asset size and listed more frequently on major stock markets than the average Compustat observations. Among the three categories, AAER and SCAL firms show such size and market characteristics more strongly. Reflecting SCALs' composition of securities suits, SCAL firms are listed more on major stock markets than other two misreporting types. Furthermore, AAER and SCAL firms also show higher levels of total accruals (*RSST*) and *Actual issuance*, implying that these firms are likely to have higher levels of motivation to misreport.

Contrary to AAER and SCAL samples, AA firms show rather lower levels of *RSST* than the Compustat population. The heterogeneities among different fraud categories are explored in more detail using multivariate analyses in the following sections. The

[24] In contrast to Kedia and Rajgopal (2011) and Correia (2014), I do not adopt Karpoff et al. (2017)'s hand-collected securities enforcement data because the research focus of this study specifically concerns the reliability of AAERs as an accounting fraud database.

characteristics of AAER firms are largely consistent with those found in Dechow et al. (2011).

2.4.4. Accounting fraud model

To maintain consistency with prior literature, I adopt the accounting fraud model proposed by Dechow et al. (2011). This model assumes that accounting fraud firms misreport to improve their earnings (*ROA (change)*) and to finance stocks and bonds at low costs (*Actual issuance*). It further assumes that accounting fraud firms are likely to utilise *RSST*, accounts receivable (*Receivables (change)*), soft assets (*Soft assets*), and even cash sales (*Cash sales (change)*) as earnings management strategies. To accommodate the optimistic prospects of accounting fraud firms, it further incorporates the rates of inventory increase (*Inventory (change)*). As in Eq. (2.1), the base model is then extended by incorporating additional controls such as *Ln*(*Assets*), *Leverage*, *Stock market*, and year and industry fixed effects adopted in major literature (e.g., Dechow et al. 1996; Khanna et al. 2015). *Ln*(*Assets*) and *Stock market* are adopted since large and listed firms are more likely to be tightly monitored by market participants (Hope et al. 2013), and it is thus more difficult for these firms to misreport. On the other hand, firms' listing status may be associated with firms' opportunistic motivation to finance from stock markets (McTier and Wald 2011). *Leverage* also has rather ambiguous implications. While high leveraged firms are more likely to be tightly bounded by creditors (Lee 2011), they also may have greater motivation to misreport to avoid debt covenant violations (Dechow et al. 1996).

Following Dechow et al. (2011), I adopt *RSST* as a main financial reporting quality measure. In addition to current working capital accruals, *RSST* includes non-current operating and financial accruals (Richardson et al. 2005). After testing various types of accruals, Dechow et al. (2011) find that *RSST* is better at predicting accounting fraud propensity. To avoid arbitrariness, however, I additionally estimate Eq. (2.1) using a wide range of alternative proxies for financial reporting quality (e.g., working capital accruals, components of accruals and discretionary accruals). To capture their accumulated reversal effects, accrual measures are mainly tested after aggregating three years of accruals (see e.g., Ettredge et al. 2010; Perols and Lougee 2011). Contemporaneous and lagged accruals, however, produce largely similar results. In addition, Eq. (2.1) incorporates *Actual issuance* to provide additional evidence that AAERs are composed of accounting irregularity firms whose financing needs are higher during the manipulation period (Dechow et al. 2011). The details of financial reporting quality and financing needs measures are explained in Appendix 2.A.

In particular, to capture the changing accounting fraud risk by time, I use the simple hazard model suggested by Shumway (2001) and employed by Davidson et al. (2015) in accounting fraud literature. According to Shumway (2001), the simple hazard model is estimated using a discrete-time logit program. Contrary to conventional binary models that use only single-point data for estimation (e.g., a year before the incidence of accounting fraud), the simple hazard model utilises all available data before the incidence of fraud and, therefore, considers the fact that the accounting fraud risk of a firm varies with time, conditional on the time spent without committing fraud.

$$
\begin{aligned}
Ln[F_t / (1-F_t)] = {} & \alpha_0 + \alpha_1 \mathit{Financial\ Reporting\ Quality} \\
& + \alpha_2 \mathit{Actual\ issuance}_t + \alpha_3 \mathit{Receivables\ (change)}_{t-1} \\
& + \alpha_4 \mathit{Inventory\ (change)}_{t-1} + \alpha_5 \mathit{Soft\ assets\ (change)}_{t-1} \\
& + \alpha_6 \mathit{Cash\ sales\ (change)}_{t-1} + \alpha_7 \mathit{ROA\ (change)}_{t-1} + \alpha_8 \mathit{Ln(Assets}_{t-1}\mathit{)} \\
& + \alpha_9 \mathit{Leverage}_{t-1} + \alpha_{10} \mathit{Stock\ market}_{t-1} + \sum\alpha \text{Year dummy} \\
& + \sum\alpha \text{Industry dummy} + \sum\alpha \text{Duration dummy} + \varepsilon_t \qquad (2.1)
\end{aligned}
$$

Where:

$F_t / (1 - F_t)$ = the probability of fraud commitment at time *t* conditional on non-fraud incidence to *t*.

2.5. Main findings

2.5.1. Univariate and graphical analyses

The pairwise correlation analyses in Table 2.3 show that, compared to SCALs, AA, and the total Compustat population, AAER firms are associated with higher levels of both *RSST*[25] prior to the incidence of each misreporting type and *Actual issuance*[26] during manipulation periods (Columns (1)-(3)). Since accruals have reversal effects on firms' financial misreporting (Lee et al. 1999), an insignificant contemporaneous difference in *RSST* between AAER and SCAL firms (Column (1)) does not necessarily mean that AAER firms are not actively involved in accruals management. On the contrary, a string of consecutive positive signs of *RSST* in the comparative analyses implies that AAERs are composed of firms that managed accruals more aggressively than the SCAL, AA, and Compustat populations. These findings provide preliminary evidence supporting *H1*.

The univariate analyses, however, still do not provide conclusive evidence that AAERs are more likely to include accounting irregularities. The results may be biased due to potentially omitted variables or the SEC having failed to detect accounting fraud cases (see Wang 2013). We cannot clearly know what the proportion of undetected cases might be (see Dyck et al. 2013). The following subsections attempt to provide

[25] Correlation analyses of seven additional types of accruals show qualitatively the same results.
[26] The negative signs of *Capital expenditure* will be explained in following sections.

supporting and additional evidence for the reliability of AAERs as an accounting fraud database by investigating whether the univariate correlations are susceptible to the inclusion of additional controls, and whether the SEC's potential bias may reduce the reliability of AAERs.

Before conducting multivariate analyses, simple but intuitive graphical analysis results are presented in Figure 2.2. The first plot illustrates the comparative trends of discretionary accruals measured by *PMJONES* of three misreporting types. The trend of AAER firms is similar to those presented by Dechow et al. (1996) and Richardson et al. (2006). The discretionary accruals of AAER firms gradually increase over three years before the incidence of financial misreporting, and the increasing trends of discretionary accruals are then drastically reversed after the first misreporting year, implying that the reversal effects of accruals would create pressure leading to fraudulent misreporting (Dechow et al. 2012).

Additionally, I overlay two trends of discretionary accruals of SCAL and AA firms.

First, SCAL firms show a similar trend with that of AAER firms, but the magnitude of discretionary accruals is much smaller. AA firms, on the other hand, show different patterns in that not only are their discretionary accrual levels much smaller than those of both AAER and SCAL firms, but they also still show increasing patterns of discretionary accruals even after financial misreporting, implying that AA firms may have not fully consumed their capacity for accruals management at the time of misreporting. These distinct patterns also support *H1* in suggesting again that AAERs are composed of firms whose financial reporting quality is relatively lower than those of SCALs and AA.

The second plot of Figure 2.2 further provides an explanation for why prior studies have produced largely similar results on the association between discretionary accruals and three distinct types of misreporting categories (e.g., Perols and Lougee 2011; Chalmers et al. 2012; Ettredge et al. 2010), despite their potential heterogeneities. Differently from SCALs and AA, which exclude duplications with AAERs, AAER-SCAL and AAER-AA firms in the graph are composed of duplications of AAERs with private civil lawsuit and restatement firms respectively. Notably, the trends of discretionary accruals in these three misreporting samples become broadly similar to each other. A likely explanation is that, through a careful sampling process, studies adopting private civil lawsuit and restatement cases have tended to analyse "accounting irregularities" and "aggressive accounting" that are closer in nature to AAERs (see Zhang et al. 2008; Hennes et al. 2008)[27]. Taken together, the initial analyses provide preliminary evidence that lower levels of financial reporting quality are mainly characteristic of AAERs, rather than SCALs and AA.

2.5.2. Financial reporting quality and financing needs

To test whether the univariate analyses are susceptible to the inclusion of additional controls, I first conduct comparative analyses of AAERs with both SCAL and AA firms after controlling for variables that prior studies have commonly adopted in accounting fraud models (Eq. (2.1)). These analyses attempt to test whether AAERs are a reliable database for material accounting irregularities, despite their evidently partial coverage of misreporting cases. Table 2.4 consistently reports that, compared to SCALs and AA, AAER firms are associated with higher levels of six types of total and discretionary accruals (Columns (1)-(6) in Panel A and Columns (3)-(8) in Panel B) and lower accruals reliability (Columns (1)-(2) in Panel B) prior to the incidence

[27] See also Efendi et al. (2007), Harris and Bromiley (2007), and Scholz (2008). Specifically, O'Connor et al. (2006) analyse restatement cases that were investigated by regulatory agencies to exclude unintentional restatements.

of accounting fraud. These results are consistent with *H1*. Columns (1)-(8) in Panel A and Panel B further report that AAER firms have financing needs that are similar to those of SCAL firms but stronger than those of AA firms during the manipulation period. These findings support *H2*.

As other symptoms of lower financial reporting quality, I find two additional heterogeneities in firm characteristics among three misreporting types. AAER firms show higher levels of *Receivables (change)* than AA firms, and higher levels of *Soft assets* than both SCAL and AA firms. These findings also provide supporting evidence that AAER firms are more likely to manage their earnings aggressively than firms in other categories. Accounts receivable is, for example, directly adopted by firms that manage earnings through "trade-loading" and "premature revenue recognition" (Richardson et al. 2005). Similarly, firms are more easily able to manage their earnings by changing assumptions and forecasts on *Soft assets* like accounts receivable and inventory than property, plant, and equipment (PP&E) (see Dechow et al. 2011; Barton and Simko 2002).

The only exception to the trend of lower levels of financial reporting quality in AAER firms is the estimation outcome when adopting Dechow and Dichev (2002)'s analysis of accrual estimation errors (*SDD*)[28]. Columns (7) and (8) in Panel A demonstrate that AAER firms merely show similar levels of *SDD* to both SCAL and AA firms. A plausible reason for this exception is that, contrary to other types of accruals, *SDD* is estimated from the relation between working capital accruals and cash flow from operation (*CFO*) of lagged (*t-1*), contemporaneous (*t*), and lead (*t+1*) points of time (Dechow and Dichev 2002). Therefore, the relatively lower *SDD* of

[28] This finding is consistent with Jones et al. (2008), who show that restatements have an association with only *SDD* among accrual types.

AAER firms may result from their cash flow levels. Based on the assumption that cash flows are not strongly affected by firms' earnings management (Burgstahler et al. 2006), Dechow and Dichev (2002) suggest that the mismatch between cash flows and accruals represents a lower quality of accruals. However, if firms manage both accruals and cash flows simultaneously to mask their financial conditions, *SDD* may overestimate the accrual quality of more opportunistic firms. In fact, the analysis results of *CFO* of three misreporting types reveal that AAER firms are more likely to have high levels not only of accruals but also cash flows than SCAL and AA firms (Columns (1) and (2) in Table 2.5). These findings are consistent with those of Dechow et al. (2011), who show that AAER firms have an increasing trend of both accruals and cash sales. Taken together, the relatively lower levels of *SDD* also support the opportunistic nature of AAER firms.

2.5.3. Market impact

To test whether AAERs are composed of firms that caused more significant market impact than SCALs and AA, I further examine whether more securities class action lawsuits (*Lawsuits*) are initiated and ultimately settled for AAERs than for AA firms. Given that a comparison of stock returns on release dates of different types of misreporting is not feasible (see footnote 20), the filing of lawsuits provides an ideal alternative. Since private civil lawsuits are filed based on the size of actual losses incurred to market investors, they capture the market impact of misreporting (see also Hennes et al. 2008). AA firms are adopted as a benchmark for the comparison since non-misreporting firms are not likely to be subject to future litigation. To address the mismatch in misreporting periods between AAERs and securities class action lawsuits[29], *Lawsuits* is constructed by observing whether misreporting years of private civil lawsuits fall within two years before and after (Column (1) in Table 2.6), or within two years after the misreporting years of AAERs (Column (2)).

Table 2.6 reports that AAER firms are associated with a higher propensity to incur the ultimate filing of private civil lawsuits than AA firms, implying that AAER firms caused more serious losses to capital market investors than AA firms. To put it differently, AAERs tend not to include misreporting cases whose market impact is less likely to be significant, even when firms admit misreporting in their financial statements. The results confirm *H3*.

2.5.4. Enforcement bias and AAERs

As an additional analysis, I test whether the SEC's potential regulatory biases affect the reliability of AAERs as an appropriate accounting fraud proxy. Despite the advantage in being able to compare AAERs with more focused samples, the analyses so far did not explicitly consider the potential biases inherent in the SEC's enforcement process. To do this, I estimate Eq. (2.1) after controlling for factors that may relate to its detection process. Seven variables are selected from major prior literature that explores the SEC's enforcement process (e.g., Correia 2014; Kedia and Rajgopal 2011; Wang 2013). As a benchmark sample, however, I adopt the whole Compustat population in this analysis because the different detection processes of two misreporting detectors cannot be considered simultaneously.

First, four detection variables are chosen from the factors that the SEC may consider through its detection process. *Audit opinion* and *Unexpected performance* (Wang 2013)

[29] The misreporting periods stated in AAERs and securities class action lawsuits do not always exactly match, because the two fraud detection channels may have different judgements on the same misreporting cases.

usually trigger SEC investigation, and the SEC is also known to focus on firms with higher visibility such as *Fortune 500* (Correia 2014) and young growth firms (*Ln*(*Firm age*) (Beneish 1999). Second, as explained earlier, three representative SEC enforcement biases - *Ln*(*Distance*), *Political contribution*, and *Ln*(*Employee*) - are also adopted to address the potential bias of undetected fraud cases. Column (1) in Table 2.7 reports that AAERs cover cases that are more likely to represent accounting irregularities even after the inclusion of potential bias variables in Eq. (2.1), again supporting the reliability of AAERs.

Differently from Kedia and Rajgopal (2011), the coefficient of *Ln*(Distance) is negative and not significant in Column (1). Negative or insignificant coefficients are also found in Correia (2014) and Heese (2015). The difference results from two main factors. First, Kedia and Rajgopal (2011) adopt U.S. county as a unit of analysis, whereas subsequent studies including this one conduct their analyses from a firm's perspective. Second, while I adopt AAERs as a financial misreporting proxy, Kedia and Rajgopal (2011) use the Government Accountability Office (GAO)'s restatements. Additionally, this measure standardises the number of income-decreasing restatements by the number of firms in each county. As will be explained later, the results become similar to those of Kedia and Rajgopal (2011) when I adopt U.S. states as a unit of analysis and *AAER deviation* [30] as a measure of financial misreporting. The implications of the different research design will be explained in the following subsections[31].

[30] The difference between a state's share of AAERs from total AAERs and its share of firms from total Compustat firms.

[31] Contrary to Correia (2014), *Political contribution* shows a positive but insignificant coefficient. The difference may result from different sources and periods of samples between Correia (2014) and this study. Another recent study by Heese (2015), who also adopts CFRM samples, shows a positive and insignificant coefficient of this variable in his accounting fraud model.

I next test whether the results are robust regarding accounting fraud cases which have potentially gone undetected due to the SEC's possible enforcement bias. In this analysis, the enforcement bias is assumed to affect the probability of our observing AAERs through the detection process of the SEC rather than through the fraud commitment process of firms (see Wang 2013). To test this alternative explanation, I adopt a bivariate probit model proposed by Poirier (1980) and adopted by Chen et al. (2006), Wang (2013), and Khanna et al. (2015) for accounting fraud research. The bivariate probit model accommodates the dual processes of accounting fraud commitment and detection by combining an accounting fraud model (Eq. (2.1)) with an accounting fraud detection model (Eq. (2.2)).

Following Wang (2013), I do not include benefits from accounting fraud (e.g., accruals, financing needs, ROA and leverage) in the fraud detection model, because they are main factors that cause firms to commit accounting fraud. Instead, I include the above seven factors that may affect the SEC's detection process in the accounting fraud detection model. Additionally, I replace year dummies in the fraud model with the SEC's average annual budgets per regulated firm (*Ln*(*SEC budget*) since they directly constrain the SEC's enforcement coverage. The substitution of year dummies with *Ln*(*SEC budget*), however, does not alter the test results qualitatively. Taken together, the probability of our observing an accounting fraud case is determined by the interaction of the accounting fraud commitment (Eq. (2.1)) and accounting fraud detection (Eq. (2.2)) models, as in Eq. (2.3)[32]. The probability of our observing AAERs

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[32] In Eq. (2.3), Eq. (2.1) is modified in the bivariate probit model by estimating it with a probit model as Eq. (2.2) rather than a discrete-time logit program. It is also instructive to note that Eq. (2.2) includes *Ln(Firm age)*, whereas Eq. (2.1) does not. Reasons for the model specifications are twofold. First, Eq. (2.1) is directly adopted from Dechow et al. (2011)'s simple accounting fraud model, which does not incorporate *Ln(Firm age)*. Second, the bivariate probit model incorporating *Ln(Firm age)* in Eq. (2.1) does not converge (for the convergence issue of maximum likelihood methods, see Agresti and Kateri (2011)). However, the unconverged result after running for 1,000 iterations is not qualitatively different

is one if a firm commits accounting fraud and it is detected by the SEC, whereas the probability is zero if either a firm does not commit accounting fraud or a firm commits accounting fraud but the SEC does not detect it (see Wang 2013).

$$
\begin{aligned}
Pr(\mathit{Detection}_t) = {} & \beta_0 + \beta_1 \mathit{Audit\ opinion}_t + \beta_2 \mathit{Fortune}_t + \beta_3 \mathit{Ln(Firm\ age)} \\
& + \beta_4 \mathit{Unexpected\ performance}_{t+1} + \beta_5 \mathit{Ln(Distance)} \\
& + \beta_6 \mathit{Political\ contribution}_t + \beta_7 \mathit{Ln(Employee}_t) + \beta_8 \mathit{Ln(Assets}_{t-1}) \\
& + \beta_9 \mathit{Stock\ market}_{t-1} + \beta_{10} \mathit{Ln(SEC\ budget}_t) + \sum \beta \text{Industry dummy} \\
& + \varepsilon_t \qquad (2.2)
\end{aligned}
$$

$$Pr\ (\text{Observing AAERs}) = \text{Fraud commitment} \times \text{Detection} \qquad (2.3)$$

Columns (2) and (3) in Table 2.7 affirm that AAER firms are still associated with lower levels of financial reporting quality and higher levels of financing needs, even after controlling for the seven detection factors as a separate process of accounting fraud detection. Columns (4) and (5) further estimate the bivariate probit model with an alternative assumption that accounting firms' distance from the SEC offices and political contributions may affect not only the SEC's fraud detection process but also firms' fraud commitment processes. For example, firms that are located far from the SEC may be more tempted to commit accounting fraud since they may believe that the SEC's regulatory coverage will not reach their areas (see Kedia and Rajgopal 2011). This alternative assumption also supports the arguments of this study that, despite the potential enforcement biases of the SEC, AAERs effectively cover financial misreporting cases that are more likely to represent accounting irregularities.

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from Table 2.7.

2.5.5. Strategic utilisation of constrained resources

To provide a rationale for the reliability of AAERs as an accounting fraud database, I first test which target firms the SEC is more likely to focus on through its accounting fraud investigation process, assuming that it will attempt to mitigate inefficiencies inherent in the process. Columns (3) and (5) in Table 2.7 reveal four main characteristics of the firms that the SEC is likely to prioritise as investigation targets. First, firms without unqualified opinion (*Audit opinion*) are associated with higher detection propensity by the SEC. Second, as Beneish (1999) pointed out, the SEC tends to select more accounting fraud cases from the pool of young growth firms (*Ln*(*Firm age*)). They are usually involved in initial public offering (IPO) processes or are financially-troubled firms that have a stronger incentive to misreport. Finally, firms with higher visibility such as Fortune 500 (*Fortune 500*) and larger firms in asset size (*Ln*(*Assets*)) are positively associated with the likelihood of accounting fraud detection (Correia 2014). These findings together support *H4a*: presumably to attain its goal as an accounting fraud detector with limited resources, the SEC is more likely to select focused investigation targets of high-risk and systematically important firms. This optimisation may decrease potential inefficiencies in the fraud investigation process.

Additionally, Figure 2.3 provides specific evidence for the SEC's ability to mitigate the potential geographic bias. The darker colours of each state represent higher quintiles of *AAER deviation* (or fraud rate), the numbers of AAERs and firms[33], and the total assets of firms. In addition, the red and yellow dots are the locations of SEC headquarters and regional offices that were designated before 1993 and elevated in

[33] I adopt Compustat population as a proxy for the SEC's regulated firms. Even though they may not perfectly match each other (see Leuz et al. 2008), Compustat provides the widest range of firms that we can access.

2007 respectively. As a result, there was no change in major offices during 1993-2007. Each variable except *AAER deviation* is the total sum in each state for the years 1993-2007.

Consistent with Kedia and Rajgopal (2011), the map in the upper-left corner shows that *AAER deviation* is high in many states where the SEC's major offices are not located, supporting their geographic bias hypothesis. Given that firms may believe that SEC monitoring would be weaker in states where its offices do not exist, but also given that the SEC cannot be everywhere, it is reasonable for the SEC to deploy its major offices where firms are more crowded and more economically-important firms are located. If the SEC allocates its offices this way, the potential geographic bias would be prevalent mainly where regulatory demand is relatively low. In fact, the SEC's major offices are largely located in states where Compustat firms are more populated and where firms' total asset sizes are bigger (two maps in the lower side of Figure 2.3). Specifically, of six newly elevated regional offices, all except one in Salt Lake (UT) were located in states whose numbers of firms, AAERs, and the total assets of firms belong to the highest quintiles. These findings provide preliminary evidence suggesting that the SEC seeks to mitigate its potential geographic bias by deploying its constrained regional offices where regulatory demand is higher (*H4b*).

To further identify which factors the SEC prioritises through its office reorganisation process, I construct a simple SEC office allocation model (Eq. (2.4)). The model is analysed using a unit of U.S. states since the SEC's office allocation decisions are made by states. In fact, 11 regional offices including the headquarters in Washington D.C. are located in separate states as of the end of 2016, except California. The model includes five factors that the SEC may consider while making its office decisions, and that have strong univariate correlations with the SEC's office locations.

First, *Ln*(*Number of AAERs*) and *Ln*(*Number of firms*) are two main factors that may affect the SEC's office decisions since they directly relate to the SEC's regulatory purpose. Second, *Ln*(*Number of Fortune 500*), *Ln*(*Major market*), and *Ln*(*Risky industry*) are additional factors that the SEC may consider regarding the market impact and higher chances of accounting fraud commitment. Consistent with the graphical analyses, *SEC offices* are SEC headquarters and regional offices.

To consider the nature of the SEC's office allocation decisions[34], these variables are aggregated for the fiscal years 1993-2007[35], resulting in state observations reduced to 53 after excluding American Samoa (AS), Guam (GU), and Northern Marianas (MP), which do not have sufficient data. Similarly, I do not scale the number of AAERs by the number of firms because, as a federal agency, the SEC is expected to consider the total numbers of misreporting and regulated firms rather than an average fraud rate. If the SEC deployed its offices based on the average fraud rate of each state, a state with an extremely high fraud rate but with only a small number of regulated firms would have one of the SEC's limited offices. The unscaled *Ln*(*Number of AAERs*) and *Ln*(*Number of firms*) are also better at highlighting their incremental effects on the SEC's office allocation decisions. In addition to the main variables, I control for firm characteristics in each state (*Average asset size* and *Average Employee*) and state characteristics (e.g., *Ln*(*Population*)). Consistent with Kedia and Rajgopal (2011), firms' accounting ratios are the average of all firms in each state.

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[34] As explained earlier, the SEC's office reorganisation decisions are not made frequently.

[35] For the same reason explained above, I exclude observations in 1992 and after 2007. However, this sample attrition does not change the results.

$$Pr(\text{SEC offices}) = \gamma_0 + \gamma_1 Ln(\textit{Number of AAERs}) + \gamma_2 Ln(\textit{Number of firms}) + \gamma_3 Ln(\textit{Number of Fortune 500}) + \gamma_4 Ln(\textit{Major market}) + \gamma_5 Ln(\textit{Risky industry}) + \gamma_6 \textit{Average asset size} + \gamma_7 \textit{Average employee} + \gamma_8 Ln(\textit{Land area}_{2000}) + \gamma_9 Ln(\textit{Population}_{2000}) + \gamma_{10} Ln(\textit{Housing units}_{2000}) + \varepsilon_t \quad (2.4)$$

Column (1) in Table 2.8 first reports that *Ln*(*Number of AAERs*) is highly correlated with SEC office locations without any control. However, its statistical significance disappears when I control for *Ln*(*Number of firms*) (Column (2)). Columns (3) and (4) further reveal that *Ln*(*Number of firms*) becomes statistically significant when I control for firm and state characteristics. These findings suggest that, among other factors, the SEC takes the number of firms as one of its main considerations, affirming *H4b* again. To mitigate potential reverse causality bias in that the existence of SEC offices may affect firms' misreporting behaviours, Columns (5) and (6) estimate Eq. (2.4) after excluding five states that had their regional offices before 2007. This exclusion largely does not change the results[36] (Column (6)). The results support the view that the SEC is likely to mitigate its geographic bias by mainly allocating its regional offices in states with higher firm population.

2.6. Additional analyses

2.6.1. Investigation targets and AAERs

To test whether the focused investigation targets indeed help the SEC prioritise accounting irregularities over simple errors, I compare the characteristics of targeted

[36] Due to limited observations, I estimate a reduced version of Eq. (2.3) incorporating only *Ln*(*Number of AAERs*) and *Ln*(*Number of firms*). The full model of Eq. (2.3) does not converge (see also Allison 2008).

firms and non-target firms using the Compustat population. *t*-test and WRS results in Columns (7) and (8) in Panel A of Table 2.9 reveal that the targeted firms (i.e., *Audit opinion*, *Ln*(*Firm age*), and *Ln*(*Assets*) are largely associated with higher levels of *RSST* and financing needs. Columns (1) and (2) in Panel B of Table 2.9 further affirm that the characteristics of targeted firms remain valid even when we adopt multivariate analyses. The targeted firms are still associated with higher levels of accruals (e.g., *Ln*(*Firm age*) and *Ln*(*Assets*)) and financing needs (all targeted firms). These findings together suggest that the relative reliability of AAERs as an accounting fraud database could be explained by the SEC's narrowing down the focus of its investigation.

4.6.2. Office reorganisation and AAERs

To test whether the SEC's office reorganisation in 2007 also affected the characteristics of AAERs, I further adopt a different-in-difference (DID) setting. Panel A of Table 2.10 summarises the sample selection process for the DID analyses. To compare the characteristics of AAER firms in states where the SEC elevated district offices to regional offices (elevated states) with AAER firms in states where the SEC did not (unelevated states), I first exclude non-AAER firms (165,781 firm-years) from the Compustat population. States are then matched based on the *ex ante* probability of elevation to regional offices (*pscore*), which is calculated using Eq. (2.4), based on a nearest neighbour method. The estimation results are summarised in Column (4) in Table 2.8. I then remove AAER firms in Texas and California (4,663 firm-years), for which I could not find comparable unelevated states. These are two states that have the highest levels of *pscore*. As a result of this matching process, I am left with 1,270 AAER firm-years from 1993 to 2012, which are composed of 683 and 587 firm-years in elevated and unelevated states respectively. Panel B of Table 2.10 affirms that the matching process produces ideally balanced states, whose *ex ante* probability of elevation to regional offices is statistically similar but for whom the SEC's actual elevation decisions were opposite. This matching process ensures that the SEC's office reorganisation in 2007 was exogeneous (see Lechner 2011).

Figure 2.4 graphically tests the parallel assumption of DID analysis (see Abadie 2005). This assumption suggests that any change in accrual levels after 2007 results from the SEC's new office decisions. Figure 2.4 affirms that AAER firms in both elevated and unelevated states have decreasing trends of accruals before 2007, implying that the trends of accruals would have been similar in the absence of the SEC's office reorganisation.

Finally, DID analysis results in Table 2.11 provide some supporting evidence for my argument that the SEC's strategic reorganisation of major offices may have helped the SEC prioritise material accounting irregularities. Columns (1), (3), and (6) reveal that the coefficients of *Elevation* × *Post* are positive and significant when I adopt *PMJONES* and *SDD* as accruals measures, implying that, relative to AAER firms in unelevated states, AAER firms in elevated states are composed of firms that are more likely to represent accounting irregularities. Among eight different types of total and discretionary accruals, accrual types other than *PMJONES* and *SDD* do not produce statistically significant coefficients. However, given that SEC offices have potentially countervailing effects in deterring financial misreporting (Kedia and Rajgopal 2011) and improving the SEC's ability to detect accounting irregularities, this marginal evidence is meaningful in that the positive and significant coefficients of *Elevation* × *Post* imply that the latter effect is stronger than the former.

Additionally, AAER firms in elevated states have similar levels of accruals *before* the office reorganisation in 2007 (coefficients of *Elevation*: not significant). The adoption of accruals by AAER firms in unelevated states is largely decreasing *through* the sample periods (coefficients of *Post*: negative), suggesting that the accruals of AAER firms in elevated states similarly would have decreased in the absence of the SEC's office reorganisation.

2.6.3. Absolute value of accruals

To test whether the relatively low levels of accruals of SCAL and AA firms result from their intentional income-decreasing activities, I further test whether the absolute value of accruals[37] has different patterns from those of signed accruals in the context of financial misreporting. If SCAL and AA firms report depreciated earnings intentionally, the absolute value of accruals would better represent firms' financial reporting quality because negative accruals also result from their intentional misreporting. In contrast to the analyses of the signed accruals (Table 2.4), AAER firms do not show consistently higher levels of absolute value of accruals than both SCAL and AA firms (Table 2.12). This implies that SCAL and AA firms have a significant portion of negative accruals.

However, these results do not necessarily mean that SCAL and AA firms decrease their earnings intentionally by producing negative accruals. Prior studies consider negative accruals as a sign of either conservative accounting (e.g., Richardson et al. 2006; Lobo and Zhou 2010) or rather aggressive income-decreasing activities (e.g., Healy 1985; Gao and Shrieves 2002; Barton and Simko 2002; Kerstein and Rai 2007).

Additional analyses eliminate these alternative hypotheses. First, Columns (3)-(6)

[37] While a majority of studies adopt signed (both positive and negative) accruals as a proxy for financial reporting quality (e.g., Dechow et al. 2011; Jones et al. 2008), several studies focus on the absolute values of accruals (e.g., Hope et al. 2013; Crutchley et al. 2007). Their rationale is largely that both negative and positive accruals imply earnings management either to report higher current earnings or to reserve earnings for future use (see Barton and Simko 2002).

in Table 2.13 report that, like AAERs (Columns (1) and (2)), SCAL and/or AA firms also show increasing patterns of *Receivable (change)* and *Cash sales* when compared with the Compustat population. These findings imply that the negative accruals do not result from an income-decreasing motivation. If SCAL and AA firms were intentionally decreasing earnings by managing accruals, these firms should have decreasing trends of accounts receivable and/or cash sales. Second, further analyses reveal that both SCAL and AA firms do not have higher levels of *Special items (change)*[38] and *Write-downs* that can be reversed in future years (see Moehrle 2002) (Table 2.14). If they had expected the effects of the cookie jar reserve, then they would have high levels of these accounts because they can be easily reversed in subsequent years at managers' discretion (see Houmes and Skantz 2010). Finally, the consistently higher levels of *PMJONES* and *PMJONES2* in Columns (5)-(6) in Panel A and Panel B of Table 2.4 confirm that my findings are not critically susceptible to the performance effects that potentially bias the estimation process of discretionary accruals[39]. Taken together, the negative accruals of SCAL and AA firms may result from their relatively less aggressive accruals manipulation.

2.6.4. Capital expenditure

This subsection provides an explanation for the relatively low levels of *Capital expenditure* of AAER firms compared with both SCAL and AA firms in the univariate analyses presented in Table 2.3 (Columns (1)-(3)). Further analyses reveal that the statistical significance of the negative coefficients of *Capital expenditure* disappears

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[38] Special items include restructuring costs and write-downs that can be easily manipulated and reversed in future years (see Marquardt and Wiedman 2004).

[39] Additional controls of performance variables (e.g., *ROA*, *Loss*, and *Small profits/losses*) also do not affect the analysis results.

in multivariate analyses of Eq. (2.1), meaning that AAER firms have similar levels of *Capital expenditure* to the other two fraud types (Table 2.15). These findings are largely consistent with Dechow et al. (2011).

Three potential explanations exist regarding firms' long-term investment decisions. First, firms with lower financial reporting quality usually do not have sufficient capacity to invest because they tend to have constrained liquidity conditions (Beatty et al. 2010). Second, from a different perspective, firms may have incentives to increase capital expenditure when they are involved in accounting fraud schemes. According to Wang (2006b), fraudulently misreporting managers may increase new investments intentionally because large investment may create "noise" that hinders outsiders from easily detecting their misreporting. From her perspective, lower levels of *Capital expenditure* thus may imply that firms' misreporting is less intentional. Finally, reducing capital investments can also be interpreted as a real activities management strategy to window-dress firms' cash flows (see Roychowdhury 2006). Postponing investment timing and/or cutting discretionary expenses are two representative cases of cash flow management.

To sort out these alternative explanations, I examine the validity of each argument in the context of financial misreporting. First, the constrained liquidity hypothesis is excluded because AAER firms show consistently higher levels of both *CFO* and *CFF* as in Table 2.5 (Columns (3) and (4)). Second, the possibility that AAER firms invest less due to their weaker intentionality regarding financial misreporting is also excluded. The consistently lower levels of financial reporting quality and higher levels of *Actual issuance* (Table 2.4) imply that their financial misreporting is more likely to fall into the category of accounting irregularities (see Hennes et al. 2008). Finally, the higher levels of cash flows (Table 2.5) and lower levels of *Abnormal discretionary* *expenses* of AAER firms (Table 2.16) than both SCAL and AA firms consistently support that AAER firms tend to manage their cash flows actively by reducing investing activities (*CFI*) and discretionary expenses[40]. These findings imply that AAER firms seek not only to inflate earnings through accruals management but also to mask their liquidity conditions. Even though cash flows are considered to be relatively free of manipulation (Burgstahler et al. 2006), firms are known to actively manage their cash flows as an alternative to accruals management (e.g., Roychowdhury 2006; Zang 2012). Taken together, the relatively low levels of capital expenditure of AAER firms result not from lower levels of financing needs or a lesser intention to misreport, but from their active cash flow management.

2.7. Robustness checks

2.7.1. Contemporaneous analysis

To test the reliability of the data analysed in this chapter, I first replicate the analysis results of Dechow et al. (2011), who estimate the contemporaneous association between accruals and AAERs. I adopt their accounting fraud model after replacing contemporaneous accruals with accumulated three-year accruals to capture their reversal effects over time. If the data of this study are valid, then I should be able to replicate similar analysis results to Dechow et al. (2011). Column (1) in Table 2.17 reveals that, despite the differences in sample periods[41], all signs of coefficients estimated using the sample of this study are exactly the same as those of Dechow et

[40] However, I do not find that AAERs firms have greater involvement in other real activities manipulation (e.g., abnormal production costs) than SCAL and AA firms (Table 2.16).

[41] While the sample period of Dechow et al. (2011) is between 1971 and 2003, that of this study is between 1992 and 2012.

al. (2011) when I adopt the contemporaneous accruals in simple probit models. These findings affirm the reliability of the samples analysed in this chapter.

On the other hand, Columns (2)-(4) report that the statistical significance of *RSST* disappears once year and industry fixed effects are controlled for in the AAER sample, whereas the SCAL sample still shows positive and significant effects on lawsuit propensity (Column (5)). A plausible reason for these results is that AAER firms may cross into GAAP violations because they do not have enough capacity to manage their earnings within legitimate boundaries of accruals management (Ettredge et al. 2010).

2.7.2. Duplications with AAERs

To further test the validity of this study, I replicate the analysis results of prior studies that have produced largely homogeneous effects of accruals across different misreporting types. While this study has focused on the comparison of AAERs with both SCAL and AA firms that are *exclusively* detected by market investors and firms' managers, prior studies have usually analysed fraud cases that are similar to AAERs in their nature. Hennes et al. (2008), for example, suggest several criteria for classifying accounting irregularities and errors from restatement samples. Two of their criteria are whether the references to restatement cases in Audit Analytics include words such as "fraud" or "irregularity", or whether the restatements were investigated by the SEC or the DOJ. Zhang et al. (2008) also analyse the GAO's restatement sample based on similar criteria: whether the cases are characterised by irregularities or aggressive accounting (see also Burns and Kedia 2006; Efendi et al. 2007). The duplicated cases between AAERs and both securities class action lawsuits and restatements, thus, should have similar empirical results to those of AAERs and prior studies. Table 2.18 consistently reveals that, contrary to the exclusive samples, duplicated fraud cases show homogeneously high levels of *RSST*, affirming the validity of this study again. These findings imply that lower levels of financial reporting quality are mainly characteristic of AAERs rather than SCAL and AA firms.

2.7.3. Alternative specifications

To test the sensitivity of the results of comparative analyses, I previously adopted eight different types of total and discretionary accruals (Table 2.4). The results were pronounced and consistent across seven accrual types except *SDD*. As explained earlier, the exception results from AAER firms' active management of *CFO*. I further test whether the results are susceptible to an alternative financing variable: *Net external financing needs,* adopted by Wang (2006b). Differing from *Actual issuance* (Dechow et al. 2011), *Net external financing needs* is a continuous variable measuring firms' financing activity in relation to both stocks and bonds. Table 2.19 affirms that the results do not change qualitatively even when a continuous financing variable is adopted, with only some exceptions depending on accrual types. Instead, the effects of actual financing of AAER firms become even stronger. In addition, the inclusion of *Capital expenditure* in Eq. (2.1) also did not alter the analysis results as in Table 2.15. Overall, the results are not susceptible to alternative specifications of both financial reporting quality and financing needs variables.

2.7.4. Censoring and sampling biases

This study may be exposed to the left censoring bias, given that I analyse fraud data since 1992 to include three different misreporting types simultaneously. However, firms certainly have misreporting and non-misreporting periods before 1992. To mitigate this potential bias, I already calculated the duration of non-misreporting periods before misreporting events using the first Compustat date. Similarly, Shumway (2001) calculated the duration from the year when firms are listed on stock markets. For the firms that had prior experience of fraud before 1992, then I calculated the duration from the last prior fraud year. Except some exceptional firms that may have had misreporting experience before 1971, this definition of duration is expected to identify exactly the years when firms do not misreport before the misreporting event captured by the sample of this study.

A second potential sampling bias is that AA mainly includes restatement cases that are filed with the SEC since 2000. In fact, the year-distribution of AA in Table 2.1 shows that the observations before 2000 are much fewer than those after 2000. To address the sampling bias that may result from analysing potentially incomplete samples, I further estimate Eq. (2.1) using data between 2000 and 2012. Table 2.20 confirms that the statistical significance of the main variables of interest become even stronger when analysing samples for the fiscal years 2000-2012. In the reduced sample, AAER firms show higher levels of financing needs than not only AA firms but also SCAL firms.

2.7.5. Growth and efficiency

I further test whether the analysis results of accruals are susceptible to the inclusion of firms' sales growth rate (*Sales growth*) and asset turnover ratio (*Asset efficiency*). Richardson et al. (2006) show that firms with a high sales growth rate tend to have high accruals, whereas firms with a high asset turnover ratio tend to have low accruals. Therefore, the heterogeneities in three databases may result from their different levels of growth and efficiency. Analysis results reveal, however, that AAER firms still show lower levels of financial reporting quality than both SCAL and AA firms even after these two potentially omitted variables are controlled for in Eq. (2.1) (Table 2.21). These results again affirm the lower levels of financial reporting quality of AAER firms.

2.7.6. Static and dynamic hazard models

To test the sensitivity of the analysis results to alternative models with different assumptions, I finally estimate Eq. (2.1) using both a static probit and dynamic hazard model (Cox and Oakes 1984). I mainly adopt the simple hazard model (see Shumway 2001) to overcome two shortcomings inherent in static probit models: (i) the conventional model does not consider differing levels of misreporting risk which change depending on the duration before the incidence of misreporting; and (ii) data during the manipulation period are not accurate (Dechow et al. 2011). On the other hand, the dynamic hazard model has similar assumptions to the simple hazard model except that of distribution of duration. Table 2.22, however, reveals that these two alternative models largely produce similar results to those of a simple hazard model despite heterogeneities in the samples analysed and the assumptions adopted by different models. These tests strongly affirm that the results of this study are robust regarding assumptions that different models adopt.

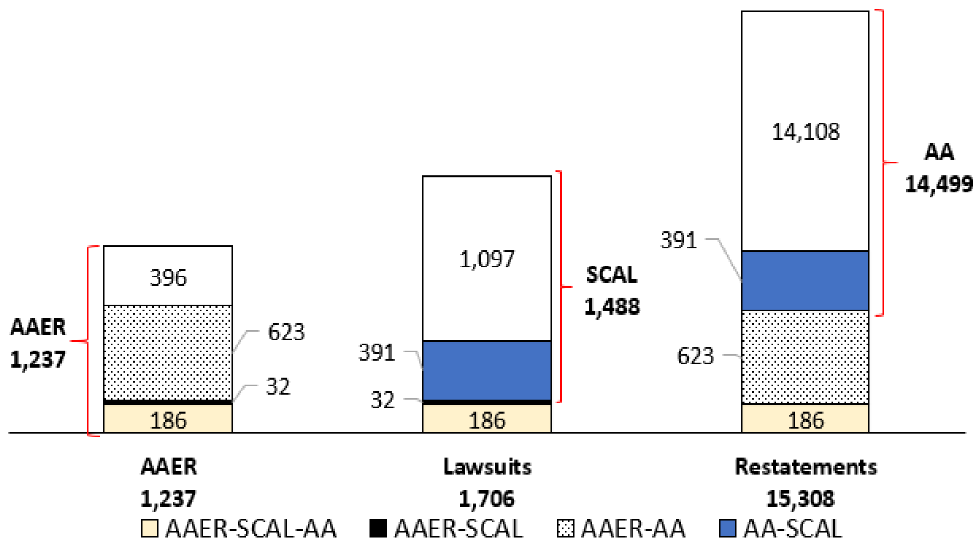
2.8. Conclusion

In this chapter, I examine whether AAERs constitute a reliable database for accounting fraud, despite their evidently partial coverage of misreporting cases and the resource constraints of the SEC. Using comparative analyses of three financial misreporting databases, I find that AAERs are composed of firms that are more likely to represent material accounting irregularities than SCAL and AA firms, which are *exclusively* identified by capital market investors and firms' managers respectively. Further analyses indicate that the reliability of AAERs can be explained by the SEC's strategic methods in utilising constrained resources, in addition to AAERs' inherently egregious nature in that they involve accountants. Specifically, the SEC tends to focus more on high-risk and systematically important firms as enforcement targets, and to allocate regional offices mainly where firms are more populated. Through this optimisation, the SEC may mitigate inefficiencies inherent in its accounting fraud investigation process and address the potential geographic bias.

As with most research of this type, the results should be interpreted with some caveats. First, the results should not be generalised to suggest that SEC enforcement is effective in general (e.g., in deterring accounting fraud incidences or illegal insider trading (see e.g., Guercio et al. 2017)). As Leuz and Wysocki (2016) and Chiras and Crea (2004) articulate, studies exploring the overall efficacy of government regulation are usually more susceptible to endogeneity issues like identification (e.g., simultaneous causality) and measurement. This study instead focuses specifically on the relative reliability of AAERs as an accounting fraud database as a result of the SEC's enforcement actions. Second, the reliability of AAERs as an accounting fraud database should be interpreted in comparison with its benchmark samples. Unfortunately, we do not have a perfect benchmark that consists of *all* financial misreporting cases. However, the selection processes of the three misreporting detection channels at least ensure that a significant portion of egregious cases are not likely to be excluded from all three complementary samples. Finally, the reliability of AAERs does not necessarily mean that AAERs are superior to other databases. As explained earlier, securities class action lawsuits and restatements have their own advantages as financial misreporting databases. Moreover, studies adopting these databases usually apply due sampling criteria to ensure they analyse material accounting irregularities rather than simple errors (see Zhang et al. 2008; Hennes et al. 2008).

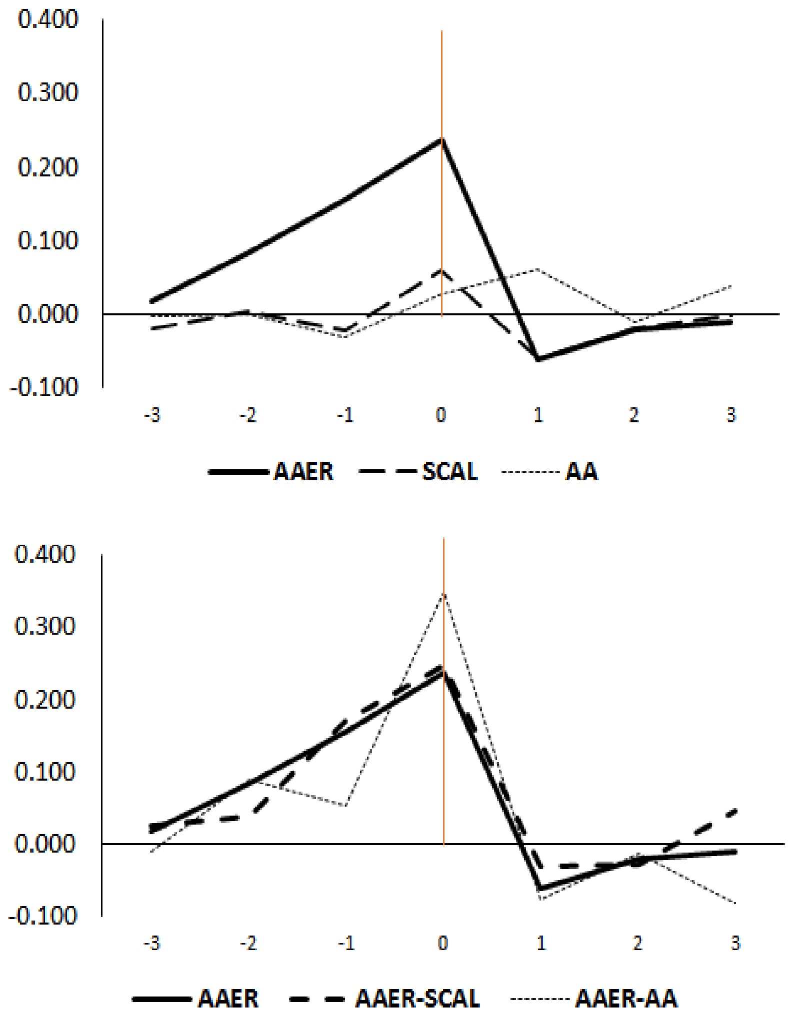
With these caveats in mind, my findings support the *relative* reliability of AAERs as a proxy for material accounting irregularities (see also Dechow et al. 2010), and should be of interest to researchers who use AAERs to proxy for accounting fraud. Complementing Karpoff et al. (2017), the findings suggest that, despite partial coverage of misreporting cases, AAERs are suitable for analysing firms' relatively intentional motivation to misreport.

FIGURE 2.1 Duplications of databases



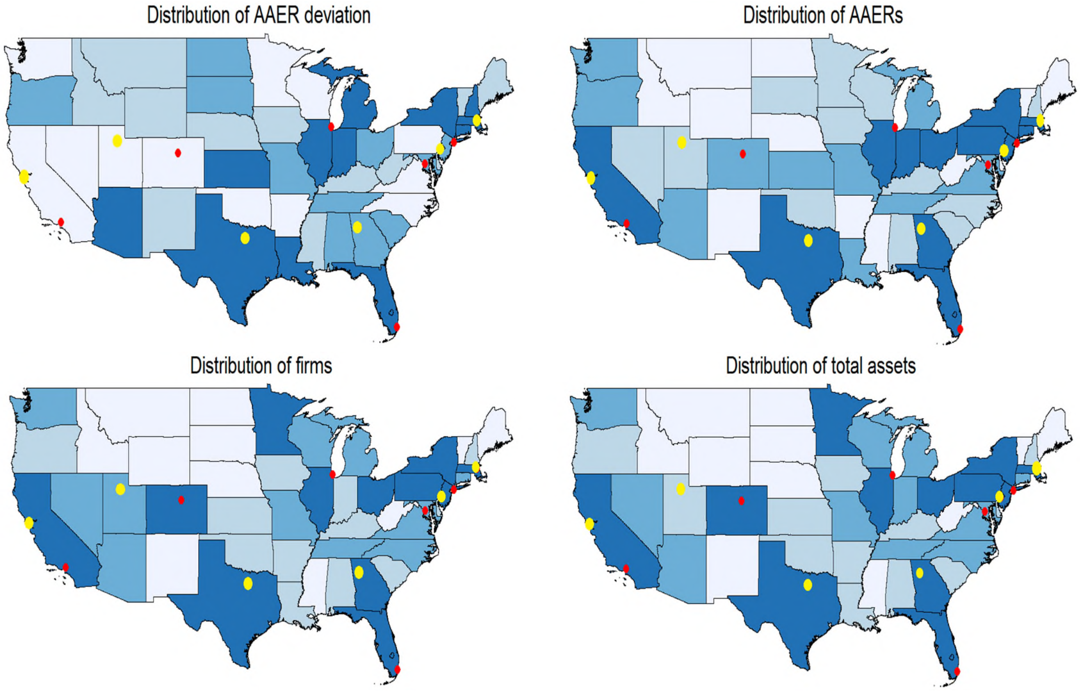
AAER-SCAL-AA refers to duplicated observations detected commonly by all three fraud detection channels, whereas AAER-SCAL, AAER-AA, AA-SCAL represent duplications between two fraud detectors.

FIGURE 2.2 Trends of accruals (*PMJONES*)



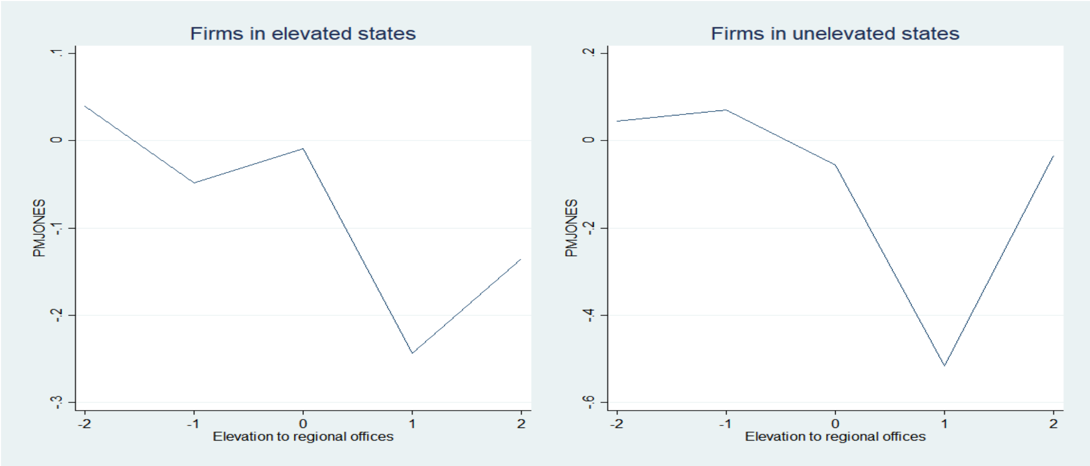
This figure illustrates the trends of discretionary accruals measured by *PMJONES* surrounding the first misreporting year of three fraud databases. Y-axis is the levels of *PMJONES* and X-axis represents the years relative to the first year of misreporting (the first fraud year = 0). AAER-SCAL and AAER-AA stand for duplicated AAERs respectively with securities class action lawsuits and restatements.

FIGURE 2.3 Distribution of SEC offices, AAER deviation, AAERs, firms and total assets



This figure illustrates the distributions of SEC offices, *AAER deviation*, AAERs, Compustat firms, and their total assets. Each variable except *AAER deviation* is the total sum for the years 1993-2007. *AAER deviation* is the difference between a state's share of AAERs from total AAERs and its share of Compustat firms from total Compustat firms. All variables are divided into four quintiles, and darker colours represent higher quintiles. Red and yellow dots are the locations of the SEC headquarters and regional offices. In particular, yellow dots represent six newly elevated regional offices in 2007.

FIGURE 2.4 Parallel trend assumption



This figure illustrates the univariate trends of *PMJONES* (mean) of firms in both states elevated to regional offices and states not elevated to regional offices in 2007. X-axis represents the years relative to the year of elevation by the SEC, Y-axis shows mean *PMJONES*.

TABLE 2.1 Sample selection

Panel A: Sample Selection Process

Database	AAER	SCAL	AA	Compustat
Panel	Panel A	Panel B	Panel C	
AAERs complied by CFRM	1,961			
Settled SCAL		4,540		
Restatements complied by AA			28,574	
Compustat				242,834
Less: Obs. without identifier or sufficient data	467	2,473	10,469	
Less: Obs. of financial firms	246	353	2,732	62,209
Less: With less than 10 year-industry obs.	10	8	65	696
Less: Obs. of audit violation	1			
Less: Duplications with AAER		218	809	
Total firm-years (1992-2012)	1,237	1,488	14,499	179,929
Frequency of Compustat firm-years	0.69%	0.83%	8.06%	100.0%
Total firms (1992-2012)	459	749	4,762	20,071

Panel B: Frequency of Fraud by Year

Year	AAER		Private Civil Lawsuits		Restatements	
	Number of obs.	Percentage	Number of obs.	Percentage	Number of obs.	Percentage
1992	43	3.48	1	0.06	17	0.11
1993	53	4.28	2	0.12	32	0.21
1994	42	3.40	7	0.41	63	0.41
1995	38	3.07	27	1.58	134	0.88
1996	54	4.37	53	3.11	230	1.50
1997	67	5.42	74	4.34	339	2.21
1998	81	6.55	84	4.92	486	3.17
1999	117	9.46	190	11.14	715	4.67
2000	141	11.40	281	16.47	966	6.31
2001	134	10.83	148	8.68	1,160	7.58
2002	115	9.30	118	6.92	1,365	8.92
2003	92	7.44	95	5.57	1,460	9.54
2004	75	6.06	102	5.98	1,539	10.05
2005	60	4.85	88	5.16	1,291	8.43
2006	37	2.99	77	4.51	1,016	6.64
2007	32	2.59	81	4.75	832	5.44
2008	20	1.62	58	3.40	724	4.73
2009	19	1.54	57	3.34	727	4.75
2010	10	0.81	59	3.46	734	4.79
2011	3	0.24	58	3.40	758	4.95
2012	4	0.32	46	2.70	720	4.70
Total	1,237	100.0	1,706	100.0	15,308	100.0

TABLE 2.2 Descriptive statistics

Variables	Compustat Mean	Compustat Median	AAER Mean diff. (1)	AAER Median diff. (2)	SCAL Mean diff. (3)	SCAL Median diff. (4)	AA Mean diff. (5)	AA Median diff. (6)
Financial reporting quality								
RSST t	0.019	0.024	0.043	0.019	0.143	0.052	-0.021	-0.006
			(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RSST t-1	0.030	0.027	0.104	0.048	0.091	0.055	-0.015	-0.005
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RSST t-2	0.034	0.028	0.090	0.047	0.059	0.039	-0.017	-0.006
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RSST t-3	0.036	0.029	0.088	0.039	0.059	0.031	-0.016	-0.004
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Aggregated *RSST*	0.061	0.080	0.272	0.147	0.236	0.143	-0.027	-0.011
(three-year)			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Financing needs								
Actual Issuance	0.871	1.000	0.097	0.000	0.099	0.000	0.029	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital expenditure	0.119	0.000	-0.062	0.000	-0.048	0.000	0.015	-0.113
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Controls								
Receivables (change)	0.016	0.005	0.032	0.019	0.032	0.018	0.000	-0.001
			(0.000)	(0.000)	(0.000)	(0.000)	(0.532)	(0.013)
Cash sales (change)	0.071	0.211	0.334	-0.040	0.452	-0.006	0.160	-0.139
			(0.000)	(0.000)	(0.000)	(0.000)	(0.056)	(0.230)
Inventory (change)	0.009	0.000	0.013	0.002	0.009	0.001	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.764)	(0.012)
Soft assets	0.502	0.520	0.121	0.139	-0.011	-0.020	0.039	0.041
			(0.000)	(0.000)	(0.137)	(0.096)	(0.000)	(0.000)
ROA (change)	-0.004	0.000	0.013	-0.001	0.038	0.000	0.003	-0.001
			(0.260)	(0.635)	(0.000)	(0.017)	(0.380)	(0.908)
Leverage	0.185	0.098	-0.013	0.035	-0.038	-0.046	0.018	0.013
			(0.081)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	18.512	18.518	1.139	1.222	0.963	0.754	0.264	0.547
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock market	0.533	1.000	0.102	0.000	0.328	0.000	0.070	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SEC enforcement bias								
Ln(Distance)	7.421	8.059	-0.365	0.087	-0.053	0.155	-0.144	0.036
			(0.000)	(0.563)	(0.442)	(0.003)	(0.000)	(0.000)
Political contribution	29.230	0.000	-14.239	0.000	-24.930	0.000	-18.593	0.000
			(0.867)	(0.000)	(0.762)	(0.000)	(0.439)	(0.332)
Ln(Employee)	0.970	0.466	0.494	0.521	0.222	0.135	0.066	0.120
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Detection factors								
Audit opinion	0.329	0.000	0.089	0.000	-0.022	0.000	0.134	0.000
			(0.000)	(0.000)	(0.072)	(0.072)	(0.000)	(0.000)
Fortune 500	0.042	0.000	0.083	0.000	0.062	0.000	0.009	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Firm age)	2.120	2.197	0.204	0.105	0.068	-0.118	0.179	0.201
			(0.000)	(0.000)	(0.011)	(0.813)	(0.000)	(0.000)
Unexpected performance	-0.193	0.015	0.118	0.003	0.029	-0.014	-0.071	-0.010
			(0.000)	(0.007)	(0.153)	(0.000)	(0.000)	(0.000)

This table reports descriptive statistics, including *p*-values for *t*-tests and Wilcoxon rank-sum (WRS) tests of mean and median differences between the Compustat population and three fraud databases. *p*-values are presented in the parentheses and variables are defined in Appendix 2.B. All continuous variables are winsorised at 1 and 99 percent levels.

TABLE 2.3 Pairwise correlation analysis

	AAERs vs. SCAL		AAERs vs. AA		AAERs vs. Full sample	
	(1)		(2)		(3)	
			AAERs			
	Corr.	N	Corr.	N	Corr.	N
Financial reporting quality						
$RSST_t$	0.010	12,526	0.017***	53,709	0.009***	140,595
$RSST_{t-1}$	0.061***	11,452	0.038***	49,214	0.022***	123,807
$RSST_{t-2}$	0.050***	10,400	0.033***	44,907	0.020***	108,687
$RSST_{t-3}$	0.047***	9,397	0.032***	40,792	0.020***	95,202
Aggregated *RSST* (three-year)	0.095***	9,004	0.055***	39,334	0.034***	91,778
Financing needs						
Actual issuance	0.039***	15,411	0.036***	64,827	0.024***	179,929
Capital expenditure	-0.021**	14,850	-0.030***	62,781	-0.017***	169,118
Total observations (max.)		15,411		64,827		179,929
AAER firm-years (max.)		1,237		1,237		1,237
% of AAER firm-years		8.03%		1.91%		0.69%

This table reports the pairwise correlation analysis results between the main variables of interest of this study and the filing of AAERs. AAER vs. SCAL represents firms whose financial misreporting is detected by either the SEC or investors at least once in their firm years, while AAER vs. AA refers to firms whose financial misreporting is detected by either the SEC or firms' managers at least once in their firm years. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B. All continuous variables are winsorised at 1 and 99 percent levels.

TABLE 2.4 Simple hazard estimation results using financial reporting quality and financing needs

Panel A: *RSST*, *WC*, *PMJONES*, *SDD*

	Dependent variable = *Pr*(AAERs)							
	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Accruals	*RSST*		*WC*		*PMJONES*		*SDD*	
Financial reporting quality								
Accruals	0.269**	0.401***	0.800**	1.048***	0.353**	0.348***	0.002	0.007
	(0.119)	(0.118)	(0.320)	(0.306)	(0.146)	(0.124)	(0.004)	(0.005)
Financing needs								
Actual issuance	0.675	0.936**	0.664	0.974**	0.798	1.143**	0.628	0.967**
	(0.457)	(0.412)	(0.461)	(0.413)	(0.500)	(0.454)	(0.456)	(0.413)
Controls								
Receivables	1.187	1.726**	1.030	1.344*	1.573	1.808**	1.750*	1.883**
(change)	(1.024)	(0.839)	(1.011)	(0.816)	(1.000)	(0.832)	(1.033)	(0.832)
Cash sales (change)	0.003	-0.011	0.025	0.024	0.044	0.029	0.045	0.029
	(0.076)	(0.048)	(0.077)	(0.050)	(0.072)	(0.047)	(0.074)	(0.048)
Inventory (change)	1.747	2.246*	0.188	0.401	0.956	1.398	0.997	0.995
	(1.465)	(1.324)	(1.435)	(1.341)	(1.450)	(1.341)	(1.494)	(1.346)
Soft assets	1.657***	1.476***	1.669***	1.450***	1.780***	1.615***	1.733***	1.526***
	(0.360)	(0.310)	(0.354)	(0.308)	(0.355)	(0.306)	(0.353)	(0.303)
ROA (change)	0.023	-0.065	0.110	0.037	-0.091	-0.131	-0.031	-0.012
	(0.255)	(0.255)	(0.286)	(0.276)	(0.260)	(0.248)	(0.269)	(0.268)
Ln(Assets)	0.024	0.189***	0.058	0.232***	0.079**	0.254***	0.063*	0.240***
	(0.037)	(0.034)	(0.038)	(0.037)	(0.037)	(0.035)	(0.037)	(0.036)
Leverage	0.303	-0.455	0.094	-0.840**	-0.023	-0.946***	-0.002	-0.935***
	(0.338)	(0.353)	(0.322)	(0.348)	(0.323)	(0.357)	(0.318)	(0.357)
Stock market	-1.27***	-0.267*	-1.31***	-0.30**	-1.30***	-0.28*	-1.31***	-0.300**
	(0.185)	(0.154)	(0.177)	(0.149)	(0.180)	(0.152)	(0.180)	(0.150)
Constant	-4.37***	-9.80***	-4.91***	-10.48***	-5.53***	-11.10***	-4.93***	-10.55***
	(0.936)	(0.895)	(0.949)	(0.940)	(0.950)	(0.927)	(0.941)	(0.936)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,496	31,064	5,767	32,249	5,676	31,608	5,665	31,566
Log likelihood	-745	-1087	-801	-1166	-788	-1147	-784	-1141

Panel B: Components, *MJONES*, *PMJONES2*, *FMJONES*

	Dependent variable = *Pr*(AAERs)							
	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Accruals	*Components*		*MJONES*		*PMJONES2*		*FMJONES*	
Financial reporting quality								
Accruals			0.333**	0.369***	0.260*	0.340***	0.560*	0.618**
			(0.138)	(0.115)	(0.134)	(0.122)	(0.332)	(0.281)
Components of accruals								
Current operating	1.201***	1.601***						
asset	(0.413)	(0.361)						
Current operating	-0.759*	-0.518						
liabilities	(0.430)	(0.375)						
Non-current	0.254	0.218						
operating assets	(0.203)	(0.178)						
Non-current	1.287	0.621						
Operating liabilities	(1.172)	(1.151)						
Financial	0.010	0.508*						
investments	(0.269)	(0.285)						
Financial liabilities	0.120	0.042*						
	(0.090)	(0.022)						
Financing needs								
Actual issuance	0.715	0.873**	0.644	0.980**	0.634	0.975**	0.722	1.094**
	(0.460)	(0.410)	(0.473)	(0.413)	(0.463)	(0.413)	(0.578)	(0.511)
Controls								
Receivables	0.221	0.164	1.538	1.773**	1.645*	1.857**	2.720***	2.268**
(change)	(1.116)	(0.913)	(0.994)	(0.828)	(0.991)	(0.823)	(1.046)	(0.897)
Cash sales	-0.018	-0.035	0.045	0.027	0.043	0.024	0.185***	0.109**
(change)	(0.073)	(0.059)	(0.073)	(0.047)	(0.072)	(0.047)	(0.066)	(0.043)
Inventory (change)	0.359	0.257	0.862	1.345	0.939	1.434	0.286	0.910
	(1.531)	(1.347)	(1.430)	(1.336)	(1.429)	(1.334)	(1.639)	(1.520)
Soft assets	1.426***	1.256***	1.752***	1.598***	1.788***	1.613***	1.807***	1.804***
	(0.385)	(0.343)	(0.353)	(0.304)	(0.352)	(0.303)	(0.411)	(0.358)
ROA (change)	0.097	0.038	-0.002	-0.059	-0.027	-0.064	-0.330	-0.463*
	(0.253)	(0.255)	(0.267)	(0.251)	(0.264)	(0.247)	(0.306)	(0.278)
Ln(Assets)	0.017	0.183***	0.071*	0.244***	0.072**	0.248***	0.091**	0.277***
	(0.039)	(0.035)	(0.037)	(0.036)	(0.037)	(0.036)	(0.042)	(0.041)
Leverage	-0.007	-0.627*	0.005	-0.904**	-0.001	-0.922***	0.190	-0.694*
	(0.345)	(0.355)	(0.317)	(0.351)	(0.316)	(0.351)	(0.345)	(0.374)
Stock market	-1.29***	-0.273*	-1.31***	-0.286*	-1.31***	-0.279*	-1.29***	-0.283*
	(0.187)	(0.155)	(0.178)	(0.150)	(0.177)	(0.149)	(0.204)	(0.168)
Constant	-4.28***	-9.747***	-5.17***	-10.71***	-5.19***	-10.79***	-6.21***	-12.01***
	(0.965)	(0.914)	(0.945)	(0.931)	(0.944)	(0.928)	(1.045)	(1.062)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,496	31,064	5,690	31,753	5,690	31,753	5,087	28,242
Log likelihood	-739	-1077	-792	-1155	-793	-1155	-659	-962

This table reports the simple hazard estimation results between (discretionary) accruals and accounting fraud. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *AAER vs. SCAL* represents firms whose financial misreporting is detected by either the SEC or investors at least once in their firm years, while *AAER vs. AA* refers to firms whose financial misreporting is detected by either the SEC or firms' managers at least once in their firm years. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. The decrease in observations from Table 2.3 mainly results from the simple hazard specification which uses only the first fraud year data. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted for these analyses. Variables are defined in Appendix 2.B.

TABLE 2.5 Simple hazard estimation results using cash flows

	Dependent variable = *Pr*(AAERs)			
AAER = 1	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(3)	(4)
Financial reporting quality				
RSST	0.313**	0.446***	0.172	0.355***
	(0.136)	(0.133)	(0.125)	(0.122)
Cash flow from operating activities				
CFO_{t+1}	0.047***	0.031***		
	(0.014)	(0.010)		
CFO_t	0.003	0.214		
	(0.396)	(0.447)		
CFO_{t-1}	0.952**	0.428***		
	(0.425)	(0.111)		
Components of cash flows				
CFO			1.929***	1.404***
			(0.619)	(0.262)
CFI			0.633	0.478
			(0.688)	(0.444)
CFF			1.260**	1.059***
			(0.562)	(0.242)
Controls				
Actual issuance	0.956*	1.146**	0.665	0.912**
	(0.563)	(0.469)	(0.468)	(0.414)
Cash sales (change)	0.002	-0.004	-0.011	-0.019
	(0.099)	(0.058)	(0.089)	(0.052)
Receivables (change)	1.244	1.694*	0.969	1.564*
	(1.089)	(0.891)	(1.090)	(0.886)
Inventory (change)	1.441	1.799	2.074	2.218*
	(1.622)	(1.459)	(1.531)	(1.343)
Soft assets	1.545***	1.496***	1.792***	1.682***
	(0.382)	(0.324)	(0.383)	(0.327)
ROA (change)	-0.127	0.126	-0.257	-0.208
	(0.380)	(0.337)	(0.302)	(0.267)
Ln(Assets)	-0.004	0.176***	0.002	0.178***
	(0.041)	(0.040)	(0.039)	(0.035)
Leverage	0.517	-0.430	0.329	-0.521
	(0.366)	(0.384)	(0.345)	(0.360)
Stock market	-1.170***	-0.221	-1.331***	-0.309**
	(0.195)	(0.164)	(0.186)	(0.154)
Constant	-4.217***	-9.817***	-4.026***	-9.675***
	(1.028)	(0.973)	(0.949)	(0.901)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Duration dummy	Yes	Yes	Yes	Yes
Observations	5,214	29,283	5,483	30,983
Log likelihood	-687	-994	-737	-1080

This table reports the simple hazard estimation results between cash flows and accounting fraud. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *AAER vs. SCAL* represents firms whose financial misreporting is detected by either the SEC or investors at least once in their firm years, while *AAER vs. AA* refers to firms whose financial misreporting is detected by either the SEC or firms' managers at least once in their firm years. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. The decrease in observations from Table 2.3 mainly results from the simple hazard specification which uses only the first fraud year data. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted for these analyses. Variables are defined in Appendix 2.B.

TABLE 2.6 Simple hazard estimation results using market impact of financial misreporting

	Dependent variable = *Pr*(Lawsuits)	
Future settlements of private civil lawsuits	Within 2 years	After2 years
	AAER vs. AA	AAER vs. AA
	(1)	(2)
Accounting fraud		
AAERs	1.951***	2.267***
	(0.184)	(0.188)
RSST	0.385***	0.370***
	(0.082)	(0.107)
Financing needs		
Actual issuance	0.401***	0.723***
	(0.155)	(0.227)
Controls		
Receivables (change)	0.671	2.631***
	(0.522)	(0.577)
Cash sales (change)	0.047*	0.043
	(0.027)	(0.032)
Inventory (change)	1.570**	2.547***
	(0.732)	(0.796)
Soft assets	0.086	0.173
	(0.119)	(0.148)
ROA (change)	-0.300*	-0.019
	(0.179)	(0.229)
Ln(Assets)	0.192***	0.184***
	(0.016)	(0.020)
Leverage	-0.914***	-0.639***
	(0.188)	(0.228)
Stock market	1.727***	1.779***
	(0.110)	(0.141)
Constant	-9.362***	-10.090***
	(0.406)	(0.506)
Year dummy	Yes	Yes
Industry dummy	Yes	Yes
Duration dummy	Yes	Yes
Observations	35,301	35,301
Log likelihood	-4843	-3505

This table reports the simple hazard estimation results between future settlements of securities class action lawsuits and financial misreporting. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *AAER vs. AA* refers to firms whose financial misreporting is detected by either the SEC or firms' managers at least once in their firm years. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. The decrease in observations from Table 2.3 mainly results from the simple hazard specification which uses only the first fraud year data. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted for these analyses. Variables are defined in Appendix 2.B.

TABLE 2.7 Simple hazard and bivariate probit estimation results after controlling for potential enforcement biases of the SEC

	Dependent variable = *Pr*(AAERs or Observing AAERs)				
	Fraud	Fraud	Detect | Fraud	Fraud	Detect | Fraud
	(1)	(2)	(3)	(4)	(5)
Financial reporting quality					
RSST	0.381***	0.463***		0.451***	
	(0.141)	(0.104)		(0.103)	
Financing needs					
Actual issuance	1.012**	0.675***		0.679***	
	(0.457)	(0.202)		(0.195)	
Controls					
Receivables (change)	2.143**	2.801***		2.822***	
	(0.888)	(0.857)		(0.837)	
Cash sales (change)	0.035	-0.003		-0.000	
	(0.048)	(0.060)		(0.059)	
Inventory (change)	1.834	0.782		0.825	
	(1.561)	(0.900)		(0.898)	
Soft assets	1.565***	1.693***		1.690***	
	(0.356)	(0.258)		(0.234)	
ROA (change)	-0.139	0.194		0.189	
	(0.330)	(0.378)		(0.376)	
Leverage	-0.093	-0.748***		-0.773***	
	(0.371)	(0.214)		(0.212)	
Ln(Assets)	0.074	-0.299***	0.259***	-0.245***	0.266***
	(0.057)	(0.061)	(0.024)	(0.075)	(0.026)
Stock market	-0.038	0.509***	-0.350***	0.408***	-0.341***
	(0.170)	(0.144)	(0.079)	(0.149)	(0.080)
Detection factors					
Audit opinion			0.216***		0.238***
			(0.046)		(0.051)
Fortune 500			0.211***		0.252**
			(0.081)		(0.105)
Ln(Firm age)			-0.164***		-0.190***
			(0.040)		(0.051)
Unexpected performance			0.038		0.036
			(0.066)		(0.072)
SEC enforcement bias					
Ln(Distance)	-0.029		-0.0258***	-0.031*	-0.012
	(0.025)		(0.006)	(0.016)	(0.009)
Political contribution	2.728		4.936**	12.680	4.791**
	(9.388)		(2.382)	(56.280)	(2.000)
Ln(Employee)	0.256**		0.025		0.023
	(0.100)		(0.029)		(0.035)
Constant	-9.708***	3.511**	-7.063***	2.079	-7.201***
	(1.617)	(1.746)	(0.619)	(2.029)	(0.653)
Year dummy	Yes	Yes	0.230**	Yes	0.225*
(SEC budget)			(0.116)		(0.120)
Industry dummy	Yes	Yes	Yes	Yes	Yes
Duration dummy	Yes	-	-	-	-
Observations	65,025	76,147		76,147	
Log likelihood	-1065	-3175		-3174	

This table reports the simple hazard (Column (1)) and bivariate probit regression estimation (Columns (2)-(5)) results between financial reporting quality/financing needs and accounting fraud after controlling for potential enforcement biases of the SEC. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. The decrease in observations from Table 2.3 mainly results from the simple hazard specification which uses only the first fraud year data. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted for these analyses. Variables are defined in Appendix 2.B.

TABLE 2.8 Probit estimation results for the SEC's office allocation decisions

	Dependent variable = *Pr*(SEC office)					
	(1)	(2)	(3)	(4)	(5)	(6)
Five existing offices:	Included	Included	Included	Included	Excluded	Excluded
Factors affecting office allocation						
Ln(Number of AAERs)	0.735***	0.286	0.242	0.216	0.958**	-0.072
	(0.245)	(0.336)	(0.287)	(0.397)	(0.400)	(0.498)
Ln(Number of firms)		0.535	2.324**	3.479**		1.416**
		(0.509)	(1.107)	(1.341)		(0.546)
Ln(Number of Fortune 500)			-0.051	-0.203		
			(0.393)	(0.358)		
Ln(Major market)			-1.998	-0.979		
			(1.220)	(1.741)		
Ln(Risky industry)			0.719	-0.529		
			(0.758)	(1.440)		
Firm characteristics						
Average asset size			1.557*	1.367**		
			(0.944)	(0.681)		
Average Employee			-4.776**	-4.118**		
			(2.404)	(1.973)		
State characteristics						
Ln(Land area)				-0.210		
				(0.239)		
Population (change)				2.238		
				(4.710)		
Housing units (change)				-3.043		
				(4.785)		
Constant	-2.696***	-5.407*	-32.944**	-24.811	-3.770***	-11.569***
	(0.835)	(3.215)	(16.378)	(15.274)	(1.406)	(3.649)
Observations	53	53	53	52	48	48
Log likelihood	-17.387	-16.850	-13.994	-12.547	-10.397	-8.961

This table reports the probit regression estimation results between potential factors affecting the SEC's office allocation decision and the locations of the SEC's major offices. Variables are aggregated by states for the years 1993-2007. Column (4) analyses 52 states excluding Virgin Island (VI), since the U.S. Census Bureau does not provide sufficient state-level data. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B.

TABLE 2.9 Focused investigation targets

Panel A: Descriptive Analysis

		Focused targets		Unfocused firms		Difference		*P*-value	
		Mean	Median	Mean	Median	Mean	Median	*t*-test	WRS
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High risk firms									
Audit opinion	*RSST*	-0.081	0.040	0.136	0.101	-0.217	-0.061	0.000	0.000
	Actual issuance	0.846	1.000	0.872	1.000	-0.026	0.000	0.000	0.000
Ln(Firm age)	*RSST*	0.146	0.167	0.021	0.060	0.125	0.107	0.000	0.000
	Actual issuance	0.884	1.000	0.857	1.000	0.027	0.000	0.000	0.000
Systematically important firms									
Ln(Assets)	*RSST*	0.159	0.097	-0.053	0.043	0.212	0.054	0.000	0.000
	Actual issuance	0.917	1.000	0.818	1.000	0.099	0.182	0.000	0.000
Fortune 500	*RSST*	0.085	0.061	0.060	0.082	0.025	-0.021	0.021	0.000
	Actual issuance	0.972	1.000	0.867	1.000	0.105	0.000	0.000	0.000

This table reports *t*-test and WRS results for the mean and median differences between focused and unfocused targets of the SEC. *p*-values are for *t*-tests and WRS tests. Variables are defined in Appendix 2.B.

Panel B: OLS and Probit Estimation Results for Focused Investigation Targets

	Dependent variable = *RSST*	Dependent variable = *Pr*(*Actual Issuance*)
	(1)	(2)
Accounting fraud		
RSST		0.155***
		(0.013)
Financing needs		
Actual issuance	0.046***	
	(0.004)	
High risk firms		
Audit opinion	-0.069***	0.060***
	(0.003)	(0.012)
Ln(Firm age)	-0.022***	-0.191***
	(0.001)	(0.008)
Systematically important firms		
Ln(Assets)	0.014***	0.134***
	(0.001)	(0.003)
Fortune 500	-0.029***	0.320***
	(0.003)	(0.040)
Controls		

Receivables (change)	0.665***	0.998***
	(0.023)	(0.063)
Cash sales (change)	0.008***	0.057***
	(0.001)	(0.004)
Inventory (change)	0.696***	1.255***
	(0.028)	(0.091)
Soft assets	-0.018***	-0.104***
	(0.006)	(0.023)
ROA (change)	0.326***	-0.114***
	(0.009)	(0.013)
Leverage	-0.227***	0.683***
	(0.008)	(0.028)
Stock market	0.040***	0.443***
	(0.002)	(0.012)
Constant	-0.143***	-1.567***
	(0.018)	(0.097)
Year dummy	Yes	Yes
Industry dummy	Yes	Yes
Observations	117,603	117,583
Adjusted R^2/Log likelihood	0.217	-38,853

This table reports the OLS and probit estimation results for the SEC's focused investigation targets. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B.

TABLE 2.10 Sample selection and covariate balance

Panel A: Sample selection	
Total firm-years (1993-2012)	171,714
Less: Firms without any fraud allegation	165,781
Firm-years with fraud allegations at least once	5,933
Less: Firms in states without matches	4,663
Total matched firm-years	1,270
Firms in states elevated to regional offices in 2007	683
Firms in states unelevated to regional offices in 2007	587

Panel B: Covariate balance	*Elevated states*	*Unelevated states*	*p*-value		
	Mean		*t*-test	WRS	KS
Ln(Number of AAERs)	3.278	2.975	0.670	1.000	1.000
Ln(Number of firms)	8.002	7.984	0.967	0.773	1.000
Ln(Number of Fortune 500)	4.624	4.752	0.894	0.564	0.699
Ln(Major market)	7.438	7.307	0.819	1.000	1.000
Ln(Risky industry)	7.439	7.235	0.717	0.773	1.000
Average asset size	17.012	17.217	0.780	0.773	1.000
Average Employee	0.687	0.798	0.612	0.564	0.699
Ln(Land area)	10.490	10.606	0.889	1.000	1.000
Population (change)	15.631	15.527	0.850	0.773	1.000
Housing units (change)	14.702	14.640	0.915	1.000	1.000
Pscore	0.439	0.469	0.898	1.000	1.000
Year				Matched	

This table reports the covariates balance between the eight matched states: Utah, Nevada, Georgia, Minnesota, Pennsylvania, Ohio, Massachusetts, and New Jersey. *pscore* stands for the propensity-score. *p*-values are for *t*-tests, Wilcoxon rank-sum (WRS) and Kolmogorov-Smirnov (KS) tests. Variables are defined in Appendix 2.B.

TABLE 2.11 DID analysis using the SEC office decision

	Dependent variable = Accruals					
	(1)	(2)	(3)	(4)	(5)	(6)
Time period	Immediate (two years)		Immediate (three years)		Overall (whole years)	
Accruals	*PMJONES*	*SDD*	*PMJONES*	*SDD*	*PMJONES*	*SDD*
Difference-in-Difference						
Elevation	-0.069	1.662	-0.080	0.593	-0.001	-0.558
	(0.069)	(1.392)	(0.053)	(0.973)	(0.020)	(0.633)
Post	-0.501***	1.585	-0.228**	1.405	-0.035	1.913
	(0.161)	(1.484)	(0.102)	(1.198)	(0.076)	(1.979)
Elevation × Post	0.272*	-1.320	0.189*	0.197	0.077	2.589***
	(0.148)	(1.640)	(0.105)	(1.208)	(0.062)	(0.970)
Financing needs						
Actual issuance	-0.330*	3.000	-0.087	0.896	0.006	3.287**
	(0.182)	(3.110)	(0.093)	(1.979)	(0.061)	(1.543)
Controls						
Receivables (change)	-0.567	24.361**	-0.504	22.737**	-0.109	7.165
	(0.466)	(11.758)	(0.407)	(9.774)	(0.197)	(5.266)
Cash sales (change)	0.136	-3.142	0.006	-1.842	0.013	-0.084
	(0.092)	(2.778)	(0.020)	(1.844)	(0.008)	(0.410)
Inventory (change)	-0.532	10.279	0.024	3.045	-0.036	14.069*
	(0.681)	(16.609)	(0.455)	(11.532)	(0.224)	(7.300)
Soft assets	0.228	-1.790	0.187*	0.381	0.002	-1.963
	(0.162)	(2.289)	(0.110)	(1.630)	(0.054)	(1.598)
ROA (change)	-0.280*	-3.509*	-0.037	-4.921***	-0.023	-0.814
	(0.144)	(2.030)	(0.118)	(1.858)	(0.061)	(1.246)
Leverage	0.180	5.971**	0.081	3.664*	0.027	-0.397
	(0.142)	(2.892)	(0.088)	(2.053)	(0.060)	(1.551)
Ln(Assets)	0.012	-0.417*	0.009	3.664*	-0.001	-0.419**
	(0.014)	(0.224)	(0.012)	(0.186)	(0.007)	(0.163)
Stock market	0.091	0.897	0.033	1.362	0.001	1.083
	(0.101)	(2.032)	(0.063)	(1.024)	(0.023)	(0.751)
Constant	-0.080	2.130	-0.172	-0.630	0.058	6.181**
	(0.282)	(5.636)	(0.211)	(3.967)	(0.112)	(3.118)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155	139	236	215	884	814
Adjusted R^2	0.154	0.232	0.078	0.196	0.036	0.035

This table reports the difference-in-difference estimation results between the SEC's office reorganisation and the accrual levels of AAER firms. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B.

TABLE 2.12 Simple hazard estimation results using absolute value of accruals

Panel A: *RSST*, *WC*, *PMJONES*, *SDD*

	Dependent variable = *Pr*(Accounting fraud)							
AAER = 1	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(4)	(5)	(7)	(8)	(10)	(11)
Accruals	*ABS_RSST*		*ABS_WC*		*ABS_PMJONES*		*ABS_SDD*	
Financial reporting quality								
Accruals	-0.259*	0.124	-0.125	0.462*	-0.036	0.001	0.055	0.139
	(0.143)	(0.104)	(0.285)	(0.239)	(0.075)	(0.017)	(0.121)	(0.130)
Financing needs								
Actual issuance	0.832*	1.151**	0.666	1.009**	0.793	1.152**	0.841*	1.169**
	(0.503)	(0.460)	(0.469)	(0.425)	(0.505)	(0.465)	(0.509)	(0.466)
Controls								
Receivables	1.545	2.009**	1.648*	1.934**	1.724*	2.139***	1.676	2.067**
(change)	(1.035)	(0.803)	(1.001)	(0.768)	(1.036)	(0.821)	(1.032)	(0.828)
Cash sales	0.060	0.013	0.022	0.019	0.043	0.042	0.040	0.031
(change)	(0.076)	(0.047)	(0.073)	(0.047)	(0.075)	(0.047)	(0.075)	(0.049)
Inventory (change)	1.773	2.291*	1.025	1.262	1.190	1.504	0.938	1.135
	(1.469)	(1.291)	(1.477)	(1.283)	(1.485)	(1.373)	(1.470)	(1.328)
Soft assets	1.691***	1.525***	1.849***	1.529***	1.817***	1.622***	1.774***	1.574***
	(0.371)	(0.311)	(0.366)	(0.308)	(0.356)	(0.304)	(0.354)	(0.299)
ROA (change)	-0.003	-0.067	0.0382	-0.029	-0.080	-0.116	-0.030	-0.060
	(0.290)	(0.202)	(0.256)	(0.210)	(0.275)	(0.261)	(0.247)	(0.225)
Ln(Assets)	0.014	0.219***	0.045	0.256***	0.061	0.246***	0.064*	0.251***
	(0.041)	(0.037)	(0.041)	(0.038)	(0.038)	(0.036)	(0.038)	(0.036)
Leverage	0.126	-0.762**	0.023	-0.942***	0.052	-0.980***	-0.045	-1.032***
	(0.327)	(0.342)	(0.319)	(0.344)	(0.318)	(0.357)	(0.322)	(0.357)
Stock market	-1.276***	-0.217	-1.298***	-0.242	-1.314***	-0.268*	-1.312***	-0.268*
	(0.182)	(0.153)	(0.177)	(0.150)	(0.179)	(0.150)	(0.180)	(0.151)
Constant	-3.971***	-10.430***	-4.662***	-11.030***	-5.178***	-10.950***	-5.175***	-10.960***
	(1.011)	(0.956)	(0.981)	(0.953)	(0.921)	(0.894)	(0.907)	(0.886)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,518	30,835	5,791	32,015	5,700	31,374	5,689	31,344
Log likelihood	-745	-1095	-805	-1176	-791	-1156	-784	-1146

Panel B: Components, *MJONES*, *MPJONES*, *FMJONES*

	Dependent variable = *Pr*(Accounting fraud)							
AAER = 1	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(4)	(5)	(7)	(8)	(10)	(11)
Accruals	*ABS_Components*		*ABS_MJONES*		*ABS_PMJONES2*		*ABS_FMJONES*	

Financial reporting quality								
Accruals			-0.024	0.104	-0.027	0.081	-0.048	0.453*
			(0.104)	(0.101)	(0.107)	(0.100)	(0.350)	(0.260)
Components of accruals								
Current operating	0.718*	0.905***						
asset	(0.407)	(0.345)						
Current operating	-0.828*	-0.306						
liabilities	(0.498)	(0.453)						
Non-current	0.050	0.081						
operating assets	(0.194)	(0.179)						
Non-current	0.602	0.072						
Operating	(1.033)	(0.935)						
liabilities								
Financial	-0.459	0.264						
investments	(0.319)	(0.261)						
Financial liabilities	0.036	-0.009						
	(0.151)	(0.111)						
Financing needs								
Actual issuance	0.826	1.130**	0.831	1.185**	0.830	1.182**	0.527	0.870*
	(0.507)	(0.461)	(0.507)	(0.467)	(0.507)	(0.466)	(0.514)	(0.469)
Controls								
Receivables	1.187	1.459*	1.734*	2.071**	1.734*	2.099**	2.890***	2.435***
(change)	(1.047)	(0.787)	(1.022)	(0.817)	(1.021)	(0.818)	(1.027)	(0.849)
Cash sales	0.044	0.009	0.036	0.028	0.036	0.030	0.180***	0.089**
(change)	(0.082)	(0.051)	(0.075)	(0.049)	(0.074)	(0.049)	(0.065)	(0.044)
Inventory (change)	1.131	1.545	1.051	1.454	1.052	1.465	0.650	1.038
	(1.470)	(1.237)	(1.455)	(1.347)	(1.456)	(1.352)	(1.676)	(1.501)
Soft assets	1.422***	1.337***	1.835***	1.615***	1.832***	1.622***	1.895***	1.796***
	(0.418)	(0.350)	(0.355)	(0.301)	(0.354)	(0.300)	(0.413)	(0.356)
ROA (change)	0.073	-0.014	-0.031	-0.073	-0.031	-0.067	-0.330	-0.417*
	(0.265)	(0.220)	(0.268)	(0.231)	(0.269)	(0.239)	(0.291)	(0.234)
Ln(Assets)	0.024	0.226***	0.054	0.244***	0.054	0.242***	0.078*	0.294***
	(0.041)	(0.037)	(0.039)	(0.037)	(0.039)	(0.038)	(0.042)	(0.042)
Leverage	0.051	-0.674*	0.037	-0.970***	0.036	-0.967***	0.231	-0.750**
	(0.349)	(0.354)	(0.319)	(0.350)	(0.317)	(0.351)	(0.345)	(0.371)
Stock market	-1.260***	-0.215	-1.329***	-0.264*	-1.329***	-0.265*	-1.299***	-0.251
	(0.184)	(0.153)	(0.178)	(0.149)	(0.177)	(0.149)	(0.205)	(0.168)
Constant	-4.196***	-10.700***	-5.045***	-10.960***	-5.039***	-10.910***	-5.816***	-12.160***
	(1.039)	(0.960)	(0.939)	(0.919)	(0.956)	(0.930)	(1.022)	(1.038)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,518	30,835	5,714	31,519	5,714	31,519	5,107	28,036
Log likelihood	-743	-1092	-795	-1162	-795	-1163	-662	-970

This table reports the simple hazard estimation results between absolute values of accruals and accounting fraud. The numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. The decrease in observations from Table 2.3 mainly results from the simple hazard specification which uses only the first fraud year data. Variables are defined in Appendix 2.B.

TABLE 2.13 Simple hazard estimation results using lagged accruals

	Dependent variable = *Pr*(Accounting fraud)					
Accounting fraud	AAER		SCAL		AA	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag	*t-1*	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
Financial reporting quality						
RSST	0.514***	0.571***	0.559**	0.563**	-0.031	-0.013
	(0.171)	(0.215)	(0.225)	(0.253)	(0.058)	(0.066)
Financing needs						
Actual issuance	1.246***	0.699*	1.264***	0.008	0.243***	0.222***
	(0.424)	(0.360)	(0.412)	(0.258)	(0.069)	(0.072)
Controls						
Receivables (change)	1.994***	1.693**	4.021***	3.044***	0.509*	0.721**
	(0.770)	(0.785)	(0.846)	(1.026)	(0.269)	(0.294)
Cash sales (change)	0.023	0.022	0.044	0.005	0.032**	-0.000
	(0.046)	(0.043)	(0.036)	(0.042)	(0.015)	(0.017)
Inventory (change)	1.300	1.753	1.356	4.189***	0.665*	0.138
	(1.182)	(1.256)	(1.315)	(1.353)	(0.390)	(0.410)
Soft assets	1.284***	0.860**	-0.610**	-0.745***	0.491***	0.266***
	(0.310)	(0.353)	(0.280)	(0.287)	(0.091)	(0.096)
ROA (change)	0.075	0.333	-0.097	-0.586**	0.078	-0.013
	(0.233)	(0.264)	(0.282)	(0.268)	(0.062)	(0.072)
Ln(Assets)	0.191***	0.189***	0.223***	0.203***	-0.075***	-0.072***
	(0.034)	(0.039)	(0.031)	(0.032)	(0.010)	(0.010)
Leverage	-0.406	-0.196	0.074	-0.007	0.399***	0.461***
	(0.318)	(0.392)	(0.335)	(0.354)	(0.077)	(0.082)
Stock market	-0.078	0.002	1.326***	1.551***	0.352***	0.362***
	(0.142)	(0.160)	(0.163)	(0.184)	(0.046)	(0.048)
Constant	-10.800***	-10.200***	-13.260***	-11.160***	-5.390***	-4.120***
	(0.905)	(0.991)	(1.167)	(1.015)	(0.518)	(0.462)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,750	71,256	92,749	79,812	81,260	69,440
Log likelihood	-1535	-1280	-2223	-1848	-11329	-10295

This table reports the simple hazard estimation results between *Receivables (change) / Cash sales (change)* and accounting fraud. *t-1* and *t-2* stand respectively for one and two years before the incidence of accounting fraud. The numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. The decrease in observations from Table 2.3 mainly results from the simple hazard specification which uses only the first fraud year data. Variables are defined in Appendix 2.B.

TABLE 2.14 Simple hazard estimation results using special items and write-downs

Panel A: Special items						
	Dependent variable = *Pr*(Accounting fraud)					
	AAER		SCAL		AA	
	(1)	(2)	(3)	(4)	(5)	(6)
RSST	*Cum.*	*t-1*	*Cum.*	*t-1*	*Cum.*	*t-1*
Financial reporting quality						
RSST	0.512***	0.433***	0.515***	0.532***	-0.009	-0.027
	(0.074)	(0.110)	(0.103)	(0.126)	(0.020)	(0.034)
Financing needs						
Actual issuance	0.874***	0.932***	1.433***	1.264***	0.355***	0.334***
	(0.244)	(0.226)	(0.317)	(0.261)	(0.042)	(0.040)
Special items						
Special items (change)	-0.563	-0.670**	0.106	-0.081	-0.053	0.016
	(0.379)	(0.320)	(0.648)	(0.444)	(0.087)	(0.081)
Controls						
Receivables (change)	2.494***	2.685***	2.596***	2.950***	0.233	0.333**
	(0.483)	(0.439)	(0.647)	(0.528)	(0.168)	(0.157)
Cash sales (change)	0.004	0.026	1.276	0.085***	0.027***	0.023**
	(0.035)	(0.028)	(0.929)	(0.020)	(0.010)	(0.009)
Inventory (change)	1.616**	1.188*	-0.133	1.127	0.444*	0.486**
	(0.765)	(0.679)	(0.192)	(0.793)	(0.245)	(0.229)
Soft assets	1.219***	1.293***	0.042	-0.344**	0.408***	0.467***
	(0.208)	(0.189)	(0.032)	(0.169)	(0.0539)	(0.051)
ROA (change)	0.142	0.077	0.156	0.028	0.035	0.011
	(0.195)	(0.159)	(0.355)	(0.195)	(0.042)	(0.040)
Ln(Assets)	0.317***	0.318***	0.253***	0.260***	-0.021***	-0.025***
	(0.019)	(0.018)	(0.021)	(0.019)	(0.006)	(0.005)
Leverage	-0.306	-0.595***	-0.280	-0.531**	0.389***	0.362***
	(0.198)	(0.184)	(0.242)	(0.217)	(0.047)	(0.044)
Stock market	-0.033	-0.050	1.404***	1.348***	0.292***	0.306***
	(0.092)	(0.083)	(0.120)	(0.103)	(0.027)	(0.026)
Constant	-12.090***	-12.190***	-12.710***	-13.980***	-5.298***	-6.028***
	(0.560)	(0.538)	(0.772)	(1.219)	(0.347)	(0.351)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,855	94,855	82,160	96,915	85,812	100,967
Log likelihood	-3414	-4014	-3965	-4825	-26533	-29564

This table reports the simple hazard estimation results between accounting fraud and *Special items (change)*. *Cum.* represents aggregate three-year accruals. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B.

Panel B: Write-downs								
	Compustat		AAER		SCAL		AA	
	Mean	Median	Mean diff.	Median diff.	Mean diff.	Median diff.	Mean diff.	Median diff.
Write-downs (change)$_t$	0.022	0.001	-0.018	0.001	-0.021	-0.001	-0.012	0.000
			(0.440)	(0.888)	(0.266)	(0.015)	(0.051)	(0.691)
Obs.	3,985	3,985	54	54	79	79	614	614
Write-downs (change)$_{t-1}$	0.023	0.001	-0.020	0.001	-0.020	-0.001	0.004	0.000
			(0.452)	(0.797)	(0.377)	(0.231)	(0.588)	(0.544)
Obs.	3,383	3,383	38	38	56	56	498	498
Write-downs (change)$_{t-2}$	0.024	0.001	-0.022	0.001	-0.037	-0.001	0.003	0.000
			(0.475)	(0.904)	(0.161)	(0.098)	(0.732)	(0.915)
Obs.	2,943	2,943	31	31	42	42	421	421
Write-downs (change)$_{t-3}$	0.026	0.001	-0.018	0.001	-0.035	0.004	0.012	0.001
			(0.660)	(0.747)	(0.222)	(0.633)	(0.200)	(0.090)
Obs.	2,509	2,509	18	18	37	37	325	325

This table reports descriptive statistics, including *p*-values for *t*-tests and Wilcoxon rank-sum (WRS) tests of mean and median differences between total observations of Compustat and accounting fraud firms. *p*-values are presented in the parentheses and variables are defined in Appendix 2.B.

TABLE 2.15 Simple hazard estimation results using capital expenditure

	Dependent variable = *Pr*(Accounting fraud)				
	AAER vs. SCAL	AAER vs. AA	AAER	SCAL	AA
	(1)	(2)	(3)	(4)	(5)
Accruals					
RSST	0.261**	0.420***	0.452***	0.534***	-0.010
	(0.121)	(0.126)	(0.130)	(0.105)	(0.020)
Financing needs					
Actual issuance	0.791	1.132**	1.157**	1.471***	0.348***
	(0.504)	(0.461)	(0.462)	(0.335)	(0.043)
Capital Expenditure	-0.388	-0.501	-0.349	0.198	0.071*
	(0.333)	(0.311)	(0.314)	(0.155)	(0.040)
Controls					
Receivables (change)	0.922	1.594*	1.720*	2.966***	0.359**
	(1.044)	(0.843)	(0.898)	(0.640)	(0.168)
Cash sales (change)	0.017	-0.010	0.005	0.039	0.031***
	(0.081)	(0.051)	(0.052)	(0.031)	(0.010)
Inventory (change)	1.675	2.217*	2.167	1.636*	0.524**
	(1.498)	(1.331)	(1.385)	(0.915)	(0.247)
Soft assets	1.587***	1.367***	1.138***	-0.233	0.409***
	(0.372)	(0.318)	(0.357)	(0.201)	(0.055)
ROA (change)	0.008	-0.065	-0.012	0.173	0.028
	(0.271)	(0.289)	(0.332)	(0.272)	(0.037)
Ln(Assets)	0.010	0.169***	0.176***	0.0261***	-0.019***
	(0.040)	(0.038)	(0.039)	(0.023)	(0.006)
Leverage	0.354	-0.425	-0.078	-0.212	0.385***
	(0.344)	(0.356)	(0.355)	(0.250)	(0.048)
Stock market	-1.278***	-0.279*	-0.051	1.383***	0.285***
	(0.185)	(0.154)	(0.163)	(0.122)	(0.027)
Constant	-4.162***	-9.480***	-10.650***	-12.800***	-5.307***
	(0.966)	(0.948)	(1.068)	(0.806)	(0.348)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	Yes
Observations	5,512	30,760	67,893	81,424	85,205
Log likelihood	-742	-1077	-1221	-3715	-26011

This table reports the simple hazard estimation results between corporate fraud and capital expenditure. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted for Columns (1) and (2). Variables are defined in Appendix 2.B.

TABLE 2.16 Probit estimation results using real activities management

AAER = 1	Dependent variable = *Pr*(Accounting fraud)					
	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(3)	(4)	(5)	(6)
	Abnormal production costs		Abnormal cash flow		Abnormal discretionary expenses	
Financial reporting quality						
RSST	0.255*	0.372***	0.220*	0.391***	-0.260	0.403
	(0.143)	(0.140)	(0.120)	(0.120)	(0.382)	(0.337)
Financing needs						
Actual issuance	0.781	1.097**	1.043*	1.341***	.	.
	(0.563)	(0.521)	(0.555)	(0.518)	(.)	(.)
Real activities management						
RAM	-0.035	-0.157***	0.003	-0.011	-0.141**	-0.127***
	(0.065)	(0.049)	(0.055)	(0.091)	(0.064)	(0.047)
Controls						
Receivables	2.467**	2.313***	1.131	1.765**	0.858	-0.051
(change)	(1.054)	(0.875)	(1.068)	(0.861)	(3.779)	(2.260)
Cash sales (change)	0.130**	0.036	0.015	-0.006	0.274	0.257**
	(0.057)	(0.039)	(0.077)	(0.051)	(0.203)	(0.116)
Inventory (change)	1.455	2.393	1.929	2.254*	12.650***	7.346**
	(1.695)	(1.561)	(1.508)	(1.337)	(4.011)	(2.874)
Soft assets	1.820***	1.798***	1.705***	1.472***	0.875	0.431
	(0.424)	(0.365)	(0.360)	(0.304)	(1.104)	(1.030)
ROA (change)	-0.272	-0.393*	0.019	-0.072	-0.175	-0.724
	(0.261)	(0.226)	(0.228)	(0.237)	(0.861)	(0.454)
Ln(Assets)	0.0502	0.230***	0.026	0.192***	0.055	0.261**
	(0.041)	(0.039)	(0.039)	(0.037)	(0.151)	(0.113)
Leverage	0.475	-0.269	0.235	-0.553	0.864	-0.670
	(0.360)	(0.375)	(0.341)	(0.364)	(0.874)	(1.197)
Stock market	-1.24***	-0.278	-1.29***	-0.276*	-2.170***	-0.187
	(0.210)	(0.171)	(0.186)	(0.155)	(0.647)	(0.550)
Constant	-5.79***	-11.39***	-4.80***	-10.22***	-2.047	-10.00***
	(0.993)	(0.995)	(0.945)	(0.917)	(3.571)	(2.848)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,981	28,319	5,456	30,485	613	2,334
Log likelihood	-618	-900	-732	-1065	-94	-138

This table reports the simple hazard model estimation results between accounting fraud and real activities management. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted. Variables are defined in Appendix 2.B.

TABLE 2.17 Probit estimation results using contemporaneous *RSST*

Accounting fraud	Dependent variable = *Pr*(Accounting fraud)					
	AAER				SCAL	AA
	(1)	(2)	(3)	(4)	(5)	(6)
Financial reporting quality						
RSST	0.071**	0.057*	0.002	-0.033	0.268***	-0.029*
	(0.036)	(0.030)	(0.045)	(0.046)	(0.046)	(0.016)
Financing needs						
Actual issuance	0.481***	0.426***	0.265***	0.279***	0.242***	0.184***
	(0.058)	(0.063)	(0.063)	(0.064)	(0.060)	(0.019)
Controls						
Receivables (change)	0.367**	0.427***	0.506***	0.504***	0.008	0.121
	(0.153)	(0.147)	(0.188)	(0.187)	(0.212)	(0.076)
Cash sales (change)	0.030***	0.026***	0.035***	0.036***	0.067***	0.018***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.008)	(0.004)
Inventory (change)	0.441**	0.618***	0.775***	0.772***	0.358	0.244**
	(0.216)	(0.217)	(0.265)	(0.265)	(0.309)	(0.113)
Soft assets	0.660***	0.524***	0.475***	0.507***	-0.320***	0.281***
	(0.051)	(0.059)	(0.065)	(0.066)	(0.060)	(0.025)
ROA (change)	-0.107***	-0.112***	-0.189***	-0.183***	-0.239***	-0.023
	(0.038)	(0.028)	(0.048)	(0.049)	(0.055)	(0.017)
Ln(Assets)			0.106***	0.011***	0.087***	-0.007***
			(0.006)	(0.006)	(0.006)	(0.003)
Leverage				-0.284***	-0.301***	0.181***
				(0.067)	(0.081)	(0.022)
Stock market		0.103***	-0.061**	-0.072***	0.444***	0.164***
		(0.028)	(0.029)	(0.029)	(0.032)	(0.012)
Constant	-3.253***	-3.097***	-4.733***	-4.803***	-5.442***	-3.259***
	(0.066)	(0.128)	(0.168)	(0.169)	(0.367)	(0.152)
Year dummy	No	Yes	Yes	Yes	Yes	Yes
Industry dummy	No	Yes	Yes	Yes	Yes	Yes
Observations	117,984	112,236	112,236	112,236	114,039	117,977
Log likelihood	-5,288	-4,938	-4,803	-4,797	-5,834	-32,031

This table reports the probit estimation results between contemporaneous *RSST* and accounting fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B.

TABLE 2.18 Simple hazard and probit estimation results using duplications with AAERs

	Dependent variable = *Pr*(Accounting fraud)							
	AAER-SCAL	AAER-AA	AAER-SCAL	AAER-AA	AAER-SCAL	AAER-AA	AAER-SCAL	AAER-AA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Accruals	*RSST*		*WC*		*PMJONES*		*SDD*	
Financial reporting quality								
Accruals	0.279***	0.476***	0.650***	1.240***	0.201***	0.418***	0.007***	0.013**
	(0.056)	(0.144)	(0.152)	(0.378)	(0.051)	(0.152)	(0.002)	(0.006)
Financing needs								
Actual issuance	0.127	1.779**	0.172	1.379**	0.170	1.736**	0.161	1.777**
	(0.182)	(0.720)	(0.181)	(0.598)	(0.181)	(0.735)	(0.181)	(0.736)
Controls								
Receivables	1.604***	1.096	1.191***	1.169	1.453***	1.634	1.435***	1.589
(change)	(0.392)	(1.184)	(0.355)	(1.103)	(0.342)	(1.136)	(0.358)	(1.104)
Cash sales	0.023	-0.053	0.045**	0.008	0.037**	0.018	0.041**	0.019
(change)	(0.020)	(0.078)	(0.019)	(0.072)	(0.018)	(0.065)	(0.019)	(0.069)
Inventory	1.221*	3.058*	0.854	1.016	1.313**	1.634	0.925	1.170
(change)	(0.641)	(1.723)	(0.591)	(1.748)	(0.587)	(1.136)	(0.592)	(1.723)
Soft assets	0.425**	1.336***	0.439***	1.266***	0.556***	1.434***	0.480***	1.322***
	(0.167)	(0.415)	(0.158)	(0.410)	(0.162)	(0.422)	(0.162)	(0.417)
ROA (change)	-0.246**	0.356	-0.240*	0.392	-0.240**	0.141	-0.227*	0.319
	(0.124)	(0.338)	(0.133)	(0.330)	(0.112)	(0.320)	(0.128)	(0.328)
Ln(Assets)	0.113***	0.135***	0.130***	0.157***	0.128***	0.183***	0.126***	0.169***
	(0.015)	(0.045)	(0.015)	(0.044)	(0.015)	(0.042)	(0.015)	(0.043)
Leverage	0.033	-0.035	-0.195	-0.271	-0.236	-0.326	-0.228	-0.331
	(0.144)	(0.433)	(0.146)	(0.398)	(0.145)	(0.403)	(0.150)	(0.405)
Stock market	0.554***	0.080	0.559***	0.150	0.584***	0.187	0.592***	0.063
	(0.107)	(0.197)	(0.101)	(0.187)	(0.105)	(0.193)	(0.109)	(0.188)
Constant	-6.693***	-10.99***	-7.049***	-11.06***	-7.090***	-11.94***	-6.999***	-11.54***
	(0.486)	(1.250)	(0.497)	(1.188)	(0.492)	(1.199)	(0.494)	(1.189)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	-	Yes	-	Yes	-	Yes	-	Yes
Observations	57,315	62,042	69,110	68,532	67,709	67,063	65,097	65,540
Log likelihood	-841	-876	-971	-965	-959	-947	-947	-942

This table reports the simple hazard estimation results between accounting fraud and accruals using duplicated dependent variables of AAERs and SCAL/AA. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Due to the limited sample size, Columns (1), (3), (5), and (7) are estimated using probit models. Variables are defined in Appendix 2.B.

TABLE 2.19 Simple hazard and bivariate probit estimation results using alternative variables

	Dependent variable = *Pr*(Accounting fraud)							
AAER = 1	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER		AAER	
	(1)	(2)	(3)	(4)	(4)	(5)	(6)	(7)
Accruals	RSST		WC		RSST		WC	
Bivariate probit					Fraud	Detect | Fraud	Fraud	Detect | Fraud
Financial reporting quality								
Accruals	0.149	0.283**	0.812***	1.069***	0.418***		1.167***	
	(0.112)	(0.119)	(0.299)	(0.295)	(0.101)		(0.238)	
Financing needs								
Net external financing	1.115***	0.974***	1.228***	1.175***	0.220		0.337**	
	(0.313)	(0.308)	(0.321)	(0.317)	(0.178)		(0.163)	
Controls								
Receivables (change)	-0.289	0.531	-0.763	-0.209	2.216***		1.418**	
	(1.117)	(0.937)	(1.124)	(0.912)	(0.818)		(0.703)	
Cash sales (change)	-0.029	-0.032	-0.028	-0.013	-0.008		0.001	
	(0.075)	(0.048)	(0.078)	(0.050)	(0.054)		(0.044)	
Inventory (change)	0.575	1.270	-1.215	-0.927	0.605		-0.685	
	(1.517)	(1.386)	(1.519)	(1.421)	(0.821)		(0.762)	
Soft assets	1.653***	1.551***	1.672***	1.543***	1.584***		1.348***	
	(0.354)	(0.305)	(0.348)	(0.301)	(0.237)		(0.218)	
ROA (change)	-0.096	-0.190	0.014	-0.115	0.078		-0.017	
	(0.227)	(0.229)	(0.267)	(0.257)	(0.317)		(0.239)	
Leverage	0.254	-0.547	0.147	-0.893**	-0.684***		-0.780***	
	(0.341)	(0.354)	(0.325)	(0.349)	(0.194)		(0.182)	
Ln(Assets)	0.011	0.184***	0.037	0.224***	-0.287***	0.264***	-0.223***	0.249***
	(0.038)	(0.034)	(0.038)	(0.037)	(0.054)	(0.024)	(0.050)	(0.023)
Stock market	-1.275***	-0.235	-1.328***	-0.270*	0.495***	-0.345***	0.450***	-0.328***
	(0.185)	(0.153)	(0.178)	(0.148)	(0.141)	(0.081)	(0.134)	(0.085)
Detection factors								
Audit opinion						0.216***		0.197***
						(0.046)		(0.045)
Fortune 500						0.214***		0.179**
						(0.082)		(0.0729)
Ln(Firm year)						-0.169***		-0.199***
						(0.039)		(0.041)
Unexpected performance						0.026		0.005
						(0.063)		(0.056)
SEC enforcement bias								
Ln(Distance)						-0.025***		-0.027***
						(0.005)		(0.005)
Political contribution						4.610*		4.758**
						(2.379)		(2.268)
Ln(Employee)						0.032		0.053**
						(0.028)		(0.026)
Constant	-3.478***	-8.823***	-3.949***	-9.476***	4.020***	-7.224***	2.931***	-6.927***
	(0.843)	(0.801)	(0.863)	(0.846)	(1.538)	(0.639)	(1.457)	(0.623)
Year dummies (SEC budget)	Yes	Yes	Yes	Yes	Yes	0.262**	Yes	0.310**
						(0.122)		(0.134)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	-	-	-	-
Observations	5,518	30,830	5,784	31,947	76,146		82,087	
Log likelihood	-741	-1083	-795	-1160	-3181		-3490	

This table reports the simple hazard estimation results between accounting fraud and financing needs using an alternative variable. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 2.B.

TABLE 2.20 Simple hazard estimation results using data after 2000

AAER = 1	Dependent variable = *Pr*(Accounting fraud)			
	AAER vs. SCAL	AAER vs. AA	AAER	
	(1)	(2)	(3)	(4)
Bivariate probit			Fraud	Detect | Fraud
Financial reporting quality				
RSST	0.283**	0.324**	0.462***	
	(0.137)	(0.134)	(0.136)	
Financing needs				
Actual issuance	1.511*	1.582**	0.685**	
	(0.783)	(0.722)	(0.272)	
Controls				
Receivables (change)	1.424	1.672	2.134**	
	(1.294)	(1.197)	(0.866)	
Cash sales (change)	-0.053	-0.041	0.015	
	(0.102)	(0.070)	(0.067)	
Inventory (change)	1.222	1.268	0.398	
	(2.057)	(1.947)	(1.072)	
Soft assets	2.357***	1.783***	1.748***	
	(0.496)	(0.390)	(0.384)	
ROA (change)	0.117	-0.032	0.307	
	(0.266)	(0.272)	(0.509)	
Leverage	0.623*	-0.211	-0.680***	
	(0.370)	(0.418)	(0.260)	
Ln(Assets)	0.012	0.139***	-0.340***	0.260***
	(0.050)	(0.048)	(0.076)	(0.034)
Stock market	-1.499***	-0.207	0.610***	-0.396***
	(0.245)	(0.212)	(0.182)	(0.107)
Detection factors				
Audit opinion				0.256***
				(0.055)
Fortune 500				0.068
				(0.093)
Ln(Firm year)				-0.161***
				(0.041)
Unexpected performance				0.278**
				(0.112)
SEC enforcement bias				
Ln(Distance)				-0.027***
				(0.007)
Political contribution				5.223**
				(2.064)
Ln(Employee)				0.046
				(0.033)
Constant	-4.403***	-9.161***	5.600***	-7.227***
	(1.241)	(1.156)	(1.929)	(1.168)
Year dummies (SEC budget)	Yes	Yes	Yes	0.261 (0.220)
Industry dummies	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes
Observations	3,941	22,204	55,601	
Log likelihood	-432	-641	-2266	

This table reports the simple hazard model estimation results between corporate fraud and the FRQ and MM measures. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted. Variables are defined in Appendix 2.B.

TABLE 2.21 Simple hazard estimation results using growth and efficiency

	Dependent variable = *Pr*(Accounting fraud)					
AAER = 1	AAER vs. SCAL	AAER vs. AA	AAER		AAER	
	(1)	(2)	(4)	(5)	(7)	(8)
Bivariate probit			Fraud	Detect | Fraud	Fraud	Detect | Fraud
Financial reporting quality						
RSST	0.293**	0.554***	0.457***		0.455***	
	(0.121)	(0.129)	(0.111)		(0.109)	
Financing needs						
Actual issuance	0.682	1.109**	0.641***		0.651***	
	(0.498)	(0.458)	(0.199)		(0.196)	
Growth and efficiency						
Sales growth	0.084	0.078	0.073		0.083	
	(0.090)	(0.083)	(0.121)		(0.125)	
Asset efficiency	0.044	-0.013	0.051		0.048	
	(0.060)	(0.045)	(0.062)		(0.062)	
Controls						
Receivables (change)	0.860	1.672*	2.196***		2.265***	
	(1.063)	(0.899)	(0.816)		(0.826)	
Cash sales (change)	-0.053	-0.052	-0.020		-0.018	
	(0.098)	(0.084)	(0.106)		(0.106)	
Inventory (change)	1.297	2.187	0.619		0.681	
	(1.479)	(1.333)	(0.844)		(0.863)	
Soft assets	1.675***	1.438***	1.702***		1.737***	
	(0.358)	(0.315)	(0.276)		(0.258)	
ROA (change)	0.0618	-0.068	0.178		0.169	
	(0.242)	(0.271)	(0.300)		(0.300)	
Leverage	0.397	-0.418	-0.703***		-0.747***	
	(0.333)	(0.353)	(0.208)		(0.214)	
Ln(Assets)	0.025	0.167***	-0.290***	0.259***	-0.250***	0.263***
	(0.034)	(0.034)	(0.055)	(0.025)	(0.068)	(0.027)
Stock market	-1.236***	-0.277*	0.498***	-0.347***	0.417***	-0.335***
	(0.179)	(0.153)	(0.142)	(0.080)	(0.146)	(0.081)
Detection factors						
Audit opinion				0.204***		0.222***
				(0.046)		(0.050)
Fortune 500				0.203**		0.227**
				(0.080)		(0.098)
Ln(Firm year)				-0.165***		-0.186***
				(0.040)		(0.050)
Unexpected performance				0.050		0.049
				(0.072)		(0.077)
SEC enforcement bias						
Ln(Distance)				-0.026***	-0.031*	-0.012
				(0.006)	(0.017)	(0.010)
Political contribution				4.899**	-194.400	298.100
				(2.452)	(135.900)	(214.900)
Ln(Employee)				0.032		0.033
				(0.028)		(0.032)
Constant	-4.759***	-10.060***	3.441**	-7.170***	2.346	-7260***
	(0.872)	(0.879)	(1.630)	(0.682)	(1.937)	(0.710)
Year dummies (SEC budget)	Yes	Yes	Yes	0.264**	Yes	0.253**
				(0.123)		(0.124)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Duration dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,833	32,342	74,653		74,653	
Log likelihood	-757	-1096	-3,146		-3143	

This table reports the probit estimation results between accounting fraud and prior-year discretionary accruals after controlling for additional variables. Accruals are aggregated for three years prior to the incidence of fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted. Variables are defined in Appendix 2.B.

TABLE 2.22 Static and dynamic hazard models

Panel A: Probit

	Dependent variable = *Pr* (Accounting fraud)															
	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	RSST		*WC*		*PMJIONES*		*SDD*		*Components*		*MJONES*		*PMJONES2*		*FMJONES*	
Financial reporting quality																
Accruals	0.277***	0.267***	0.662***	0.624***	0.110**	0.106***	0.004***	0.005***			0.133***	0.135***	0.057	0.081**	0.270***	0.275***
	(0.039)	(0.0325)	(0.100)	(0.0805)	(0.044)	(0.034)	(0.001)	(0.001)			(0.041)	(0.030)	(0.040)	(0.032)	(0.076)	(0.060)
Financing needs																
Actual issuance	0.211*	0.284***	0.222*	0.300***	0.248**	0.320***	0.249**	0.315***	0.175	0.244***	0.263**	0.326***	0.258**	0.326***	0.218*	0.294***
	(0.116)	(0.085)	(0.114)	(0.0834)	(0.115)	(0.085)	(0.115)	(0.085)	(0.116)	(0.085)	(0.116)	(0.085)	(0.115)	(0.084)	(0.120)	(0.089)
Current operating asset									0.778***	0.774***						
									(0.119)	(0.091)						
Current operating liabilities									-0.514***	-0.320***						
									(0.126)	(0.095)						
Non-current									0.250***	0.151***						
operating assets									(0.0631)	(0.048)						
Non-current									-0.140	-0.243						
Operating liabilities									(0.303)	(0.247)						
Financial investments									0.211***	0.390***						
									(0.079)	(0.072)						
Financial liabilities									0.037	0.013						

									(0.047)	(0.024)						
Controls																
Receivables (change)	1.489***	1.139***	1.425***	0.998***	1.826***	1.338***	1.758***	1.246***	0.949***	0.507**	1.814***	1.306***	1.879***	1.365***	1.852***	1.288***
	(0.293)	(0.211)	(0.280)	(0.202)	(0.275)	(0.199)	(0.282)	(0.202)	(0.313)	(0.226)	(0.273)	(0.198)	(0.275)	(0.198)	(0.290)	(0.212)
Cash sales (change)	0.014	0.005	0.036*	0.028**	0.037*	0.027**	0.040*	0.026*	-0.005	-0.010	0.038*	0.027**	0.037*	0.027**	0.084***	0.056***
	(0.022)	(0.015)	(0.021)	(0.014)	(0.020)	(0.014)	(0.021)	(0.014)	(0.023)	(0.016)	(0.021)	(0.014)	(0.020)	(0.013)	(0.023)	(0.015)
Inventory (change)	0.814**	0.696**	0.113	0.0561	0.794**	0.634**	0.635	0.389	0.029	-0.104	0.725*	0.593*	0.809**	0.655**	0.511	0.440
	(0.409)	(0.317)	(0.406)	(0.317)	(0.396)	(0.309)	(0.402)	(0.310)	(0.432)	(0.328)	(0.393)	(0.309)	(0.392)	(0.309)	(0.427)	(0.335)
Soft assets	0.782***	0.690***	0.730***	0.653***	0.798***	0.737***	0.795***	0.716***	0.716***	0.640***	0.792***	0.729***	0.800***	0.732***	0.848***	0.818***
	(0.100)	(0.074)	(0.097)	(0.073)	(0.097)	(0.073)	(0.098)	(0.073)	(0.104)	(0.079)	(0.097)	(0.073)	(0.097)	(0.073)	(0.105)	(0.079)
ROA (change)	0.050	-0.023	0.041	-0.008	-0.020	-0.046	-0.005	-0.028	0.071	0.010	-0.006	-0.036	-0.016	-0.038	-0.065	-0.104
	(0.078)	(0.065)	(0.080)	(0.067)	(0.071)	(0.057)	(0.071)	(0.059)	(0.072)	(0.057)	(0.072)	(0.058)	(0.072)	(0.058)	(0.076)	(0.064)
Ln(Assets)	0.072***	0.114***	0.089***	0.130***	0.089***	0.129***	0.086***	0.127***	0.075***	0.118***	0.087***	0.129***	0.087***	0.129***	0.092***	0.137***
	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.010)	(0.008)
Leverage	-0.036	-0.405***	-0.179*	-0.576***	-0.216**	-0.596***	-0.226**	-0.608***	-0.210**	-0.516***	-0.208**	-0.585***	-0.208**	-0.587***	-0.173*	-0.546***
	(0.100)	(0.085)	(0.093)	(0.082)	(0.091)	(0.082)	(0.092)	(0.083)	(0.102)	(0.087)	(0.091)	(0.081)	(0.091)	(0.081)	(0.095)	(0.084)
Stock market	-0.532***	-0.104***	-0.531***	-0.100***	-0.523***	-0.092**	-0.515***	-0.087**	-0.542***	-0.107***	-0.519***	-0.092**	-0.524***	-0.092**	-0.485***	-0.078**
	(0.056)	(0.037)	(0.054)	(0.036)	(0.054)	(0.036)	(0.055)	(0.037)	(0.056)	(0.037)	(0.054)	(0.036)	(0.054)	(0.036)	(0.058)	(0.039)
Constant	-3.352***	-5.064***	-3.652***	-5.347***	-3.663***	-5.366***	-3.604***	-5.301***	-3.351***	-5.118***	-3.647***	-5.356***	-3.643***	-5.356***	-3.832***	-5.606***
	(0.236)	(0.200)	(0.237)	(0.203)	(0.234)	(0.199)	(0.231)	(0.198)	(0.243)	(0.205)	(0.232)	(0.199)	(0.233)	(0.198)	(0.244)	(0.211)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,815	37,672	9,626	40,463	9,486	39,694	9,473	39,686	8,815	37,672	9,517	39,871	9,517	39,871	8,744	35,934
Log likelihood	-2160	-3136	-2389	-3443	-2375	-3422	-2354	-3383	-2143	-3105	-2382	-3434	-2386	-3438	-2137	-3070

Panel B: Dynamic Hazard Model

	Dependent variable = *Pr* (Accounting fraud)															
	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA	AAER vs. SCAL	AAER vs. AA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	RSST		*WC*		*PMJIONES*		*SDD*		*Components*		*MJONES*		*PMJONES2*		*FMJONES*	
Financial reporting quality																
Accruals	0.264**	0.511***	0.704**	1.188***	0.336**	0.375***	0.002	0.010*			0.316***	0.386***	0.252**	0.354***	0.470*	0.615**
	(0.109)	(0.117)	(0.282)	(0.295)	(0.135)	(0.123)	(0.004)	(0.005)			(0.122)	(0.115)	(0.124)	(0.123)	(0.266)	(0.276)
Financing needs																
Actual issuance	0.694	1.154**	0.517	1.004**	0.656	1.175**	0.706	1.186**	0.705	1.032**	0.701	1.210***	0.701	1.205***	0.366	0.884*
	(0.475)	(0.457)	(0.440)	(0.420)	(0.476)	(0.462)	(0.478)	(0.463)	(0.477)	(0.459)	(0.478)	(0.463)	(0.477)	(0.462)	(0.481)	(0.464)
Components of accruals																
Current operating asset									0.941***	1.683***						
									(0.351)	(0.339)						
Current operating liabilities									-0.533	-0.464						
									(0.368)	(0.372)						
Non-current									0.148	0.258						
operating assets									(0.174)	(0.175)						
Non-current									1.298	0.440						
Operating liabilities									(1.057)	(1.116)						
Financial investments									0.150	0.628**						
									(0.235)	(0.277)						
Financial liabilities									0.110	0.043*						
									(0.079)	(0.024)						
Controls																

Receivables (change)	0.967	1.787**	1.048	1.418*	1.445*	1.978**	1.653*	2.002**	0.195	0.058	1.400	1.931**	1.512*	2.027**	2.301***	2.381***
	(0.906)	(0.825)	(0.880)	(0.810)	(0.855)	(0.819)	(0.891)	(0.817)	(0.987)	(0.896)	(0.859)	(0.819)	(0.855)	(0.813)	(0.867)	(0.881)
Cash sales (change)	0.008	-0.004	0.042	0.052	0.056	0.053	0.053	0.051	-0.011	-0.032	0.395	0.052	0.055	0.050	0.163***	0.123***
	(0.068)	(0.044)	(0.066)	(0.046)	(0.062)	(0.043)	(0.063)	(0.044)	(0.069)	(0.058)	(1.240)	(0.043)	(0.062)	(0.043)	(0.059)	(0.040)
Inventory (change)	1.192	2.230*	-0.070	0.358	0.497	1.458	0.472	0.926	0.009	0.120	1.546***	1.389	0.458	1.490	-0.203	0.891
	(1.305)	(1.299)	(1.261)	(1.306)	(1.254)	(1.310)	(1.329)	(1.328)	(1.337)	(1.301)	(0.329)	(1.311)	(1.244)	(1.308)	(1.386)	(1.482)
Soft assets	1.481***	1.360***	1.465***	1.344***	1.567***	1.526***	1.525***	1.429***	1.354***	1.152***	0.056	1.504***	1.577***	1.518***	1.604***	1.752***
	(0.333)	(0.308)	(0.331)	(0.311)	(0.330)	(0.310)	(0.328)	(0.306)	(0.354)	(0.339)	(0.063)	(0.307)	(0.328)	(0.307)	(0.386)	(0.361)
ROA (change)	0.098	-0.053	0.159	0.028	-0.016	-0.128	0.0269	-0.004	0.106	0.063	0.067	-0.059	0.040	-0.064	-0.185	-0.432
	(0.232)	(0.253)	(0.248)	(0.271)	(0.227)	(0.236)	(0.244)	(0.262)	(0.233)	(0.253)	(0.235)	(0.240)	(0.235)	(0.237)	(0.270)	(0.271)
Ln(Assets)	0.022	0.166***	0.054*	0.207***	0.068**	0.222***	0.053*	0.211***	0.022	0.170***	0.060*	0.213***	0.060*	0.216***	0.089***	0.254***
	(0.032)	(0.033)	(0.032)	(0.034)	(0.031)	(0.033)	(0.031)	(0.034)	(0.034)	(0.035)	(0.031)	(0.033)	(0.031)	(0.033)	(0.033)	(0.037)
Leverage	0.368	-0.430	0.160	-0.893**	0.018	-1.006***	0.042	-0.998***	0.072	-0.649*	0.039	-0.974***	0.041	-0.989***	0.260	-0.713*
	(0.284)	(0.349)	(0.281)	(0.351)	(0.291)	(0.363)	(0.280)	(0.361)	(0.292)	(0.349)	(0.287)	(0.357)	(0.283)	(0.357)	(0.302)	(0.372)
Stock market	-1.143***	-0.277*	-1.185***	-0.296**	-1.161***	-0.281*	-1.171***	-0.303**	-1.133***	-0.279*	-1.169***	-0.293**	-1.169***	-0.283*	-1.119***	-0.276*
	(0.156)	(0.150)	(0.151)	(0.146)	(0.152)	(0.150)	(0.152)	(0.148)	(0.158)	(0.151)	(0.151)	(0.147)	(0.150)	(0.148)	(0.167)	(0.165)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,132	35,042	6,640	37,541	6,540	36,808	6,534	36,806	6,132	35,042	6,558	36,972	6,558	36,972	5,934	33,176
Log likelihood	-1126	-1463	-1239	-1600	-1219	-1575	-1209	-1561	-1122	-1452	-1225	-1584	-1225	-1584	-993	-1290

This table reports the probit and dynamic hazard model estimation results between accounting fraud and accruals, CEOs' equity incentives, and financing needs. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. To facilitate the convergence of the maximum likelihood estimations, a reduced industry dummy is adopted. Variables are defined in Appendix 2.B.

APPENDIX 2.A Measures for financial reporting quality and financing needs

In Appendix 2.A, I review the details of nine different types of financial reporting quality and two financing needs measures. Since there is no single agreed-upon measure for financial reporting quality, the adoption of multiple proxies may increase the power and generalisability of the analyses of this study (see Dechow et al. 2010; Hope et al. 2013; Burgstahler et al. 2006).

1. Working Capital Accruals (*Working Capital*) and Total Accruals (*RSST*)

Ever since Healy (1985), most accrual models have focused on working capital as a main earnings management tool (e.g., Sloan 1996; Dechow et al. 1995). Working capital accruals (*Working capital*) are relatively easy to manipulate by, for example, increasing accounts receivables (see Ettredge et al. 2010). Richardson et al. (2005) further recommend a comprehensive accrual model that incorporates not only working capital accruals but also non-current operating and financial accruals (*RSST*). As with working capital accruals, non-current operating assets such as capital expenditure may be utilised in decreasing firms' current-year costs and deferring them to following years[42]. After comparing the effectiveness of a wide range of accrual types in predicting fraud probability, Dechow et al. (2011) find that *RSST* is superior to other financial reporting quality measures in predicting accounting fraud probabilities. *Working capital* and *RSST* are calculated as below (Eq. (2.5) and (2.6)).

$$\textit{Working capital} = \Delta\text{current operating assets} - \Delta\text{current operating liabilities} \qquad (2.5)$$

[42] As an alternative view, non-current assets are known to be relatively difficult to manage since the depreciation mechanism is rather transparent (Barton and Simko 2002; Dechow et al. 2011).

$$RSST = \Delta WC + \Delta NCO + \Delta FIN \tag{2.6}$$

where:

WC (working capital) = current operating assets – current operating liabilities;

NOC (non-current operating assets) = non-current operating assets – non-current operating liabilities;

FIN (financial assets) = financial investments – financial liabilities.

2. Components of Accruals

Richardson et al. (2005) provide a simple but clear categorisation of the reliability of accrual components. According to their arguments, current and non-current operating assets are less reliable than other components of accruals. In particular, *Current operating assets* is supposed to be the least reliable component since the majority of accounting fraud is committed to overstate revenues (Dechow et al. 1996)[43]. *Non-current operating assets* such as PP&E are also less reliable since they can sometimes be aggressively capitalised instead of being expensed (Richardson et al. 2005). On the other hand, financial assets and liabilities are more reliable since the prices of financial products are readily observable in the markets. Therefore, if firms' accruals are composed more of unreliable components such as *Current operating assets* and *Non-current operating assets*, the reporting quality of these firms would be lower than other firms. The equations for six components of accruals are presented in Eq. (2.7)-(2.12).

[43] According to their analysis, 55.4 percent of accounting fraud cases in their sample (N = 92) are related to overstatement of revenues.

Current operating assets = current assets (*act*) – cash (*che*) (2.7)

Current operating liabilities = current liabilities (*lct*) – debt in current liabilities (*dlc*)[44] (2.8)

Non-current operating assets = total assets (*at*) – total current assets (*act*) – investment and advances (*ivao*) (2.9)

Non-current operating liabilities = total liabilities (*lt*) – total current liabilities (*lct*) – long-term debt (*dltt*) (2.10)

Financial assets = short-term investments (*ivst*) + investment and advances (*ivao*) (2.11)

Financial liabilities = long-term debt (*dltt*) + debt in current liabilities (*dlc*) + preferred stock (*pstk*). All variables are deflated by total assets (at_{t-1}) (2.12)

3. Modified Jones Model (*MJONES*)

The modified Jones model (*MJONES*) is the most conventional measure for the discretionary portion of working capital accruals (see Dechow et al. 1995). While preceding measures focus on the magnitude of total or working capital accruals, *MJONES* helps to capture the discretionary portion of working capital accruals compared to firms' peers in the same industries. Differently from the original Jones model (Jones 1991), *MJONES* assumes that all accounts receivable belongs to the discretionary portion of accruals. *MJONES* is the residual from Eq. (2.13). This study estimates Eq. (2.13) for each two-digit SIC-year grouping, with at least 10 observations. Other modified versions of discretionary accrual models are usually variations of the original Jones model (Jones 1991) and *MJONES*.

[44] To maintain consistency with Richardson et al. (2005), tax payable (tap) is not deducted in this equation.

$$\Delta WC = \alpha_0 + \alpha_1 (1/\text{total assets } (at_{t-1})) + \alpha_2 (\Delta\text{sale } (sale) - \Delta\text{receivables } (rect)) + \alpha_3 (\Delta\text{PP\&E } (ppegt)) + \varepsilon \quad (2.13)$$

where:

WC = current assets (*act*) – cash (*che*) – current liabilities (*lct*) + debt in current liabilities (*dlc*) + tax payable (*tap*). All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).

4. Forward-looking Modified Jones Model (*FMJONES*)

The forward-looking discretionary accrual model (*FMJONES*) modifies *MJONES* mainly by reclassifying parts of accounts receivable to a normal portion of accruals (Dechow et al. 2003). While *MJONES* assumes that all credit sales are discretionary, *FMJONES* considers that parts of them result from a normal increase in sales. The normal portion of accounts receivable is estimated from the relation between accounts receivable and sales (k in Eq. (2.14)), and it is then added back to the non-discretionary accruals. In addition, *FMJONES* controls for the prior-year working capital accruals and sales growth to exclude the remaining portion of non-discretionary accruals from discretionary accruals. This study estimates the following model for each two-digit SIC-year grouping, with at least 10 observations (Eq. (2.14)).

$$\Delta WC = \alpha_0 + \alpha_1 [(1+k)\Delta\text{sale } (sale) - \Delta\text{receivables } (rect)] + \alpha_2 (\Delta\text{PP\&E } (ppegt)) + \alpha_3 (\Delta WC_{t-1}) + \alpha_4(\Delta\text{sale} / \text{sale}_{t-1}) + \varepsilon \quad (2.14)$$

where,

Δreceivables (*rect*) = β_0 + $k\Delta$sales (*sale*) + γ. All variables except Δsale / sale$_{t-1}$ are deflated by total assets (at_{t-1}).

5. Modified Jones Model with Current-year ROA (*PMJONES*)

The modified Jones model with current-year ROA (*PMJONES*) modifies *MJONES* by controlling for firms' performance effects (Kothari et al. 2005). Since the levels of accruals are determined by firms' net income, *MJONES* may be biased if the performance effects are not addressed properly. The simplest version of this model is to control for current-year ROA in *MJONES* as in Eq. (2.15). The performance effects can also be controlled for by adopting matching methods that are explained in the following subsection.

$$\Delta WC = \alpha_0 + \alpha_1 (1/\text{total assets } (at_{t-1})) + \alpha_2 (\Delta \text{sale } (sale) - \Delta \text{receivables } (rect)) + \alpha_3 (\Delta \text{PP\&E } (ppegt)) + \alpha_4 (ROA) + \varepsilon \quad (2.15)$$

where:

ROA = income before extraordinary items (*ibc*) / average total assets. All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).

6. Performance-adjusted Modified Jones Model (*PMJONES2*)

As an alternative for *PMJONES*, Kothari et al. (2005) further adopt a matching method to control for performance effects. The ROA-based matching method identifies pairs of firms whose ROA is the closet in the same year and two-digit SIC industries. The difference in *MJONES* of the matched pairs is then used as Performance-adjusted modified Jones accruals (*PMJONES2*). To mitigate variations of this measure resulting from different firm characteristics, this study instead uses the difference between *MJONES* of each firm and the average *MJONES* of the firms belonging to the same two-digit SIC-year and ROA quintile grouping as the firm.

7. Studentised DD Estimation Error (*SDD*)

Instead of using cash sales to measure discretionary accruals, Dechow and Dichev (2002) focuses on the association between accruals and cash flows. Their argument is that accruals are of high quality when they are ultimately realised into cash flows. The unrealised accruals are called errors in their model. Mean-adjusted absolute Dechow-Dichev estimation error (*SDD*) explicitly evaluates the accrual quality by estimating Eq. (2.16) that relates working capital accruals to past, present and future cash flow from operation. *SDD* represents the residuals of the model deflated by the standard errors of the residuals of the firms belonging to the same two-digit SIC-year grouping as each firm.

$$\Delta WC = \alpha_0 + \alpha_1 (\mathrm{CFO}\ (oancf_{t-1})) + \alpha_2 (\mathrm{CFO}\ (oancf_t)) + \alpha_3 (\mathrm{CFO}\ (oancf_{t+1})) + \varepsilon \tag{2.16}$$

8. Mean-adjusted Absolute Dechow-Dichev Estimation Error (*ADD*)

Based on an alternative assumption that both positive and negative errors imply lower accrual quality in that the divergence between accruals and cash flows is sizable, Dechow et al. (2011) further adopt a measure for accrual quality. Mean-adjusted absolute Dechow-Dichev estimation error (*ADD*) is calculated by taking the difference between the absolute value of the residual estimated from Eq. (2.16) and the average absolute residuals of the firms belonging to the same two-digit SIC-year grouping as each firm.

9. Actual Issuance and Capital Expenditure

Observing whether a firm actually issues stocks and/or debts or whether a firm invests in big projects provides clear evidence for firms' financing needs. Following Dechow et al. (2011), two measures are adopted to proxy financing needs. First, *Actual issuance* is an indicator variable equal to 1 for firms whose sale of common and preferred stock (*sstk*) or long-term debt (*dltis*) is greater than 0, and 0 otherwise. Second, *Capital expenditure* is also an indicator variable equal to 1 for firms whose financing needs index (Eq. (2.17)) is less than -0.5, and 0 otherwise. Financing needs index is calculated as the difference between *CFO* and three-year average of capital expenditure.

$$\text{Financing needs index} = [\text{CFO} - (\text{Capital expenditures}_{t-1}\ (capx) + \text{Capital expenditures}_{t-2} + \text{Capital expenditures}_{t-3}) / 3] / \text{Total current assets}\ (act) \tag{2.17}$$

APPENDIX 2.B Variable definitions

Variables	Definitions
Dependent variable	
AAERs	An indicator variable equal to 1 for firms for which the SEC published AAERs for alleged GAAP violations, and 0 otherwise (AAERs compiled by CFRM) (Dechow et al. 2011).
SCALs	An indicator variable equal to 1 for firms for which securities class action lawsuits were filed and settled but the SEC did not publish AAERs, and 0 otherwise. (http://securities.stanford.edu/).
AA	An indicator variable equal to 1 for firms whose managers restated their prior-year financial statements, but for which AAERs were not filed, and 0 otherwise (Audit Analytics).
Lawsuits	An indicator variable equal to 1 for firms for which securities class action lawsuits were filed and settled within two years before and after the misreporting years of AAERs, and 0 otherwise.
AAER-SCAL	An indicator variable equal to 1 for firms for which AAERs and securities class action lawsuits were filed simultaneously, and 0 otherwise.
AAER-AA	An indicator variable equal to 1 for firms for which AAERs were filed, and whose managers restated their prior-year financial statements simultaneously, and 0 otherwise.
Accruals	
RSST	Total accruals = ΔWC (working capital) + ΔNCO (non-current operating assets) + ΔFIN (financial assets) (Richardson et al. 2005; Dechow et al. 2011). where, WC = current assets (*act*) – cash (*che*) – current liabilities (*lct*) + debt in current liabilities (*dlc*);

	NOC = total assets (*at*) – total current assets (*act*) – investment and advances (*ivao*) – total liabilities (*lt*) + total current liabilities (*lct*) + long-term debt (*dltt*); *FIN* = short-term investments (*ivst*) + investment and advances (*ivao*) – long-term debt (*dltt*) – debt in current liabilities (*dlc*) – preferred stock (*pstk*). All variables are deflated by total assets (at_{t-1}).
MJONES (Modified Jones)	The residuals (ε) from $\Delta WC = \alpha_0 + \alpha_1$ (1/total assets (at_{t-1})) + α_2 (Δsale (*sale*) – Δreceivables (*rect*)) + α_3 (ΔPP&E (*ppegt*)) + ε, estimated for each two-digit SIC-year grouping (Dechow et al. 1995; Dechow et al. 2011). where, *WC* = current assets (*act*) – cash (*che*) – current liabilities (*lct*) + debt in current liabilities (*dlc*) + tax payable (*tap*); All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).
PMJONES (Modified Jones with current-year ROA)	The residuals (ε) from $\Delta WC = \alpha_0 + \alpha_1$ (1/total assets (at_{t-1})) + α_2 (Δsale (*sale*) – Δreceivables (*rect*)) + α_3 (ΔPP&E (*ppegt*)) + *ROA* + ε, estimated for each two-digit SIC-year grouping (Kothari et al. 2005; Jones et al. 2008). All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).
PMJONES2 (Performance-matched modified Jones)	The differences between *MJONES* of each firm and the average *MJONES* of the firms belonging to the same two-digit SIC-year and *ROA* quintile grouping as each firm. Modified from (Kothari et al. 2005) to decrease the variations of *PMJONES*.
FMJONES (Forward-looking modified Jones)	The residuals (ε) from $\Delta WC = \alpha_0 + \alpha_1$ [(1+*k*)Δsale (*sale*) – Δreceivables (*rect*)] + α_2 (ΔPP&E (*ppegt*)) +

	α_3 (ΔWC_{t-1}) + α_4(Δsale / sale$_{t-1}$) + ε, estimated for each two-digit SIC-year grouping (Dechow et al. 2003). where, Δreceivables (*rect*) = β_0 + $k\Delta$sales (*sale*)+ γ; All variables except Δsale / sale$_{t-1}$ are deflated by total assets (at_{t-1}).
SDD (Studentised accrual estimation error)	The residuals of $\Delta WC = \alpha_0 + \alpha_1$ (CFO ($oancf_{t-1}$)) + α_2 (CFO ($oancf_t$)) + α_3 (CFO ($oancf_{t+1}$)) + ε, which are then deflated by the standard errors of the residuals of the firms belonging to the same two-digit SIC year grouping as each firm (Dechow and Dichev 2002; Dechow et al. 2011).
ADD (Mean-adjusted absolute value of accrual estimation error)	The differences between the absolute value of the residuals ($\vert\varepsilon\vert$), which are estimated from $\Delta WC = \alpha_0 + \alpha_1$ (CFO ($oancf_{t-1}$)) + α_2 (CFO ($oancf_t$)) + α_3 (CFO ($oancf_{t+1}$)) + ε, and the average absolute residuals of the firms belonging to the same two-digit SIC year grouping as each firms (Dechow and Dichev 2002; Dechow et al. 2011).
Financial ratios	
Receivables (change)	The ratio of Δreceivables (*rect*) and average total assets (*at*) (Dechow et al. 2011).
Inventory (change)	The ratio of Δinventory (*invt*) and average total assets (*at*) (Dechow et al. 2011).
Soft assets	The ratio of (total assets (*at*) – net PP&E (*ppent*) – cash (*che*)) and total assets (*at*) (Dechow et al. 2011).
Cash sales (change)	The percentage change of (sales (*sale*) – Δreceivables (*rect*)) (Dechow et al. 2011).
ROA (change)	The difference between income before extraordinary items (*ib*) / average total assets (*at*) and income before extraordinary items (ib_{t-1}) / average total assets (at_{t-1}) (Dechow et al. 2011).

Leverage	Long-term debt (*dltt*) / total assets (*at*) (Dechow et al. 2011).
Ln(Assets)	The natural logarithm of total assets (*at*).
Special items (change)	The ratio of Δspecial items (*spi*) and average total assets (*at*) (see Marquardt and Wiedman 2004). *SPI* includes restructuring costs (*rca*), writedowns (*wda*), gain/losses (*gla*), settlement (litigation/insurance) (*seta*), other special items (*spioa*), acquisition/merger (*aqa)*, impairments of goodwill (*gdwlia*), and extinguishment of debt (*dtea*).
Write-downs (change)	The ratio of Δwritedowns (*wda*) and average total assets (*at*) (see Marquardt and Wiedman 2004).
Financing needs	
Actual issuance	An indicator variable equal to 1 for firms whose sale of common and preferred stock (*sstk*) or long-term debt issuance (*dltis*) is greater than 0, and 0 otherwise (Dechow et al. 2011).
Capital expenditure	An indicator variable equal to 1 for firms whose financing needs index is less than -0.5 (Dechow et al. 2011). where, Financing needs index = [CFO (*oancf*) – (Capital expenditures$_{t-1}$ (*capx*) + Capital expenditures$_{t-2}$ + Capital expenditures$_{t-3}$) / 3] / Total current assets (*act*).
Net external financing needs	The sum of changes in common equity (*ceq*), preferred stock (*pstk*) and total liability (*lt*), deflated by total assets (*at*) (Wang 2006b).
Cash Flow	
CFO	The ratio of cash flow from operating activities (*oancf*) and average total assets.
CFI	The ratio of cash flow from investing activities (*invcf*) and average total assets.

CFF	The ratio of cash flow from financing activities (*fincf*) and average total assets.
Real Activities Management	
Abnormal production costs	The residuals (ε) from *Production costs* = α_0 + α_1 (1/total assets (at_{t-1})) + α_2 (sale (*sale*)) + α_3 (Δsale (*sale*)) + α_4 (Δsale$_{t-1}$ (*sale*)) + ε, estimated for each two-digit SIC-year grouping (Roychowdhury 2006). where, *Production costs* = COGS (*cogs*) + inventory ($\Delta invt$); All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).
Abnormal cash flow	The residuals (ε) from *CFO* (*oancf*) = α_0 + α_1 (1/total assets (at_{t-1})) + α_2 (sale (*sale*)) + α_3 (Δsale (*sale*)) + ε, estimated for each two-digit SIC-year grouping (Roychowdhury 2006; Ettredge et al. 2010). All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).
Abnormal discretionary expense	The residuals (ε) from *Discretionary expenses* = α_0 + α_1 (1/total assets (at_{t-1})) + α_2 (sale (*sale*)) + ε, estimated for each two-digit SIC-year grouping (Roychowdhury 2006). where, *Discretionary expense* = advertising expenses (*xad*) + R&D expenses (*xrd*) + selling, general, and administrative expenses (*xsga*); All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).
Suspect factors	
ROA	The ratio between income before extraordinary items (*ib*) and average total assets
Loss	An indicator variable equal to 1 for a firm whose income before extraordinary items (*ib*) is negative, and 0 otherwise (Houmes and Skantz 2010).

Small profits/losses	An indicator variable equal to 1 for a firm whose ratio between net income (*ni*) and lagged total asset (*at*) is less than 0.01 and greater than -0.01, and 0 otherwise (Burgstahler et al. 2006).
Other controls	
Stock market	An indicator variable equal to 1 for firms which are listed on major stock markets such as NYSE, AMEX, and NASDAQ, and 0 otherwise.
Industry	An indicator variable equal to 1 for seven two-digit SIC codes, which account for 51.9 percent of the total sample, and 0 otherwise. The seven industries are Business service (7300), Chemical and applied products (2800), Electronic & other electric equipment (3600), Instruments and related products (3800), Oil and gas extraction (1300), Industrial machinery & equipment (3500), and Electric, gas & stationary services (4900).
Growth	Sales growth measured by Δsale (*sale*) / $sale_{t-1}$ (Richardson et al. 2006).
Efficiency	Asset growth measured by Δtotal assets (*at*) / total $assets_{t-1}$ (Richardson et al. 2006).
SEC enforcement bias	
Audit opinion	An indicator variable equal to 1 for firms whose audit opinion is not unqualified, and 0 otherwise
Ln(Distance)	The natural logarithm of the distance between a firm's headquarters and the closest SEC offices in Washington, New York, Miami, Chicago, Denver, Los Angeles, Boston, Philadelphia, Atlanta, Fort Worth, Salt Lake, and San Francisco (Kedia and Rajgopal 2011; Heese 2015). The latitude and longitude of the offices of a firm and the SEC are acquired from the U.S. Census Bureau Gazetteer, and

	the distance is calculated using the Haversine formula.
Political contribution	5-year accumulation of Political Action Committee (PAC) contribution by a firm, divided by average total assets (Correia 2014; Heese 2015). The PAC data are collected from www.fec.gov.
Fortune 500	An indicator variable equal to 1 for firms which are included in the Fortune 500 list, and 0 otherwise (Correia 2014). The data are collected from http://fortune.com.
Unexpected performance	The residuals (ε) from $ROA_{t+1} = \alpha_0 + \alpha_1 ROA_t + \alpha_2 ROA_{t-1} + \varepsilon$, estimated for each firm (Wang 2013).
Ln(Firm age)	The natural logarithm of the years that have passed since the first Compustat year.
Budget (year)	The natural logarithm of SEC budget as reported in the SEC website (http://www.sec.gov/foia/docs/ udgetact.htm.). The SEC budget is deflated by the number of Compustat firms in each year (Kedia and Rajgopal 2011).
Ln(Employee)	The natural logarithm of the number of employees of a firm (*emp*) (Heese 2015).
Distance model	
Ln(Number of AAERs)	The natural logarithm of the number of AAER firms in each state for the years 1993-2007.
Ln(Number of firms)	The natural logarithm of the number of firms headquartered in each state for the years 1993-2007.
Average asset size	The average *Ln*(Assets) of firms located in a state for the years 1993-2007.
Average Employees	The average *Ln*(Employee) of firms located in a state for the years 1993-2007.
Ln(Number of Fortune 500)	The natural logarithm of the number of Fortune 500 firms in each state for the years 1993-2007.

Ln(Major markets)	The natural logarithm of the number of *Stock market* in each state for the years 1993-2007.
Ln(Risk industry)	The natural logarithm of the number of *Industry* in each state for the years 1993-2007.
Ln(Land area)	The natural logarithm of the land area in square miles of each state as of 2000 (www.census.gvo).
Ln(Population)	The natural logarithm of population in a state in 2000 (www.census.gvo).
Ln(Housing units)	The natural logarithm of housing units in a state in 2000 (www.census.gvo).

* Compustat mnemonics are presented in parentheses.

Chapter 3

Excessive Equity Incentives and Accounting Fraud

3.1. Introduction

Ever since Sanders (2001) showed that options and stocks have diametrically opposite impacts on CEOs' strategic decisions (see also Devers et al. 2007), it has been well established in the literature that options and stocks have *differing linear* effects on CEOs' misreporting decisions. Based mainly on their different payoff structure[45], prior studies have shown that options increase the likelihood of restatement (e.g., Efendi et al. 2007), litigation (e.g., Denis et al. 2006), and the combination of SEC enforcement actions and litigation (e.g., Khanna et al. 2015), whereas stocks decrease or do not have a significant impact on financial misreporting (e.g., Burns and Kedia 2006; Efendi et al. 2007; Zhang et al. 2008). However, excessive equity incentives increase the risk of accounting fraud commitment (Armstrong et al. 2013) because the SEC tends to target egregious cases (see also Richardson et al. 2002; Dechow et al. 2010) and the size of ill-gotten gains is a main consideration when deciding on the level of sanctions. Therefore, it is unclear whether CEOs would ignore the increasing risk when making accounting fraud decisions as prior studies above have inherently assumed. This chapter provides empirical analyses for this question by examining whether CEOs change their misreporting behaviours at higher levels of equity

[45] In contrast to the convex payoff structure of options (Burns and Kedia 2006), that of stocks is linear. Based on this difference, prior studies largely rely on the assumption that option holders are "self-interested agents" (Efendi et al. 2007) whereas stock holders are "loss avoiders" as stated in the prospect theory (see Zhang et al. 2008).

incentives, where they may begin to seriously consider the dark side of incentives in the context of accounting fraud.

According to the economics of crime (Becker 1968), CEOs' misreporting decisions are influenced by both the marginal costs (MC) and marginal benefits (MB) of their monetary incentives, and the MC and MB are assumed to eventually increase and diminish respectively. For example, the existence of aggregated punishments in the U.S. legal system supports the increasing MC. While additional criminal penalties like imprisonment are imposed on egregious fraud offenders, minor fraud cases are usually not punished or punished mainly by civil fines. Thus, rational CEOs would make optimal misreporting decisions so that their net benefits equal zero, resulting in a hump-shaped curve between option incentives and accounting fraud.

Due to two main heterogeneities, the analysis of stock ownership diverges from that of option incentives. First, as prior studies have posited (e.g., Burns and Kedia 2006), owner-CEOs tend to be conservative reporters because they are exposed to the downside risk of stock price changes. Second, the controlling power (e.g., voting rights) uniquely attached to stock ownership may induce CEOs to underestimate the potential risk of accounting fraud schemes because their discretionary power may deepen information asymmetry between insiders and accounting fraud detectors (see also Fan and Wong 2002). As a result, compared against CEOs as option holders, owner-CEOs are less likely to misreport at normal levels of stock ownership, whereas they are more likely to misreport once they acquire sufficient control over their board of directors. These combined effects result in a U-shaped curve between CEOs' stock incentives and accounting fraud.

Taking these considerations collectively, I hypothesise that options and stocks have *differing non-linear* impacts on CEOs' accounting fraud decisions. This hypothesis extends prior studies, which have already shown *distinct linear* associations between the two types of equity incentives and financial misreporting. Specifically, I expect that the non-linearity is characteristic of accounting irregularities because CEOs may not consider the risk effect regarding error misreporting. Thus, I provide a range of analysis results adopting relatively unintentional misreporting or earnings management measures simultaneously.

Using both matched and unmatched samples of AAERs and its alternative proxies (i.e., accruals, restatements, and lawsuits) for the fiscal years 1992-2012, I find that the distinct linear impacts of CEOs' option delta[46] and stock ownership on accounting fraud are indeed reversed once they reach respective threshold levels. Specifically, option delta increases accounting fraud propensity until it reaches a level of approximately $7 million and then reverses that upward trend from that point (producing a hump-shaped curve). Conversely, stock ownership initially decreases accounting fraud propensity and then reverses its downward trend at approximately 22 percent of stock ownership (a U-shaped curve). These findings affirm my hypothesis that CEOs' excessive equity incentives change their misreporting behaviours in the context of accounting fraud.

To shed light on the changes, I analyse whether CEOs' strength of motivation to misreport changes depending on their risk perception. After controlling for CEO power, CEO overconfidence, and firm characteristics, and using the inflection points of the non-linear curves of option delta and stock ownership as a measure of motivational strength to misreport, I find that CEOs as equity holders are more strongly motivated when they have more discretionary power over the board and are overconfident about future firm performance. More specifically, CEOs as option

[46] The value sensitivity of stock options to a 1 percent change in stock price (Core and Guay 2002).

holders reach their inflection points at higher levels of option delta when they are also the founders, have fewer outside directors on the board, or hold stock options that are more than 67 percent in the money (see Campbell et al. 2011). Conversely, owner-CEOs reach their inflection points at lower levels of stock ownership when they have longer tenures or stock price exceeds the average exercise price of their stock options by more than 67 percent. These findings provide supporting evidence for my argument that CEOs' risk perception matters when making accounting fraud decisions.

To provide more specific evidence for the heterogeneities in CEOs' misreporting patterns at higher levels of option delta and stock ownership, I further test whether CEOs as option and stock holders react differently toward an external shock that may affect their risk perceptions. The passage of the SOX constitutes an ideal setting to test this question since it increased the detection risk of financial misreporting by imposing a set of regulations regarding both internal and external governance (Miller and Pashkoff 2002). After controlling for CEOs' power, overconfidence, and competence, I find that SOX negatively moderates the relation between accounting fraud and the dummy for the higher level of *Option delta*, which is determined at its median. On the contrary, SOX does not have any significantly moderating effect on the relation between accounting fraud and the dummy for the higher level of *Stock ownership*[47]. These findings imply that, at higher levels of equity incentives, owner-CEOs are less susceptible to SOX than CEOs with excessive option incentives.

However, it is still not definitely clear whether CEOs' misreporting patterns at higher levels of equity incentives may indeed be explained by their risk perceptions and the inherent differences between options and stocks. Therefore, I identify three

[47] To avoid the potential inaccuracy in computing the marginal effects of interaction terms in binary models, I adopt the STATA command *inteff* suggested by Norton et al. (2004).

alternative explanations for my main arguments. First, Hanlon et al. (2003) argue that excessive option grants do not strongly motivate managers to improve future earnings (i.e., return on assets (ROA)) because the marginal utility of options diminishes as more options are granted. In the context of accounting fraud, CEOs may also be discouraged from misreporting due to the diminishing reward effect of options. Therefore, it is an empirical issue whether the decreasing "reward effect" or the increasing "risk effect" would be more influential in CEOs' accounting fraud decisions (see also Armstrong et al. 2013).

Using two unique settings where financial misreporting or earnings management is less likely to be intentional and, thus, CEOs may consider the risk effect less seriously, I test these two competing perspectives. To begin, I adopt accruals (i.e., *WC*, *PMJONES*, and *SDD*) as proxies for relatively less egregious earnings management strategies when compared to AAERs. In this context, I expect that any concave relation between option delta and accruals measures is more likely to be driven by the reward effect. However, I do not find a significant non-linear impact of option delta on accruals management, implying that CEOs are not strongly affected by the diminishing reward effect even in less intentional earnings management contexts. Further, I adopt two financial misreporting proxies that are likely to represent errors rather than accounting irregularities. Consistent with Hennes et al. (2008)[48], I classify restatements and securities class action lawsuits respectively into these two categories of misreporting (i.e., accounting irregularities and errors). However, I also do not find strong concave relation between option delta and error misreporting cases. Conversely, I do find a strong concave impact of option delta on accounting irregularity cases.

[48] Hennes et al. (2008) classify restatement cases as intentional accounting irregularities when they include words like "fraud". Consistent with this, I consider duplications with AAERs respectively with restatement and lawsuit cases as intentional cases.

These results together suggest that the diminishing reward effect is not a decisive factor that changes CEOs' misreporting behaviours at higher levels of option incentives.

Second, Mohd-Sulaiman (2013) argues that accounting fraud does not necessarily result from managers' intentional motivation and that the lack of professional competence is an alternative factor that causes financial misreporting. From this viewpoint, we can also consider that the increasing misreporting pattern at higher levels of stock ownership may be explained by CEOs' reduced competence. However, using three proxies for CEO competence acquired from the BoardEx database (i.e., *Degree*, *CPA*, and *Experience*), I do not find that these additional controls alter owner-CEOs' aggressive misreporting behaviours. These findings imply that CEOs' competence levels also do not seriously undermine my argument.

Finally, I test whether owner-CEOs' increasing misreporting patterns at the higher levels of stock ownership are driven by their overconfidence about future firm performance. Since managers' optimism is not necessarily realised, overconfident CEOs tend to be less conservative in financial reporting (Ahmed and Duellman 2013) and are likely to ultimately lead to intentional financial misreporting (Schrand and Zechman 2012) to attain their inflated expectations. Consistent with this perspective, I also find that CEO overconfidence (i.e., *Holder67*, *CAPEX*, and *Over_invest*) is positively associated with accounting fraud. However, the additional control of these variables does not affect the dual non-linear impacts of options and stocks on accounting fraud. This finding implies that the relation between CEOs' equity incentives and accounting fraud propensity is not seriously confounded by their overconfidence or optimism levels in my analyses.

Taken together, my results strongly suggest that, in the context of accounting fraud, CEOs' excessive equity incentives drastically change their misreporting behaviours in differing ways, and the discrepancy results from their different perception of risk regarding accounting fraud as two distinct equity holders. Additionally, given that my main findings are not susceptible to these controls (i.e., CEO overconfident and competence) nor to corporate governance levels, CEO power, and their risk-taking incentives measured by portfolio vega[49], I posit that CEOs' *differing* misreporting patterns at the higher end of equity incentives result from the inherent features of options and stocks (e.g., controlling power attached to shares).

As an additional test, I check the validity of my implicit assumption underlying the adoption of a percentage measure of stock ownership instead of a dollar measure (stock delta[50]), which suggests that options and stocks are differentiated by the controlling power attached to stock ownership. To check the validity of this assumption, I analyse whether these two stock ownership measures do indeed have heterogeneous impacts on accounting fraud. Unlike the percentage measure, I find no evidence of reversing effects of stock ownership when incorporating the dollar measure in my accounting fraud model. These results provide supporting evidence that the monetary measure of stock ownership alone does not fully capture the dynamic effects of stock ownership on CEOs' accounting fraud decisions.

The study makes distinct contributions to existing literature. To begin, this study builds on research exploring heterogeneities of options and stocks. Based largely on the different risk characteristics of options and stocks, these studies have reported that options and stocks have *distinct linear* impacts on CEOs' acquisition and divestiture

[49] The value sensitivity of both stocks options and stock holdings to a 1 percent change in stock volatility (Armstrong et al. 2013).
[50] Stock delta is the value sensitivity of stocks to a 1 percent change in stock price (Johnson et al. 2009).

decisions (Sanders 2001), market reactions to firms' IPOs (Certo et al. 2003), and financial misreporting (e.g., Burns and Kedia 2006; Efendi et al. 2007; Zhang et al. 2008; Peng and Röell 2008). This study extends this literature by showing that the diametrically opposite impacts of equity incentives are ultimately reversed at the higher levels of option delta and stock ownership.

When it comes to the non-linearity of equity incentives, there is also a strand of literature in various management contexts. Regarding stock options, Hanlon et al. (2003) argue that managers are less likely to be motivated by excessive option grant due to its diminishing marginal utility. However, my study differs from theirs in that I show that, in the context of accounting fraud, the non-linearity results not from the decreasing reward effect of options but from *the increasing risk effect* of accounting fraud, which is one of my main contributions.

On the other hand, since Morck et al. (1988) reported a non-monotonic association between managerial stock ownership and Tobin's Q, a considerable volume of literature has grown up around this theme in the context of debt costs (e.g., Anderson et al. 2003), information content of reporting earnings (e.g., Ghosh and Moon 2010), and firm value (e.g., Kim and Lu 2011). To my knowledge, however, this is the first study to show the contrasting non-linear impacts of both stocks and options *simultaneously*. In particular, I show that the differing non-linearity results from CEOs' different perception of risk regarding accounting fraud as option and stock holders respectively.

This study further contributes to the literature exploring the relation between managerial equity incentives and accounting fraud by explicitly adopting AAERs as a fraud proxy (e.g., Erickson et al. 2006; Johnson et al. 2009; Armstrong et al. 2010; Feng et al. 2011). Although AAERs are usually considered to be an appropriate sample to analyse motivational determinants of accounting fraud (Dechow et al. 2010), these studies have produced mixed and weak evidence on the impact of managerial equity incentives on accounting fraud: no effects (Erickson et al. 2006; Schrand and Zechman 2012; Armstrong et al. 2010) and positive effects (Johnson et al. 2009; Feng et al. 2011). As an extension of this strand of studies, Armstrong et al. (2013) show that managers' risk-taking incentives measured by portfolio vega subsume the effect of portfolio delta[51]. One plausible reason for these unexpectedly mixed findings may be the use of a combined measure of options and stocks despite their differing payoff structures. In fact, by separating options and stocks, I show consistent and pronounced non-linear relations between CEOs' equity incentives and accounting fraud measured by AAERs. I further document that the non-linearity is mainly characteristic of AAERs rather than other less intentional misreporting proxies. In particular, my results complement Armstrong et al. (2013)'s argument by showing that the effect of portfolio delta is rather subsumed by those of separate and quadratic specifications of option delta and stock ownership, not vice versa.

The remaining parts of this chapter are organised as follows. Section 3.2 summarises prior research and section 3.3 outlines my hypotheses. Section 3.4 describes my data and research design. Sections 3.5 and 3.6 provide empirical results and a battery of additional analyses and robustness checks respectively. Section 3.7 concludes.

[51] The sum of the value sensitivities of stocks and options to a 1 percent change in stock price (Erickson et al. 2006).

3.2. Review of literature

This chapter focuses on the change in misreporting behaviours at the higher levels of CEOs' equity incentives. There are broadly three streams of relevant literature that investigate the relation between various research focuses and managerial equity incentives. First, a considerable amount of literature has explored the heterogeneities between options and stocks. The study by Sanders (2001) is probably the first that highlights their diametrically opposite impacts on CEOs' strategic decisions. Based on the different risk characteristics of options and stocks, he finds that CEOs with higher option value are more likely to engage in acquisitions and divestitures, whereas CEOs with higher stock value are less likely to do so. His argument for these findings is that owner-CEOs are risk-averse because they bear the downside risk of stock price changes, whereas CEOs as option holders are aggressive risk-takers since they are not exposed to that risk. Subsequent studies such as Burns and Kedia (2006), Efendi et al. (2007), Peng and Röell (2008) and Zhang et al. (2008) have produced similar findings in the contexts of both restatement and litigation propensities. Option incentives increase firms' misreporting propensity, whereas their stock ownership decreases or does not have significant effects on financial misreporting decisions. For example, Peng and Röell (2008) find that top five managers' option delta is positively associated with the filings of securities class action lawsuits, whereas their stock delta does not have a significant association with the litigation propensity.

Second, a large body of literature provides empirical evidence that managerial stock ownership has non-linear effects in various management contexts. Contrary to the above research, this strand of literature focuses on the controlling power attached to stock ownership. Therefore, studies exploring non-linearity of stock incentives usually adopt the percentage metric of stock ownership as their main variable of interest since they believe that it more effectively captures both monetary incentives and controlling power underlying stock ownership. A key study in this research area is that of Morck et al. (1988), which shows that managerial ownership has a non-monotonic association with firm value measured by Tobin's Q. They attribute their finding to the combined convergence-of-interests and managerial entrenchment theories. Specifically, managerial ownership increases firm value at the lower level of ownership since the interests of managers and outside shareholders are aligned due to this insider ownership. However, an excessive level of ownership may depreciate firm value, since managers with influential shares may be entrenched by their increased controlling power within firms. Several lines of empirical evidence have followed the initiative of Morck et al. (1988) in the contexts of information content of reported earnings (e.g., Ghosh and Moon 2010), firm value (e.g., McConnell and Servaes 1990; Kim and Lu 2011) and debt costs (e.g., Anderson et al. 2003). Ghosh and Moon (2010), for example, show that CEOs' stock ownership has an inverted U-shaped association with the information content of firms' reported earnings. They attribute their finding to the investors' perception that CEO stock ownership improves the information quality of earnings at the lower level, whereas it rather deteriorates at the higher level.

On the other hand, there are relatively few studies that report non-linear effects of stock options. Hanlon et al. (2003), for example, show that the dollar value of top five managers' stock option grant has an inverted U-shaped association with firms' future earnings measured by ROA. They attribute the non-linearity to the diminishing marginal returns of stock option grants. Tian (2004), using simulation analyses, further demonstrates that an excessive level of stock options does not strongly motivate managers to boost stock price, presumably because the value of each stock option diminishes as executives have more option grants.

Finally, several studies have examined the relation between managerial equity incentives and accounting fraud by explicitly adopting AAERs rather than restatements and securities class action lawsuits. Due to the SEC's focused enforcement targets and standardised investigation process, AAERs are usually considered to be a reliable and appropriate sample to test managers' intentional motivation to misreport (see Dechow et al. 2010).

However, the empirical findings of these studies are relatively mixed and weaker than those of other studies adopting restatements and lawsuits. For example, the first empirical study in this research area, Erickson et al. (2006), does not find any association between CEOs' portfolio delta and accounting fraud. Subsequent studies by Johnson et al. (2009) and Feng et al. (2011) report that top five managers' stock delta and CEOs' portfolio delta deflated by their total pay respectively increase the probability of accounting fraud. Armstrong et al. (2010), on the other hand, show some negative impacts of CEOs' portfolio delta on the filings of lawsuits, but not on the filings of AAERs. A key characteristic of these studies, except Johnson et al. (2009)[52], is that they adopt the combined measure of portfolio delta as their primary incentive proxy. An assumption underlying this research design is that options and stocks have congruent impacts on accounting fraud. However, options and stocks have differing payoff structures and, therefore, may have distinct implications in the context of accounting fraud. Moreover, while these studies usually adopt dollar measure of stock-based incentives, the dollar metric of stock ownership may not fully capture its unique controlling power within firms.

In sum, prior studies have focused mainly on the linear impacts of options and stocks on financial misreporting, and they are often based on the "untested assumption"

[52] They adopt separate dollar measures of option delta and stock delta.

(Sanders 2001) that options and stocks are substitutes for each other. The theoretical development in the next subsection begins from exactly these research gaps in the existing literature and attempts to provide a more comprehensive view on the dynamic association between equity incentives and accounting fraud.

3.3. Theory and hypothesis development

3.3.1. Common origins

Equity-based incentives have long been considered to have countervailing effects on potential agency problems regarding interest conflicts between shareholders and managers (see Jensen and Meckling 1976). However, CEOs with call options may have incentive to distort accounting choices since their option value increases in stock price. This particular condition creates adverse effects that shareholders may not anticipate when granting options to align managers' interests with their own.

According to the economics of crime, fraud offenders consider the marginal costs (MC) and marginal utility (MU) of their monetary incentives (see Uygur 2013) and the MC and MU are assumed to ultimately increase and diminish respectively (Becker 1968; Ehrlich 1996).

First, due to general legal penalties, the MC of option incentives rises in the context of accounting fraud because sensitive option incentives inevitably increase the magnitude of CEOs' ill-gotten gains (see also Thevenot 2012). In fact, minor accounting fraud cases are usually not investigated by the SEC due to its limited resources (see Dechow et al. 1996; Richardson et al. 2002; Dechow et al. 2010). Therefore, the SEC does not file cases for a considerable number of self-admitted restatements. However, if financial misreporting is material and flagrant, the SEC brings legal proceedings against those cases, usually to impose monetary fines and/or administrative penalties on the offenders (see also Bremser et al. 1991). In addition, the Department of Justice (DOJ) brings egregious cases to criminal courts to impose greater penalties like imprisonment (Ramphal 2007). The U.S. punishment system implies that the MC of option incentives increases. Second, the utility of option incentives would decrease as its magnitude increases. As shown in Hanlon et al. (2003) and Tian (2004), an excessive level of stock option does not strongly motivate managers to continue pursuing increases in future earnings and stock prices. Tian (2004) explains that this may be because the value of each stock option declines as more options are granted to managers.

Taken together, the increasing MC and the diminishing MU of option incentives suggest that rational CEOs would make optimal misreporting decisions by equalising the MU and MC (see Becker 1968; Thevenot 2012). That is, CEOs would commit accounting fraud only if the MU is greater than the MC, and once the MC exceeds the MU, the increasing misreporting patterns would be reversed or at least weakened.

One potential counter-argument for the simple equilibrium analysis is that assumptions about the MC and MU curves may be incorrect. However, the analysis holds only if either the MC or MU curve is increasing or diminishing respectively. If any one of these curves changes, then CEOs would simply maximise their net utility at a different level of option incentives. Nonetheless, the base effect of the hump-shaped curve fundamentally does not change. Moreover, the drastic situation in which both the MC and MU are constant, or the MC is decreasing and the MU is increasing, is not conceivable since it would amount to a state of anarchy wherein no one is punished for committing accounting fraud.

Even if we relax the assumption that the MU of option incentives is decreasing, my argument remains valid. Instead of considering the utility of monetary value, we may simply assume that CEOs would accept the face value of monetary incentives as their benefits. Under this assumption, the total benefits from option incentives are linearly proportional to the size of option incentives (Eq. (3.1)) and, therefore, its marginal benefits (MB) would be always constant (Eq. (3.2)). On the other hand, the MC of option incentives would be positive as is assumed above (Eq. (3.3)). Any change in the functional forms of the MC does not affect the argument as long as it is ultimately increasing.

$$\text{Option incentives} = O \times [\partial (OV) / \partial (P)] \times (P \times 0.01) \tag{3.1}$$

$$\text{MB of option incentives} = c \text{ (when } c = \text{constant)} \tag{3.2}$$

$$\text{MC of financial misreporting} = [\partial (IGO) / \partial (P)] > 0 \tag{3.3}$$

where, O = the number of options;

P = the market price of stocks;

OV = the Black-Scholes value of an individual stock option;

IGO = the size of ill-gotten gains from option incentives.

The story is the same with stock incentives if we ignore its linear payoff structure and the effects of controlling power attached to shares. Despite the difference in the equations (Eq. (3.1) and (3.4)), the MB in this context is constant and the MC is greater than zero (Eq. (3.5)-(3.6)).

$$\text{Stock incentives} = S \times 1 \times (P \times 0.01) \tag{3.4}$$

$$\text{MB of stock incentives} = c \text{ (when } c = \text{constant)} \tag{3.5}$$

$$\text{MC of financial misreporting} = [\partial (IGS) / \partial (P)] > 0 \tag{3.6}$$

where, S = the number of stocks;

IGS = the size of ill-gotten gains from stock incentives.

The graph in the LHS of Figure 3.1 shows that CEOs would commit accounting fraud until MB equals MC, and they would decrease their misreporting once their net benefit is maximised. Thus, the relaxation of the original assumption, that the MB of option incentives may be constant, does not change my predictions regarding the relation between accounting fraud and equity incentives as in the RHS of Figure 3.1. Based on the equi-marginal principal, we can reasonably expect that accounting fraud propensity increases at the lower level of monetary incentives, whereas it decreases at the higher level, mainly due to the increasing MC of option incentives. Leaving the potential variations of stock incentives from this base relation open for discussion in the following subsection, I present my hypothesis on the relation between CEOs' option incentives and accounting fraud as below.

> H1: CEOs' option incentives increase (decrease) accounting fraud propensity at the lower (higher) level, i.e. a hump-shaped association between option incentives and accounting fraud.

3.3.2. Divergence

Owner-CEOs' misreporting decisions diverge from the base hypothesis mainly due to two heterogeneities of stock incentives from option incentives. First, at normal levels of shareholding, owner-CEOs are known to be more conservative in risk preference than CEOs as options holders. The linear payoff structure of stocks exposes CEOs to the downside risk of change in stock prices (Gao and Shrieves 2002; Burns and Kedia 2006). This price sensitivity may induce owner-CEOs to avoid risky reporting decisions that are susceptible to SEC enforcement actions.

Second, at higher levels of ownership, the controlling power attached to stock ownership may cause influential owner-CEOs to underestimate the costs of misreporting. Voting rights linked to stock ownership tends to provide CEOs with increased controlling power within firms (see also Morck et al. 1988). The above equilibrium analysis assumes that CEOs would perceive the MC of their monetary incentives as it is generally estimated in legal markets. However, if CEOs believe that they can so effectively control the board as to prohibit any fraud evidence from leaking (Fan and Wong 2002; Wang 2006a), they might misperceive the ultimate risks of misreporting.

Taken together, these two variations from the above base effects produce a combined hypothesis: that owner-CEOs with potentially conservative risk preference are less likely to commit accounting fraud at normal levels of stock incentives, whereas they are more likely to commit accounting fraud once they acquire sufficient control over the board at the higher level of stock incentives. As a result, I hypothesise the relation between CEOs' stock incentives and accounting fraud as follows.

> H2: CEOs' stock incentives decrease (increase) accounting fraud propensity at the lower (higher) level, i.e. a U-shaped association between CEOs' stock incentives and accounting fraud.

3.3.3. Risk perception

The main hypotheses of this study are based on an assumption that CEOs' perception of risk regarding accounting fraud alter their misreporting behaviours at the higher levels of equity incentives. Specifically, CEOs as option holders are less likely to misreport once their potential ill-gotten gains exceed certain critical levels. Owner-CEOs are rather more likely to misreport once their ownership levels exceed the critical points to provide them with sufficient control over the board. Commonly, these predictions assume that CEOs consider not only the reward effect of equity incentives but also the risk effect of accounting fraud commitment (see O'Connor et al. 2006; Armstrong et al. 2013).

To test the validity of this underlying assumption, I develop a hypothesis regarding CEOs' risk perception. I use the term "perception" because, regardless of the actual risk levels, they may have different perceptions of the risk in mind depending on the factors that may affect that perceived risk (e.g., discretionary power). More specifically, CEOs' perceptions about the risk of accounting fraud would ultimately affect the *strength* of their motivation to misreport. If they believe that the risk level is low, CEOs as option holders would keep misreporting even when they reach the critical level of option incentives, from where they would normally stop misreporting due to the increased risk. Conversely, owner-CEOs would start to misreport from lower than the critical level of stock incentives, from where they would normally begin to misreport due to their increased controlling power within firms. The relevant hypotheses are presented below.

> H3: The inflection point of a non-linear curve representing the misreporting pattern of CEOs as option (stock) holders moves forward (backward) when they have greater discretionary power over the board.

3.3.4. An external shock

An external shock such as the passage of SOX may also affect CEOs' risk perception; in this case, it increased the detection risk of financial misreporting by introducing a set of new regulations which are designed to strengthen both internal and external governance (Miller and Pashkoff 2002). In particular, if CEOs as option and stock holders had inherently distinct risk perceptions as I posit, they would react to SOX in different ways. Specifically, CEOs as option holders would naturally decrease their misreporting in response to SOX. On the contrary, owner-CEOs with sufficient controlling power may be less susceptible to the enhanced risk levels because they are likely to misperceive the risk due to the intensified information asymmetry by their ownership concentration. Therefore, I expect that the passage of SOX decreases accounting fraud propensity when CEOs' option delta is higher, whereas the effect may not be so strong for CEOs with sufficient stock ownership as to underestimate the enhanced risk. To capture the setting where CEOs should consider the risk of financial misreporting more seriously, my analyses focus on the higher levels of CEOs' equity incentives. Collectively, I present the two hypotheses below.

> H4: The passage of SOX is related to accounting fraud propensity when CEOs' equity incentives are higher[53].

[53] Since I posit that owner-CEOs with controlling power would be less susceptible to SOX, I lay out *H4* in a null form.

3.4. Data and research design

3.4.1. Sample selection

Table 3.1 reports my sample selection process. I begin with the merged file of Compustat, ExecuComp and Coles et al. (2006)'s open portfolio delta data[54] for the fiscal years 1992-2012. The initial observations are comprised of 24,544 firm-year-CEOs after excluding financial firms[55]. The sample starts from 1992 to include option and stock data on ExecuComp, which begins in that year. The ending year 2012 is determined for the SEC to have had enough time to detect accounting fraud cases[56]. To avoid inconsistency in calculating option delta, I use Coles et al. (2006)'s open data, which provide portfolio delta for each firm-year-executive annually.

The base sample is then merged with 1,961 fraud firm-years (1992-2012) included in AAERs, leaving us with 370 fraud firm-years after eliminating firm-years without sufficient data on Compustat and ExecuComp (Full sample). I use the comprehensive list of AAERs compiled by the Center for Financial Reporting and Management (CFRM) (Dechow et al. 2011). The loss of a significant number of cases from the whole CFRM database is mainly due to the requirement that AAERs must be covered on ExecuComp. This requirement is similar to that of Feng et al. (2011), who select 86 fraud firms out of 896 AAER firms.

To address sampling bias inherent in the panel-type fraud data, I further construct two additional sets of cross-sectionally matched samples. Despite the advantage of large observations, the full sample has broadly three limitations. First, the unequal

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[54] See http://sites.temple.edu/lnaveen/data/.

[55] Due to different levels of regulation and capital structure, financial institutions are usually excluded from estimation samples (see Dechow et al. 1996; Beneish 1997; Erickson et al. 2006; Markelevich and Rosner 2013).

[56] According to Karpoff et al. (2017), it takes approximately 55.9 months (4.65 years) from a GAAP violation to SEC legal proceedings.

proportion of fraud firm-years in the total sample raises doubts on the validity of random sampling (see Palepu 1986; King and Zeng 2001). The fraud firm-years make up only 1.50 percent of the total observations. Second, financial ratios during manipulation periods are not reliable. Many fraud firms do not restate their misreporting since either they declare bankruptcy (Dechow et al. 1996; Cao et al. 2015) or relevant data do not exist several years after the incidence of accounting fraud (see Dechow et al. 2011). Third, reverse causality may cause an endogeneity issue. CEOs may misreport to compensate for price decreases caused by accounting fraud commitment. Cross-sectionally matched samples address these issues by selecting approximately same number of fraud and non-fraud firms, and by analysing lagged accounting data (*t-1*) with the first firm-year observation (*t*) from multiple fraud firm-years (see Beasley 1996; Uzun et al. 2004; Chen et al. 2006; Erickson et al. 2006; Johnson et al. 2009). From 739 distinct fraud firms in the CFRM database, I identify 100 fraud firms that are covered on ExecuComp and whose first fraud years fall between 1992 and 2012.

To avoid another sampling bias potentially resulting from solely analysing ExecuComp observations (see Cadman et al. 2010), I complement the 100 ExecuComp (S&P 1500) fraud firms with an additional 61 fraud firms that are mostly not covered on ExecuComp. These firms are selected from 70 fraud firms from AAERs, whose violation periods match those of 100 ExecuComp fraud firms (96.7 percent). Option and stock data for the additional fraud firms are manually collected directly from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) and the National Archives and Records Administration (NARA). The combined sample constitutes Generalized propensity-score matching (GPSM) sample, resulting in 155 fraud firms after excluding six duplications. To exploit the benefits of hand-collected data of 61 fraud firms, they are further analysed separately for several additional analyses (Partial matching (PM) sample).

Descriptive statistics for the three panels are reported in Table 3.2, along with *p*-values of *t*-tests and Wilcoxon rank-sum (WRS) tests. *t*-test results in Columns (1), (2), and (3) reveal that CEOs in fraud firms largely have higher levels of option delta but do not necessarily have higher levels of stock ownership than the average of ExecuComp firms, implying that CEOs in fraud firms may be more strongly motivated to misreport by option incentives. Further, Column (4) reports that there are also statistically significant differences in incentive levels between fraud firms in two respectively matched samples (GPSM and PM). Specifically, CEOs in the PM sample, which is mostly not covered on ExecuComp, hold more concentrated stock ownership but are exposed to rather lower option delta. These findings are consistent with Cadman et al. (2010), who argue that ExecuComp and non-ExecuComp firms are potentially heterogeneous. However, as will be presented in subsequent sections, three separate panels produce qualitatively similar empirical results, suggesting that the potential sampling bias does not cause serious issues at least in my analyses.

I next compile non-fraud matches for each fraud firm in the GPSM and PM samples. To mitigate confounding bias inherent in observational studies (Rosenbaum 2002), non-fraud firms are identified using two representative matching methods, which will randomise my non-random samples: the propensity score (e.g., Armstrong et al. 2010; Davidson et al. 2015) and partial (e.g., Dechow et al. 1996; Feng et al. 2011) matching methods. I explain the details of the matching process in the following subsections.

3.4.2. Generalized propensity-score matching (GPSM)

GPSM expands the conventional propensity-score matching (PSM), which has been widely used in standard binary cases, to continuous treatment cases (Hirano and Imbens 2004). As with the propensity score in PSM, the generalized propensity-score (*gpscore*) also has a "balancing property" in that, within the strata of the same *gpscore*, the probability of treatment is not dependent upon the matched covariates. The *gpscore* is the conditional density of the treatment given confounders, and it is estimated using both a treatment model (Eq. (3.7)) and a *gpscore* model (Eq. (3.8)). First, the propensity of the variation of CEOs' stock ownership is estimated using the following OLS regression model:

$$\begin{aligned} Ln(Stock\ ownership_t) = {} & \alpha_0 + \alpha_1 ROA_{t-1} + \alpha_2 Leverage_{t-1} + \alpha_3 Ln(Assets_{t-1}) \\ & + \alpha_4 Tobin's\ Q_{t-1} + \alpha_5 Working\ Capital_{t-1} + \alpha_6\ Ln(Tenure_{t-1}) \\ & + \alpha_7 Stock\ market_{t-1} + \varepsilon_t \end{aligned} \quad (3.7)$$

To mitigate confounding effects, I select the variables from potential confounders that may affect both CEO stock ownership and accounting fraud propensity. For example, *ROA*, *Leverage*, *Tobin's Q* and *Working capital* are chosen since they are not only conditions that may trigger accounting fraud incidences but also common factors that stock investors consider before commencing their investments. Similarly, CEO tenure (*Ln(Tenure)*) is a primary determinant of stock ownership since the longer CEOs hold their tenures in firms, the more chance they have to acquire shares by either purchasing stocks or exercising stock options (Kim and Lu 2011). *Stock market* and firm size (*Ln(Assets*) are also important factors that determine ownership structure since large and public firms usually have a more diffuse ownership structure than over-the-counter (OTC) market firms (Himmelberg et al. 1999)[57]. Further, I require that matched pairs are selected from firms not only in the same year but also in the same two-digit SIC as each fraud firm. Prior studies exploring the relation between CEOs' stock-based incentives and accounting fraud also have the same requirement (e.g., Erickson et al. 2006; Johnson et al. 2009; Feng et al. 2011), since industry characteristics affect firms' accounting fraud propensity. Firms in same industries usually have similar patterns of earnings management (Khanna et al. 2015). As will be shown in the following subsection, it inevitably decreases the covariate balances of matched samples. However, I believe that this tight requirement could address more critical biases that may be caused in its absence. The estimation results of Eq. (3.7) show that, as expected, most of the covariates are significantly associated with CEOs' stock ownership (Table 3.3).

I acknowledge that it may be relevant to use two treatment variables of options and stocks in Eq. (3.7). Instead, I adopt stock ownership as a representative treatment variable since I cannot use two dependent variables simultaneously. However, it is plausible that CEO stock ownership and option holdings have similar determinants in that they are commonly CEOs' equity incentives.

Second, I then use the estimation from the treatment model (Eq. (3.8)) to calculate *gpscore*. Following prior literature (e.g., Kluve et al. 2012), I adopt the probability density function of the normal distribution as a *gpscore* model as below (see also Hirano and Imbens 2004).

[57] Since corporate governance variables (e.g., *Outside directors*) are constructed using the Riskmetrics database which begins in 1996, I do not include them in Eq. (3.7). However, to mitigate the omitted variable bias, I control for the variables in the accounting fraud model (Eq. (3.10)) with a reduced sampling window (1996-2012).

$$\hat{R}_t = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{1}{2\sigma^2}(T_i - \hat{T}_t))$$

(3.8)

where,

T_i	=	the level of *Stock ownership* between 0 and 1;
$\hat{T}_t$ and σ	=	the estimations from the treatment model in Eq. (3.7).

Finally, using the calculated *gpscore*, I identify one or two non-fraud matches for each fraud firm. To find matches whose *ex ante* probability of having high CEO ownership levels are most similar but whose actual ownership levels are most dissimilar, I use the distance measure proposed by Armstrong et al. (2013) as in Eq. (3.9). The distance measure identifies matched pairs of fraud and non-fraud firms using a minimum distance criterion, without replacement. The final sample size as a result of the GPSM process ranges between 291 and 426 firms for the fiscal years 1992-2012 depending on two different matching ratios (1:1 and 1:2; GPSM sample).

$$Distance_{i,j} = \frac{(gpscore_i - gpscore_j)^2}{(CEO\ ownership_i - CEO\ ownership_j)^2}$$

(3.9)

where,

gpscore$_{i,j}$	=	the generalized propensity-score for firm *i* and *j* calculated using Eq. (3.7) and (3.8);
Stock ownership$_{i,j}$	=	CEOs' stock ownership for firm *i* and *j* respectively;
Stock ownership$_i$	$\neq$	*Stock ownership*$_j$.

3.4.3. Partial matching (PM)

As an alternative matching method, I next adopt the PM method. PM is a more conventional tool that has been widely adopted in both accounting (e.g., Dechow et al. 1996; Feng et al. 2011) and finance (e.g., Altman 1968) research. PM is suitable for a manual sample selection as GPSM cannot be used for firms with hand-collected data. Despite a limitation in that PM considers a relatively small number of covariates compared with GPSM, it is also a powerful method of matching by which researchers can balance their non-random samples in terms of the most critical covariates such as asset size, year and industry (two-digit SIC). Following Feng et al. (2011), I identify matched pairs based on these three criteria as of the beginning of the first fraud year. The final sample size resulting from the PM process is 122 firms for the fiscal years 1992-2012 (PM sample).

3.4.4. Covariate balance

Table 3.4 reports the covariate balance between matched pairs identified with both GPSM and PM methods. Balanced covariates mitigate another potential bias: observed effects of options and stocks on accounting fraud propensity may result from other confounding effects than my variables of interest. The *p*-values for a parametric *t*-test of the differences in means, and two non-parametric WRS and Kolmogorov-Smirnov (KS) tests for the differences in medians and distributions respectively, indicate that the two matching algorithms have successfully identified matches whose covariates are well balanced. Specifically, the *gpscores* of the GPSM sample are not statistically different (p-values: 0.768-0.944), and the matched rates[58] of both GPSM and PM samples range between 67 percent and 100 percent depending on test types.

3.4.5. Accounting fraud model

Due to the binary characteristics of accounting fraud cases, I estimate the effects of CEOs' equity incentives on accounting fraud using the following probit regression model. In the interests of brevity, I attach the detailed definitions of variables in Appendix 3.A.

$$\begin{aligned} Pr(Accounting\ fraud_t) = \beta_0 &+ \beta_1\ Option\ delta_{t-1} + \beta_2 Option\ delta^2_{t-1} \\ &+ \beta_3 Stock\ ownership_{t-1} + \beta_4 Stock\ ownership^2_{t-1} \\ &+ \sum \beta \text{CEO power} + \sum \beta \text{Corporate governance} \\ &+ \sum \beta \text{Overconfidence} + \sum \beta \text{Competence} \\ &+ \sum \beta \text{Financial ratios} + \sum \beta \text{Other controls} + \sum \beta \text{Year dummy} \\ &+ \sum \beta \text{Industry dummy} + \varepsilon_t \end{aligned} \tag{3.10}$$

where,

t = the year-end of fraud year.

Consistent with prior studies exploring determinants of accounting fraud (e.g., Dechow et al. 1996; Schrand and Zechman 2012; Davidson et al. 2015), I adopt AAERs as a proxy for intentional financial misreporting. AAERs are considered to be a more appropriate sample to analyse intentional GAAP violations than other proxies for misreporting, since the standardised SEC enforcement process tends to ensure a

[58] The number of balanced covariates divided by the total number of covariates (%).

homogeneous accounting fraud sample (see Dechow et al. 2011). Due to its limited budget, the SEC is known to prioritise more material and flagrant cases of GAAP violation (Bremser et al. 1991; Dechow et al. 1996; Richardson et al. 2002; Dechow et al. 2010). However, I also analyse alternative proxies for earnings quality and financial misreporting (i.e., accruals, restatements, and securities class action lawsuits) to provide a more comprehensive view of my arguments.

Contrary to most prior literature exploring CEOs' equity incentives in the context of financial misreporting (e.g., Burns and Kedia 2006; Johnson et al. 2009), I use distinct metrics for stocks and options: a dollar measure for options (*Option delta*) and a percentage measure for stocks (*Stock ownership*). The percentage measure of stock ownership captures not only monetary incentives but also the controlling power that is attached to shares (see also Ghosh and Moon 2010; Khanna et al. 2015). However, I also analyse the dollar measure of stocks (*Stock delta*) for comparison purposes. For *Option delta*, I use Coles et al. (2006)'s open data by subtracting *Stock delta* (Eq. (3.4)) from *Portfolio delta*. For hand-collected matched pairs, *Option delta* is calculated following Core and Guay (2002) and Coles et al. (2006)'s calculation method. As an additional motivational variable, I include *First public offering* and *Debt covenant violation*. *First public offering* captures CEOs' motivation to misreport as controlling shareholders (see Ehrhardt and Nowak 2001), and *Debt covenant violation* represents CEOs' intention to misreport to avoid imminent triggering of debt covenants (Dechow et al. 1996).

I adopt six categories of control variables: CEO power, corporate governance, CEO overconfidence, CEO competence, financial ratios, and other controls. For the CEO power and corporate governance categories, I include six variables that may increase or decrease CEOs' discretionary power within firms. Firms' governance structures are known to affect CEO's equity incentives (Davila and Penalva 2006). Following Dechow et al. (1996), Beasley (1996), Chen et al. (2006) and Khanna et al. (2015), *CEO=Chairman*, *CEO=Founder*, *Ln(Tenure)* and *Appointment-based connectedness (ABS)* are proxies for CEOs' ability to affect board composition and operations. For example, CEOs with longer tenures may have more opportunity and freedom to affect the appointment process of directors and executives (Hermalin and Weisbach 1988) and CEOs working with connected board members may have more influence on management decision-making (Khanna et al. 2015). On the contrary, *Outside director* and *Outside blockholder* have the opposite effect on CEO power from inside and outside of firms respectively.

For overconfidence measures, I adopt *Holder67*, *CAPEX*, and *Over_invest*. *Holder67* is an option-based proxy for CEOs' overconfidence about future stock price, which is equal to one for firms whose CEOs hold stock options that are more than 67 percent in the money (Campbell et al. 2011). On the other hand, *CAPEX* and *Over_invest* are investment-based measures for overconfidence representing abnormal levels of investment compared to those of firms' industry peers (Schrand and Zechman 2012; Ahmed and Duellman 2013). For competence measures, I adopt *Degree*, *CPA*, and *Experience*. While *Degree* and *CPA* represent CEOs' professional knowledge, *Experience* proxies for their professional experience before joining current firms as a CEO[59].

For the remaining two categories, I add major financial ratios (e.g., *ROA* and *Leverage*) and *Stock market*, which are proposed in major prior literature (e.g.,

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[59] Through the merging process of BoardEx with ExecuComp, I lose a significant portion of firms (remaining observations = 7,031). The loss of observations results from two factors. First, not all CEOs on ExecuComp are covered by BoardEx. Second, the two databases have different identifiers for CEOs and thus I require name matching (see also Huang et al. 2011).

Beneish 1999; Ettredge et al. 2010; Dechow et al. 2011). I also adopt *Portfolio vega* as a proxy for CEOs' risk-taking incentives (Armstrong et al. 2013).

Due to data availability[60], I estimate a more parsimonious model excluding *Degree*, *CPA*, *Experience*, *Outside director*, *ABC*, *Outside blockholder*, *First public offering*, and *Debt covenant violation* for my main analyses of the full and GPSM samples. However, by exploiting limited or hand-collected data, I analyse more extended models incorporating these variables for various additional analyses.

3.5. Main findings

3.5.1. Univariate quintile analysis

Table 3.5 reports univariate quintile analysis results of *Option delta* and *Stock ownership* in relation to accounting fraud frequencies. To mitigate endogeneity issues, these analyses concern the GPSM sample, whose covariates are already balanced (Table 3.4). The analysis results reveal that *Option delta* has largely positive associations with accounting fraud frequencies (Columns (1) and (2)), whereas *Stock ownership* has negative associations (Columns (3) and (4)). These initial findings are largely consistent with those of the previous literature on restatements and class action lawsuits (e.g., Peng and Röell 2008). Further, the lower and higher quintiles of option delta and stock ownership show asymmetrically opposite impacts on accounting fraud frequencies even though they are not statistically significant. These results imply that there may be more dynamic and non-monotonic associations between accounting fraud and CEOs' equity incentives (Armstrong et al. 2010).

[60] For example, corporate governance variables can be constructed from 1996, since Riskmetrics begins in that year.

3.5.2. Different non-linear effects

The hypothesis tests in Table 3.6 (Panel A) examine whether CEOs' option delta and stock ownership influence their accounting fraud decisions in differing and non-linear ways (*H1* and *H2*). To mitigate sampling bias, I analyse both unmatched and matched samples (full and GPSM) in tandem. Columns (1)-(2) report that the coefficients for *Option delta* and *Option delta²* are both significant, and positive and negative respectively, when adopting the full sample. The regression estimates indicate that the relation between option delta and accounting fraud is hump-shaped[61] (LHS of Figure 3.2), supporting *H1*. Option holdings increases accounting fraud propensity at the lower level of *Option delta*, but the effect is ultimately reversed presumably due to the increasing risk of financial misreporting. The inflection point of *Option delta*, from where CEOs are discouraged to commit accounting fraud, is approximately $7 million[62].

Conversely, the coefficients for *Stock ownership* and *Stock ownership²* are both significant, but negative and positive respectively in the same columns. These estimates indicate that the relation between stock ownership and accounting fraud is U-shaped (RHS of Figure 3.2), supporting *H2*. Contrary to stock options, stock ownership seems to curb CEOs' accounting fraud behaviours at its lower level, but it starts to motivate them to misreport once ownership exceeds certain critical levels. CEOs who have acquired sufficient controls over the board may underestimate the risk of misreporting. The inflection points of *Stock ownership* in Panel A are at levels of

[61] To identify the shape of the concave relation, I adopt three strategies. First, using the coefficients and their signs of quadratic terms in Eq. (3.10), I check their preliminary shapes and whether their inflection points are within the ranges of our interest (e.g., 1-100 percent of stock ownership). Second, using predicted values of Eq. (3.10), I illustrate their graphical shapes as in Figure 3.2. Finally, using piecewise spline specifications, I confirm both hump-shaped and U-shaped curves of option delta and stock ownership respectively (the PM sample).

[62] I calculated the inflection points using the marginal effects presented in Panel C.

22-23 percent. These threshold levels are consistent with those in prior research, which posits that CEOs acquire effective control over their firms at ownership levels of 5-35 percent (see e.g., Ghosh and Moon 2010). Taken together, these results affirm *H1* and *H2* that CEOs' equity incentives affect their accounting fraud decisions in differing and non-linear ways.

The analyses of alternative GPSM samples provide supporting evidence that my results are not susceptible to potential sampling bias. To address the bias resulting from analysing solely non-random ExecuComp firms (Cadman et al. 2010), GPSM sample is composed of both ExecuComp and non-ExecuComp firms. Columns (4)-(5) consistently reveal that options and stocks have significant and differing non-linear impacts on accounting fraud, affirming *H1* and *H2* again.

Despite the matching processes adopted for GPSM sample, some coefficients for control variables are still statistically significant (Columns (4)-(5)). There are three main reasons for these results. First, matching does not guarantee perfect covariate balances (see King and Nielsen 2016). Second, not all covariates in the fraud model (Eq. (3.10)) are included in the treatment model (Eq. (3.7)). Third, there may be some hidden effects that multivariate analyses bring about. For instance, the coefficients for *CEO=Chairman*, which was not considered through the matching algorithm[63], are highly significant in Columns (4) and (5), since CEOs who are also the Chairmen of the board may have greater influence over reporting decisions (Dechow et al. 1996).

Finally, it is informative to note that, despite some differences from Armstrong et al. (2013)[64], I also find that the effect of *Portfolio vega* subsumes that of *Portfolio*

[63] I did not include *CEO=Chairman* in Eq. (3.7) since it is not clear whether the duality increases CEO ownership or, conversely, CEOs with higher ownership exploit the duality opportunity.
[64] Three main differences are: unit of analysis (top five executives vs. CEO), the calculation of variables (self-calculated vs. Coles et al. (2006)'s open data), and sample periods (1992-2009 vs. 1992-2012).

delta (Columns (1)-(2) in Panel B). However, the statistical significance of *Portfolio vega* disappears when I incorporate the separate and quadratic specifications of *Option delta* and *Stock ownership* (Column (4)). This implies that the effect of *Portfolio vega* is rather subsumed by those of *Option delta* and *Stock ownership*, or that there is multicollinearity among these variables. To avoid potential multicollinearity issues, I adopt *Portfolio vega* only in the main analysis (Column (4) in Panel A), but the results are not susceptible to this additional control.

3.5.3. Risk perception

My main analyses are based on the assumption that CEOs consider the risk of financial misreporting while committing accounting fraud. To provide empirical evidence for this assumption, I examine whether CEOs' concerns over that risk affect their *strength* of motivation to misreport (*H3*).

Table 3.7 reports the comparative analysis results by different levels of CEOs' discretionary power and overconfidence. Columns (1), (2), (5), and (6) in Panel A consistently show that the inflection points of the quadratic curves of both option delta and stock ownership do indeed change depending on the levels of CEO power, supporting *H3*. As for option holders, CEOs reach their inflection points at higher levels of *Option delta* when they are also the founders (*CEO=Founder*) ($4.13 mil. → $ 6.22 mil.; LHS of Figure 3.3). This result implies that CEOs with more discretionary power are less susceptible to being influenced by the increased risk of misreporting. Conversely, CEOs as stock holders reach their inflection points at lower levels of *Stock ownership* when they have longer tenure (24.3 percent → 15.7 percent; RHS of Figure 3.3), suggesting that powerful CEOs are likely to underestimate the risk. These results affirm that CEOs' risk perception ultimately affects their strength of motivation to misreport.

We also find that CEOs in firms with a lower percentage of outside directors (*Outside director*) and overconfident CEOs measured by the option-based measure (*Holder67*) reach their inflection points of stock options at higher levels than CEOs without these conditions (Columns (4)-(5) in Panel B and Columns (1)-(2) in Panel C). However, I do not find similar results when adopting alternative investment-based overconfidence measures (*CAPEX* and *Over_invest* in Columns (3)-(6)). A plausible explanation for these differences is that CEOs spending more on long-term investment opportunities tend not to be strongly motivated to misreport even when they are overconfident about their future firm performance.

3.5.4. Decomposition of stock incentive

Another theory underpinning my argument is the managerial entrenchment effect discussed by Morck et al. (1988), which would provide an explanation for why relatively conservative owner-CEOs drastically change their misreporting patterns at higher levels of stock ownership. In spite of intense research around this theme (e.g., Kim and Lu 2011), we still lack direct empirical support for the effect. Using Kalay et al. (2014)'s voting premium measure, I provide empirical evidence for the entrenchment argument in the context of accounting fraud. Voting premium is calculated by deducting the price of a synthetic stock ($\hat{S}(T)$), which is estimated by the put-call parity in Eq. (3.11), from its stock market price (S)[65]. Since the synthetic

[65] The sample is composed of the merged observations of Optionmetrics and ExecuComp, resulting in 12,954 firm-year observations for the fiscal years 1996-2012. Consistent with Kalay et al. (2014) and Lin et al. (2018), we adopt pairs of American-style call and put options whose strike prices and maturities are the same. We then exclude options whose maturities exceed 90 days, quotes are locked or crossed, and volume and implied volatility data are missing. Instead, we keep options whose moneyness is between 0.1 and -0.1. We finally require that these pairs have at least 10 observations in each year.

stock price represents the value of a stock without voting rights, voting premium ideally captures shareholders' control rights or willingness to exercise their voting rights by paying an additional premium to the synthetic stock price. The premium is then scaled by the market price (S) to normalise and averaged for a year (*Voting premium*). By multiplying *Voting premium* with *Stock delta* in Eq. (3.10), I finally decompose CEOs' stock incentive into its control rights (i.e., *Stock delta* × *Voting premium*) and monetary portions (i.e., *Stock delta*).

Consistent with the entrenchment effect, Columns (1) and (2) in Table 3.8 reveal that the coefficient of *Stock delta* × *Voting premium* is positive and significant whereas that of *Stock delta* is negative and significant. These findings indicate that, among two separate portions of stock incentive, control rights (i.e., voting premium) may engender GAAP violations whereas its monetary portion does the opposite. To address a potential confounding effect in that voting premium may increase due to control contest in a mergers and acquisitions context (see Lin et al. 2018), I further control for firms' *ex ante* probability of takeover (*Pr*(*Takeover*)) in Column 3. The additional control, however, does not alter our results.

$$\hat{S}(T) = C - P + PV(X) + PV(Div) - EEP_{call} + EEP_{put} \qquad (3.11)$$

where,

$\hat{S}(T)$	=	the price of synthetic stock implied in the put-call parity with maturity T;
$C\,/\,P$	=	premiums of call/put options;
$PV(X)$	=	present value of a bond with par value X;
$PV(Div)$	=	present value of dividend payments;
$EEP_{call\,(put)}$	=	early exercise premium for call (put) option.

2.5.5. The Sarbanes-Oxley Act (SOX)

To provide more specific evidence that CEOs as option and stock holders react to the risk of financial misreporting *differently*, I further test whether the passage of the SOX moderates the relation between accounting fraud and CEOs' equity incentives in distinct ways (*H4*). In particular, I focus on CEOs' misreporting behaviours at higher levels of option delta and stock ownership, which are my main areas of research.

Figure 3.4 illustrates two trends of accounting fraud rates[66] committed by CEOs with higher levels of option delta and stock ownership, which are determined at their respective medians. From this illustration, I can affirm that the accounting fraud rate of option holders are generally higher than those of stock holders, and the increasing patterns of accounting fraud rates of both CEO types (i.e., option and stock holders) are reversed downward after the IT bubble around 2000. Surprisingly, after the passage of the SOX in 2002 (the vertical line), the accounting fraud rate of option holders drops more drastically than that of owner-CEOs. This implies that option holders reacted to the enhanced risk of financial misreporting more actively than stock holders.

I also test the two interaction effects of the passage of the SOX (*SOX*) with the higher levels of option delta (H_o) and stock ownership (H_s) respectively (Eq. (3.12)). If CEOs' as option and stock holders had different risk perceptions about SOX, $SOX \times H_o$ and $SOX \times H_s$ would show distinct signs and/or statistical significance. As expected, Table 3.9 reports that the statistical significance of the coefficients of these two interaction terms are heterogeneous. Specifically, Column (1) shows that $SOX \times H_o$ has a significant and negative association with accounting fraud whereas $SOX \times H_s$ does not have a significant association with accounting fraud (*H4*). A similar difference is also found when I additionally incorporate a CEO competence variable

[66] The number of AAERs scaled by total ExecuComp firms.

(i.e., *Degree*) in the model (Column (2)). From these findings, I can reasonably infer that CEOs as option and stock holders have reacted to the passage of SOX in different ways: CEOs as stock holders were less susceptible to SOX than as option holders, supporting *H4*.

It is also informative to note that the signs and statistical significance of the interaction terms in binary models may be incorrect[67]. To address this bias, I adopt Ai and Norton (2003)'s method to compute interaction effects and find that my analyses are robust (Figure 3.5).

$$
\begin{aligned}
Pr(Accounting\ fraud_t) = {} & \gamma_0 + \gamma_1 Option\ delta_{t-1} + \gamma_2 Option\ delta_{t-1} \times H_o \\
& + \gamma_3 Stock\ ownership_{t-1} + \gamma_4 Stock\ ownership_{t-1} \times H_s \\
& + \gamma_5 SOX + \gamma_6 SOX \times H_o + \gamma_7 SOX \times H_s + \gamma_8 H_o + \gamma_9 H_s \\
& + \textstyle\sum \gamma \text{Financial ratios} + \sum \gamma \text{CEO power} \\
& + \textstyle\sum \gamma \text{CEO overconfidence} + \sum \gamma \text{CEO competence} \\
& + \textstyle\sum \gamma \text{Corporate governance} + \sum \gamma \text{Other controls} \\
& + \textstyle\sum \gamma \text{Year dummy} + \sum \gamma \text{Industry dummy} + \varepsilon_t \qquad (3.12)
\end{aligned}
$$

where,

H_o = an indicator variable equal to 1 if CEOs' option delta is greater than or equal to its median, and 0 otherwise;

H_s = an indicator variable equal to 1 if CEOs' stock ownership is greater than or equal to its median, and 0 otherwise.

[67] Contrary to linear models, the interaction effect in binary models is the cross derivative of the expected value of dependent variable. However, standard software does not consider this (Ai and Norton 2003).

3.5.6. Decreasing marginal utility of stock option

To sort out alternative explanations for the non-linearity of CEOs' misreporting behaviours, I conduct three additional analyses. To begin, Hanlon et al. (2003) argue that excessive option grants to managers tend rather to demotivate them in improving firm performance (i.e., ROA) due to the diminishing marginal utility of stock options. In the context of accounting fraud, excessive option delta may instead discourage CEOs from misreporting either due to the decreasing reward or increasing risk of penalties. I test these alternatives using two unique contexts, in which CEOs may not seriously consider the risk of earnings management or financial misreporting.

First, compared to AAERs, accruals are a relatively legitimate earnings management strategy that is originally allowed within managerial discretion. Second, Hennes et al. (2008) suggest a straightforward procedure to distinguish accounting irregularity and error restatements. For example, they classify restatement cases containing the words like "fraud" or irregularities" in reference to accounting irregularities, and errors otherwise. Consistent with this method, I categorise restatement and securities class action lawsuit cases into irregularities and errors[68]. If the diminishing marginal utility effect were a main driver of the non-linearity of stock options, then I might expect that option delta would show non-linearity even in these two contexts, in which CEOs may not be exposed to the critical risks of financial misreporting. The sample selection process of restatements and lawsuits is summarised in Table 3.10 (Panel B)[69].

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[68] Specifically, I consider the duplicated misreporting cases with AAERs as accounting irregularities (i.e., *Non-AAER Restatements* and *Non-AAER Lawsuits*) and the remaining exclusions as errors (i.e., *AAER-Restatements* and *AAER-Lawsuits*).

[69] Dismissed or ongoing lawsuit cases are deleted to mitigate the risk of analysing frivolous lawsuits, and cases that are not relevant to financial misreporting or disclosure issues are also not included in the sample.

However, contrary to the decreasing marginal utility hypothesis, I do not find strong concave relations between option delta and these two categories of relatively less intentional earnings management (i.e., *WC*, *PMJONES*, and *SDD*) and financial misreporting measures (Columns (1), (3), and (5) in Panel A, and Columns (1) and (3) in Panel C). Instead, I do find that the duplicated misreporting cases with AAERs (i.e., *AAER-Restatements* and *AAER-Lawsuits*) have strong non-linear relations with CEOs' option delta (Columns (2) and (4) in Panel C). These findings imply that the non-linearity of stock options may not be driven by the reward effect but by the risk effect, and the non-linearity is mainly characteristic of AAERs.

3.5.7. Lack of professional competence

I further test whether the increasing misreporting pattern at the higher levels of stock ownership is driven by CEOs' lack of professional competence. Mohd-Sulaiman (2013) posits that accounting fraud does not necessarily result from managers' intentional motivation, but simply results from CEOs' insufficient oversight over firms' reporting process. In fact, CEOs with excessive stock ownership (> 22.4 percent) in my main analysis are significantly less competent (i.e., *Degree*, *CPA*, and *Experience*) than CEOs with normal levels of shares.

Table 3.11 reports that, as expected, CEOs with PhD/ MBA (*Degree*) or more working experience before their current tenure (*Experience*) are less likely to misreport (Columns (1) and (5)). Moreover, Columns (1)-(6) consistently show that owner-CEOs' increasing misreporting patterns do not change even when I explicitly control for CEOs' competence levels in Eq. (3.11). These findings imply that CEO competence is not a critical factor in determining owner-CEOs' increasing misreporting patterns at the higher levels of stock ownership. On the other hand, the insignificance of the linear term of *Stock ownership* does not result from the additional control of CEO competence but from the loss of observations through the merging process of ExecuComp and BoardEx (24,544 → 7,031) as I can check from Columns (2), (4), and (6).

3.5.8. Overconfidence

I finally test whether CEOs' aggressive misreporting behaviours at higher level of stock ownership result from their overconfidence about future firm performance. Overconfident CEOs may hold more shares in expectation of an increase in stock returns. In that case, owner-CEOs' misreporting patterns may be driven by their optimism, not by the inherent characteristics of stock ownership (i.e., controlling power). In fact, Ahmed and Duellman (2013) and Schrand and Zechman (2012) argue that overconfident managers tend to be less conservative in financial reporting and are likely to ultimately lead to intentional accounting fraud.

Using three proxies for CEO overconfidence (i.e., *Holder67*, *CAPEX*, and *Over_invest*), I find that, consistent with prior studies (e.g., Ahmed and Duellman 2013), optimistic CEOs are more likely to misreport (Columns (1) and (2) in Table 3.12). However, I do not find that the additional controls of the overconfidence variables in Eq. (3.11) alter the non-linearity of stock ownership. These findings imply that CEOs' overconfidence does not undermine my argument that the aggressive misreporting behaviours of CEOs at higher ownership levels are driven by the inherent differences between stocks and options (i.e., controlling power), not seriously by other confounding factors.

In sum, my analyses so far consistently demonstrate that *differing non-linear* effects of options and stocks on CEOs' misreporting decisions can be explained by their different perception of the risk regarding accounting fraud commitment. Based on the findings of prior studies that have already shown *distinct linear* effects of stocks and option on firms' restatement and lawsuit propensities (e.g., Zhang et al. 2008; Peng and Röell 2008; Efendi et al. 2007; Burns and Kedia 2006), this study extends them by providing new empirical findings showing that the differing linear effects are ultimately reversed when the reward effect of equity incentives is overtaken by the risk effect of financial misreporting.

3.6. Robustness checks

3.6.1. Sampling bias

To mitigate sampling bias, I already analysed two distinct estimation samples (i.e., full and GPSM samples) and showed that my findings are not susceptible to the choice of these alternative samples (Table 3.6). One remaining sampling issue is that the full and GPSM samples include mainly ExecuComp firms, whose characteristics may be different from those of non-ExecuComp firms (Cadman et al. 2010). Therefore, I further construct a Partial Matching (PM) sample which is mostly composed of non-ExecuComp firms (90.1 percent). This additional sample is analysed using the piecewise spline specifications (PS) of *Stock ownership* (see Morck et al. 1988). The PS method enables us to find a parsimonious way to fit to the rather skewed stock ownership variable in the PM sample[70] by dividing it into the lower and higher levels at its knots (Eq. (3.13) and (3.14)). To avoid arbitrariness in determining the knot (2.4 percent), I develop an algorithm that automatically identifies an ownership level where the two slopes of PS variables are the most statistically different[71]. For a robustness

[70] The inflection point of CEOs' stock ownership in PM sample is 2.4 percent, whereas those in full and GPSM samples are between 22.4 percent and 23.1 percent.

[71] The knot is automatically identified using the following algorithms. First, the coefficients of both

check, the results do not change within wide intervals of alternative knots between 1.7 and 5.0 percent of stock ownership.

Using this PM sample and the PS specifications, I affirm that the distinct non-linear impacts of CEOs' equity incentives are still valid even in this alternative sample (Columns (1)-(2) in Table 3.13).

$$\begin{aligned}
&\text{Stock ownership (1)}\ (\textit{Stock ownership} < \text{knot}) \\
&\quad = \textit{Stock ownership} \text{ if } \textit{Stock ownership} < \text{knot} \\
&\quad = \text{knot if } \textit{Stock ownership} \geq \text{knot}
\end{aligned} \tag{3.13}$$

$$\begin{aligned}
&\text{Stock ownership (2)}\ (\textit{Stock ownership} \geq \text{knot}) \\
&\quad = 0 \text{ if } \textit{Stock ownership} < \text{knot} \\
&\quad = \textit{Stock ownership} - \text{knot if } \textit{Stock ownership} \geq \text{knot}
\end{aligned} \tag{3.14}$$

3.6.2. Omitted incentives

To mitigate potentially omitted variable bias, I already adopted a comprehensive range of controls in Eq. (3.10) (i.e., CEO power, overconfidence, competence, risk-taking incentives, and corporate governance). However, the association between accounting fraud and CEOs' equity incentives may be spurious, particularly when uncontrolled incentives that are associated with firm performance or stock prices (e.g., *First public offering*) motivate CEOs to keep misreporting even after they have benefited sufficiently from their own equity holdings (e.g., *Option delta*). Therefore, by exploiting the benefits of hand-collected data in the PM sample, I further test whether

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higher and lower levels of stock ownership are statistically significant. Second, the multiplication of two coefficients is negative. Finally, their slope differences are most statistically significant (the lowest sum of squared errors).

my main findings are robust regarding this bias. Column (2) in Table 3.13 confirms that the significant and non-linear coefficients for both option delta and stock ownership remain unchanged even after I control for two additional incentive variables, i.e., *First public offering* and *Debt covenant violation*.

3.6.3. Alternative variables

To check the sensitivity of the findings to other specifications of equity incentive variables, I estimate Eq. (3.10) after substituting *Option delta* and *Stock ownership* with three alternatives. First, I adopt top management team (TMT) as an alternative unit of analysis for CEOs. Despite the potential heterogeneities among TMT members (see Hambrick et al. 1996), TMT has been widely analysed by prior studies based on the assumption that the TMT may decide together on management issues (e.g., Haleblian and Finkelstein 1993). Table 3.14 reveals that *TMT stock ownership* and *TMT option delta* have similar effects on accounting fraud to those of *Option delta* and *Stock ownership*. These findings suggest that my main test results are not susceptible to the alteration of the unit of analysis. However, this does not directly imply that CEOs and TMT are mutual substitutes in analysing equity incentives as determinants of accounting fraud. The impact of TMT on accounting fraud may be mostly attributed to the effects of CEOs. In fact, CEOs' equity incentives account for the majority of TMT incentives[72] (see Aggarwal and Samwick 2003).

Second, I further adopt a combined measure of CEOs' stock-based incentives (*Portfolio delta*) as a substitute for the separate proxies, *Option delta* and *Stock ownership*. Despite scepticism over "the assumption of substitution" between options

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[72] CEOs' stock ownership, for example, occupies 73.6 percent of TMT stock ownership in GPSM sample.

and stocks (Sanders 2001), many studies have adopted *Portfolio delta* as a measure for CEOs' stock-based incentives (e.g., Feng et al. 2011; Armstrong et al. 2010). However, I have already pointed out a potential limitation of this combined measure: it may not capture the heterogeneities of options and stocks. Consistent with the findings of prior studies (e.g., Erickson et al. 2006), Table 3.15 affirms this argument by showing that there are no significant associations between accounting fraud and *Portfolio delta*. These findings imply that separate measures of options and stocks are better at estimating the effects of CEOs' equity incentives on accounting fraud. Overall, the results of these additional analyses validate the adoption of distinct measures for options and stocks in the context of accounting fraud.

Finally, I test whether the monetary and percentage measures of stock ownership are indeed heterogeneous in the context of accounting fraud. Based on the assumption of their heterogeneities, I have so far adopted the percentage measure of stock ownership (*Stock ownership*) to capture the controlling power of stock ownership (see e.g., Khanna et al. 2015; Lilienfeld-Toal and Ruenzi 2014). To test the validity of this assumption, I estimate Eq. (3.10) by substituting *Stock ownership* with a monetary measure, *Stock delta*. As in Eq. (3.4), *Stock delta* is the value sensitivity of stock ownership to a one percent change in stock price (Burns and Kedia 2006; Johnson et al. 2009).

Table 3.16 reports the analysis results. As expected, Column (2) reveals that *Stock delta* does not have significant and non-linear impact on accounting fraud. Instead, *Stock delta* has a negative but insignificant association with accounting fraud (Column (1)) as in Burns and Kedia (2006). These results imply that the monetary portion of stock ownership alone does not fully capture the dynamic effects of stock ownership on accounting fraud. Contrary to option holdings, stock ownership provides CEOs with controlling power over their firms and it affects their misreporting decisions. By acquiring these controls, CEOs may underestimate the risks related to accounting fraud commitment and this misperception encourages them to misreport despite the actual level of the risk. The comparison of the effects of monetary and percentage measures of stock ownership in Table 3.6 and Table 3.14 provides firm evidence to support my argument that owner-CEOs' controlling power causes the non-linear effects of stock ownership in the context of accounting fraud.

3.6.4. Reverse causality

To test the sensitivity of the results regarding reverse causality bias, I already adopted probit cross-sectional regression analyses (GPSM and PM samples) as in Dechow et al. (1996), in addition to probit panel regressions (full sample). By analysing lagged independent variables (*t-1*) and the first-year observation of dependent variable (*t*), the cross-sectional setting avoids the possibility that fraud incidence, in turn, affects CEOs' equity incentives. As reported in previous sections (e.g., Table 3.6), the analyses of probit cross-sectional regression produce qualitatively similar results to those of panel regression.

Further, I address one remaining issue regarding the simultaneity bias in the cross-sectional regression analyses. Reverse causality bias may arise if CEOs increase their option and stock holdings in the *expectation* of committing accounting fraud in the future (see Viswanathan and Wei 2008). To mitigate this bias, I estimate Eq. (3.10) after controlling for the potentially intentional changes in equity incentives between *t-1* and *t-2*. Table 3.17 affirms that the main findings of this study are not susceptible to both CEOs' potentially intentional changes (increase or decrease) and increase in equity incentives before the incidence of accounting fraud. Overall, the potential reverse causality issue does not cause serious bias to my results.

3.6.5. Partial observability

As a final robustness check, I test whether the findings are robust regarding potentially undetected fraud cases. By research design, I analyse AAERs that have been detected by the SEC as material GAAP violations. Like most research of this type, this research design causes partial observability bias (Poirier 1980), in that not all material misreporting cases are included in AAERs. To mitigate this bias, I already analysed alternative misreporting proxies to AAERs. Additionally, I adopt the bivariate probit regression model proposed by Poirier (1980) and adopted by Chen et al. (2006), Wang (2013), and Khanna et al. (2015) in the research exploring corporate fraud. Contrary to a normal probit regression model, this extended model combines an accounting fraud commitment model with an accounting fraud detection model to adjust the coefficients in the accounting fraud model conditional on the detection probability. The model requires that the fraud and detection models do not have exactly the same variables (Wang 2013). Following Wang (2013), benefits from accounting fraud (e.g., *Option delta* and *Stock ownership*) are excluded from the detection model. Instead, audit opinions (*Audit opinion*) are included in the detection model since they usually trigger SEC investigations. However, the analysis results do not alter even when I incorporate options and stocks in the detection model. *Audit opinion* is an indicator variable set to one if the audit opinion in the first fraud year is not unqualified. Table 3.18 affirms that the main findings of this study do not change even in the bivariate probit regression settings[73].

[73] Due to frequent convergence failures of the bivariate probit model, I conduct this analysis only for

3.7. Conclusion

Using both unmatched and matched samples and by adopting option delta and stock ownership as proxies for CEOs' equity incentives, I find that options and stocks have differing non-linear effects on CEOs' accounting fraud decisions. Specifically, I report that CEOs as option and stock holders, respectively, drastically change their misreporting behaviours at certain critical levels of option delta and stock ownership. Once reaching these critical levels, CEOs as option holders are less likely to misreport, whereas owner-CEOs are more likely to misreport. Further analyses indicate that these behavioural changes may be driven by CEOs' different perceptions of the risks regarding accounting fraud as two types of equity holders. At higher levels of equity incentives, CEOs as option holders are seriously concerned about the risk due to increased ill-gotten gains, whereas owner-CEOs underestimate the risk due to their increased control within firms. I also sort out three alternative explanations for the change in misreporting patterns and document that they are not strongly driven by the diminishing marginal utility of option holdings or CEOs' lack of professional competence and overconfidence.

Like most research of this type, this study is also subject to some caveats. First, even though I adopt both GPSM and PM sampling methods, matching itself does not eliminate bias resulting from unobservable covariates (Rosenbaum 2002). However, I mitigate these concerns by controlling for a wide range of additional variables. Further, as explained earlier, omitted motivational factors may bias against the findings regarding stock options. If the accounting fraud model (Eq. (3.10)) had omitted critical

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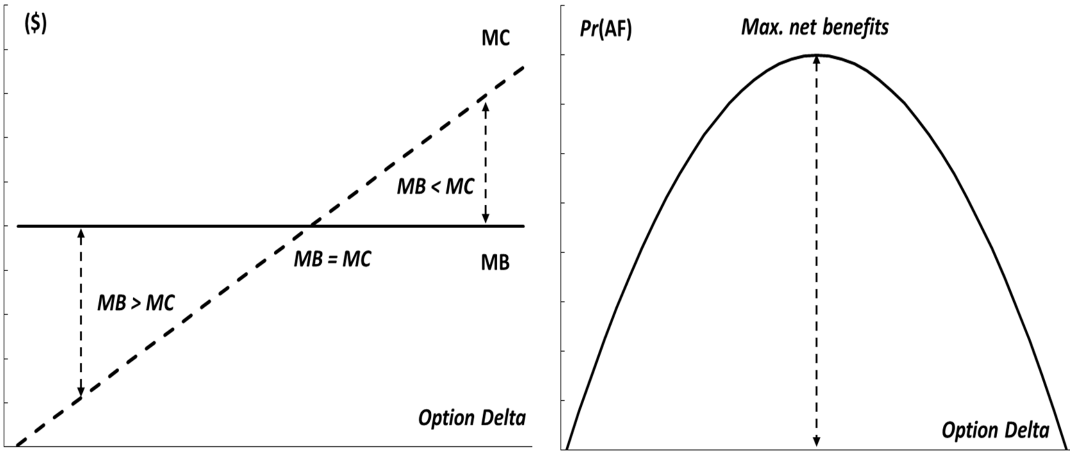
this robustness check. For the convergence issue of maximum likelihood methods, see Agresti and Kateri (2011).

incentive variables, the reversing effect of options would not be observed. Second, the accounting fraud model does not explicitly control for CEOs' personal wealth levels since they are not directly observable in the U.S. context. To a limited extent, however, *Stock ownership* mitigates this bias since CEOs' stock ownership is known to account for approximately 45 percent of CEOs' wealth (Elsilä et al. 2013). Finally, the accounting fraud proxy, AAERs, may be exposed to the partial observability bias. By adopting alternative misreporting proxies and the bivariate probit regression model, however, I aimed to address this issue.

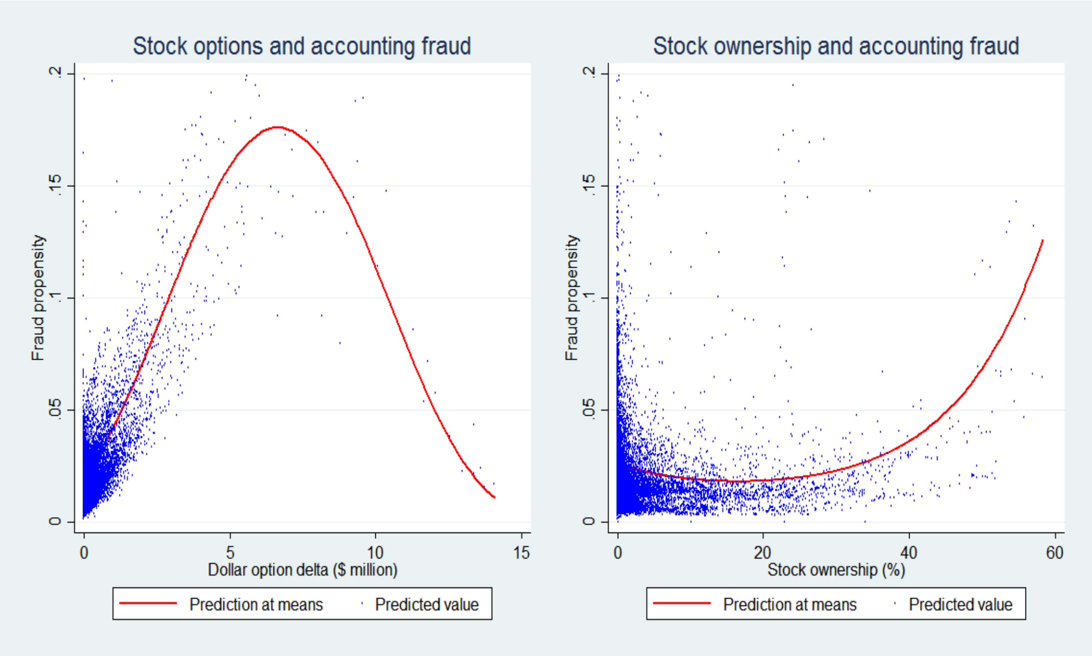
In addition to the theoretical contributions mentioned in the introduction section, my results provide practical implications for both accounting regulators and capital market investors. First, the findings should be of interest to accounting regulators, who have a responsibility to detect accounting fraud: CEOs with average option incentives or excessive stock incentives are more likely to misreport. Second, the differing non-linear effects of options and stocks on accounting fraud suggest that, as a compensation plan, shareholders should consider not only the choice between options and stocks, but also their respective levels of existing equity incentives.

Figure 3.1 Equilibrium analysis of accounting fraud



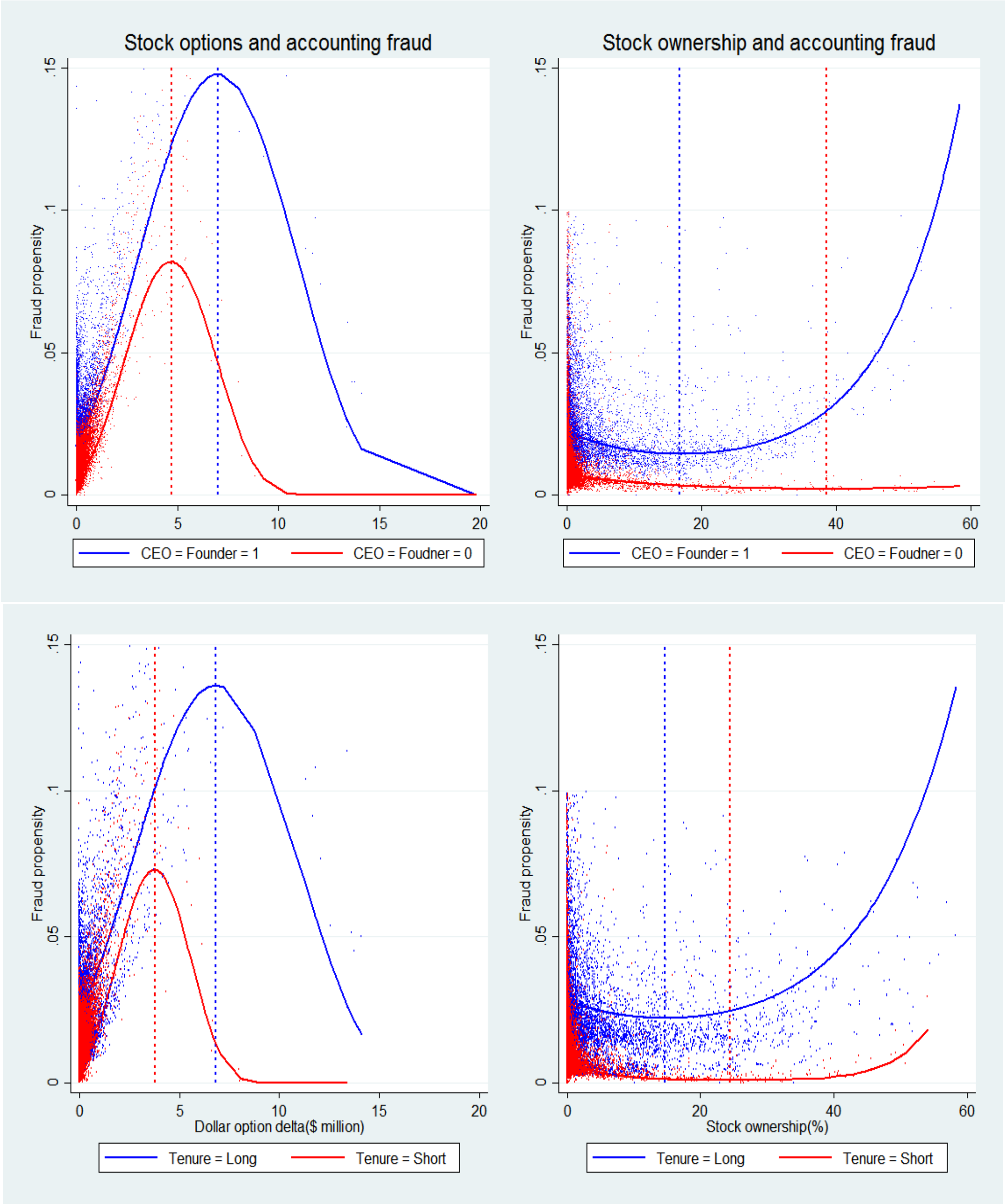
This figure illustrates an equilibrium analysis of the marginal benefit and cost of option delta in the context of accounting fraud, along with a prediction on the relation between option delta and accounting fraud propensity (*Pr*(AF)). Option delta is the value sensitivity of stock options to a 1 percent change in stock price. MB represents marginal benefit and MC stands for marginal cost.

Figure 3.2 Differing non-monotonic effects



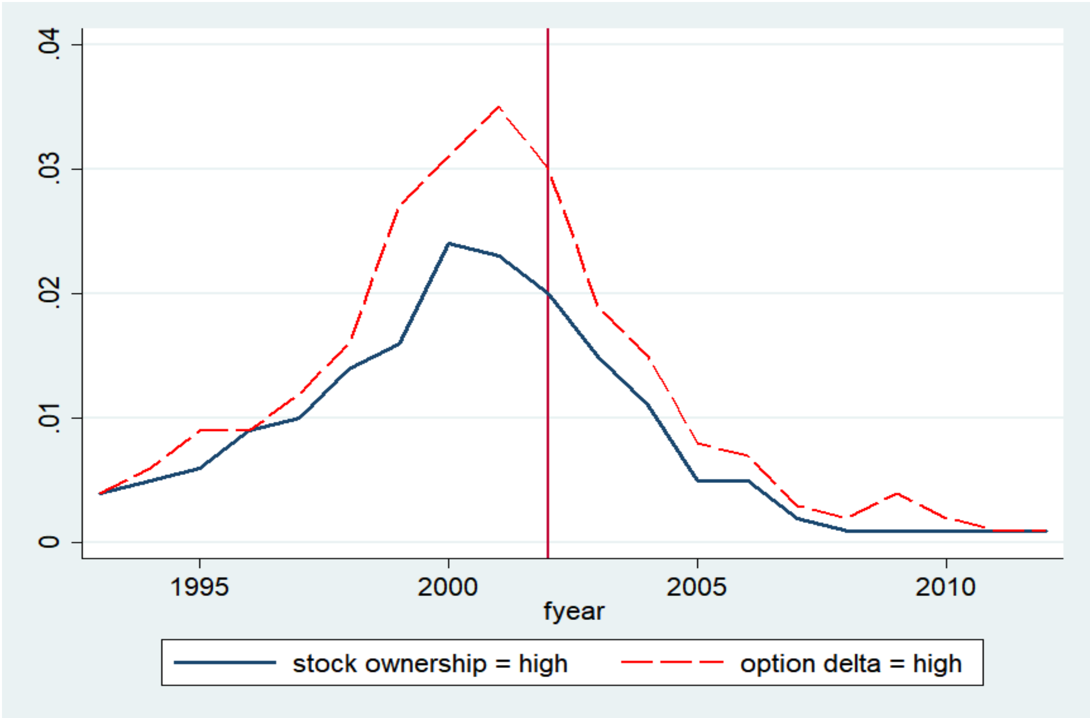
This figure illustrates differing non-linear effects of option delta and stock ownership on accounting fraud propensity (full sample). Lines are the predicted values of accounting fraud propensity estimated using Eq. (3.10) after setting controlling variables at their respective means, whereas dots are those estimated without adjusting control variables. Variables are defined in the Appendix 3.A.

Figure 3.3 Changing inflection points



This figure illustrates changing inflection points of the non-monotonic curves of option delta and stock ownership in the context of accounting fraud (full sample). Lines are the predicted values of accounting fraud propensity estimated using Eq. (3.10) after setting control variables at their respective means, whereas dots are those estimated without adjusting control variables. Variables are defined in the Appendix 3.A.

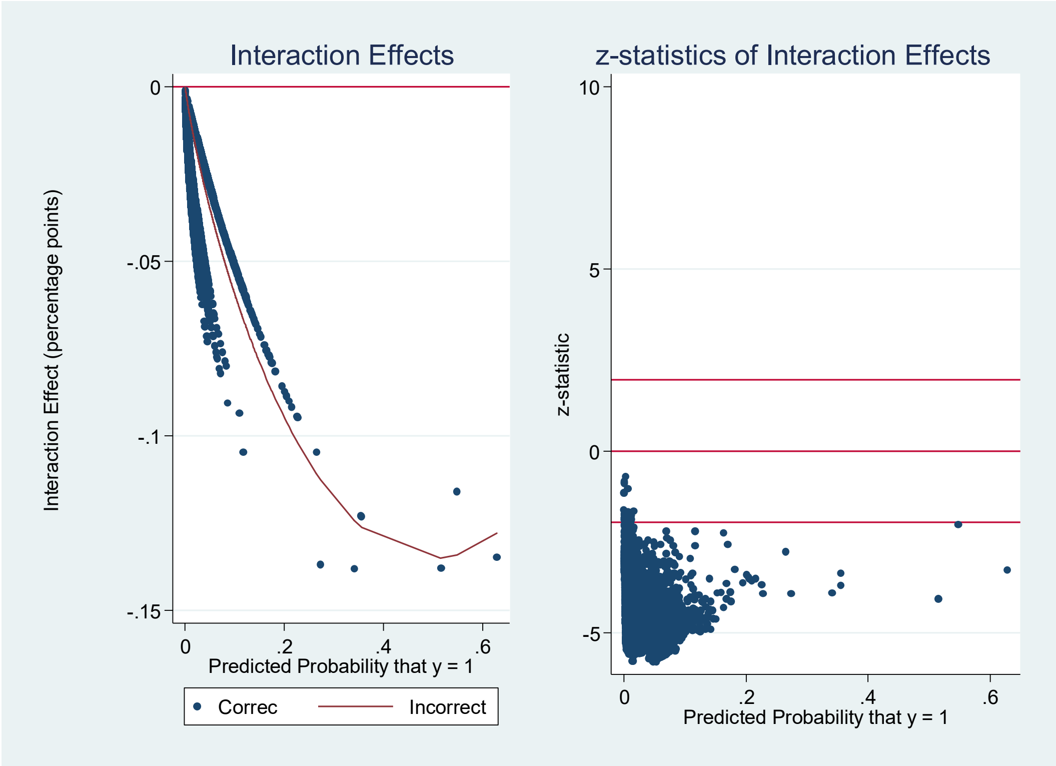
Figure 3.4 The effects of SOX on CEOs' misreporting patterns



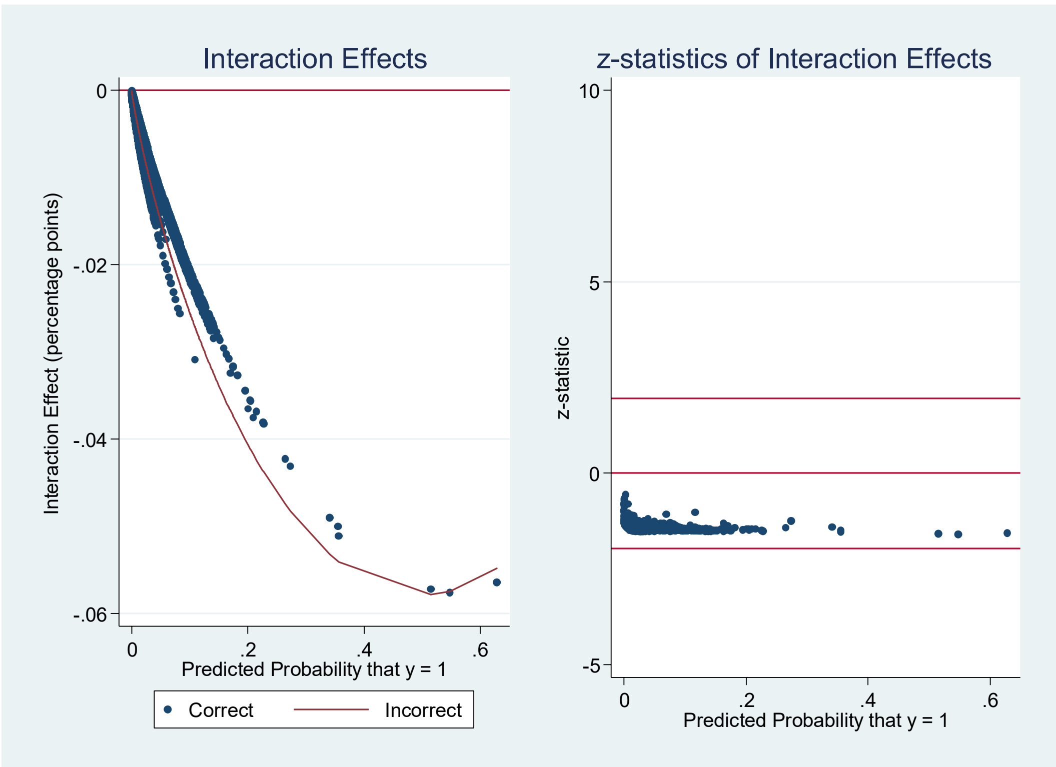
This figure illustrates changing trends of misreporting patterns around the passage of the Sarbanes-Oxley Act (SOX) in 2002 (full sample). Lines are accounting fraud rates of firms whose CEOs belong to the higher levels of *Option delta* and *Stock ownership* respectively. Accounting fraud rate is the number of AAERs scaled by total ExecuComp firms in each year. Variables are defined in the Appendix 3.A.

Figure 3.5 Interaction effect estimation for probit models

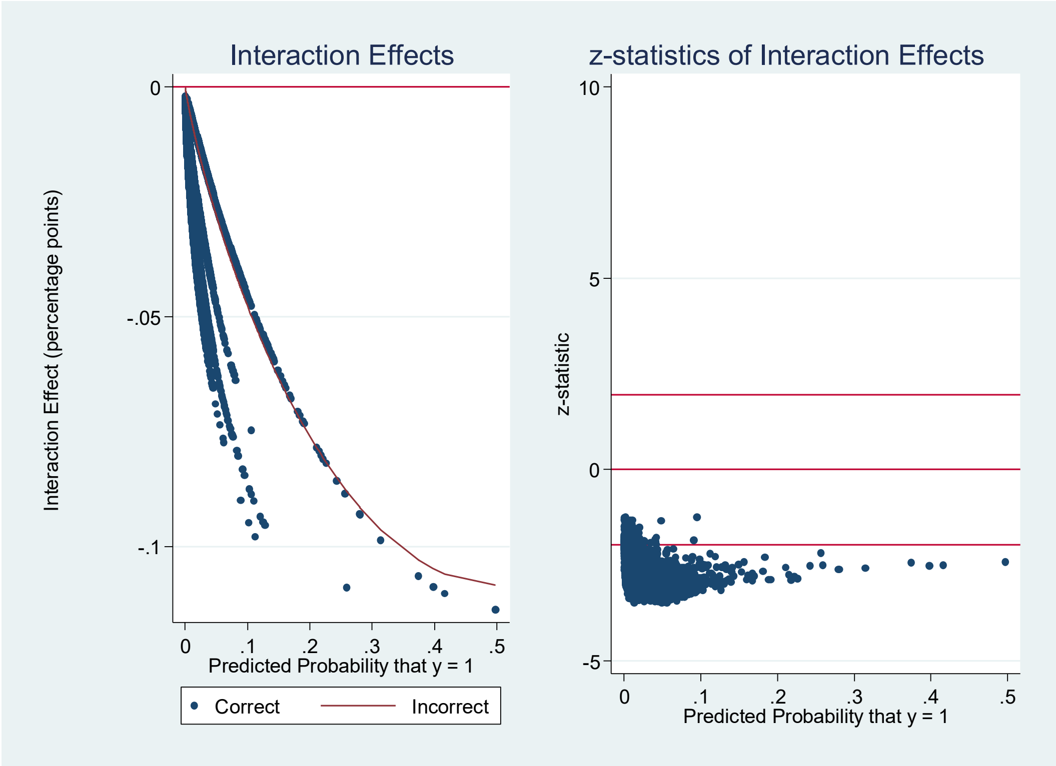
Panel A: *Option delta* (Column (1))



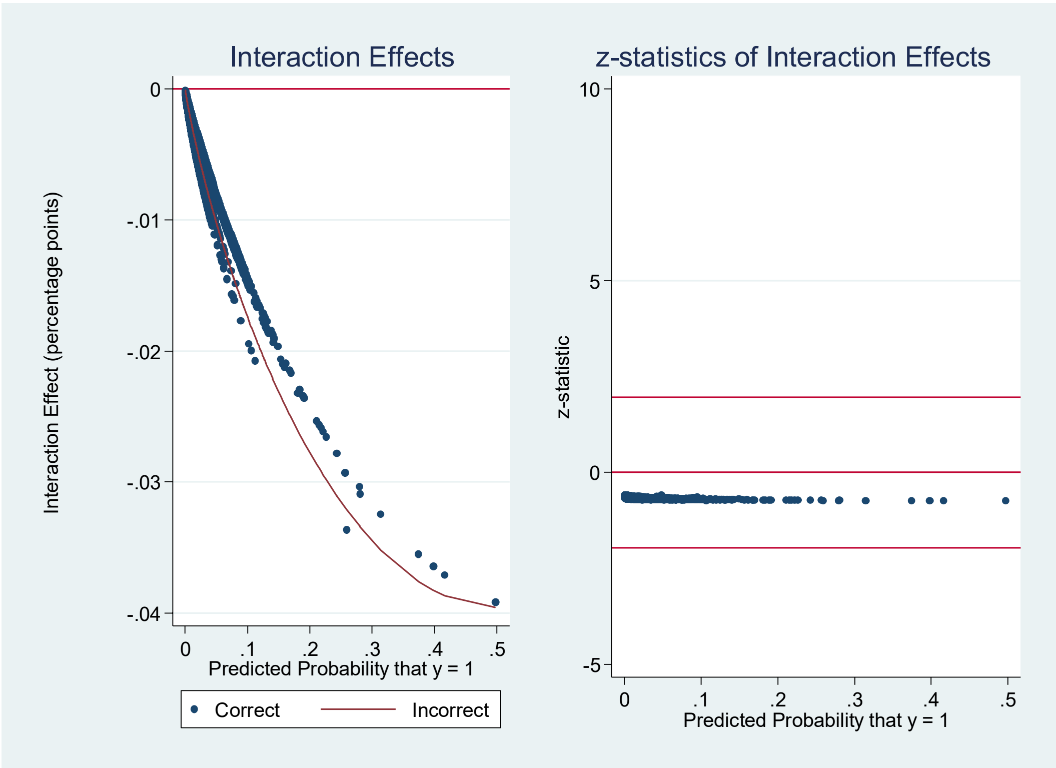
Panel B: *Stock ownership* (Column (1))



Panel A: *Option delta* (Column (2))



Panel B: *Stock ownership* (Column (2))



This figure illustrates the interaction effects of the frim-years after the passage of the Sarbanes-Oxley Act (SOX) and the higher levels of *Option delta* / *Stock ownership* (LHS), and their z-statistics computed using Ai and Norton (2003)'s method (RHS). Variables are defined in the Appendix 3.A.

Table 3.1 Sample selection

Full Sample excluding financial firms (1992-2012)	24,544	firm-years	
AAERs compiled by CFRM	1,961	firm-years	
Less: Firm-years without sufficient data	(1,591)		
ExecuComp fraud firm-years	370		
Propensity-score matching sample	291-426	firms	B + C
Distinct fraud firms complied by CFRM	739	firms	
Less: Firms without sufficient data	(639)		
ExecuComp fraud firms	100		
Non-ExecuComp fraud firms	61		A
Less: Duplications	(6)		
ExecuComp and Non-ExecuComp fraud firms	155		B
Non-fraud matches	136-271		C
Partial matching sample	122	firms	A + D
Distinct fraud firms published by the SEC	70	firms	
Less: Firms without sufficient data	(9)		
Non-ExecuComp fraud firms	61		A
Non-fraud matches	61		D

Table 3.2 Descriptive statistics

Panel A: Mean

Variables	Compustat and ExecuComp Obs	Mean (A)	*Full Sample* Obs	Mean (B)	(1) *t*-test *p*-value (A-B)	*GPSM* Obs	Mean (C)	(2) *t*-test *p*-value (A-C)	*PM* Obs	Mean (D)	(3) *t*-test *p*-value (A-D)	(4) *t*-test *p*-value (C-D)
Option delta	24,544	0.025	370	0.026	0.212	155	0.505	0.000	61	0.168	0.370	0.077
Stock ownership	24,544	0.250	370	0.635	0.000	155	0.095	0.000	61	0.192	0.000	0.001
ROA	24,541	0.041	370	0.034	0.346	155	-0.104	0.000	61	-0.362	0.000	0.247
Leverage	24,460	0.228	370	0.216	0.316	153	0.256	0.091	61	0.257	0.272	0.937
Ln(Assets)	24,542	21.053	370	21.442	0.000	155	20.154	0.000	61	18.120	0.000	0.000
Working Capital	23,869	0.230	370	0.242	0.199	151	0.172	0.003	61	0.093	0.000	0.651
Tobin's Q	24,486	1.684	370	2.342	0.000	154	3.001	0.000	61	3.649	0.000	0.450
CEO=Chairman	24,069	0.559	358	0.659	0.000	154	0.714	0.000	61	0.656	0.133	0.361
CEO=Founder	23,618	0.326	358	0.520	0.000	151	0.497	0.000	61	0.459	0.028	0.543
Ln(Tenure)	22,827	1.748	357	1.859	0.035	147	1.815	0.353	61	1.756	0.942	0.625
Stock market	24,544	0.929	370	0.878	0.000	155	0.800	0.000	61	0.672	0.000	0.039
Portfolio delta	23,337	1.222	346	3.958	0.000	155	2.474	0.214	61	2.001	0.630	0.783
Stock delta	24,073	0.970	356	3.249	0.000	155	1.971	0.318	61	1.839	0.588	0.942
Holder67	24,544	0.311	370	0.476	0.000							
CAPEX	24,544	0.168	370	0.162	0.852							
Over_invest	24,544	0.293	370	0.335	0.065							
Portfolio vega	24,544	0.011	370	0.020	0.000							
% Fraud				1.50%			0.63%			0.25%		

Panel B: Median

Variables	Compustat and ExecuComp Obs	Median (A)	*Full Sample* Obs	Median (B)	(1) WRS *p*-value (A-B)	*GPSM* Obs	Median (C)	(2) WRS *p*-value (A-C)	*PM* Obs	Median (D)	(3) WRS *p*-value (A-D)	(4) WRS *p*-value (C-D)
Option delta	24,544	0.079	370	0.215	0.000	155	0.089	0.983	61	0.002	0.000	0.000
Stock ownership	24,544	0.003	370	0.003	0.499	155	0.005	0.613	61	0.125	0.000	0.046
ROA	24,541	0.052	370	0.047	0.060	155	0.050	0.560	61	0.030	0.042	0.211
Leverage	24,460	0.216	370	0.228	0.927	153	0.228	0.841	61	0.070	0.032	0.085
Ln(Assets)	24,542	20.922	370	21.380	0.000	155	20.144	0.000	61	18.266	0.000	0.000
Working Capital	23,869	0.198	370	0.197	0.563	151	0.228	0.412	61	0.271	0.080	0.243
Tobin's Q	24,486	1.282	370	1.380	0.017	154	1.395	0.068	61	1.812	0.001	0.110
CEO=Chairman	24,069	1.000	358	1.000	0.000	154	1.000	0.000	61	1.000	0.133	0.360
CEO=Founder	23,618	0.000	358	1.000	0.000	151	0.000	0.000	61	0.000	0.028	0.541
Ln(Tenure)	22,827	1.792	357	2.079	0.005	147	1.946	0.225	61	1.946	0.718	0.702
Stock market	24,544	1.000	370	1.000	0.000	155	1.000	0.000	61	1.000	0.000	0.040
Portfolio delta	23,337	0.192	346	0.397	0.000	155	0.284	0.011	61	0.146	0.090	0.010
Stock delta	24,073	0.055	356	0.070	0.007	155	0.081	0.010	61	0.070	0.928	0.182
Holder67	24,544	0.000	370	0.000	0.000							
CAPEX	24,544	0.000	370	0.000	0.852							
Over_invest	24,544	0.000	370	0.000	0.065							
Portfolio vega	24,544	0.004	358	0.002	0.000							
% Fraud				1.50%			0.63%			0.25%		

This table reports descriptive statistics, including *p*-values for Wilcoxon rank-sum (WRS) tests of median differences among three samples and ExecuComp observations. Since GPSM and PM samples include non-ExecuComp samples that are collected manually, they do not have statistics for *Holder67*, *CAPEX*, *Over_invest*, and *Portfolio vega*. Variables are defined in the Appendix 3.A.

Table 3.3 GPSM estimation using OLS regression

Variables	Dependent variable = *Ln* (*Stock ownership*)
ROA	0.423***
	(0.139)
Leverage	0.608***
	(0.124)
Ln(Assets)	-0.939***
	(0.016)
Working Capital	0.535***
	(0.112)
Tobin's Q	0.018
	(0.011)
Ln(Tenure)	1.373***
	(0.025)
Stock market	0.052
	(0.087)
Constant	9.595***
	(0.345)
Observations	21,783
Adjusted R^2	0.259

This table reports the OLS estimation results between *Ln*(*Stock ownership*) and potential confounders of both *Stock ownership* and accounting fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.4 Covariate balance

Variables	*GPSM*					*PM*				
	Median		*p*-value			Median		*p*-value		
	Fraud	Non-Fraud	*t*-test	WRS	KS	Fraud	Non-Fraud	*t*-test	WRS	KS
ROA	0.050	0.044	0.201	0.869	0.273	0.032	0.021	0.865	0.711	0.520
Leverage	0.228	0.167	0.199	0.290	0.336	0.070	0.056	0.532	0.321	0.385
Ln (Assets)	20.144	20.481	0.184	0.408	0.004	18.266	18.220	0.990	0.986	1.000
Working Capital	0.228	0.256	0.222	0.263	0.294	0.271	0.313	0.361	0.639	0.520
Tobin's Q	1.395	1.372	0.086	0.834	0.583	1.812	1.569	0.478	0.941	0.671
Ln (Tenure)	1.946	2.197	0.037	0.034	0.029	1.946	1.792	0.815	0.951	0.929
Stock market	1.000	1.000	0.002	0.002	0.197	1.000	1.000	0.019	0.019	0.274
Year				Matched					Matched	
Industry				Matched					Matched	
% Matched (A)			67%	78%	78%			89%	89%	100%
% Matched (B)			71%	86%	86%			100%	100%	100%
gpscore	0.084	0.083	0.944	0.768	0.986	-	-	-	-	-
Stock ownership	0.005	0.033	0.843	0.003	0.001	0.125	0.010	0.000	0.001	0.000
Option delta	0.089	0.055	0.005	0.053	0.012	0.002	0.007	0.293	0.126	0.007
Observations	155	136	291	291	291	61	61	122	122	122

This table reports the covariates balance of matched pairs (1:1 matches of both GPSM and PM samples). *% Matched (A)* is the number of balanced covariates divided by the total number of covariates. *% Matched (B)* is the number of balanced covariates divided by the total number of covariates excluding *Market* and *Ln(Assets)*. *gpscore* stands for the Generalized Propensity-Score. *P*-values are for *t*-tests, Wilcoxon rank-sum (WRS) and Kolmogorov-Smirnov (KS) tests. Variables are defined in the Appendix 3.A.

Table 3.5 Quintile analysis

		Option delta					*Stock ownership*				
					(1)	(2)				(3)	(4)
Q (T)	Q(C)	Fraud Freq.	SE	Obs.	Mean diff.	*p* -value	Fraud Freq.	SE	Obs.	Mean diff.	*p* -value
5	4	0.506	0.503	85	0.141	0.064	0.365	0.484	85	0.136	0.054
5	3				0.212	0.005				0.066	0.359
5	2				0.306	0.000				0.024	0.748
5	1				0.053	0.493				-0.216	0.005
4	3	0.365	0.484	85	0.071	0.328	0.229	0.423	83	-0.070	0.302
4	2				0.165	0.017				-0.112	0.107
4	1				-0.088	0.238				-0.352	0.000
3	2	0.294	0.458	85	0.094	0.155	0.299	0.460	87	-0.042	0.552
3	1				-0.159	0.031				-0.282	0.002
2	1	0.200	0.402	85	-0.253	0.004	0.341	0.477	85	-0.240	0.002
1	-	0.453	0.501	86			0.581	0.496	86		
TTL				426					426		

This table reports the quintile analysis results of *Option delta* and *Stock ownership* (GPSM). *Q(T)*, treatment quintile, is the higher quintiles of *Option delta* and *Stock ownership* respectively than *Q(C)*, control quintile. *Fraud Freq.* is the number of fraud firms divided by the total number of firms in GPSM sample. Reported data in *Fraud Freq.* are for quintiles in *Q(T)*. *SE* represents the standard error of the *Fraud. Freq*. *Obs.* stands for the number of observations in each quintile. *Mean diff.* represents the difference in *Fraud Freq.* between *Q(T)* and *Q(C)*. *P*-values are for the *Mean diff.* Variables are defined in the Appendix 3.A.

Table 3.6 Probit estimation results using equity incentives

Panel A: Regression

	Dependent variable = *Pr* (AAERs)				
	(1)	(2)	(3)	(4)	(5)
		Full Sample		*GPSM*	
Motivation					
Option delta	0.205***	0.160***	0.196***	0.844***	1.092***
	(0.055)	(0.058)	(0.064)	(0.200)	(0.265)
Option delta^2	-0.016**	-0.0140*	-0.015**	-0.047**	-0.068***
	(0.007)	(0.007)	(0.007)	(0.021)	(0.021)
Stock ownership	-0.021**	-0.034***	-0.032***	-9.908***	-9.379***
	(0.008)	(0.009)	(0.010)	(1.817)	(2.155)
Stock ownership^2	0.001***	0.001***	0.001***	21.326***	19.920***
	(0.000)	(0.000)	(0.000)	(4.043)	(4.779)
Financial ratios					
ROA	-0.255**	-0.155	-0.172	0.043	0.134
	(0.104)	(0.101)	(0.121)	(0.314)	(0.311)
Leverage	-0.334**	-0.048	-0.081	0.439	0.313
	(0.132)	(0.136)	(0.142)	(0.420)	(0.501)
Ln(Assets)	0.110***	0.120***	0.124***	-0.241***	-0.247***
	(0.018)	(0.021)	(0.021)	(0.058)	(0.066)
Working Capital	0.240**	0.106	0.096	-0.395	-0.390
	(0.119)	(0.136)	(0.138)	(0.293)	(0.358)
Tobin's Q	0.002	0.002	0.000	0.010	0.015
	(0.010)	(0.010)	(0.010)	(0.017)	(0.024)
CEO power					
CEO=Chairman	-0.020	-0.020	-0.009	0.544***	0.468**
	(0.050)	(0.053)	(0.054)	(0.153)	(0.181)
CEO=Founder	0.260***	0.264***	0.250***	0.413	0.291
	(0.048)	(0.051)	(0.052)	(0.169)	(0.199)
Ln(Tenure)	0.050	0.077**	0.071**	-0.164*	-0.184*
	(0.031)	(0.032)	(0.032)	(0.085)	(0.101)
CEO overconfidence					
Holder67	0.185***	0.170***	0.168***		
	(0.049)	(0.052)	(0.054)		
Other controls					
Stock market	-0.248***	-0.275***	-0.242***	-0.554**	-0.649**
	(0.072)	(0.077)	(0.080)	(0.235)	(0.294)
Portfolio vega			-1.292		
			(1.167)		
Year dummy	Yes	Yes	Yes	Yes & Matched	Yes & Matched
Industry dummy	No	Yes	Yes	Matched	Matched
Constant	-4.974***	-5.499***	-5.578***	4.863***	5.588***
	(0.525)	(0.630)	(0.638)	(1.174)	(1.346)
Observations	21,975	18,703	18,426	412	277
Log likelihood	-1,653	-1,513	-1,467	-217	-157

Panel B: Reduced form

	Dependent variable = *Pr* (AAERs)			
	(1)	(2)	(3)	(4)
		Full Sample		
Motivation				
Portfolio delta	0.002**	0001		
	(0.001)	(0.001)		
Portfolio vega		1.731***	1.492***	-0.238
		(0.448)	(0.511)	(0.755)
Option delta			0.023	0.289***
			(0.018)	(0.052)
Option delta^2				-0.023***
				(0.007)
Stock ownership			-0.002	-0.014*
			(0.004)	(0.008)

Stock ownership^2				0.000**
				(0.000)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Constant	-2.754***	-2.706***	-2.695***	-2.675***
	(0.453)	(0.377)	(0.377)	(0.377)
Observations	20,355	20,355	20,352	20,352
Log likelihood	-1,691	-1,685	-1,683	-1,668

Panel C: Marginal effects

	Dependent variable = *Pr* (AAERs)				
	(1)	(2)	(3)	(4)	(5)
		Full Sample		*GPSM*	
Motivation					
Option delta	0.009**	0.191***	0.008***	0.251***	0.345***
	(0.001)	(0.062)	(0.003)	(0.054)	(0.078)
Option delta^2	-0.001***	-0.014**	-0.001**	-0.014**	-0.022***
	(0.000)	(0.007)	(0.000)	(0.006)	(0.006)
Stock ownership	-0.002**	-0.074***	-0.001***	-2.913***	-2.935***
	(0.001	(0.015)	(0.000)	(0.496)	(0.631)
Stock ownership^2	0.000***	0.002***	0.000***	6.279***	6.286***
	(0.000)	(0.015)	(0.000)	(1.107)	(1.413)
Financial ratios					
ROA	-0.012**	-0.238*	-0.007	0.016	0.024
	(0.005)	(0.132)	(0.005)	(0.093)	(0.100)
Leverage	-0.007***	0.109	-0.003	0.123	0.099
	(0.005)	(0.135)	(0.006)	(0.123)	(0.160)
Ln(Assets)	0.004***	0.103***	0.005***	-0.072***	-0.078***
	(0.001)	(0.023)	(0.001)	(0.016)	(0.020)
Working Capital	0.009**	0.097	0.004	-0.120	-0.134
	(0.005)	(0.149)	(0.006)	(0.086)	(0.115)
Tobin's Q	0.000	-0.007	0.000	0.003	0.004
	(0.001)	(0.016)	(0.000)	(0.005)	(0.007)
CEO power					
CEO=Chairman	-0.002	-0.047	-0.000	0.158***	0.157**
	(0.002)	(0.058)	(0.002)	(0.044)	(0.056)
CEO=Founder	0.009***	0.253***	0.010***	0.124	0.093
	(0.002)	(0.053)	(0.002)	(0.049)	(0.063)
Ln(Tenure)	0.002*	0.076**	0.003**	-0.049*	-0.062*
	(0.001)	(0.035)	(0.001)	(0.025)	(0.032)
CEO overconfidence					
Holder67	0.009***	0.217***	0.007***		
	(0.002)	(0.056)	(0.002)		
Other controls					
Stock market	-0.012***	-0.008***	-0.012***	-0.152**	-0.199**
	(0.004)	(0.003)	(0.004)	(0.069)	(0.095)
Portfolio vega			-0.052		
			(0.047)		
Year dummy	Yes	Yes	Yes	Yes & Matched	Yes & Matched
Industry dummy	No	Yes	Yes	Matched	Matched
Observations	21,975	18,703	18,426	412	277
Inflection point:					
Options	7.33	6.90	6.60	8.95	7.95
Stocks	0.231	0.224	0.161	0.232	0.233

This table reports the probit estimation results between accounting fraud, and both *Option delta* and *Stock ownership*. Due to data availability, Columns (4) and (5) in Panel A do not incorporate *Holder67* and *Portfolio vega*. Consistent with Armstrong et al. (2013), Panel B is estimated using contemporaneous variables. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.7 Analysis of sub-samples

Panel A: CEO power						
	Dependent variable = *Pr*(AAERs)					
	(1)	(2)	(3)	(4)	(5)	(6)
CEO power	*CEO=Founder*		*CEO=Chairman*		*Ln(Tenure)*	
	Yes	No	Yes	No	Long	Short
Motivation						
Option delta	0.181**	0.304***	0.188***	0.152	0.147**	0.328***
	(0.080)	(0.115)	(0.073)	(0.114)	(0.071)	(0.127)
Option delta^2	-0.015*	-0.037*	-0.016*	-0.022	-0.012	-0.046**
	(0.009)	(0.019)	(0.009)	(0.016)	(0.008)	(0.020)
Stock ownership	-0.046***	-0.017	-0.031***	-0.028	-0.036***	-0.071**
	(0.013)	(0.024)	(0.011)	(0.033)	(0.012)	(0.028)
Stock ownership^2	0.001***	0.000	0.001***	-0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Financial ratios						
ROA	-0.165	-0.253	0.119	-0.412**	-0.316**	0.099
	(0.122)	(0.262)	(0.176)	(0.189)	(0.156)	(0.187)
Tobin's Q	0.009	-0.059	-0.005	0.013	0.011	-0.002
	(0.009)	(0.038)	(0.012)	(0.013)	(0.015)	(0.019)
Leverage	0.056	-0.177	-0.044	-0.190	0.100	-0.211
	(0.194)	(0.223)	(0.216)	(0.157)	(0.207)	(0.202)
Ln(Assets)	0.090***	0.113***	0.131***	0.115***	0.145***	0.093***
	(0.033)	(0.031)	(0.028)	(0.031)	(0.033)	(0.029)
Working Capital	0.293	-0.269	0.198	-0.123	0.282	-0.115
	(0.188)	(0.230)	(0.188)	(0.200)	(0.193)	(0.205)
CEO power						
CEO=Founder	.	.	0.230***	0.306***	0.397***	0.082
	.	.	(0.066)	(0.081)	(0.082)	(0.082)
CEO=Chairman	-0.123*	0.111	.	.	-0.156**	0.129*
	(0.073)	(0.079)	.	.	(0.073)	(0.076)
Ln(Tenure)	0.181***	-0.022	0.068*	0.087	0.031	-0.138**
	(0.051)	(0.048)	(0.041)	(0.057)	(0.075)	(0.070)
CEO overconfidence						
Holder67	0.193**	0.176**	0.172**	0.190**	0.129*	0.147*
	(0.075)	(0.077)	(0.068)	(0.086)	(0.072)	(0.081)
Other controls						
Stock market	-0.481***	-0.092	-0.129	-0.463***	-0.331***	-0.258**
	(0.104)	(0.132)	(0.104)	(0.120)	(0.107)	(0.122)
Constant	-4.413***	-5.466***	-4.165***	-5.196***	-5.599***	-5.076***
	(0.862)	(0.788)	(1.021)	(0.721)	(0.890)	(0.723)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,146	10,671	9,598	7,010	8,051	9,204
Log likelihood	-735	-700	-940	-520	-790	-646
Inflection point:						
Options	6.22	4.13	5.95	-	-	3.59
(p-value for diff.)		0.000				
Stocks	16.1	-	14.1	-	15.7	24.3
(p-value for diff.)						0.000

Panel B: Corporate governance					
	Dependent variable = *Pr*(AAERs)				
	(1)	(2)	(3)	(4)	(5)
Corporate governance		*ABC*		*Outside director*	
		High	Low	High	Low
Motivation					
Option delta	0.126**	0.161**	0.092	0.200*	0.167**
	(0.059)	(0.078)	(0.163)	(0.109)	(0.069)
Option delta^2	-0.012*	-0.0149*	-0.012	-0.020*	-0.016**
	(0.007)	(0.009)	(0.024)	(0.010)	(0.008)
Stock ownership	-0.047***	-0.0565***	0.392*	0.004	-0.076***
	(0.013)	(0.015)	(0.231)	(0.032)	(0.016)
Stock ownership^2	0.001***	0.0017***	-0.205**	0.0012	0.002***
	(0.000)	(0.000)	(0.083)	(0.001)	(0.000)
Financial ratios					
ROA	-0.165	-0.163	-0.396	0.361	-0.135
	(0.119)	(0.135)	(0.284)	(0.713)	(0.121)
Tobin's Q	0.023*	0.026	0.029	-0.129**	0.040***
	(0.014)	(0.019)	(0.021)	(0.063)	(0.013)
Leverage	0.033	-0.166	0.562**	-0.473	0.288
	(0.172)	(0.229)	(0.266)	(0.309)	(0.216)
Ln(Assets)	0.145***	0.165***	0.154***	0.172***	0.131***
	(0.026)	(0.038)	(0.044)	(0.046)	(0.031)
Working Capital	0.027	0.033	0.287	0.116	-0.130
	(0.166)	(0.221)	(0.283)	(0.339)	(0.193)
CEO power					
CEO=Founder	0.196***	0.224***	0.205*	0.157	0.287***
	(0.063)	(0.077)	(0.124)	(0.102)	(0.081)
CEO=Chairman	0.113*	-0.074	0.429***	-0.058	0.166**
	(0.064)	(0.082)	(0.110)	(0.112)	(0.083)
Ln(Tenure)	-0.019	0.070	-0.317***	-0.050	-0.019
	(0.039)	(0.047)	(0.092)	(0.067)	(0.050)
CEO overconfidence					
Holder67	0.127**	0.089	0.156	0.075	0.224***
	(0.064)	(0.080)	(0.112)	(0.109)	(0.081)
Corporate governance					
ABC	0.546***	-0.980	0.381	0.342*	0.754***
	(0.132)	(0.675)	(0.283)	(0.190)	(0.192)
Outside director	-0.728***	-0.507	-1.205*	1.715	-0.703*
	(0.274)	(0.322)	(0.638)	(2.166)	(0.372)
Other controls					
Stock market	-0.155	-0.049	-0.273	-0.408**	-0.003
	(0.120)	(0.160)	(0.207)	(0.191)	(0.159)
Constant	-3.710***	-2.786**	-4.568***	-6.602***	-1.932**
	(0.964)	(1.334)	(0.985)	(1.964)	(0.798)
Year dummy	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes
Observations	11,597	5,343	4,362	4,987	5,166
Log likelihood	-1048	-647	-338	-358	-625
Inflection point:					
Options	5.25	5.43	-	4.97	5.17
(p-value for diff.)					0.000
Stocks	18.4	16.8	-	-	20.4

Panel C: CEO overconfidence						
	Dependent variable = *Pr*(AAERs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Overconfidence	*Holder67*		*CAPEX*		*Over_invest*	
	Yes	No	Yes	No	Yes	No
Motivation						
Option delta	0.232***	0.568**	0.295	0.189***	0.155	0.214***
	(0.073)	(0.226)	(0.236)	(0.067)	(0.098)	(0.074)
Option delta^2	-0.016**	-0.119*	-0.055	-0.014*	-0.020	-0.016*
	(0.008)	(0.069)	(0.060)	(0.008)	(0.014)	(0.009)
Stock ownership	-0.097***	-0.049***	-0.105**	-0.029***	-0.044**	-0.034***
	(0.026)	(0.016)	(0.046)	(0.011)	(0.018)	(0.012)
Stock ownership^2	0.002***	0.001***	0.003**	0.001***	0.001***	0.001***
	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Financial ratios						
ROA	-0.143	-0.252	0.400	-0.216	0.079	-0.272
	(0.160)	(0.226)	(0.304)	(0.190)	(0.137)	(0.183)
Tobin's Q	0.004	-0.134*	0.011	-0.216	0.006	-0.002
	(0.015)	(0.078)	(0.010)	(0.190)	(0.014)	(0.013)
Leverage	0.314	-0.014	-1.131**	-0.017	-0.109	-0.173
	(0.230)	(0.208)	(0.529)	(0.148)	(0.278)	(0.171)
Ln(Assets)	0.076**	0.106***	0.195***	0.105***	0.081**	0.127***
	(0.036)	(0.036)	(0.059)	(0.023)	(0.037)	(0.025)
Working Capital	-0.012	0.128	0.026	0.132	0.097	-0.036
	(0.201)	(0.233)	(0.402)	(0.150)	(0.206)	(0.185)
CEO power						
CEO=Founder	0.256***	0.221***	0.858***	0.178***	0.418***	0.165**
	(0.081)	(0.073)	(0.167)	(0.057)	(0.093)	(0.064)
CEO=Chairman	0.022	-0.131	-0.458***	0.052	-0.032	0.004
	(0.083)	(0.081)	(0.142)	(0.059)	(0.091)	(0.067)
Ln(Tenure)	0.079	0.075	0.255***	0.064*	0.116**	0.068*
	(0.054)	(0.048)	(0.086)	(0.035)	(0.058)	(0.040)
Other controls						
Stock market	-0.393***	-0.161	0.247	-0.261***	0.028	-0.342***
	(0.132)	(0.117)	(0.348)	(0.085)	(0.157)	(0.094)
Constant	-4.163***	-2.273*	-6.699***	-5.482***	-4.247***	-5.858***
	(0.814)	(1.246)	(1.394)	(0.621)	(0.957)	(0.726)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,160	9,033	1,543	14,883	4,727	12,431
Log likelihood	-616	-633	-187	-1229	-471	-959
Inflection point:						
Options	7.25	2.39	-	6.56	-	6.71
(p-value for diff.)		0.000				
Stocks	24.25	24.50	17.50	15.61	17.04	17.02
(p-value for diff.)		0.000		0.001		0.796

This table reports the probit estimation results between accounting fraud, and both *Option delta* and *Stock ownership* by sub-samples of distinct CEO power, corporate governance, CEO overconfidence, and CEO competence (Full sample). Due to small sample size, the sub-sample analyses of CPA do not converge. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.8 Interactive analysis of voting premium.

	Dependent variable = *Pr* (AAERs)		
	(1)	(2)	(3)
Motivation			
Voting premium	-0.023	-0.008	-0.006
	(0.033)	(0.036)	(0.036)
Stock delta	-0.005*	-0.007*	-0.005**
	(0.003)	(0.004)	(0.003)
Stock delta × Voting premium	0.011**	0.011**	0.008**
	(0.005)	(0.005)	(0.003)
Option delta	0.299***	0.195***	0.203***
	(0.054)	(0.068)	(0.068)
Option delta^2	-0.022***	-0.015**	-0.016**
	(0.007)	(0.007)	(0.007)
Financial ratios			
ROA		-0.235	-0.212
		(0.143)	(0.145)
Tobin's Q		0.022*	0.021
		(0.013)	(0.013)
Leverage		0.188	0.190
		(0.181)	(0.183)
Ln(Assets)		0.062**	0.065**
		(0.028)	(0.028)
Working Capital		-0.060	-0.073
		(0.177)	(0.180)
CEO power			
CEO=Founder		0.209***	0.189***
		(0.064)	(0.165)
CEO=Chairman		0.023	0.028
		(0.068)	(0.069)
Ln(Tenure)		0.059	0.058
		(0.043)	(0.043)
CEO overconfidence			
Holder67		0.093	0.097
		(0.069)	(0.070)
Other controls			
Stock market		-0.158	-0.135
		(0.114)	(0.118)
Pr(Takeover)			-0.995**
			(0.497)
Year dummy	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes
Constant	-2.287***	-1.887*	-1.677
	(0.463)	(1.131)	(1.129)
Observations	9,433	8,565	8,499
Log likelihood	-1015	-919	-907

This table reports the probit estimation results between accounting fraud and *Stock delta* using its interaction term with *Voting premium* (full sample). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.9 Interactive analysis of SOX effect

	Dependent variable = *Pr* (AAERs)	
	(1)	(2)
Motivation		
Option delta	3.563**	4.600**
	(1.539)	(2.012)
Option delta × H_o	-3.548**	-4.600**
	(1.539)	(2.010)
Stock ownership	0.047	0.674
	(0.353)	(0.482)
Stock ownership × H_s	-0.041	-0.663
	(0.353)	(0.482)
SOX	-0.191**	-0.205
	(0.096)	(0132)
SOX × H_o	-0.292***	-0.327**
	(0.101)	(0.141)
SOX × H_s	-0.136	-0.009
	(0.095)	(0.135)
H_o	0.495***	0.605***
	(0.087)	(0.114)
H_s	0.020	0.018
	(0.085)	(0.118)
CEO power		
CEO=Founder	0.282***	0.307***
	(0.050)	(0.074)
CEO=Chairman	0.030	0.129*
	(0.051)	(0.076)
Ln(Tenure)	0.029	-0.045
	(0.033)	(0.045)
Financial ratios		
ROA	-0.305***	-0.363**
	(0.104)	(0.162)
Leverage	-0.027	0.067
	(0.124)	(0.194)
Ln(Assets)	0.106***	0.114***
	(0.021)	(0.032)
Working Capital	0.063	0.559***
	(0.135)	(0.210)
Tobin's Q	0.011	0.010
	(0.007)	(0.015)
CEO overconfidence		
Holder67	0.113**	0.046
	(0.053)	(0.079)
CEO competence		
Degree		-0.267***
		(0.066)
Other controls		
Stock market	-0.325***	-0.366***
	(0.080)	(0.115)
Industry dummy	Yes	Yes
Constant	-4.898***	-3.389***
	(0.520)	(1.069)
Observations	18,703	8,224
Log likelihood	-1578	-758

This table reports the probit estimation results between accounting fraud, and both *Option delta* and *Stock ownership* using their interaction terms with SOX (full sample). *H* is an indicator variable equal to 1 if *Option delta* or *Stock ownership* is greater than or equal to their respective medians. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.10 OLS and probit estimation results using alternative misreporting measures

Panel A: Accruals

	Dependent variable = Accruals					
	(1)	(2)	(3)	(4)	(5)	(6)
Accruals	*WC*		*PMJONES*		*SDD*	
Motivation						
Option delta	-0.000	0.001	-0.009**	-0.003	-0.050	0.022
	(0.00)	(0.001)	(0.004)	(0.002)	(0.054)	(0.047)
Option delta^2	0.000		0.000***		0.0046*	
	(0.000)		(0.000)		(0.003)	
Stock ownership	0.000	0.000	-0.000	-0.001**	0.012	-0.008
	(0.000)	(0.001)	(0.001)	(0.000)	(0.013)	(0.006
Stock ownership^2	-0.000		-0.000		-0.001*	
	(0.000)		(0.000)		(0.000)	
Financial ratios						
ROA	0.031***	0.032***	-0.088***	-0.088**	1.287***	1.293***
	(0.009)	(0.009)	(0.019)	(0.019	(0.458)	(0.459)
Tobin's Q	0.001*	0.001**	0.001	0.001	0.052*	0.051
	(0.000)	(0.000)	(0.001)	(0.001)	(0.031)	(0.031)
Leverage	-0.002	-0.002	-0.008	-0.008	-0.144	-0.138
	(0.005	(0.005)	(0.012)	(0.011	(0.258)	(0.257)
Ln(Assets)	-0.003**	-0.003***	-0.003**	-0.004***	-0.165***	-0.178***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.028)	(0.027)
Working Capital	-0.009*	-0.009**	-0.008	-0.008	-0.214	-0.215
	(0.004)	(0.004)	(0.010)	(0.011	(0.209)	(0.209)
CEO power						
CEO=Founder	0.001	0.001	0.004	0.004	0.104	0.115*
	(0.001)	(0.001)	(0.003)	(0.003)	(0.066)	(0.065)
CEO=Chairman	0.001	0.001	-0.004	-0.003	0.028	0.031
	(0.001	(0.001)	(0.003)	(0.003	(0.058)	(0.058)
Ln(Tenure)	-0.000	-0.000	-0.000	-0.000	-0.014	-0.006
	(0.001)	(0.001)	(0.002)	(0.002	(0.037)	(0.036
CEO overconfidence						
Holder67	0.009***	0.009***	0.007**	0.006	0.299***	0.287***
	(0.001)	(0.000977)	(0.003)	(0.003)	(0.065)	(0.065)
Other controls						
Stock market	0.009***	0.009***	-0.002	-0.001	0.167	0.170
	(0.003)	(0.003)	(0.005)	(0.005)	(0.142)	(0.142)
Constant	0.060*	0.063***	0.096***	0.116***	2.868***	3.098***
	(0.014)	(0.013)	(0.032)	(0.031	(0.711)	(0.695)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,255	21,255	21,158	21,158	20,239	20,239
Adjusted R-squared	0.043	0.043	0.091	0.091	0.031	0.031

Panel B: Sample selection

Database	*Restatements*	*Lawsuits*
Settled securities class action lawsuits (1990-2015)		3,008
Restatements complied by Audit Analytics (1980-2012)	28,301	
Less: Obs. not covered on Compustat	10,178	379
Less: Obs. Of financial firms	2,732	837
Less: Obs. before 1992 or after 2012	18	78
Less: Obs. not covered on ExecuComp	11,812	1,185
ExecuComp fraud firm-years (1992-2012)	3,561	529

Panel C: Restatements and securities class action lawsuits				
	Dependent variable = *Pr*(financial misreporting)			
Financial misreporting	*Non-AAER Restatements*	*AAER-Restatements*	*Non-AAER Lawsuits*	*AAER-Lawsuits*
	(1)	(2)	(3)	(4)
Motivation				
Option delta	-0.0312	0.150**	0.118	0.472***
	(0.029)	(0.062)	(0.081)	(0.134)
Option delta^2	0.002	-0.012*	-0.032*	-0.088***
	(0.001)	(0.007)	(0.018)	(0.030)
Stock ownership	0.010**	-0.040***	-0.003	-0.039
	(0.005)	(0.011)	(0.008)	(0.025)
Stock ownership^2	-0.000**	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Financial ratios				
ROA	-0.115	-0.275**	-0.230**	-0.259**
	(0.075)	(0.107)	(0.115)	(0.120)
Leverage	0.190***	-0.083	-0.146	0.203
	(0.064)	(0.151)	(0.130)	(0.177)
Ln(Assets)	-0.0249**	0.117***	0.102***	0.139***
	(0.010)	(0.022)	(0.021)	(0.037)
Working Capital	0.116*	-0.072	0.645***	0.401*
	(0.070)	(0.146)	(0.127)	(0.212)
Tobin's Q	-0.026**	0.014*	0.041***	0.023***
	(0.012)	(0.008)	(0.008)	(0.009)
CEO power				
CEO=Chairman	-0.070***	-0.036	0.043	-0.030
	(0.025)	(0.058)	(0.049)	(0.091)
CEO=Founder	0.057**	0.274***	0.104**	0.108
	(0.026)	(0.060)	(0.049)	(0.096)
Ln(Tenure)	0.015	0.121***	-0.003	0.301***
	(0.016)	(0.038)	(0.030)	(0.066)
CEO overconfidence				
Holder67	-0.011	0.166***	0.012	0.007
	(0.027)	(0.059)	(0.050)	(0.099)
Other controls				
Stock market	0.022	-0.157	0.516***	-0.033
	(0.046)	(0.096)	(0.138)	(0.180)
Constant	-0.803**	-6.175***	-5.406***	-7.171***
	(0.379)	(0.599)	(0.530)	(0.940)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Observations	21,698	18,009	19,102	12,003
Log likelihood	-7,934	-1,137	-1,732	-395

This table reports the probit estimation results between alternative earnings management or financial misreporting proxies, and both *Option delta* and *Stock ownership* (Full sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.11 Probit estimation results using CEO competence

	Dependent variable = *Pr* (AAERs)					
	(1)	(2)	(3)	(4)	(5)	(6)
CEO competence	*Degree*		*CPA*		*Experience*	
Motivation						
Option delta	0.524***	0.510***	0.511***	0.510***	0.527***	0.510***
	(0.130)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
Option delta^2	-0.083***	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***
	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)	(0.029)
Stock ownership	-0.011	-0.009	-0.009	-0.009	-0.013	-0.009
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Stock ownership^2	0.001**	0.001**	0.001**	0.006**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Financial ratios						
ROA	-0.470**	-0.422*	-0.423*	-0.422*	-0.428*	-0.422*
	(0.232)	(0.231)	(0.231)	(0.231)	(0.235)	(0.231)
Tobin's Q	-0.040	-0.039	-0.039	-0.0391	-0.038	-0.039
	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)
Leverage	0.169	0.165	0.164	0.165	0.206	0.165
	(0.217)	(0.214)	(0.214)	(0.214)	(0.211)	(0.214)
Ln(Assets)	0.134***	0.127***	0.127***	0.127***	0.129***	0.127***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Working Capital	0.755***	0.709***	0.709***	0.709***	0.676***	0.709***
	(0.230)	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)
CEO power						
CEO=Founder	0.306***	0.310***	0.309***	0.310***	0.293***	0.310***
	(0.080)	(0.079)	(0.079)	(0.079)	(0.080)	(0.079)
CEO=Chairman	0.143*	0.149*	0.148*	0.149*	0.163**	0.149*
	(0.081)	(0.080)	(0.080)	(0.080)	(0.081)	(0.080)
Ln(Tenure)	-0.017	-0.016	-0.016	-0.016	-0.0550	-0.016
	(0.048)	(0.048)	(0.047)	(0.048)	(0.050)	(0.048)
CEO overconfidence						
Holder67	0.091	0.086	0.086	0.0856	0.089	0.086
	(0.084)	(0.084)	(0.0836)	(0.084)	(0.084)	(0.084)
CEO competence						
Competence	-0.274***		0.027		-0.117***	
	(0.075)		(0.145)		(0.030)	
Other controls						
Stock market	-0.304**	-0.306**	-0.303**	-0.306**	-0.314***	-0.306**
	(0.121)	(0.120)	(0.121)	(0.120)	(0.120)	(0.120)
Constant	-3.912***	-3.794***	-3.798***	-3.794***	-3.736***	-3.794***
	(1.142)	(1.146)	(1.147)	(1.146)	(1.148)	(1.146)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,031	7,031	7,031	7,031	7,031	7,031
Log likelihood	-649	-655	-655	-655	-650	-655

This table reports the probit estimation results between accounting fraud, and both *Dollar option delta* and *Stock ownership* after controlling for CEO overconfidence (Full sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.12 Probit estimation results using CEO overconfidence

	Dependent variable = *Pr* (Accounting fraud)		
	(1)	(2)	(3)
Overconfidence	*Holder67*	*CAPEX*	*Over_invest*
Motivation			
Dollar option delta	0.160***	0.196***	0.185***
	(0.058)	(0.058)	(0.059)
Dollar option delta^2	-0.014*	-0.016**	-0.016**
	(0.007)	(0.007)	(0.007)
Stock ownership	-0.034***	-0.035***	-0.036***
	(0.009)	(0.010)	(0.010)
Stock ownership^2	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Financial ratios			
ROA	-0.155	-0.123	-0.164
	(0.101)	(0.121)	(0.123)
Leverage	-0.048	-0.095	-0.117
	(0.136)	(0.142)	(0.142)
Ln(Assets)	0.120***	0.112***	0.113***
	(0.020)	(0.021)	(0.021)
Working Capital	0.106	0.108	0.060
	(0.136)	(0.139)	(0.137)
Tobin's Q	0.002	0.003	0.004
	(0.010)	(0.009)	(0.010)
CEO power			
CEO=Chairman	-0.020	-0.011	-0.007
	(0.053)	(0.053)	(0.054)
CEO=Founder	0.264***	0.257***	0.248***
	(0.051)	(0.052)	(0.052)
Ln(Tenure)	0.077**	0.078**	0.079**
	(0.032)	(0.032)	(0.032)
CEO overconfidence			
Overconfidence	0.170***	0.006	0.150***
	(0.052)	(0.065)	(0.0542)
Other controls			
Stock market	-0.275***	-0.229***	-0.233***
	(0.077)	(0.079)	(0.080)
Year dummy	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes
Constant	-5.499***	-5.290***	-5.328***
	(0.630)	(0.630)	(0.630)
Observations	18,703	18,426	18,406
Log likelihood	-1513	-1473	-1469

This table reports the probit estimation results between accounting fraud, and both *Dollar option delta* and *Stock ownership* after controlling for CEO competence (full sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.13 Probit estimation results after controlling for addition variables

	Dependent variable = *Pr* (AAERs)			
	(1)	(2)	(3)	(4)
		PM		*PM (Marginal effects)*
Motivation				
Option delta	5.010***	5.780***	1.997***	2.278***
	(1.731)	(2.050)	(0.690)	(0.810)
Option delta^2	-1.565***	-1.826**	-0.624***	-0.719**
	(0.608)	(0.714)	(0.242)	(0.282)
Stock ownership	-35.800**	-38.401**	-14.274**	-15.132**
	(16.658)	(17.122)	(6.639)	(6.756)
Stock ownership^2	3.778***	3.205**	1.506***	1.263**
	(1.243)	(1.427)	(0.495)	(0.568)
Financial ratios				
ROA	0.215*	0.312*	0.086*	0.123*
	(0.123)	(0.163)	(0.049)	(0.063)
Leverage	-0.102	-1.080*	-0.041	-0.426*
	(0.298)	(0.638)	(0.119)	(0.247)
Ln(Assets)	-0.103	-0.035	-0.041	-0.014
	(0.102)	(0.104)	(0.041)	(0.014)
Working Capital	-0.304*	-0.550*	-0.121*	-0.217*
	(0.176)	(0.308)	(0.070)	(0.119)
Tobin's Q	-0.062*	-0.101**	-0.025*	-0.040**
	(0.032)	(0.039)	(0.013)	(0.015)
CEO power				
CEO=Chairman	-0.058	0.074	-0.023	0.029
	(0.311)	(0.355)	(0.124)	(0.140)
CEO=Founder	1.045***	1.071**	0.416***	0.422**
	(0.333)	(0.433)	(0.133)	(0.168)
Ln(Tenure)	-0.510**	-0.416	-0.203**	-0.164
	(0.212)	(0.288)	(0.084)	(0.123)
Corporate governance				
ABC	2.771***	2.841***	1.105***	1.119***
	(0.740)	(0.898)	(0.295)	(0.352)
Outside director	-0.273	-0.989	-0.109	-0.390
	(0.784)	(0.829)	(0.313)	(0.324)
Outside blockholder	0.443	0.160	0.177	0.063
	(0.946)	(1.094)	(0.377)	(0.431)
Other controls				
Stock market	-0.482	-0.638	-0.192	-0.251
	(0.371)	(0.396)	(0.148)	(0.155)
First public offering		0.721*		0.637*
		(0.426)		(0.144)
Debt covenant violation		1.617***		0.284***
		(0.373)		(0.169)
Year dummy	Yes	Yes	Yes	Yes
	& Matched	& Matched	& Matched	& Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	1.075	-0.464	4.896***	5.474***
	(1.905)	(2.052)	(1.173)	(1.348)
Observations	122	122	122	122
Log likelihood	-57	-44	-	-
Inflection point:				
Options			1.60	1.58
Stocks			2.40	2.40

This table reports the probit estimation results between accounting fraud, and both *Option delta* and *Stock ownership* after controlling for *Outside blockholder*, *First public offering*, and *Debt covenant violation* (PM sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.14 Probit estimation results using alternative unit of analysis

	Dependent variable = *Pr* (AAERs)		
	(1)	(2)	(3)
	Full Sample	*GPSM*	
Motivation			
TMT stock ownership	-1.405**	-7.767***	-12.06***
	(0.682)	(1.873)	(2.637)
TMT stock ownership ^{2}	2.778**	11.44***	21.59***
	(1.156)	(3.711)	(5.640)
TMT option delta	0.060**	0.264**	0.383**
	(0.027)	(0.118)	(0.169)
TMT option delta^2	-0.002	-0.009	-0.015**
	(0.001)	(0.006)	(0.007)
Financial ratios			
ROA	-0.153	1.100	1.901
	(0.122)	(0.803)	(1.293)
Leverage	-0.083	-0.067	-0.397
	(0.147)	(0.510)	(0.639)
Ln(Assets)	0.122***	0.124*	0.127
	(0.020)	(0.073)	(0.089)
Working Capital	0.116	-0.083	-0.155
	(0.141)	(0.455)	(0.607)
Tobin's Q	-0.000	0.015	0.007
	(0.010)	(0.017)	(0.018)
CEO power			
CEO=Chairman	-0.006	0.439**	0.462**
	(0.054)	(0.173)	(0.206)
CEO=Founder	0.237***	0.408**	0.330
	(0.053)	(0.190)	(0.226)
Ln(Tenure)	0.060*	-0.089	-0.111
	(0.032)	(0.099)	(0.120)
Other controls			
CEO overconfidence			
Holder67	0.181***	0.231	0.186
	(0.053)	(0.171)	(0.207)
Stock market	-0.234***	-0.353	-0.700**
	(0.082)	(0.285)	(0.350)
Constant	-5.525***	-3.082**	-2.247
	(0.632)	(1.551)	(1.904)
Year dummy	Yes	Yes & Matched	Yes & Matched
Industry dummy	Yes	Matched	Matched
Observations	17,655	351	223
Log likelihood	-1,438	-159	-114

This table reports the probit estimation results between accounting fraud, and both *TMT stock ownership* and *TMT option delta* (full sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 3.A.

Table 3.15 Probit estimation results using portfolio delta

	Dependent variable = *Pr* (Accounting fraud)			
	(1)	(2)	(3)	(4)
	Full Sample		*GPSM*	
Motivation				
Portfolio delta	-0.001	-0.000	-0.003	-0.001
	(0.001)	(0.003)	(0.004)	(0.012)
Portfolio delta^2		-0.000		-0.000
		(0.000)		(0.000)
Financial ratios				
ROA	-0.151	-0.151	-0.107	-0.105
	(0.102)	(0.102)	(0.241)	(0.242)
Leverage	-0.057	-0.056	0.259	0.255
	(0.139)	(0.139)	(0.382)	(0.384)
Ln(Assets)	0.156***	0.155***	-0.054	-0.056
	(0.018)	(0.019)	(0.047)	(0.048)
Working Capital	0.148	0.146	-0.166	-0.167
	(0.138)	(0.138)	(0.270)	(0.270)
Tobin's Q	0.004	0.004	0.049**	0.047**
	(0.008)	(0.008)	(0.023)	(0.024)
CEO power				
CEO=Chairman	-0.024	-0.024	0.541***	0.542***
	(0.052)	(0.052)	(0.145)	(0.146)
CEO=Founder	0.248***	0.247***	0.137	0.136
	(0.051)	(0.051)	(0.160)	(0.161)
Ln(Tenure)	0.070**	0.069**	-0.216***	-0.216***
	(0.031)	(0.031)	(0.082)	(0.082)
CEO overconfidence				
Holder67	0.209***	0.209***	0.215	0.215
	(0.050)	(0.050)	(0.150)	(0.150)
Other controls				
Stock market	-0.267***	-0.267***	-0.575***	-0.575***
	(0.077)	(0.077)	(0.218)	(0.218)
Constant	-6.312***	-6.291***	1.016	1.052
	(0.592)	(0.598)	(0.952)	(0.975)
Year dummy	Yes	Yes	Yes & Matched	Yes & Matched
Industry dummy	Yes	Yes	Matched	Matched
Observations	18,703	18,703	412	122
Log likelihood	-1,525	-1,525	-243	-50

This table reports the probit estimation results between accounting fraud and *Portfolio delta*. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 3.A.

Table 3.16 Monetary measure of stock ownership

	Dependent variable = *Pr* (AAERs)	
	(1)	(2)
Motivation		
Option delta	0.164***	0.164***
	(0.0587)	(0.059)
Option delta^2	-0.015**	-0.015**
	(0.007)	(0.007)
Stock delta	-0.001	-0.001
	(0.002)	(0.004)
Stock delta^2		0.000
		(0.000)
Financial ratios		
ROA	-0.155	-0.155
	(0.100)	(0.100)
Tobin's Q	0.002	0.002
	(0.010)	(0.010)
Leverage	-0.022	-0.023
	(0.136)	(0.136)
Ln(Assets)	0.126***	0.126***
	(0.020)	(0.020)
Working Capital	0.107	0.108
	(0.137)	(0.137)
CEO power		
CEO=Founder	0.248***	0.248***
	(0.051)	(0.051)
CEO=Chairman	-0.023	-0.023
	(0.052)	(0.052)
Ln(Tenure)	0.057*	0.057*
	(0.031)	(0.031)
CEO overconfidence		
Holder67	0.171***	0.171***
	(0.052)	(0.052)
Other controls		
Stock market	-0.265***	-0.265***
	(0.077)	(0.077)
Constant	-5.640***	-5.642***
	(0.626)	(0.626)
Year dummy	Yes	Yes
Industry dummy	Yes	Yes
Observations	18,703	18,703
Log likelihood	-1,520	-1,520

This table reports the probit estimation results between accounting fraud, and both *Option delta* and *Stock delta* (Full sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in the Appendix 3.A.

Table 3.17 Reverse causality

	Dependent variable = *Pr* (AAERTs)			
	(1)	(2)	(3)	(4)
	GPSM (1:2)		*GPSM (1:1)*	
Change in:	Change	Increase only	Change	Increase only
Motivation				
Option delta	0.850***	0.697**	1.189***	1.076***
	(0.206)	(0.351)	(0.271)	(0.265)
Option delta^2	-0.048**	-0.0353	-0.066***	-0.072***
	(0.022)	(0.0603)	(0.023)	(0.0267)
Stock ownership	-10.13***	-10.58***	-9.735***	-10.12***
	(1.903)	(2.017)	(2.216)	(2.309)
Stock ownership^2	20.00***	19.13***	18.62***	17.73***
	(4.261)	(4.562)	(4.917)	(5.092)
Change in equity incentives				
Change in ownership	1.531*	3.054***	1.637*	3.025**
	(0.852)	(1.080)	(0.929)	(1.296)
Change in option delta	-0.000	0.262	-0.144	0.108
	(0.170)	(0.329)	(0.179)	(0.414)
Financial ratios				
ROA	0.032	0.057	0.143	0.148
	(0.314)	(0.314)	(0.309)	(0.309)
Leverage	0.384	0.353	0.307	0.286
	(0.426)	(0.432)	(0.512)	(0.519)
Ln(Assets)	-0.228***	-0.210***	-0.231***	-0.215***
	(0.0577)	(0.059)	(0.066)	(0.068)
Working Capital	-0.402	-0.409	-0.331	-0.299
	(0.297)	(0.305)	(0.361)	(0.365)
Tobin's Q	0.009	0.0073	0.0148	0.012
	(0.017)	(0.018)	(0.0227)	(0.023)
CEO power				
CEO=Chairman	0.504***	0.479***	0.406**	0.396**
	(0.154)	(0.154)	(0.182)	(0.182)
CEO=Founder	0.381**	0.346**	0.248	0.211
	(0.172)	(0.173)	(0.204)	(0.205)
Ln(Tenure)	-0.133	-0.098	-0.142	-0.116
	(0.0866)	(0.087)	(0.103)	(0.104)
CEO overconfidence				
Holder67	-0.005	-0.000	-0.114	-0.098
	(0.165)	(0.168)	(0.197)	(0.197)
Other controls				
Stock market	-0.568**	-0.559**	-0.678**	-0.642**
	(0.236)	(0.235)	(0.295)	(0.296)
Constant	4.622***	4.226***	5.277***	4.882***
	(1.185)	(1.212)	(1.363)	(1.396)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched
Observations	412	412	277	277
Log likelihood	-215	-212	-155	-154

This table reports the probit estimation results between accounting fraud, and both *Option delta* and *Stock ownership* after controlling for prior-year changes in equity incentives (GPSM sample). Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 3.A.

Table 3.18 Bivariate probit estimation results using equity incentives

	(1)		(2)	
Model	*Fraud*	*Detect | Fraud*	*Fraud*	*Detect | Fraud*
Motivation				
Stock ownership	-0.071***		-0.100***	0.011***
	(0.021)		(0.026)	(0.004)
Stock ownership^2	0.003***		0.004***	
	(0.001)		(0.001)	
Option delta	0.209***		0.184***	1.189***
	(0.058)		(0.068)	(0.223)
Option delta^2	-0.016**		-0.014**	
	(0.006)		(0.007)	
Financial ratios				
ROA	-1.459***		-1.721***	
	(0.422)		(0.238)	
Leverage	-0.727**		-0.696***	
	(0.330)		(0.200)	
Ln(Assets)	-0.000	0.527***	-0.004	0.367***
	(0.025)	(0.052)	(0.027)	(0.059)
Working Capital	0.269		0.335**	
	(0.266)		(0.136)	
Tobin's Q	0.006		0.002	
	(0.004)		(0.018)	
CEO power				
CEO=Chairman	-0.036	0.235***	-0.000	0.106
	(0.070)	(0.089)	(0.059)	(0.068)
CEO=Founder	0.031	0.954***	0.032	0.837***
	(0.068)	(0.138)	(0.068)	(0.121)
Ln (Tenure)	0.133***	-0.166**	0.138***	-0.146***
	(0.044)	(0.0664)	(0.045)	(0.045)
CEO overconfidence				
Holder67	0.250***		0.191**	
	(0.0913)		(0.090)	
Detection factors				
Audit opinion		-0.072		0.010
		(0.294)		(0.074)
Other controls				
Stock market	-0.041	-0.677***	-0.271***	-0.168
	(0.124)	(0.217)	(0.094)	(0.103)
Constant	-0.668	-14.81***	-0.620	-11.52***
	(0.878)	(1.240)	(0.000)	(1.394)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Observations	17,608		17,608	
Log likelihood	-1345		-1338	

This table reports the bivariate probit estimation results between accounting fraud, and both *Option delta* and *Stock ownership* (Full sample). To facilitate the convergence of models, a reduced industry dummy is adopted. It is constructed to set for 1 for firms included in the top 50 percent of two-digit SIC industries. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 3.A.

APPENDIX 3.A Variable definitions

Variable	Definition
Dependent variable	
Accounting fraud	An indicator variable equal to 1 for firms for which the SEC published AAERs for alleged GAAP violations, and 0 otherwise (AAERs are compiled by CFRM) (Dechow et al. 2011).
Restatements	An indicator variable equal to 1 for firms that restated their misreporting, and 0 otherwise (Audit Analytics).
Lawsuits	An indicator variable equal to 1 for firms for which securities class action lawsuits regarding financial misreporting are filed (Stanford Law School).
WC	Current operating assets deducted by current operating liabilities.
PMJONES (Modified Jones with current-year ROA)	The residuals (ε) from $\Delta WC = \alpha_0 + \alpha_1$ (1/total assets (at_{t-1})) + α_2 (Δsale (*sale*) – Δreceivables (*rect*)) + α_3 (ΔPP&E (*ppegt*)) + ROA + ε, estimated for each two-digit SIC-year grouping (Kothari et al. 2005; Jones et al. 2008). All variables except 1/total assets (at_{t-1}) are deflated by total assets (at_{t-1}).
SDD (Studentised accrual estimation error)	The residuals of $\Delta WC = \alpha_0 + \alpha_1$ (CFO ($oancf_{t-1}$)) + α_2 (CFO ($oancf_t$)) + α_3 (CFO ($oancf_{t+1}$)) + ε, which are then deflated by the standard errors of the residuals of the firms belonging to the same two-digit SIC year grouping as each firm (Dechow and Dichev 2002; Dechow et al. 2011).
Motivation	
Option delta	The value sensitivity of option value to a 1 percent change in stock price (Core and Guay 2002). The

	scale is adjusted by dividing by 1,000,000 (Johnson et al. 2009).
Stock ownership	The shares excluding stock options of each CEO divided by total shares (*shrown _excl_opts_pct*).
Stock delta	The value sensitivity of stocks to a 1 percent change in stock price.
Portfolio delta	The sum of the sensitivities of stocks and options to a 1 percent change in stock price (Coles et al. 2006).
Portfolio vega	The value sensitivity of both stock options and stock holdings to a 1 percent change in stock volitivity (Armstrong et al. 2013).
TMT stock ownership	The shares of all officers on the BOD divided by total shares (Haleblian and Finkelstein 1993).
TMT option delta	The sum of *Option delta* of all officers on the BOD.
First public offering	An indicator variable equal to 1 if a firm's IPO date for major exchanges (NYSE, AMEX, and NASDAQ) or first going public date for OTC markets (OTC Pink Sheet and OTCBB) falls during or up to two years before accounting fraud, and 0 otherwise.
Debt covenant violation	An indicator variable equal to 1 if a firm violated debt covenants during or two years after accounting fraud, and 0 otherwise (Dechow et al. 1996). If firms with debts do not file 10-Q/10-K with the SEC or filed for bankruptcies, this paper assumes them to be debt covenant violations since they are usually automatic violations of debt covenants.
Financial ratios	
ROA	The ratio of income before extraordinary items (*ib*) to average assets (*at*).
Leverage	The ratio of debt in current liability (*dlc*) and long-term debt (*dltt*) to total assets (*at*).
Ln(Assets)	The natural logarithm of total assets (*at*).

Working Capital	The ratio of working capital (current asset – current liability; *wcap*) to total assets (*at*).
Tobin's Q	The ratio of the sum of market value of equity (*mktval*) and book value of liability (*lt*) to total assets (*at*).
CEO power	
CEO = Founder	An indicator variable equal to 1 for firms in which a CEO is also a founder of the firm, and 0 otherwise. A CEO is assumed to be a founder if his/her tenure (*becameceo*) is longer than or equal to CRSP *first date* or Compustat's *first data date*.
CEO = Chairman	An indicator variable equal to 1 for firms in which a CEO is also a Chairman of the board, and 0 otherwise.
Ln(Tenure)	The natural logarithm of the number of years that a CEO holds his/her position until current year.
CEO overconfidence	
Holder67	An indicator variable equal to 1 for firms whose CEOs hold stock options that are more than 67 percent in the money, and 0 otherwise (Campbell et al. 2011).
CAPEX	An indicator variable equal to 1 for firms whose ratio of capital expenditure to lagged total assets is greater than the medians of their industry peers (12 Fama-French industries), and 0 otherwise (Ahmed and Duellman 2013).
Over_invest	An indicator variable equal to 1 for firms whose residual of a regression of asset growth on sales growth, which is estimated for each two-digit SIC-year grouping, is greater than 0, and 0 otherwise (Schrand and Zechman 2012).
CEO competence	

Degree	An indicator variable equal to 1 for firms whose CEOs hold PhD, MBA, or JD/LLM, and 0 otherwise (BoardEx).
CPA	An indicator variable equal to 1 for firms whose CEOs hold CPA, CFA, CMA, or CTA, and 0 otherwise (BoardEx).
Experience	The natural logarithm of the number of professional career years that a CEO spent before joining current CEO position (BoardEx).
Corporate governance	
ABC (Appointment-based connectedness)	The ratio of directors and the four-highest paid named executives who have been appointed during the current CEO's tenure (Khanna et al. 2015).
Outside director	The ratio of outsider directors on the BOD to the total number of directors.
Outside blockholder	The shares held by outside blockholders divided by total shares.
Other controls	
Stock market	An indicator variable equal to 1 if a firm is listed on major stock markets such as NYSE, AMEX, and NASDAQ, and 0 otherwise.
SOX	An indicator variable equal to 1 if 1 firm-years fall behind 2002, and 0 otherwise.
Pr(*Takeover*)	The fitted value of $Pr(Takeover_t) = \alpha_0 + \alpha_1 ROA_{t-1} + \alpha_2 Leverage_{t-1} + \alpha_3 Ln(Assets)_{t-1} + \alpha_4 Tobin's\ Q_{t-1} + \alpha_5 Asset\ structure_{t-1} + \alpha_6 Blockholder\ ownership_{t-1} + \sum Year + \sum Industry + \varepsilon$ (Lin et al. 2018).
Year dummy	An indicator variable equal to 1 for the IT bubble (1999-2000) and 2 for the financial crisis (2007-2009), and 0 otherwise. This unique definition is used only for matched samples (GPSM and PM samples).

* Compustat and ExecuComp mnemonics are presented in parentheses.

Chapter 4

Controlling Shareholders' Control-Ownership Wedge

4.1. Introduction

It is well established in the literature that controlling shareholders'[74] voting rights exceeding their cash investment in firms, i.e., control-ownership wedge, causes firms' aggressive earnings management, as measured by relatively indirect proxies such as discretionary accruals (Fan and Wong 2002; Francis et al. 2005; Kim and Yi 2006; Gopalan and Jayaraman 2012). However, the specific context of accounting fraud entails substantial costs of financial misreporting (e.g., losses from a drop in stock prices or legal costs for fraud allegations) for controlling shareholders (see Karpoff et al. 2008b). Moreover, these costs are amplified when the control-ownership wedge is combined with controlling shareholders' ownership concentration (a common feature of business groups) and the additional imposition of government regulation uniquely associated with Korean *chaebols*. Although prior research claims that control-ownership wedge induces firms' "opportunistic earnings management" (Kim and Yi 2006), it is unclear whether controlling shareholders would ignore the increased economic and legal costs associated with accounting fraud. This study fills the void in the literature by testing the extent to which these two cost factors interact with the potentially exacerbating effect of control-ownership wedge on firms' accounting fraud

[74] Following La Porta et al. (1999), Fan and Wong (2002), Haw et al. (2004), and Lin et al. (2011), I focus on the largest ultimate owners as a proxy for controlling shareholders.

decisions.

According to the *expropriation hypothesis* widely adopted by prior researchers including Kim and Yi (2006), firms would manage their earnings to conceal the economic distortions caused by controlling shareholders' expropriating activities (e.g., related-party transactions). Consistent with prior research relying on this theory, I expect that firms with deeper control-ownership wedge are more likely to commit accounting fraud. However, I conversely hypothesise that firms affiliated with business groups or *chaebols* are less likely to commit accounting fraud because, in these two settings, controlling shareholders incur more serious and direct costs of accounting fraud. For example, controlling shareholders in business groups are exposed to substantial losses from any stock price crash once disputed misreporting is announced to markets. Furthermore, controlling shareholders in *chaebols* are faced with higher chances of detection due to the additional imposition of stringent regulation that tightens monitoring over their expropriating activities. The relative legitimacy of earnings management strategies (accruals management vs. accounting fraud) distinguishes the hypotheses and empirical results of prior studies (e.g., Kim and Yi 2006) from my study, because controlling shareholders may not seriously consider these cost factors when managing earnings generally within GAAP.

In contrast to "opportunism by executives" in the U.S. context, "opportunism by controlling shareholders" (Bebchuk and Weisbach 2010) is prevalent in many Asian and European countries (see e.g., La Porta et al. 1999; Claessens et al. 2000). In particular, the Korean sample provides an ideal setting to investigate my research question, because *chaebols* are usually controlled by their individual ultimate owners[75].

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[75] Conversely, business groups, for example, in China, Japan, and Germany are largely influenced by the government, professional managers, and big banks respectively (see Darrough et al. 1998; Chen et al. 2006; Ding et al. 2007; Lee and Lee 2014).

This implies a higher likelihood of expropriation by controlling shareholders. Moreover, *chaebols* are regulated by the Korea Fair Trade Commission (KFTC)[76] rules, the like of which rarely exist in other jurisdictions (Kim et al. 2008). In contrast to the generic definition of business groups[77], Korean *chaebols* are required to disclose the details of their ownership structure and related-party transactions (RPTs), and are prohibited from increasing the additional control-ownership wedge. These characteristics provide a unique set of conditions in which to test not only the impact of the control-ownership wedge but also its potential variations in business groups and *chaebols*. My study is the first to provide separate analyses of *unregulated* business groups and *regulated chaebols* by the KFTC rules, and to report their incremental impact on firms' accounting fraud propensity.

Using 433-465 matched pairs of fraud and non-fraud firms from Korea for the fiscal years 1998-2014, I first find that control-ownership wedge is positively associated with firms' accounting fraud propensity, when controlling shareholders' voting rights are held constant. This implies that control-ownership wedge motivates controlling shareholders not only to deteriorate firms' financial reporting quality as evidenced by prior research (e.g., Kim and Yi 2006), but also ultimately to violate GAAP. Further analyses reveal that the detrimental effect of control-ownership wedge is stronger when the levels of RPTs among affiliated firms, dividend pay-outs, and debt leverage are higher (presumably to avoid debt covenant violations). These are potential mechanisms by which controlling shareholders may expropriate their affiliated firms.

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[76] The Korea Fair Trade Commission (KFTC) is a "ministerial-level central administrative organisation under the authority of the Prime Minister and also functions as a quasi-judiciary body". See http://www.ftc.go.kr/eng/index.jsp.

[77] Prior studies such as La Porta et al. (1999), Claessens et al. (2000), and Faccio et al. (2001) define business groups as a group of firms whose ultimate owners hold both control-ownership wedge and concentrated voting rights of over 10-20 percent. The rationale for this definition is that 10-20 percent of ownership may provide shareholders with sufficient power to control their firms.

However, in contrast to prior research adopting relatively indirect and legitimate proxies for financial reporting quality (e.g., Kim and Yi 2006), I further find that, in the context of accounting fraud, the detrimental effect of control-ownership wedge is mitigated or even reversed when combined with controlling shareholders' ownership concentration and government regulation. Specifically, at most of the ownership concentration levels of controlling shareholders between 10 percent and 60 percent, I do not find that firms affiliated with business groups are more likely to commit accounting fraud, implying that ownership concentration may mitigate the detrimental effect of control-ownership wedge. The detrimental effect persists only at the extremely high levels of ownership of over 70 percent.

Further analyses suggest that the non-monotonic effect of business group affiliation can be explained by the costs that the cash component of voting rights (i.e., cash flow rights) may incur to controlling shareholders. Consistent with Wang (2006a), ownership concentration has a non-linear association with accounting fraud propensity in my sample (see also Khanna et al. 2015). Regarding control-ownership wedge and cash flow rights, the latter, particularly, has a mitigating effect on accounting fraud propensity. In contrast to control-ownership wedge, cash flow rights cause more direct costs to controlling shareholders because, as owners with substantial cash investment in firms, they also suffer from any inefficiency resulting from their expropriating activities.

I also document that firms affiliated with *chaebols* are less likely to commit accounting fraud, implying that government regulation may even reverse the detrimental effect of control-ownership wedge. In particular, additional difference-in-difference (DID) analyses strongly support the reversing effect of government regulation. Accounting fraud propensity significantly decreases *after* firms are designated as *chaebols* by the KFTC, presumably because *chaebols* are placed under tighter monitoring for expropriation by the public as well as the government. Tighter monitoring inevitably results in these increased economic and legal costs of expropriation. I also show that the reversing effect is unlikely to be strongly dominated by the political influence of large business groups.

I make a number of contributions to the literature. First, to my knowledge, my study is the first examining the distinct effects of business groups and *chaebols* from those of control-ownership wedge, in the context of accounting fraud. Prior research shows congruent effects of control-ownership wedge, business groups, and *chaebols* using relatively indirect proxies for financial reporting quality (e.g., Fan and Wong 2002; Kim and Yi 2006; Gopalan and Jayaraman 2012). This study, however, extends the literature by providing novel evidence that the detrimental effect of control-ownership wedge is countered by the existence of potential exposure to economic and legal cost considerations inherent to accounting fraud.

Second, my study adds to the literature exploring the characteristics of business groups and *chaebols* (e.g., Riyanto and Toolsema 2008; Byun et al. 2013; Almeida et al. 2015) by highlighting that they are shrewd enough to actively manage their earnings (as shown by prior research e.g., Kim and Yi 2006) *without* seriously crossing into GAAP violations. The findings provide insight into their enduring popularity as investment targets (e.g., Samsung and Hyundai[78]), despite the concerns over their potential aggressiveness in earnings management.

The remainder of this chapter is structured as follows. Section 4.2 summarises prior research and discusses my hypotheses. Section 4.3 describes my data and research

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[78] The top four largest *chaebols* occupy approximately 60 percent of the total market capitalisation of Korean stock markets (See http://www.businesskorea.co.kr/english/news/insight/19558-led-top-4-top-4-conglomerates-take-60-korean -stock-market-cap-increase).

design. Sections 4.4, 4.5, and 4.6 provide empirical results, a battery of additional analyses and robustness checks respectively. Section 3.7 concludes.

4.2. Review of literature and hypothesis development

My study focuses on the potential variations in the detrimental impact of control-ownership wedge on firms' reporting decisions, especially in the context of accounting fraud. A large volume of literature provides empirical evidence that control-ownership wedge is negatively associated with firms' financial reporting quality in both Asian and European countries. Most previous studies adopted relatively indirect proxies such as discretionary accruals (e.g., Haw et al. 2004; Kim and Yi 2006), income smoothing activities (e.g., Gopalan and Jayaraman 2012) and earnings-return relation (e.g., Fan and Wong 2002), and are based on the *expropriation hypothesis*. Francis et al. (2005) extend these studies by analysing U.S. data. By adopting dual class ownership structure and earnings-return relation as respective proxies for control-ownership wedge and earnings informativeness, they show that earnings are less likely to be informative for firms with dual class shares.

Similarly, other studies report that business group and *chaebol* affiliations are positively associated with firms' discretionary accruals (e.g., Kim and Yi 2006; Gopalan and Jayaraman 2012) and are negatively related to the magnitude of value-relevance of earnings and book value (e.g., Bae and Jeong 2007). Despite the heterogeneity in the definition of business groups and *chaebols*, these studies report qualitatively similar results, implying that government regulations may not cause heterogeneities in the context of firms' relatively legitimate earnings management strategies.

On the other hand, two competing empirical findings exist regarding the impact of controlling shareholders' ownership concentration on firms' earnings management. While Jaggi et al. (2009) and Hasnan et al. (2013) show that concentrated family ownership is negatively associated with firms' discretionary accruals or accounting fraud incidences, Fan and Wong (2002) report that controlling shareholders' ownership concentration is negatively associated with firms' earnings-return relation. A mediating finding is reported by Wang (2006a), who demonstrates that founding family ownership has a U-shaped association with firms' accruals management in the U.S. context. Specifically, firms with concentrated family ownership are initially more likely to produce quality financial reporting because controlling families have stronger incentives to monitor managers than minor shareholders do. This helps reduce agency conflicts between managers and shareholders. Conversely, firms with an excessive level of ownership are rather less likely to report quality earnings because controlling shareholders with increased control over the board of directors may not be tightly disciplined by corporate governance systems.

From the review of literature exploring the link between controlling shareholders' ownership structure and firms' earnings management, I identify two research gaps. First, prior studies examine the influence of business group and *chaebol* affiliations on various relatively legitimate proxies for financial reporting quality (e.g., discretionary accruals), potentially ignoring variations in their impact on firms' accounting fraud decisions which expose controlling shareholders to economic and legal costs. However, the increased costs that accounting fraud incurs to controlling shareholders may change their incentive mechanisms to avoid the costs. Second, despite the wide adoption of the *expropriation hypothesis* in the literature (e.g., Kim and Yi 2006), we still do not have empirical evidence on the moderating effect of control-ownership wedge on the relation between controlling shareholders' expropriation and firms' misreporting behaviours. I provide a discussion of institutional background and my hypotheses in the following sections.

4.2.1. Institutional background

Chaebols have contributed to the rapid economic growth of Korea ever since the end of the Korean War in 1953. With the help of ample financing opportunities centrally organised by the government at the initial stage of Korean economic development, *chaebols* have thrived in the global markets, and the Korean economy, in return, has grown to be the 11th largest as of 2015 (see IMF 2016).

On the other hand, *chaebols* have been criticised due to their opaque ownership structure. In contrast to average U.S. firms with diffuse stock ownership, *chaebols* are characterised by combined ownership and control, deep control-ownership wedge, and prevalence of family businesses. Their shareholders usually exercise increased voting rights using various control enhancing mechanisms among affiliated firms. Moreover, they often influence firms' management decisions "from outside the boardroom" without holding responsible management positions, presumably to reduce potential legal liabilities (Seo 2016).

To address side effects of *chaebols*, the Korean government adopted tight regulations in 1987. The KFTC designates *chaebol*-affiliated firms annually, whose total assets as a group exceed about $4.2 billion and whose ultimate owners hold more than 30 percent of shares of each firm. The designated *chaebol* firms are then required to disclose details of their RPTs as well as ownership structure, and prohibited from increasing new cross-holding of shares and providing guarantees for bank loans of affiliated firms (KFTC 2015). This unique regulation distinguishes *chaebols* from the generic definition of business groups.

4.2.2. Expropriation hypothesis and control-ownership wedge

Controlling shareholders may affect firms' accounting fraud decisions directly and indirectly. First, their stock holdings constitute a direct incentive to influence firms' misreporting decisions, and control-ownership wedge helps facilitate that influence (see also Francis et al. 2005). Second, their expropriating activities such as RPTs may indirectly induce firms to manage earnings. According to the *expropriation hypothesis*, firms would manage earnings to conceal the economic distortions caused by controlling shareholders' expropriation, because they would invite outside interventions (e.g., litigation or regulatory enforcement) if not properly addressed (Kim and Yi 2006; Gopalan and Jayaraman 2012). Controlling shareholders with control-ownership wedge may be incentivised to expropriate their firms because the costs of expropriation (e.g., inefficiencies caused by RPTs) are shared by outside investors in business groups (see Fan and Wong 2002), and their economic costs are ultimately limited to their cash investment in firms.

I thus expect that firms whose controlling shareholders have deeper control-ownership wedge are more likely to commit accounting fraud when their voting rights are held constant, as they may not be able to conceal their inefficiencies through legitimate earnings management strategies.

> H1. Control-ownership wedge of controlling shareholders is positively associated with firms' accounting fraud propensity.

4.2.3. Business group affiliation

In the context of accounting fraud, the detrimental effect of control-ownership wedge may be curbed when combined with the ownership concentration that is a common feature of typical business groups. In contrast to other earnings management strategies conducted mainly within GAAP, accounting fraud incurs additional economic and legal costs to controlling shareholders (see also Karpoff et al. 2008b). Moreover, their concentrated ownership amplifies the costs because it inevitably entails a significant portion of cash flow rights (see Khanna and Rivkin 2001; Almeida et al. 2015; KFTC 2015). In fact, controlling shareholders in my samples hold 79.9-80.1 percent of their voting rights as cash flow rights. Due to these increased costs, business groups, on average, are less likely to commit accounting fraud than non-business group affiliated firms.

On the other hand, excessive levels of ownership concentration are known in fact to deteriorate firms' financial reporting quality because controlling shareholders may be entrenched by their controlling power over firms (Wang 2006a), resulting in a non-monotonic effect of business group affiliation on firms' accounting fraud decisions. I thus hypothesise that firms affiliated with business groups are likely to show differing misreporting behaviours at different ownership concentration levels of controlling shareholders as below.

> H2. Business group affiliation is negatively (positively) associated with firms' accounting fraud propensity at the lower (higher) level of ownership concentration of controlling shareholders.

4.2.4. *Chaebol* affiliation

Large business groups in Korea are under more scrutiny by the government as it additionally imposes a set of stringent regulations that make controlling shareholders' expropriation more costly. Once designated, *chaebols* are put under tighter monitoring by the public and the government, resulting in controlling shareholders' higher costs of expropriation. The increased costs would then curb the detrimental effect of their control-ownership wedge. Therefore, I further hypothesise that firms affiliated with *chaebols* are less likely to commit accounting fraud than non-*chaebol* affiliated firms.

> H3. *Chaebol* affiliation is negatively associated with firms' accounting fraud propensity.

4.2.5. Expropriating activities

According to the *expropriation hypothesis*, controlling shareholders' control-ownership wedge would affect the strength of the relation between controlling shareholders' expropriating activities and accounting fraud propensity. To test this, I adopt three readily testable expropriating mechanisms.

First, controlling shareholders with deep control-ownership wedge are more likely to be involved in RPTs. For example, they can benefit by transferring their affiliated firms' resources to the firms where they have more cash flow rights (see Kang et al. 2014). Second, firms with a higher level of control-ownership wedge are likely to pay more dividend to outside shareholders to offset their concerns about the opportunistic nature of their ownership structure (Faccio et al. 2001). Since excessive RPTs conducted at lower than market prices and dividend pay-outs exceeding firms' capacity cause economic distortions in firms, they are more likely to misreport to conceal those inefficiencies (see Appendix 4.A).

Finally, firms with a high level of leverage and control-ownership wedge are more likely to commit accounting fraud. Since highly leveraged firms may have higher chances of violating debt covenants (see Dechow et al. 1996), controlling shareholders may influence firms' misreporting decisions, for instance, to avoid losses from firms' bankruptcy declaration.

> H4. Controlling shareholders' control-ownership wedge positively moderates the relation between their expropriating activities and firms' accounting fraud propensity.

4.3. Data and research design

4.3.1. Sample selection

The sample selection process is summarised in Table 4.1. The base sample is chosen from the KIS-Value database, which is equivalent to Compustat in the U.S. The base sample begins in 1998 because the Financial Supervisory Service (FSS), which is equivalent to the SEC in the U.S., started providing audited financial statements electronically in that year. The resulting sample consists of 113,498 firm-years from 1998 to 2014, after excluding financial institutions and firms without sufficient data for matching samples. I manually construct the control-ownership wedge variable using the open data provided by the FSS.

To synchronise the sample window, I collect data for 405 accounting fraud firms whose first fraud year also falls between 1998 and 2014. Similar to the SEC in the U.S., the FSS releases its enforcement actions regarding egregious financial misreporting cases. Due to resources constraints, however, inevitably the FSS investigates and sanctions only a proportion of misreporting cases, even when firms voluntarily restate their financial statements. Therefore, the accounting fraud cases analysed in this chapter do not include misreporting cases that are likely to be due to simple error or minor misreporting cases from the FSS's perspective. Due to data unavailability, I do not analyse restatement cases that are not included in FSS's database (i.e., Korean AAERs). The sample ends in 2014 in order for the FSS to have had sufficient time to finish their investigation. The fraud firms are then merged with the base sample after eliminating financial firms and firms without sufficient data for matching, leaving 235 fraud firms. The loss of fraud firms with missing data is largely either because firms do not disclose their lists of shareholders or because their ultimate owners are funds, banks or the government, in which cases these ultimate owners are not expected to have an impact on firms' accounting fraud decisions.

Descriptive statistics of the total KIS-Value observations and accounting fraud firms are reported in Table 4.2, along with *p*-values of *t*-tests and Wilcoxon rank-sum (WRS) tests. *t*-tests and WRS results in Columns (1) and (2) reveal that fraud firms are larger in asset size and more likely to be listed on major stock markets than the average KIS-Value observations. Furthermore, the performance (*ROA*) of fraud firms is poorer in the year before the first fraud year. These characteristics are potential confounders for both the incidence of accounting fraud and firms' ownership structure.

In order to address this potential endogeneity issue, I adopt three strategies. To begin with, I employ propensity score matching, which increases the average covariate balance of my sample firms by identifying matches whose average characteristics (propensity scores) are most similar. However, the balanced propensity score does not guarantee that each covariate of sample firms is also balanced (see King and Nielsen

2016). As a complementing matching method, I thus adopt a conventional partial matching method, which focuses more on key variables that may cause endogeneity issues (see Dechow et al. 1996). I expect that the potential confounding bias inherent in observational studies (see Rosenbaum 2002) may be mitigated through these two matching processes. Finally, to address the remaining bias, I control again for major covariates, including the variables used in the matching processes, in my accounting fraud model to be presented in the following subsection. The total sample size as a result of the matching processes ranges between 433 and 465 firms.

4.3.2. Generalized propensity-score matching (GPSM)

Generalized propensity-score matching (GPSM) proposed by Hirano and Imbens (2004) expands the conventional propensity-score matching (PSM) to continuous treatment cases like the variation of control-ownership wedge as in this study. The generalized propensity-score (*gpscore*), which is the probability of treatment given confounders, is estimated using both a treatment model (Eq. (4.1)) and a *gpscore* model (Eq. (4.2)). First, the treatment model is estimated using the OLS regression presented below. Even though it may be more appropriate to have adopted control-ownership wedge as the dependent variable of the treatment model, the largest immediate owners' ownership concentration (*Immediate voting rights*[79]) is used as an alternative because it is the only ownership variable available currently on the KIS-Value database. However, as seems plausible, both *Immediate voting rights* and *Wedge*

[79] *The largest immediate owner* is the largest stockholder among shareholders who directly own the stocks of a firm (see e.g., Chen et al. 2006). Differently from *the largest ultimate owner*, who is always an individual, *the largest immediate owner* may be either an individual or an institution. However, their ownership concentrations are highly correlated (ρ = 0.895-0.900, p-value = 0.000).

ratio may have common determinants in that they are fundamentally similar types of ownership variables.

$$Ln(\textit{Immediate voting rights})_t = \beta_0 + \beta_1 ROA_{t-1} + \beta_2 Leverage_{t-1} + \beta_3 \textit{Working Capital}_{t-1} + \beta_4 Market_{t-1} + \beta_5 Ln(Assets)_{t-1} + \beta_6 Ln(\textit{Firm age})_{t-1} + \varepsilon_t \quad (4.1)$$

I select the determinants of *Immediate voting rights* so that confounding bias is mitigated. The selected covariates are potential confounders that may affect both the ownership structure of controlling shareholders and firms' accounting fraud decisions. For example, *ROA*, *Leverage*, and *Working capital* are major financial ratios that may affect firms' fraudulent misreporting and, simultaneously, shareholders' investment decisions. Additionally, a firm's age increases the chances that the ownership structure is more diffuse since the greater the firm's age (*Ln*(*Firm age*)), the more shareholders could have traded their stocks in markets (see Beneish 1999). According to Himmelberg et al. (1999), stock market (*Market*) and firm size (*Ln*(*Assets*)) also affect firms' ownership structure since public and larger firms usually have more diffuse ownership structures than small non-listed firms do. Consistent with my predictions, the estimation of Eq. (4.1) reported in Table 4.3 confirms that all covariates are significantly associated with *Immediate voting rights*.

Second, the estimation of the treatment model is then used to calculate *gpscore*, which is the probability of having a higher level of ownership concentration (Eq. (4.2)). Following prior literature (e.g., Kluve et al. 2012), I adopt the probability density function of the normal distribution as a *gpscore* model as below (see also Hirano and Imbens 2004).

$$\hat{R}_t = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{1}{2\sigma^2}\left(T_i - \hat{T}_t\right)) \tag{4.2}$$

where,

T_i	=	the level of *Immediate voting rights* between 0 and 1;
$\hat{T}_t$ and σ	=	the estimations from the treatment model in Eq. (4.1).

Finally, I identify a non-fraud match for each fraud firm using the *gpscore* calculated above. To find matches whose *gpscores* are most similar but the level of actual ownership concentration is most dissimilar, I use the distance measure (Eq. (4.3)) proposed by Armstrong et al. (2010). I choose matched pairs based on the closest distance criteria and on a without-replacement basis, from firms in the same year and industry (two-digit SIC) as of the beginning of the first fraud year.

$$Distance_{i,j} = \frac{(gpscore_i - gpscore_j)^2}{(IVR_i - IVR_j)^2} \tag{4.3}$$

where,

$gpscore_{i,j}$	=	the generalized propensity-score for firm *i* and *j* calculated using Eq. (4.1) and (4.2);
$IVR_{i,j}$	=	*Immediate voting rights* for firm *i* and *j* respectively;
IVR_i	≠	IVR_j.

4.3.3. Partial matching

To complement GPSM, I further construct an alternative sample using more conventional partial matching (PM). Instead of focusing on the average covariate balance of fraud and non-fraud firms summarised as *gpscore*, PM aims at balancing several key variables selected based on the nature of the research focus. Due to the advantage of balancing key variables almost perfectly, a large body of research exploring determinants of accounting fraud in the U.S. setting has adopted the PM method using various matching criteria (see Schrand and Zechman 2012). Following Feng et al. (2011), I identify matched pairs whose asset sizes are most similar among firms in the same year and industry as of the beginning of the first fraud year.

4.3.4. Covariate balance

Table 4.4 reports the covariate balance between fraud and non-fraud firms identified by the two complementary matching processes explained above. Despite the strict matching requirements of this study (i.e. the same industry requirement), the *p*-values for a parametric *t*-test of the differences in means and two non-parametric WRS and Kolmogorov-Smirnov (KS) tests for the differences in medians and distributions respectively indicate that the identified matches are well balanced in terms of both *gpscore* and respective covariates. As seen in Table 4.4, the *gpscores* of the GPSM sample are not statistically different (*p*-values: 0.883-0.986), and the matched rates (*% Matched*) of *t*-test and the results of WRS and KS tests range between 50 percent and 83 percent in both the GPSM and PM samples.

4.3.5. Accounting fraud model

Due to the dichotomous nature of fraud and non-fraud matches, I estimate the effects of control-ownership wedge, firms' affiliation with business groups, and their association with *chaebols* on firms' accounting fraud decisions using the following probit regression model (Eq. (4.4)). Consistent with prior research exploring accounting fraud in the U.S. context (e.g., Dechow et al. 1996; Davidson et al. 2015), I adopt accounting fraud allegations filed by the FSS after a lengthy investigation process as a proxy for accounting fraud.

To test my hypotheses, I adopt three main variables of interest. To begin, *Wedge ratio* is considered as a proxy for control-ownership wedge. This variable captures the controlling shareholders' decision-making process, which is expected to be influenced by the relative size of benefits to costs of their expropriating activities. In line with prior research (e.g., Claessens et al. 2000), it is defined as control-ownership wedge over total voting rights. Following La Porta et al. (1999), Fan and Wong (2002), Haw et al. (2004), and Lin et al. (2011), I identify controlling shareholders and their control-ownership wedge by tracing the largest ultimate shareholder of each firm, from the lowest to the highest firm along the ownership chain of each business group (see Figure 4.1 of Appendix 4.A.)[80].

Following Claessens et al. (2000) and Faccio et al. (2001), *Business group (X%)* is defined as a group of firms with both control-ownership wedge and controlling shareholders with more than *X*% of shares. *X%* ranges between 10 percent and 70

[80] Controlling shareholders' total voting rights (*Voting rights*), i.e., the denominator of *Wedge ratio*, is calculated using *the final link method*, which assumes that controlling shareholders exercise voting rights equalling the sum of the direct ownership of a controlling shareholder and its affiliate on each ownership chain (see Ryu and Yoo 2011). This is consistent with KFTC regulation.

percent of stock ownership. *Regulation* is an indicator variable equal to one for firms which are designated as *chaebol* affiliated firms by the KFTC[81].

Additionally, I incorporate four categories of control variables. First, potential expropriation is controlling shareholders' key incentive to influence firms' accounting fraud decisions. To control for the effects of expropriation and to test the *expropriation hypotheses* empirically, I adopt three representative expropriation variables, i.e., *RPTs*, *Dividend*, and *Leverage*. Second, controlling power over firms may provide controlling shareholders with the means to influence firms' misreporting decisions. To control for these potential effects, I adopt three variables. As with the duality of CEO and Chairman in the U.S. setting, controlling shareholders who are also CEO of their firms (*Largest=CEO*) may exert more power over the board of directors and, thus, increase the probability of accounting fraud. On the other hand, *Outside directors* and *BigN auditor* are expected to curb the incidence of accounting fraud from inside and outside of firms respectively. Finally, to mitigate the remaining omitted variable bias, I control for major financial ratios and other variables (such as *ROA*, *Ln*(*Assets*), *Working capital*) suggested in prior research (e.g., Dechow et al. 1996).

$$\begin{aligned} Pr(\mathit{Accounting\ fraud}_t) = {} & \alpha_0 + \alpha_1 \mathit{Wedge\ ratio\ (or\ Business\ group\ (X\%))}_{t-1} \\ & + \alpha_2 \mathit{Regulation}_{t-1} + \alpha_3 \mathit{RPTs}_{t-1} + \alpha_4 \mathit{Dividend}_{t-1} + \alpha_5 \mathit{Leverage}_{t-1} \\ & + \alpha_6 \mathit{ROA}_{t-1} + \alpha_7 \mathit{Ln(Assets}_{t-1}) + \alpha_8 \mathit{Working\ Capital}_{t-1} \\ & + \alpha_9 \mathit{Largest{=}CEO}_{\,t-1} + \alpha_{10} \mathit{Outside\ directors}_{t-1} \\ & + \alpha_{11} \mathit{BigN\ auditor}_{t-1} + \alpha_{12} \mathit{Stock\ market}_{t-1} + \alpha_{13} \mathit{Ln}(\mathit{Firm\ age})_{t-1} \\ & + \alpha_{14} \mathit{Government\ bank}_{t-1} + \textstyle\sum \alpha \mathit{Year\ dummy} + \varepsilon_t \end{aligned} \tag{4.4}$$

[81] To avoid potential multicollinearity among ownership variables, I introduce *Business group (X%)* and *Wedge ratio* separately in my estimation of Eq. (4.4). On the other hand, I include *Regulation* in all specifications of accounting fraud model because different levels of regulation may cause endogeneity of *Wedge ratio* and *Business group (X%)*.

4.3.6. Difference-in-difference (DID) analysis

Cross-sectional probit regression analyses may not be sufficient to test *H3*. First, I have so far matched my main samples based on the controlling shareholders' probability of having similar levels of ownership concentration. However, to directly test the effect of *chaebol* affiliation, I should match them based on the probability of *chaebol* designation. Second, a simple regression model does not fully capture the dynamic impact of government regulation on firms' accounting fraud decisions around the timing of *chaebol* designation. Therefore, I further adopt a DID design and a newly matched sample.

To use a DID design, two assumptions must be satisfied. First, the designation of *chaebol* by the KFTC must be exogenous (see Lechner 2011). To meet this condition, I match *chaebol* and non-*chaebol* firms using the PSM of Eq. (4.5) incorporating two formal screening criteria for *chaebol* designation adopted by the KFTC[82]. Matched pairs are selected from firms in the same year. Second, the trends of accounting fraud frequency before the designation of *chaebol* must be parallel (see Abadie 2005). Figure 4.1 graphically shows that both *chaebol* and non-*chaebol* firms in the PSM sample have increasing trends of fraud frequencies one year before the *chaebol* designation, implying that their fraud frequencies would have been similar in the absence of the KFTC regulation. However, the assumption is not perfectly fulfilled over the one-year window. To test the sensitivity of DID analyses to different year

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[82] To designate *chaebols*, the KFTC considers controlling shareholders' ownership concentration (30 percent) and group assets size ($4.2 billion). As with in GPSM, I adopt *Immediate voting rights* as a proxy for ownership structure. For group asset size, I use each firm's total assets as a substitute measure, because group asset size is not readily available for all firms on KIS-Value. Moreover, even if it were available, it is not suitable for identifying matches of *individual* firms with similar asset sizes. I construct a PSM sample without replacement and using a nearest neighbour method.

windows, I thus conduct the analyses over four different time periods, i.e., one to three years before and after *chaebol* designation, and the whole sample period (see Chang et al. 2016).

$$Pr(Chaebol\ designation_t) = \beta_0 + \beta_1 Immediate\ voting\ rights_{t-1} + \beta_2 Ln(Assets_{t-1}) + \varepsilon_t \quad (4.5)$$

Panel A of Table 4.5 summarises the sample selection process and its resulting covariate balance of *chaebol* and non-*chaebol* firms. From the base sample of KIS-Value in Table 4.1, I first select 261 distinct *chaebol* firms with sufficient data for PSM for the fiscal years 1998-2014. For each *chaebol* affiliated firm, I then identify one non-*chaebol* match wherever possible, resulting in 509 firm observations, or 5,414 firm-year observations.

Reports on covariate balance in Panel B of Table 4.5 further affirm that the covariates of the matched sample are ideally balanced, supporting the assumption that government regulation is exogenous in these matched samples. The *pscores* of the PSM sample are not statistically different (p-values: 0.226) and each covariate is also well randomised (p-values: 0.165-0.600).

Using the matched sample, I then estimate the following probit regression model in Eq. (4.6). To construct DID specifications, I re-define *Regulation*. While in Eq. (4.4) it was an indicator variable equal to one for the specific firm years when firms are affiliated with *chaebols*, it now represents *all* firm years of firms that are designated as *chaebol* at least once during the whole sample window. Conversely, it is zero for *all* firm years of firms that are never designated as *chaebol* during the sample period. *Post* is set to one for the firm years since firms were designated as *chaebol*, and zero otherwise. For non-*chaebol* firms, it is equal to one for firm years since they are matched with *chaebol* firms, and zero otherwise. Therefore, the coefficient for *Regulation* × *Post* (γ_3) captures the effect of *chaebol* designation on accounting fraud propensity for *chaebol* firms relative to non-*chaebol* firms. *Wedge ratio* and several control variables such as *Largest= CEO* and *Outside directors* are not included in Eq. (4.6) because they should be manually collected for large samples. However, to control for firms' ownership structure, I incorporate *Immediate voting rights* instead of *Wedge ratio* (see also Himmelberg et al. 1999). The inclusion of *Immediate voting rights*, however, does not alter my findings.

$$\begin{aligned} Pr(Accounting\ fraud_t) = {} & \gamma_0 + \gamma_1 Regulation + \gamma_2 Post_t + \gamma_3 Regulation \times Post_t \\ & + \gamma_4 Immediate\ voting\ rights + \gamma_5 Immediate\ voting\ rights_t^2 \\ & + \gamma_6 Dividend_t + \gamma_7 Leverage_t + \gamma_8 ROA_t + \gamma_9 Ln(Assets_t) \\ & + \gamma_{10} Working\ Capital_t + \gamma_{11} BigN\ auditor_t \\ & + \gamma_{12} Ln(Firm\ age) + \gamma_{13} Government\ bank_t \\ & + \textstyle\sum \gamma Year\ dummy + \sum \gamma Industry\ dummy + \varepsilon_t \end{aligned} \qquad (4.6)$$

4.4. Main findings

4.4.1. Pairwise correlation analysis

Table 4.6 reports the results of pairwise correlation analyses between ownership variables and accounting fraud. The results show that *Accounting fraud* is positively correlated with *Wedge ratio*. However, *Accounting fraud* has some non-monotonic associations with *Business group (X%)* depending on the levels of controlling shareholders' ownership concentration and on negative relations with *Regulation*.

The initial analysis results of *Wedge ratio* are consistent with those of prior literature adopting discretionary accruals as a proxy for firms' financial reporting quality (e.g., Kim and Yi 2006). However, the results of *Business group (%)* and *Regulation* are heterogeneous from those studies, implying that GAAP violations may have different implications in the context of controlling shareholders' ownership structure.

4.4.2. Control-ownership wedge and accounting fraud

Table 4.7 reports the estimates of Eq. (4.4) regarding the relation between *Wedge ratio* and accounting fraud. Columns (1)-(6) show that *Wedge ratio* has positive and significant associations with accounting fraud propensity. These findings support *H1*. The results are robust regarding alternative matching methods (i.e., GPSM and PM), and the inclusion of additional controls such as government regulation (*Regulation*), controlling shareholders' expropriating activities (*RPTs*, *Dividend*, and *Leverage*), and firms' corporate governance (e.g., *Outside directors*) and financing opportunities (*Government bank*).

Due to the matching algorithms, control variables are statistically significant only excepting that (1) the matching processes are not perfect, (2) some covariates are not included in the treatment model (Eq. (4.1)), or (3) there are hidden effects that multivariate analyses may cause. In fact, *ROA* and *Stock market*, which are not balanced even after applying two matching algorithms, show negative and positive associations with accounting fraud propensity respectively. On the other hand, *BigN auditor*, which is not included in the treatment model since it is not expected to influence the ownership structure of controlling shareholders, is negatively associated with accounting fraud propensity, suggesting that major auditors may have a deterring effect on the incidences of accounting fraud.

4.4.3. Business group affiliation and accounting fraud

Columns (1)-(8) in Table 4.8 further reveal that, in contrast to the effect of *Wedge ratio*, *Business group (X%)* largely does not have statistically significant associations with accounting fraud at most of the ownership levels. This implies that the detrimental effect of *Wedge ratio* is mitigated by controlling shareholders' ownership concentration. A negative and significant association is observed only at extremely high levels of ownership - over approximately 70 percent (Columns (3) and (4)) - suggesting a non-monotonic effect of ownership concentration. These findings support *H2*.

Table 4.9 provides a likely explanation for the non-monotonic effect by showing where the mitigating effect originates from. First, Columns (1) and (2) reveal that the ownership concentration of controlling shareholders has a non-linear association with accounting fraud propensity, whose inflection points range between 63.1 percent and 68.0 percent. This implies that ownership concentration mitigates the detrimental effect of *Wedge ratio* below the critical points from where controlling shareholders may be entrenched by their concentrated ownership (see Morck et al. 1988).

Second, Columns (3) and (4) further show that the non-monotonic effect is mainly characteristic of the cash component of voting rights (*Cash flow rights (%)*). Specifically, *Cash flow rights (%)* is negatively associated with accounting fraud propensity for most of the ownership ranges (0-81.1 percent), whereas *Wedge (%)* does not have such an effect. Taken together, these findings suggest that firms affiliated with business groups are not more likely to commit accounting fraud than non-business group affiliated firms, because controlling shareholders' ownership concentration backed by their own cash investment may curb the detrimental effect of control-ownership wedge in the context of accounting fraud.

4.4.4. *Chaebol* affiliation and accounting fraud

To test the additional effects of government regulation, I further estimate both a simple probit regression (Eq. (4.4)) and a DID model (Eq. (4.6)). DID analyses provide more direct evidence for the role of government regulation in curbing financial misreporting by adopting the designation of *chaebol* affiliation as an exogeneous event. First, Columns (1)-(4) in Table 4.7 and Columns (3)-(4) in Table 4.8 show that *Regulation* largely has negative and significant associations with accounting fraud propensity, supporting *H3*. Even though the statistical significance of these associations is not as strong as those of *Wedge ratio* and its statistical significance even disappears in alternative samples (Columns (5)-(6) in Table 4.7) and specifications of ownership variables (Table 4.8), the consistently negative coefficients of *Regulation* imply that the detrimental effect of control-ownership wedge may be at least marginally mitigated by the government regulation imposed on *chaebol* affiliated firms.

Second, additional DID analyses further affirm *H3*. Columns (1)-(8) in Table 4.10 consistently report that the coefficients of *Regulation* × *Post* are negative and highly significant, implying that, relative to non-*chaebol* firms, *chaebol* firms experience a drop in accounting fraud frequency *after* they are designated as *chaebol*. On the other hand, *chaebol* affiliated firms are more likely to commit accounting fraud than non-*chaebol* affiliated firms *before* the *chaebol* designation (coefficients of *Regulation*: positive), implying that the financial reporting quality of *chaebol* firms was originally poorer than non-*chaebol* firms. The accounting fraud propensity of non-*chaebol* firms is increasing *through* the sample periods (coefficients of *Post*: positive), suggesting that the accounting fraud frequencies of *chaebol* affiliated firms would have increased even in the absence of the KFTC regulations. In particular, Columns (1)-(6) report the focused estimation results of Eq. (4.6) using narrower windows of sample periods: one to three years before and after *chaebol* designation (see also Chang et al. 2016). These analyses capture the more immediate effect of *chaebol* designation on firms' accounting fraud propensity during the time period in which the parallel assumption is more likely to hold.

4.4.5. Expropriation mechanisms

I finally test the *expropriation hypothesis* by adopting three potential expropriating activities of controlling shareholders. First, Columns (1) and (4) in Table 4.11 show some evidence that *RPTs* and *Dividend* are, indeed, positively associated with accounting fraud propensity when *Wedge ratio* is higher. The main effects of expropriations, when their interaction terms are controlled for separately, are not statistically significant (Columns (1) and (3)) or instead show a negative effect (Columns (2) and (4)), implying that these expropriation mechanisms alone may not cause accounting fraud incidences. The main effect of *Dividend*, in particular, is negatively associated with accounting fraud propensity because fraud firms usually do not have a consistent ability to pay dividend (Caskey and Hanlon 2013), but controlling shareholders with high levels of control-ownership wedge have an incentive to pay more dividend to offset the concerns of outside shareholders over their opportunistic ownership structure.

Second, Columns (5) and (6) further show that *Leverage* is also positively associated with accounting fraud propensity when *Wedge ratio* is higher. Additionally, Columns (1) and (2) in Table 4.9 provide evidence on controlling shareholders' potential incentive to directly benefit from their stock holdings. These findings, together, support the *expropriation hypothesis* (*H4*).

4.5. Additional analyses

4.5.1. Political connectedness

An alternative explanation for the distinct effects of business groups and *chaebols* from those of control-ownership wedge is that the effects may be driven by the political influence of large business groups. To rule out such an alternative, I conduct two additional analyses. The long history of government-driven economic growth in Korea implies that business and government elites may be connected with each other and that these connections may hinder the incidence and detection of accounting fraud, not only by providing favourable financing opportunities to firms but also by influencing the auditing or investigation processes of disputed misreporting cases.

The distinction between business groups and *chaebols*, however, provides an ideal setting to identify a unique mechanism through which large business groups react to government regulation, by enabling the adoption of a DID analysis around *chaebol* designations. In particular, the analysis results of the immediate effect (one to two years after *chaebol* designation) of government regulation suggest that the lower levels of accounting fraud propensity of *chaebol* affiliated firms may not be driven by their political influence (Columns (1)-(2) in Table 4.10). It is not conceivable that firms' political influence has changed drastically for the short period of time around *chaebol* designations.

Additionally, I control for two variables that represent the potentially political influence of business groups and *chaebols*. To begin, the main results presented in Table 4.7 and Table 4.8 already included *Government Bank,* which is an indicator variable set to one if a firm's main creditor bank is owned by the government (Byun et al. 2013). The effects of *Business group (X%)* and *Regulation* were robust regarding the inclusion of this variable, implying that favourable funding opportunities may not be a seriously confounding factor. Furthermore, I estimate the sensitivity of Eq. (4.4) to the inclusion of a more direct proxy for firms' political connectedness with the government, i.e., *Political connectedness*. It is an indicator variable set to one if any executive or director of a firm is a former member of parliament (MP) or minister (Byun et al. 2013)[83]. Columns (1)-(4) in Table 4.12 confirm that the effects of *Business group (X%)* and *Regulation* on accounting fraud also do not change even after controlling for this additional political connectedness variable. These tests suggest that business groups and *chaebols*' potentially political influence does not seriously undermine my argument.

4.5.2. Managerial influence

Alternatively, the detrimental effect of control-ownership wedge or ownership concentration may be driven by controlling shareholders' duality in key management positions like CEO. However, as widely accepted by prior research and even by the KFTC, I assumed that controlling shareholders are able to influence firms' misreporting decisions even without holding CEO positions. To test this assumption, I provide two further analyses.

First, Table 4.7 and Table 4.8 report that *Largest=CEO* does not have any significant association with accounting fraud propensity or rather decreases it depending on

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[83] Since non-listed and some listed high-tech firms are not required to disclose the members of their board of directors, I plausibly assume that these firms do not have political connectedness with the government. Compared to listed firms, non-listed firms in Korea are usually smaller in asset size and younger in firm ages, and, thus, they may not have sufficient ability to recruit ex politicians and high-ranking government officials. To avoid arbitrariness, I adopt *Political connectedness* only in this additional analysis.

model specifications and sampling methods (Columns (2) and (5)-(8) in Table 4.8). This finding implies that controlling shareholders may not intentionally hold CEO positions for accounting fraud purposes. In fact, the duality mechanism is not so popular in Korea[84]. Conversely, it is known that controlling shareholders of *chaebols* are averse to holding CEO positions to avoid potential legal liabilities, and prefer unofficial influence "from outside the boardroom" (see Seo 2016).

Second, Table 4.13 further reveals that, differently from controlling shareholders' ownership concentration, CEO ownership (*CEO ownership*) mainly has a negative and significant association with accounting fraud propensity, and non-linear effects on accounting fraud propensity influenced by CEOs do not exist or they are weaker if present. These findings imply that CEO ownership in Korean firms tends to improve firms' financial reporting quality. Taken together, the detrimental effect of controlling shareholders' ownership structure on firms' reporting decisions may not be critically influenced by their managerial influence as a CEO.

4.5.3. Outside blockholders

I finally test whether the impacts of three ownership variables are confounded by the existence of outside blockholders (*Outside blockholder*). Blockholders other than the largest controlling shareholders may exert their influence on firms' accounting fraud decisions by increasing governance levels ("voice") or by selling shares when firms are not reliable ("exit") (Edmans 2014). To test this potential effect, I additionally incorporate *Outside blockholder* into Eq. (4.4) and find that *Outside blockholder* is indeed negatively associated with accounting fraud despite being insignificant.

[84] In my sample, 49.4 percent of fraud firms have the same controlling shareholders and CEOs, whereas 61.7-62.0 percent of non-fraud firms have this duality.

However, I report that my findings are not susceptible to the ownership levels of blockholders (Columns (1)-(6) in Table 4.14), affirming my main argument.

4.6. Robustness checks

4.6.1. Family ownership

I have so far analysed individual controlling shareholders' control-ownership wedge and ownership concentration because, in Korea, non-listed firms and some listed high-tech firms are not required to disclose the family ownership of their controlling shareholders to the public. However, family owners potentially vote together with controlling shareholders, and controlling shareholders may hold their own shares under their family names. To address this potential bias, I construct a reasonable proxy for the family ownership variable[85] and show that the results do not change even after I include family ownership in the existing ownership structure variables (Table 4.15).

4.6.2. The final or weakest link method

I also test whether the findings are robust regarding an alternative calculation method of the wedge ratio variable. Following La Porta et al. (2002) and the regulation of the KFTC, I assumed that controlling shareholders can exercise their voting rights up to the final link on their ownership chains in addition to their direct cash flow rights (i.e., *the final link method*). However, other studies have alternatively assumed that

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[85] First, actual family ownership data are collected for most listed firms. Second, if family relationship is identified by news articles, obituaries and footnotes of other disclosed financial statements, then the family ownership variable is constructed by matching the identified family names with their disclosed ownership data. Third, the family ownership variable is also constructed if both the first and last names of shareholders are the same, because Koreans have that tradition when naming brothers and sisters. Using these data, I test whether my findings are susceptible to the inclusion of family ownership into *Wedge ratio*, *Business group (X%)*, and *Regulation* respectively. To avoid arbitrariness, however, *Family ownership* is used only in this additional analysis. Moreover, to economise the data collection process, I do not conduct DID analyses again, after including family ownership.

controlling shareholders' voting rights may be limited to the weakest link on their ownership chains - *the weakest link method* (e.g., Claessens and Fan 2002). To check the sensitivity of the findings to these alternatives, I estimate Eq. (4.4) by substituting *Wedge ratio* with *Wedge ratio (weakest)*.

Despite the different assumptions on the size of voting rights that controlling shareholders may exercise, Table 4.16 confirms that my analysis results do not alter even when I adopt *Wedge ratio (weakest)* as a proxy for controlling shareholders' control-ownership wedge.

4.6.3. Direct or indirect ownership through affiliated firms

I further test the validity of *Wedge ratio* (alternatively, *Cash flow rights ratio*) as my main explanatory variable. My construction of this variable relies on the assumption that controlling shareholders' impact on firms' misreporting decisions is determined by the cash and non-cash components of voting rights. A rationale for this assumption is that controlling shareholders ultimately incur costs from their cash investment in firms. However, the direct and indirect portions of cash flow rights may also have distinct effects on firms' misreporting decisions as *Wedge ratio*, which is all indirect ownership, does. To test this potential effect, I estimate Eq. (4.4) after decomposing *Cash flow rights ratio* into direct and indirect components.

Analysis results reveal that both *Direct cash flow rights ratio* and *Indirect cash flow rights ratio* congruently have negative and significant associations with accounting fraud propensity (Table 4.17). This finding implies that the immediacy of ownership (direct or indirect) does not matter, critically, so long as controlling shareholders have invested their own cash flows in their firms.

4.6.4. Multicollinearity

To avoid potential multicollinearity among ownership variables in that shareholders with control-ownership wedge usually hold concentrated ownership, I did not include *Voting rights* in Eq. (4.4). The selection of ownership variables in prior literature is not consistent. While Haw et al. (2004) and Kim and Yi (2006) do not control for ownership concentration, Fan and Wong (2002) and Gopalan and Jayaraman (2012) include both control-ownership wedge and ownership concentration in their empirical models, presumably to isolate the effect of their main variable of interest. Additional analysis results affirm that the findings are largely robust regarding the inclusion of *Voting rights* in Eq. (4.4) (Table 4.18).

4.6.5. Partial observability

Finally, I test whether the findings are also robust regarding potentially undetected fraud cases by the FSS. Since we cannot consider all misreporting firms from Korean AAERs (see Poirier 1980), it is meaningful that this type of study tests the robustness of their findings regarding the partial observability bias. Following Chen et al. (2006), Wang (2013), and Khanna et al. (2015), I adopt the bivariate probit model, which adjusts the coefficients of a fraud commitment model by combining it with a fraud detection model. In addition to the accounting fraud model of reporting firms presented in Eq. (4.4), I construct a simple fraud detection model for the FSS by removing benefits from accounting fraud (e.g., *Wedge* and *ROA*) (see Wang 2013), which are the main motivations for accounting fraud. On the other hand, I incorporate *Audit opinion* as a unique variable for the detection model, because it could trigger investigation by the FSS. The bivariate regression estimates consistently affirm that my results are not susceptible to potential partial observability bias (Table 4.19)[86].

4.7. Conclusion

In this chapter, I test the extent to which the potentially detrimental effect of control-ownership wedge interacts with controlling shareholders' ownership concentration and the additional imposition of government regulation, particularly in the context of accounting fraud. Using matched samples of Korean firms, I find that control-ownership wedge is positively associated with accounting fraud propensity, but business groups and *chaebols* are not: firms' affiliation with *chaebols* is, in fact, negatively associated with accounting fraud propensity. These are novel findings suggesting that business groups and *chaebols*, which have long been considered as aggressive earnings manipulators, do not seriously cross into accounting fraud commitment.

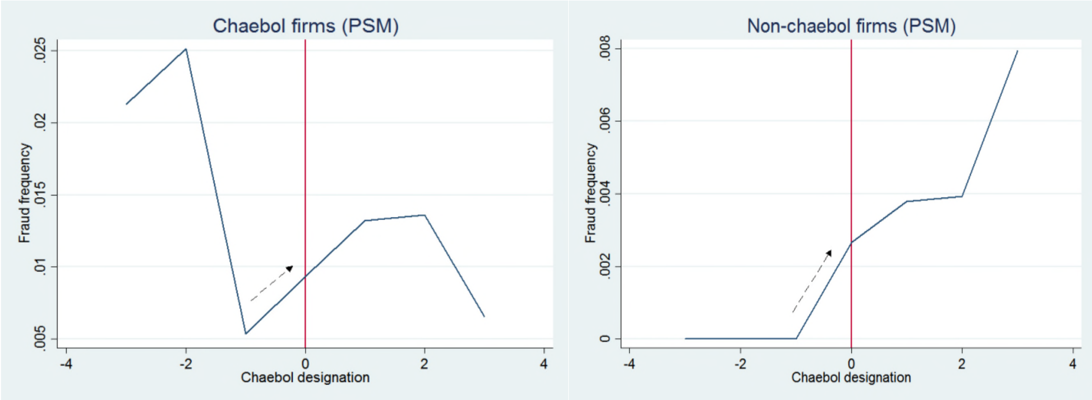
As with most research of this type, the findings should be interpreted with some caveats. First, this research relies on the assumption that controlling shareholders could influence firms' accounting fraud decisions even without holding key management positions. However, this assumption is widely accepted by prior cross-country studies (e.g., Fan and Wong 2002), the media (e.g., Evans 2016) and the KFTC in the institutional context of Korea. I further empirically demonstrate the mechanism through which controlling shareholders affect firms' accounting fraud decisions (e.g.,

[86] Due to frequent convergence failures of the bivariate probit model, I conduct this analysis only for this robustness check. For the convergence issue of maximum likelihood methods, see Agresti and Kateri (2011).

RPTs) and, conversely, I do not find strong evidence that the detrimental effect of control-ownership wedge is associated with managerial opportunism. Second, I also assume that expropriation by controlling shareholders is controlled for in my accounting fraud model by incorporating *RPTs*, *Dividend*, and *Leverage*. However, potential expropriating activities cannot be limited to these three mechanisms. Despite this limitation, I believe that the inclusion of *RPTs* in the model may reduce the potential endogeneity issue, because RPTs are the main expropriating mechanism that the *expropriation hypothesis* suggests.

With these caveats in mind, my study suggests that the detrimental effect of control-ownership wedge is countered by the cost factors inherent in an accounting fraud context. In particular, my findings validate the role of government regulation in curbing firms' fraudulent misreporting and provide valuable insights into the enduring popularity of large business groups as investment targets, despite the long-held concerns over their aggressiveness in earnings management.

Figure 4.1 Parallel trend assumption



This figure illustrates the univariate trends of fraud frequencies of both *chaebol* and non-*chaebol* firms. PSM stands for Propensity-Score Matching. X-axis represents the years relative to the year of *chaebol* designation by the KFTC, Y-axis shows mean fraud frequencies.

Table 4.1 Sample selection

Sample selection	Obs.	Firms
Original file of KIS-VALUE excluding financial firms (1998-2014)	120,492	firm-years
Less: Observations without sufficient data	6,994	
Total unmatched firm-years (1998-2014)	113,498	firm-years
Distinct fraud firms detected by the FSS (1993-2014)	414	Firms
Less: Firms before 1998	(9)	
Distinct fraud firms detected by the FSS (1998-2014)	405	firms
Less: Financial firms	(80)	
Less: Duplications	(10)	
Less: Firms without sufficient data	(80)	
Fraud firms (1998-2014)	235	firms
Non-fraud matches (1998-2014)	200-230	firms
Total matched firms (1998-2014)	433-465	firms

Table 4.2 Descriptive statistics

	Total observation			Fraud firms				
Variables	Obs.	Mean (A)	Median (B)	Obs.	Mean (C)	Median (D)	(1) t-test p-value (A-C)	(2) WRS p-value (B-D)
ROA	113,498	0.049	0.038	234	-0.195	-0.005	0.000	0.000
Leverage	113,498	0.611	0.610	235	0.607	0.563	0.501	0.005
Working Capital	113,498	0.063	0.065	235	0.075	0.128	0.206	0.006
Ln(Assets)	113,498	24.284	23.975	235	24.583	24.336	0.000	0.000
Stock market	113,498	0.186	0.000	235	0.800	1.000	0.000	0.000
Ln(Firm age)	113,470	2.628	2.708	235	2.699	2.708	0.068	0.242
Big*N* auditor	112,975	0.314	0.000	235	0.264	0.000	0.041	0.041
Government bank	108,216	0.413	0.000	232	0.440	0.000	0.561	0.561
Regulation	113,498	0.059	0.000	235	0.038	0.000	0.305	0.305
Wedge ratio	-	-	-	235	0.256	0.589	-	-
Business group (70%)	-	-	-	235	0.060	0.000	-	-
RPTs	-	-	-	235	0.634	0.032	-	-
Dividend	-	-	-	235	0.117	0.000	-	-

This table reports descriptive statistics, including p-values for t-tests and Wilcoxon rank-sum (WRS) tests of mean and median differences between total observations of KIS-Value and fraud firms. Variables are defined in Appendix 4.B. *Wedge ratio*, *Business group (70%)*, *RPTs*, and *Dividend* do not have statistics for the total observations because they are manually collected only for matched firms.

Table 4.3 GPSM estimation using OLS regression

Variables	Dependent variable = *Ln*(*Immediate voting rights*)
ROA	0.251***
	(0.010)
Leverage	-0.044***
	(0.006)
Working Capital	-0.011**
	(0.006)
Stock market	-0.775***
	(0.005)
Ln(Assets)	0.010***
	(0.001)
Ln(Firm age)	-0.005***
	(0.000)
Constant	-0.720***
	(0.034)
Observations	113,498
Adjusted R^2	0.269

This table reports the OLS estimation results between the *Ln*(*Immediate voting rights*) and potential confounders of both controlling shareholders' ownership structure and accounting fraud. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.4 Covariate balance

Variables	Panel A (GPSM)					Panel B (PM)				
	Mean		*p*-value			Mean		*p*-value		
	Fraud	Non-Fraud	*t*-test	WRS	KS	Fraud	Non-Fraud	*t*-test	WRS	KS
ROA	-0.197	0.041	0.000	0.000	0.000	-0.195	0.054	0.000	0.000	0.000
Ln(Firm age)	2.711	2.606	0.124	0.114	0.194	2.699	2.649	0.483	0.843	0.380
Leverage	0.607	0.611	0.939	0.217	0.190	0.607	0.551	0.217	0.666	0.904
Working Capital	0.073	0.044	0.584	0.130	0.078	0.075	0.116	0.364	0.458	0.706
Stock market	0.798	0.195	0.000	0.000	0.000	0.800	0.389	0.000	0.000	0.000
Ln(Assets)	24.596	24.182	0.001	0.001	0.005	24.583	24.548	0.792	0.704	0.928
Year				Matched					Matched	
Industry				Matched					Matched	
% Matched (A)			63%	63%	50%			75%	75%	75%
% Matched (B)			83%	83%	67%			83%	83%	83%
gpscore	0.471	0.475	0.883	0.882	0.986	-	-	-	-	-
Wedge ratio	0.258	0.130	0.000	0.000	0.000	0.256	0.143	0.000	0.000	0.001
Business group (20%)	0.326	0.250	0.082	0.082	0.560	0.323	0.274	0.245	0.244	0.938
Business group (70%)	0.060	0.301	0.124	0.124	0.995	0.060	0.104	0.078	0.078	0.974
Regulation	0.039	0.050	0.566	0.565	1.000	0.038	0.073	0.095	0.095	0.999
Observations (Max.)	233	200	433	433	433	235	230	465	465	465

This table reports the covariates balance between the matched pairs. *% Matched (A)* is the number of balanced covariates divided by the total number of covariates. *% Matched (B)* is the number of balanced covariates divided by the total number of covariates excluding *Market* and *Ln(Assets)*. *gpscore* stands for the Generalized Propensity-Score. *P*-values are for *t*-tests, Wilcoxon rank-sum (WRS) and Kolmogorov-Smirnov (KS) tests. Variables are defined in Appendix 4.B.

Table 4.5 Sample selection and covariate balance

Panel A: Sample selection	PSM
Distinct *chaebol* firms (1998-2014)	1,019
Less: Firms without sufficient data	595
Less: Firms that did not exist both before and after *chaebol* designation	332
Total matched firms (1998-2014)	509
Chaebol firms	261
Non-*chaebol* firms	248
Total firm-years (1998-2014)	5,414

Panel B: Covariate balance	*chaebol*	Non-*chaebol*		*p*-value	
PSM		Mean	*t*-test	WRS	KS
Immediate voting rights	0.468	0.493	0.342	0.600	0.597
Ln(Assets)	25.168	24.987	0.165	0.166	0.466
Pscore	0.121	0.105	0.226	0.289	0.758
Year				Matched	

This table reports the covariates balance between the matched pairs. PSM represents Propensity-Score Matching. *pscore* stands for the propensity-score. *p*-values are for *t*-tests, Wilcoxon rank-sum (WRS) and Kolmogorov-Smirnov (KS) tests. Variables are defined in Appendix 4.B.

Table 4.6 Pairwise correlation analysis

	Panel A (GPSM)	Panel B (PM)
	Accounting fraud	
Wedge ratio	0.198***	0.176***
Business group (10%)	0.181***	0.130***
Business group (40%)	-0.072	-0.027
Business group (70%)	-0.074	-0.082*
Regulation	-0.028	-0.078*
Observations (Max.)	433	465

This table reports the pairwise correlation analyses results between ownership variables and accounting fraud. GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.7 Probit estimation results using wedge ratio

	Dependent variable = *Pr*(Accounting fraud)					
	(1)	(2)	(3)	(4)	(5)	(6)
Matching	GPSM	GPSM	GPSM	PM	PM	PM
Ownership structure						
Wedge ratio	0.550**	0.690**	0.683**	0.860***	0.970***	0.931***
	(0.270)	(0.283)	(0.289)	(0.249)	(0.259)	(0.264)
Regulation	-1.000**	-0.898**	-0.891**	-0.763**	-0.582	-0.555
	(0.414)	(0.444)	(0.448)	(0.345)	(0.376)	(0.381)
Potential expropriation						
RPTs			0.006			0.031
			(0.027)			(0.022)
Dividend			-0.015			-0.076
			(0.076)			(0.046)
Leverage	0.332	0.362	0.360	0.583*	0.422	0.372
	(0.285)	(0.272)	(0.272)	(0.330)	(0.326)	(0.327)
Financial ratios						
ROA	-0.305	-0.403*	-0.404*	-1.606***	-1.497***	-1.537***
	(0.233)	(0.224)	(0.224)	(0.388)	(0.372)	(0.382)
Ln(Assets)	0.035	0.122	0.123	-0.061	-0.005	0.000
	(0.073)	(0.075)	(0.075)	(0.069)	(0.071)	(0.071)
Working Capital	0.266	0.386	0.385	0.117	0.183	0.165
	(0.299)	(0.294)	(0.294)	(0.281)	(0.279)	(0.281)
CMS power						
Largest=CEO	-0.187	-0.180	-0.180	-0.155	-0.117	-0.115
	(0.150)	(0.157)	(0.158)	(0.141)	(0.147)	(0.148)
Outside directors	-0.390	-0.902	-0.902	0.862	0.719	0.672
	(0.712)	(0.737)	(0.733)	(0.649)	(0.677)	(0.677)
Big*N* auditor		-0.636***	-0.637***		-0.635***	-0.644***
		(0.180)	(0.180)		(0.159)	(0.158)
Political connectedness						
Government bank		0.282*	0.284*		0.068	0.070
		(0.148)	(0.149)		(0.141)	(0.142)
Other controls						
Stock market	1.841***	2.006***	2.007***	0.919***	1.006***	1.015***
	(0.224)	(0.232)	(0.232)	(0.199)	(0.204)	(0.204)
Ln(Firm age)	-0.265**	-0.302**	-0.304**	-0.091	-0.123	-0.128
	(0.122)	(0.129)	(0.131)	(0.108)	(0.112)	(0.112)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
	& Matched	& Matched	& Matched	& Matched	& Matched	& Matched
Industry dummy	Matched	Matched	Matched	Matched	Matched	Matched
Constant	-1.108	-3.154*	-3.173*	0.775	-0.312	-0.404
	(1.621)	(1.647)	(1.656)	(1.588)	(1.614)	(1.615)
Observations	432	427	427	456	450	450
Log likelihood	-201	-191	-191	-239	-229	-227

This table reports the probit estimation results between accounting fraud and *Wedge ratio*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.8 Probit estimation results using business group

	Dependent variable = *Pr*(Accounting fraud)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Matching	GPSM	GPSM	GPSM	GPSM	PM	PM	PM	PM
X %	10%	40%	70%	70%	10%	40%	70%	70%
Ownership structure								
Business group	0.209	-0.212	0.596**	0.589**	0.230	0.175	0.278	0.209
(X %)	(0.176)	(0.219)	(0.281)	(0.282)	(0.164)	(0.212)	(0.288)	(0.291)
Regulation	-0.632	-0.509	-0.715*	-0.709*	-0.367	-0.365	-0.399	-0.381
	(0.422)	(0.426)	(0.393)	(0.395)	(0.390)	(0.386)	(0.377)	(0.383)
Potential expropriation								
RPTs	0.020	0.023		0.018	0.046*	0.047*		0.047*
	(0.026)	(0.028)		(0.026)	(0.025)	(0.026)		(0.026)
Dividend	-0.015	-0.020		-0.009	-0.076	-0.077*		-0.074
	(0.078)	(0.080)		(0.080)	(0.047)	(0.044)		(0.046)
Leverage	0.348	0.315	0.397	0.387	0.315	0.312	0.387	0.310
	(0.268)	(0.268)	(0.266)	(0.266)	(0.323)	(0.326)	(0.323)	(0.323)
Financial ratios								
ROA	-0.411*	-0.404*	-0.396*	-0.402*	-1.646***	-1.666***	-1.568***	-1.639***
	(0.226)	(0.230)	(0.220)	(0.222)	(0.383)	(0.383)	(0.367)	(0.379)
Ln(Assets)	0.121	0.139**	0.128*	0.128*	0.022	0.037	0.031	0.038
	(0.074)	(0.071)	(0.0720)	(0.073)	(0.070)	(0.068)	(0.068)	(0.068)
Working Capital	0.379	0.350	0.417	0.411	0.194	0.187	0.199	0.176
	(0.286)	(0.285)	(0.286)	(0.286)	(0.278)	(0.280)	(0.277)	(0.280)
CMS power								
Largest=CEO	-0.244	-0.354**	-0.248	-0.244	-0.244*	-0.282**	-0.303**	-0.295**
	(0.153)	(0.152)	(0.156)	(0.157)	(0.146)	(0.141)	(0.141)	(0.142)
Outside directors	-0.901	-0.960	-0.749	-0.768	0.693	0.675	0.828	0.752
	(0.724)	(0.703)	(0.736)	(0.732)	(0.665)	(0.663)	(0.658)	(0.660)
Big*N* auditor	-0.630***	-0.560***	-0.633***	-0.635***	-0.605***	-0.601***	-0.587***	-0.597***
	(0.180)	(0.177)	(0.174)	(0.175)	(0.156)	(0.156)	(0.155)	(0.155)
Political connectedness								
Government	0.263*	0.236	0.278*	0.282*	0.084	0.088	0.0937	0.096
bank	(0.146)	(0.146)	(0.148)	(0.149)	(0.140)	(0.139)	(0.139)	(0.139)
Other controls								
Stock market	2.011***	2.038***	2.117***	2.118***	0.968***	1.017***	1.016***	1.012***
	(0.231)	(0.227)	(0.229)	(0.229)	(0.203)	(0.204)	(0.205)	(0.205)
Ln(Firm age)	-0.316**	-0.314**	-0.318**	-0.319**	-0.169	-0.166	-0.157	-0.164
	(0.128)	(0.126)	(0.125)	(0.127)	(0.109)	(0.109)	(0.108)	(0.108)
Year dummy	Yes &	Yes &	Yes &	Yes &	Yes &	Yes &	Yes &	Yes &
	Matched	Matched	Matched	Matched	Matched	Matched	Matched	Matched
Industry dummy	Matched	Matched	Matched	Matched	Matched	Matched	Matched	Matched
Constant	-2.998*	-3.265**	-3.221**	-3.227**	-0.634	-0.969	-0.890	-0.986
	(1.633)	(1.586)	(1.609)	(1.619)	(1.607)	(1.565)	(1.567)	(1.566)
Observations	427	427	427	427	450	450	450	450
Log likelihood	-193	-193	-192	-192	-233	-234	-236	-234

This table reports the probit estimation results between accounting fraud and *Business group (%)*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.9 Probit estimation results using voting rights and cash flow rights

	Dependent variable = *Pr*(Accounting fraud)			
	(1)	(2)	(3)	(4)
Matching	GPSM	PM	GPSM	PM
Ownership structure				
Voting rights (%)	-4.109***	-2.764***		
	(1.129)	(1.058)		
Voting rights^2 (%)	3.022***	2.190**		
	(1.025)	(0.952)		
Wedge (%)			-0.451	0.965
			(1.288)	(1.192)
Wedge^2 (%)			0.479	-0.574
			(1.753)	(1.635)
Cash flow rights (%)			-3.659***	-3.640***
			(1.075)	(1.012)
Cash flow rights^2 (%)			2.255**	2.663***
			(1.094)	(0.982)
Regulation	-0.393	-0.324	-0.896**	-0.603
	(0.394)	(0.394)	(0.429)	(0.372)
Potential expropriation				
RPTs	0.016	0.051*	0.000	0.029
	(0.032)	(0.030)	(0.028)	(0.024)
Dividend	0.007	-0.069	0.003	-0.071
	(0.080)	(0.046)	(0.076)	(0.045)
Leverage	0.369	0.272	0.419	0.373
	(0.274)	(0.324)	(0.287)	(0.330)
Financial ratios				
ROA	-0.340	-1.564***	-0.343	-1.380***
	(0.222)	(0.370)	(0.226)	(0.364)
Ln(Assets)	0.164**	0.069	0.158**	0.019
	(0.0732)	(0.069)	(0.078)	(0.073)
Working Capital	0.345	0.179	0.345	0.187
	(0.286)	(0.280)	(0.305)	(0.283)
CMS power				
Largest=CEO	-0.359**	-0.323**	-0.233	-0.113
	(0.155)	(0.139)	(0.161)	(0.150)
Outside directors	-1.478**	0.594	-1.509**	0.559
	(0.714)	(0.651)	(0.717)	(0.673)
Big*N* auditor	-0.538***	-0.603***	-0.598***	-0.688***
	(0.174)	(0.156)	(0.177)	(0.158)
Political connectedness				
Government bank	0.257*	0.114	0.302**	0.081
	(0.151)	(0.140)	(0.154)	(0.142)
Other controls				
Stock market	1.813***	0.784***	1.702***	0.719***
	(0.238)	(0.228)	(0.242)	(0.233)
Ln(Firm age)	-0.286**	-0.164	-0.264**	-0.112
	(0.124)	(0.105)	(0.130)	(0.110)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	-2.864*	-0.932	-2.967*	0.119
	(1.654)	(1.599)	(1.739)	(1.690)
Observations	427	450	427	450
Log likelihood	-185	-231	-183	-222
Inflection point (*Voting rights*)	0.680	0.631		
Inflection point (*Cash flow rights*)			0.811	0.683

This table reports the probit estimation results between accounting fraud and *Voting rights*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.10 DID analysis using regulation

	Dependent variable = *Pr*(Accounting fraud)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time period	Immediate (one year)		Immediate (two years)		Immediate (three years)		Overall (whole years)	
Difference-in-Difference								
Regulation	3.810***	3.965***	3.970***	5.782***	4.057***	5.420***	3.897***	4.651***
	(0.302)	(0.811)	(0.180)	(0.744)	(0.161)	(0.536)	(0.123)	(0.387)
Post	3.875***	4.886***	3.749***	5.371***	3.793***	5.138***	3.714***	4.495***
	(0.253)	(0.661)	(0.196)	(0.627)	(0.152)	(0.438)	(0.136)	(0.380)
Regulation × Post	-3.48***	-3.658***	-3.66***	-4.63***	-3.90***	-4.724***	-3.73***	-4.34***
	(0.402)	(1.008)	(0.272)	(0.759)	(0.231)	(0.566)	(0.198)	(0.470)
Ownership structure								
Immediate ownership		-1.169		-5.472*		-4.442*		-5.549***
		(3.997)		(3.000)		(2.520)		(1.763)
Immediate ownership^2		1.218		5.436*		4.124*		6.823***
		(4.345)		(3.197)		(2.465)		(1.835)
Potential expropriation								
Dividend		-		-96.01**		-117.7**		-60.65***
				(38.26)		(58.29)		(20.99)
Leverage		0.829		0.784*		0.711*		0.241
		(0.915)		(0.412)		(0.417)		(0.288)
Financial ratios								
ROA		-1.659		-1.220		-1.366**		-0.590*
		(1.508)		(1.028)		(0.664)		(0.340)
Ln(Assets)		-0.144		-0.229*		-0.109		-0.109
		(0.167)		(0.132)		(0.108)		(0.074)
Working Capital		0.316		0.664		0.755*		-0.069
		(0.581)		(0.479)		(0.429)		(0.345)
CMS power								
Big*N* auditor		0.191		0.544		0.087		0.317
		(0.455)		(0.334)		(0.308)		(0.251)
Political connectedness								
Government bank		-		-0.861*		-0.598*		-0.513
				(0.485)		(0.354)		(0.315)
Other controls								
Ln(Firm age)		0.648*		0.444**		0.521***		0.594***
		(0.338)		(0.187)		(0.190)		(0.189)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-6.02***	-4.649	-6.34***	-2.705	-6.10***	-5.064*	-6.18***	-5.62***
	(0.319)	(4.094)	(0.375)	(3.190)	(0.296)	(2.753)	(0.403)	(2.035)
Observations	556	113	1,466	371	2,037	485	4,720	1,307
Log likelihood	-44	-23	-86	-34	-122	-47	-199	-88

This table reports the difference-in-difference estimation results between accounting fraud and *Regulation*, using the PSM sample. PSM represents Propensity-Score Matching. Overall effect represents the DID effects during the whole sample periods, while immediate effects are estimated using data one year/three years before and after *chaebol* designations. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. To facilitate the convergence of maximum likelihood estimations, a reduced industry dummy is adopted for these analyses. Variables are defined in Appendix 4.B.

Table 4.11 Interactive analysis of expropriation

	Dependent variable = *Pr*(Accounting fraud)					
	(1)	(2)	(3)	(4)	(5)	(6)
Matching	GPSM	PM	GPSM	PM	GPSM	PM
Interaction	RPTs	RPTs	Dividend	Dividend	Leverage	Leverage
Ownership structure						
Wedge ratio	0.573*	0.927***	0.623**	0.897***	-1.250**	0.042
	(0.303)	(0.272)	(0.298)	(0.264)	(0.570)	(0.496)
Regulation	-0.900**	-0.558	-0.904**	-0.602	-0.446	-0.465
	(0.449)	(0.385)	(0.453)	(0.386)	(0.455)	(0.404)
Potential expropriation						
Wedge ratio × Interaction	0.199*	0.007	0.876	0.347*	3.394***	1.375**
	(0.113)	(0.048)	(0.820)	(0.207)	(0.966)	(0.685)
RPTs	-0.089	0.028	0.006	0.031	-0.026	0.025
	(0.062)	(0.025)	(0.026)	(0.022)	(0.036)	(0.023)
Dividend	-0.014	-0.075	-0.280	-0.209*	-0.052	-0.077*
	(0.075)	(0.046)	(0.216)	(0.126)	(0.073)	(0.045)
Leverage	0.338	0.370	0.368	0.357	0.162	0.210
	(0.270)	(0.328)	(0.273)	(0.328)	(0.284)	(0.329)
Financial ratios						
ROA	-0.420*	-1.538***	-0.396*	-1.530***	-0.570***	-1.535***
	(0.228)	(0.382)	(0.223)	(0.382)	(0.205)	(0.398)
Ln(Assets)	0.121	0.001	0.117	-0.004	0.095	-0.010
	(0.075)	(0.071)	(0.075)	(0.071)	(0.077)	(0.073)
Working Capital	0.381	0.165	0.389	0.159	0.538*	0.201
	(0.293)	(0.281)	(0.295)	(0.281)	(0.303)	(0.285)
CMS power						
Largest=CEO	-0.182	-0.115	-0.192	-0.118	-0.127	-0.138
	(0.158)	(0.148)	(0.159)	(0.148)	(0.160)	(0.150)
Outside directors	-0.906	0.673	-1.065	0.551	-0.791	0.680
	(0.731)	(0.677)	(0.746)	(0.679)	(0.755)	(0.681)
Big*N* auditor	-0.634***	-0.644***	-0.647***	-0.648***	-0.591***	-0.637***
	(0.181)	(0.159)	(0.182)	(0.158)	(0.184)	(0.159)
Political connectedness						
Government bank	0.295**	0.071	0.277*	0.0575	0.228	0.081
	(0.149)	(0.142)	(0.149)	(0.142)	(0.153)	(0.144)
Other controls						
Stock market	2.013***	1.015***	2.065***	1.039***	2.033***	1.001***
	(0.231)	(0.204)	(0.238)	(0.206)	(0.239)	(0.207)
Ln(Firm age)	-0.296**	-0.129	-0.295**	-0.109	-0.275**	-0.099
	(0.131)	(0.112)	(0.131)	(0.113)	(0.131)	(0.113)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
	& Matched	& Matched	& Matched	& Matched	& Matched	& Matched
Industry dummy	Matched	Matched	Matched	Matched	Matched	Matched
Constant	-3.098*	-0.410	-3.018*	-0.299	-2.493	-0.143
	(1.649)	(1.620)	(1.662)	(1.620)	(1.712)	(1.673)
Observations	427	450	427	450	410	434
Log likelihood	-190	-227	-190	-226	-176	-220

This table reports the probit estimation results between accounting fraud and *Wedge ratio/Regulation* using interaction terms. GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.12 Probit estimation results using political connectedness

	Dependent variable = *Pr*(Accounting fraud)			
	(1)	(2)	(3)	(4)
Matching	GPSM	PM	GPSM	GPSM
X%			30%	70%
Ownership structure				
Wedge ratio	0.686**	1.002***		
	(0.290)	(0.270)		
Business group (*X%*)			-0.074	0.590**
			(0.199)	(0.282)
Regulation	-0.902**	-0.460	-0.561	-0.717*
	(0.449)	(0.389)	(0.423)	(0.396)
Potential expropriation				
RPTs	0.006	0.027	0.022	0.018
	(0.027)	(0.022)	(0.027)	(0.026)
Dividend	-0.003	-0.069	-0.012	0.001
	(0.085)	(0.049)	(0.087)	(0.089)
Leverage	0.357	0.420	0.330	0.383
	(0.273)	(0.335)	(0.270)	(0.267)
Financial ratios				
ROA	-0.404*	-1.639***	-0.402*	-0.403*
	(0.225)	(0.393)	(0.230)	(0.223)
Ln(Assets)	0.124	-0.024	0.137*	0.128*
	(0.075)	(0.072)	(0.072)	(0.073)
Working Capital	0.379	0.235	0.356	0.406
	(0.295)	(0.287)	(0.287)	(0.287)
CMS power				
Largest=CEO	-0.182	-0.125	-0.323**	-0.246
	(0.158)	(0.151)	(0.150)	(0.157)
Outside directors	-0.865	0.356	-0.899	-0.737
	(0.722)	(0.707)	(0.695)	(0.718)
Big*N* auditor	-0.636***	-0.667***	-0.579***	-0.634***
	(0.180)	(0.162)	(0.177)	(0.174)
Other controls				
Stock market	2.004***	1.183***	2.038***	2.116***
	(0.231)	(0.211)	(0.226)	(0.228)
Ln(Firm age)	-0.302**	-0.155	-0.313**	-0.317**
	(0.131)	(0.115)	(0.127)	(0.127)
Political connectedness				
Government bank	0.291*	0.151	0.251*	0.287*
	(0.150)	(0.145)	(0.147)	(0.150)
Political connectedness	-0.204	-0.435	-0.149	-0.167
	(0.495)	(0.446)	(0.483)	(0.496)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	-3.190*	0.212	-3.266**	-3.238**
	(1.660)	(1.651)	(1.599)	(1.621)
Observations	427	445	427	427
Log likelihood	-191	-218	-193	-192

This table reports the probit estimation results between accounting fraud and *Wedge ratio* after controlling for *Political connectedness*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.13 Probit estimation results using CEO ownership

	Dependent variable = *Pr*(Accounting fraud)			
	(1)	(2)	(3)	(4)
Matching	GPSM	GPSM	PM	PM
Ownership structure				
CEO ownership (%)	-1.105***	-1.935*	-1.033**	-2.710***
	(0.408)	(1.035)	(0.420)	(0.989)
CEO ownership^2 (%)		0.999		1.977*
		(1.150)		(1.049)
Regulation	-0.374	-0.393	-0.057	-0.080
	(0.331)	(0.333)	(0.326)	(0.330)
Potential expropriation				
RPT	0.010	0.011	0.025	0.023
	(0.027)	(0.027)	(0.017)	(0.017)
Dividend	-0.072	-0.069	-0.086*	-0.085*
	(0.071)	(0.071)	(0.051)	(0.050)
Financial ratios				
ROA	-0.474**	-0.450**	-1.661***	-1.662***
	(0.215)	(0.218)	(0.404)	(0.399)
Leverage	0.377	0.394	0.648*	0.708**
	(0.276)	(0.277)	(0.344)	(0.338)
Ln(Assets)	0.072	0.064	-0.047	-0.056
	(0.067)	(0.068)	(0.067)	(0.068)
Working Capital	0.212	0.234	0.183	0.258
	(0.258)	(0.257)	(0.280)	(0.275)
Tobin's Q	-0.233*	-0.238*	-0.158	-0.160
	(0.140)	(0.142)	(0.121)	(0.121)
CMS power				
CEO=Largest	0.116	0.180	0.002	0.145
	(0.175)	(0.191)	(0.163)	(0.183)
Outside directors	-0.817	-0.817	0.519	0.502
	(0.647)	(0.648)	(0.646)	(0.652)
Big*N* auditor	-0.634***	-0.654***	-0.636***	-0.664***
	(0.168)	(0.168)	(0.156)	(0.155)
Other controls				
Stock market	1.932***	1.929***	1.210***	1.222***
	(0.233)	(0.233)	(0.223)	(0.226)
Ln(Firm year)	-0.288**	-0.286**	-0.211*	-0.204*
	(0.116)	(0.116)	(0.108)	(0.108)
Government bank	0.198	0.196	0.102	0.089
	(0.140)	(0.140)	(0.135)	(0.135)
Year dummy	Yes	Yes	Yes	Yes
	& Matched	& Matched	& Matched	& Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	-1.514	-1.304	1.204	1.440
	(1.537)	(1.569)	(1.571)	(1.626)
Observations	479	479	497	497
Log likelihood	-211	-211	-234	-229

This table reports the probit estimation results between accounting fraud and *CEO ownership*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.14 Probit estimation results after controlling for outside blockholder

	Dependent variable = *Pr*(Accounting fraud)					
	(1)	(2)	(3)	(4)	(5)	(6)
Matching	GPSM	GPSM	GPSM	GPSM	GPSM	GPSM
X %				10%	40%	70%
Ownership structure						
Wedge ratio	0.559**	0.693**	0.686**			
	(0.276)	(0.287)	(0.294)			
Business group				0.211	-0.213	0.580**
(X %)				(0.177)	(0.220)	(0.282)
Regulation	-1.010**	-0.905**	-0.899**	-0.637	-0.512	-0.713*
	(0.419)	(0.447)	(0.450)	(0.424)	(0.426)	(0.397)
Potential expropriation						
RPTs			0.007	0.021	0.024	0.018
			(0.027)	(0.026)	(0.029)	(0.026)
Dividend			-0.011	-0.011	-0.016	-0.006
			(0.075)	(0.077)	(0.079)	(0.079)
Leverage	0.325	0.360	0.357	0.349	0.317	0.389
	(0.283)	(0.271)	(0.272)	(0.267)	(0.268)	(0.265)
Financial ratios						
ROA	-0.280	-0.386*	-0.388*	-0.393*	-0.388*	-0.386*
	(0.229)	(0.222)	(0.222)	(0.224)	(0.229)	(0.221)
Ln(Assets)	0.041	0.125*	0.126*	0.124*	0.141**	0.130*
	(0.073)	(0.074)	(0.075)	(0.073)	(0.071)	(0.072)
Working Capital	0.257	0.380	0.378	0.376	0.349	0.409
	(0.297)	(0.293)	(0.293)	(0.286)	(0.285)	(0.285)
CMS power						
Largest=CEO	-0.178	-0.173	-0.173	-0.238	-0.349**	-0.240
	(0.152)	(0.158)	(0.159)	(0.154)	(0.152)	(0.158)
Outside directors	-0.360	-0.887	-0.890	-0.885	-0.941	-0.756
	(0.724)	(0.745)	(0.741)	(0.731)	(0.709)	(0.737)
Big*N* auditor		-0.625***	-0.626***	-0.620***	-0.549***	-0.625***
		(0.182)	(0.182)	(0.182)	(0.179)	(0.176)
Political connectedness						
Government bank		0.277*	0.279*	0.258*	0.231	0.277*
		(0.149)	(0.149)	(0.147)	(0.147)	(0.149)
Other controls						
Stock market	1.876***	2.032***	2.033***	2.036***	2.062***	2.138***
	(0.226)	(0.232)	(0.231)	(0.231)	(0.227)	(0.229)
Ln(Firm age)	-0.277**	-0.308**	-0.309**	-0.320**	-0.318**	-0.322**
	(0.121)	(0.127)	(0.130)	(0.127)	(0.125)	(0.126)
Outside blockholder	-1.178	-0.803	-0.801	-0.808	-0.800	-0.683
	(0.760)	(0.815)	(0.814)	(0.824)	(0.845)	(0.846)
Year dummy	Yes &	Yes &	Yes &	Yes &	Yes &	Yes &
	Matched	Matched	Matched	Matched	Matched	Matched
Industry dummy	Matched	Matched	Matched	Matched	Matched	Matched
Constant	-1.212	-3.213*	-3.226*	-3.049*	-3.304**	-3.277**
	(1.625)	(1.647)	(1.656)	(1.632)	(1.586)	(1.618)
Observations	432	427	427	427	427	427
Log likelihood	-200	-190	-190	-193	-193	-191

This table reports the probit estimation results between accounting fraud and *Wedge ratio* / *Business group (%)*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.15 Probit estimation results using family ownership

	Dependent variable = *Pr*(Accounting fraud)					
	(1)	(2)	(3)	(4)	(5)	(6)
Matching	GPSM	GPSM	PM	PM	GPSM	GPSM
Family ownership	Yes	Yes	Yes	Yes	Yes	Yes
X%					30%	70%
Ownership structure						
Wedge ratio	0.616**		1.017***			
	(0.291)		(0.290)			
Business group (*X%*)					-0.187	0.538*
					(0.199)	(0.287)
Cash flow rights ratio		-0.459		-0.831***		
		(0.307)		(0.299)		
Family ownership ratio		-1.249***		-1.673***		
		(0.455)		(0.465)		
Regulation	-0.753*	-0.720	-0.313	-0.315	-0.438	-0.623
	(0.446)	(0.447)	(0.395)	(0.399)	(0.430)	(0.406)
Potential expropriation						
RPT	0.011	0.015	0.007	0.007	0.027	0.026
	(0.027)	(0.028)	(0.029)	(0.029)	(0.028)	(0.028)
Dividend	0.004	0.009	-0.082*	-0.074	-0.000	0.011
	(0.074)	(0.073)	(0.049)	(0.048)	(0.077)	(0.078)
Financial ratios						
ROA	-1.040***	-0.986***	-1.434***	-1.406***	-1.127***	-1.052***
	(0.377)	(0.376)	(0.390)	(0.387)	(0.374)	(0.369)
Leverage	0.698**	0.648*	0.692*	0.658*	0.610*	0.702**
	(0.346)	(0.352)	(0.367)	(0.362)	(0.346)	(0.338)
Ln(Assets)	0.092	0.113	-0.076	-0.061	0.117	0.099
	(0.084)	(0.085)	(0.079)	(0.079)	(0.081)	(0.082)
Working Capital	0.240	0.195	0.237	0.164	0.214	0.311
	(0.358)	(0.356)	(0.312)	(0.312)	(0.353)	(0.349)
Tobin's Q	-0.134	-0.136	-0.142	-0.142	-0.119	-0.128
	(0.120)	(0.117)	(0.119)	(0.118)	(0.113)	(0.113)
CMS power						
CEO=Largest	-0.139	-0.126	-0.145	-0.178	-0.288*	-0.207
	(0.166)	(0.168)	(0.157)	(0.158)	(0.161)	(0.165)
Outside directors	-0.964	-1.085	0.111	0.009	-1.012	-0.830
	(0.769)	(0.787)	(0.708)	(0.712)	(0.744)	(0.768)
Big*N* auditor	-0.522***	-0.547***	-0.648***	-0.643***	-0.453**	-0.531***
	(0.186)	(0.188)	(0.165)	(0.166)	(0.183)	(0.184)
Other controls						
Stock market	2.049***	2.067***	1.402***	1.440***	2.041***	2.136***
	(0.257)	(0.260)	(0.232)	(0.237)	(0.252)	(0.254)
Ln(Firm year)	-0.287**	-0.271*	-0.169	-0.145	-0.296**	-0.314**
	(0.137)	(0.140)	(0.120)	(0.121)	(0.132)	(0.135)
Government bank	0.227	0.258	0.160	0.165	0.177	0.226
	(0.162)	(0.162)	(0.151)	(0.151)	(0.158)	(0.161)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched	Matched	Matched
Constant	-2.512	-2.460	1.430	2.000	-2.814	-2.580
	(1.867)	(1.896)	(1.786)	(1.898)	(1.813)	(1.838)
Observations	386	386	411	411	386	386
Log likelihood	-166	-164	-196	-194	-167	-166

This table reports the probit estimation results between accounting fraud and *Wedge ratio* including family ownership. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.16 Probit estimation results using alternative specifications of wedge

	Dependent variable = *Pr*(Accounting fraud)			
	(1)	(2)	(3)	(4)
Matching	GPSM	PM	GPSM	PM
Ownership structure				
Wedge (%)	0.042	1.019**		
	(0.480)	(0.467)		
Cash flow rights (%)	-1.521***	-0.919**		
	(0.408)	(0.428)		
Wedge ratio (*weakest*)			0.709**	0.979***
			(0.317)	(0.318)
Regulation	-0.705*	-0.460	-0.669	-0.231
	(0.426)	(0.374)	(0.453)	(0.397)
Potential expropriation				
RPT	0.001	0.026	0.009	0.040
	(0.026)	(0.024)	(0.029)	(0.026)
Dividend	0.000	-0.076	-0.010	-0.082
	(0.077)	(0.050)	(0.077)	(0.050)
Financial ratios				
ROA	-0.377*	-1.460***	-0.401*	-1.617***
	(0.220)	(0.385)	(0.222)	(0.400)
Leverage	0.584*	0.568	0.540*	0.518
	(0.307)	(0.351)	(0.295)	(0.343)
Ln(Assets)	0.131*	-0.022	0.100	-0.032
	(0.078)	(0.075)	(0.076)	(0.073)
Working Capital	0.355	0.222	0.427	0.273
	(0.300)	(0.291)	(0.287)	(0.288)
Tobin's Q	-0.158	-0.150	-0.166	-0.141
	(0.112)	(0.119)	(0.120)	(0.120)
CMS power				
Largest=CEO	-0.222	-0.124	-0.195	-0.141
	(0.161)	(0.151)	(0.156)	(0.147)
Outside directors	-1.391*	0.102	-0.949	0.007
	(0.725)	(0.690)	(0.729)	(0.670)
Big*N* auditor	-0.599***	-0.689***	-0.585***	-0.615***
	(0.177)	(0.163)	(0.182)	(0.165)
Other controls				
Stock market	1.818***	1.169***	2.084***	1.275***
	(0.253)	(0.252)	(0.239)	(0.224)
Ln(Firm year)	-0.253*	-0.163	-0.298**	-0.186
	(0.130)	(0.114)	(0.131)	(0.113)
Government bank	0.291*	0.187	0.274*	0.152
	(0.153)	(0.144)	(0.148)	(0.145)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	-2.714	0.635	-2.620	0.565
	(1.724)	(1.723)	(1.664)	(1.673)
Observations	427	441	427	441
Log likelihood	-183	-214	-190	-216

This table reports the probit estimation results between accounting fraud and different specifications of the wedge variable. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.17 Probit estimation results using cash flow rights ratio

	Dependent variable = *Pr*(Accounting fraud)			
	(1)	(2)	(3)	(4)
Matching	GPSM	GPSM	PM	PM
Ownership structure				
Cash flow rights ratio	-0.720**		-1.005***	
	(0.292)		(0.279)	
Direct cash flow right ratio		-0.826***		-0.988***
		(0.311)		(0.285)
Indirect cash flow rights ratio		-1.417**		-0.889*
		(0.537)		(0.489)
Regulation	-0.773*	-0.860*	-0.405	-0.397
	(0.456)	(0.468)	(0.392)	(0.392)
Potential expropriation				
RPT	0.003	-0.003	0.026	0.027
	(0.027)	(0.028)	(0.022)	(0.022)
Dividend	-0.017	-0.027	-0.084*	-0.084*
	(0.076)	(0.078)	(0.050)	(0.050)
Financial ratios				
ROA	-0.391*	-0.399*	-1.575***	-1.577***
	(0.219)	(0.226)	(0.395)	(0.396)
Leverage	0.551*	0.572*	0.549	0.546
	(0.299)	(0.298)	(0.345)	(0.345)
Ln(Assets)	0.097	0.103	-0.039	-0.038
	(0.076)	(0.074)	(0.074)	(0.075)
Working Capital	0.424	0.448	0.274	0.271
	(0.293)	(0.297)	(0.287)	(0.288)
Tobin's Q	-0.170	-0.175	-0.146	-0.145
	(0.121)	(0.121)	(0.120)	(0.120)
CMS power				
Largest=CEO	-0.157	-0.200	-0.090	-0.084
	(0.158)	(0.159)	(0.152)	(0.154)
Outside directors	-0.926	-0.942	0.029	0.021
	(0.740)	(0.743)	(0.703)	(0.701)
Big*N* auditor	-0.627***	-0.611***	-0.670***	-0.670***
	(0.182)	(0.182)	(0.164)	(0.164)
Other controls				
Stock market	2.113***	2.172***	1.349***	1.345***
	(0.241)	(0.239)	(0.224)	(0.225)
Ln(Firm year)	-0.293**	-0.287**	-0.173	-0.175
	(0.130)	(0.130)	(0.115)	(0.115)
Government bank	0.281*	0.283*	0.166	0.170
	(0.150)	(0.152)	(0.145)	(0.145)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	-1.897	-1.914	1.591	1.564
	(1.703)	(1.675)	(1.778)	(1.779)
Observations	427	427	441	441
Log likelihood	-189	-188	-214	-214

This table reports the probit estimation results between accounting fraud and *Cash ratio*/*Direct cash ratio* and *Indirect cash ratio*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.18 Probit estimation results using components of voting rights

	Dependent variable = *Pr*(Accounting fraud)			
	(1)	(2)	(3)	(4)
Matching	GPSM	PM	GPSM	PM
Ownership structure				
Wedge (%)	-0.078	0.917*	-0.287	1.427
	(0.502)	(0.479)	(1.302)	(1.256)
$Wedge^2$ (%)			0.303	-0.764
			(1.764)	(1.695)
Cash flow rights (%)	-3.717***	-3.172***	-3.720***	-3.121***
	(1.065)	(1.026)	(1.068)	(1.031)
Cash flow $rights^2$ (%)	2.337**	2.388**	2.335**	2.349**
	(1.088)	(0.992)	(1.089)	(0.997)
Regulation	-0.784*	-0.501	-0.789*	-0.482
	(0.443)	(0.381)	(0.440)	(0.376)
Potential expropriation				
RPT	-0.002	0.022	-0.002	0.024
	(0.028)	(0.022)	(0.028)	(0.022)
Dividend	-0.000	-0.077	0.001	-0.079*
	(0.075)	(0.048)	(0.076)	(0.048)
Financial ratios				
ROA	-0.335	-1.426***	-0.333	-1.430***
	(0.218)	(0.381)	(0.218)	(0.385)
Leverage	0.601*	0.576*	0.602*	0.573*
	(0.308)	(0.348)	(0.308)	(0.347)
Ln(Assets)	0.131*	-0.017	0.133*	-0.022
	(0.078)	(0.077)	(0.078)	(0.077)
Working Capital	0.388	0.302	0.388	0.299
	(0.303)	(0.289)	(0.303)	(0.290)
Tobin's Q	-0.166	-0.148	-0.165	-0.148
	(0.113)	(0.115)	(0.113)	(0.115)
CMS power				
Largest=CEO	-0.208	-0.093	-0.211	-0.085
	(0.162)	(0.153)	(0.162)	(0.154)
Outside directors	-1.529**	0.059	-1.531**	0.034
	(0.725)	(0.700)	(0.724)	(0.700)
Big*N* auditor	-0.591***	-0.715***	-0.589***	-0.713***
	(0.178)	(0.163)	(0.179)	(0.163)
Other controls				
Stock market	1.802***	1.109***	1.807***	1.110***
	(0.253)	(0.255)	(0.251)	(0.255)
Ln(Firm year)	-0.255**	-0.157	-0.255**	-0.157
	(0.129)	(0.113)	(0.129)	(0.113)
Government bank	0.297*	0.176	0.297*	0.170
	(0.155)	(0.146)	(0.155)	(0.146)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched
Constant	-2.375	0.863	-2.423	0.962
	(1.742)	(1.758)	(1.745)	(1.763)
Observations	427	441	427	441
Log likelihood	-181	-211	-180	-210

This table reports the probit estimation results using components of *Voting rights (%)*: *Wedge (%)* and *Cash flow rights (%)*. Each column reports the test results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching respectively. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

Table 4.19 Bivariate probit estimation results using wedge ratio and business group

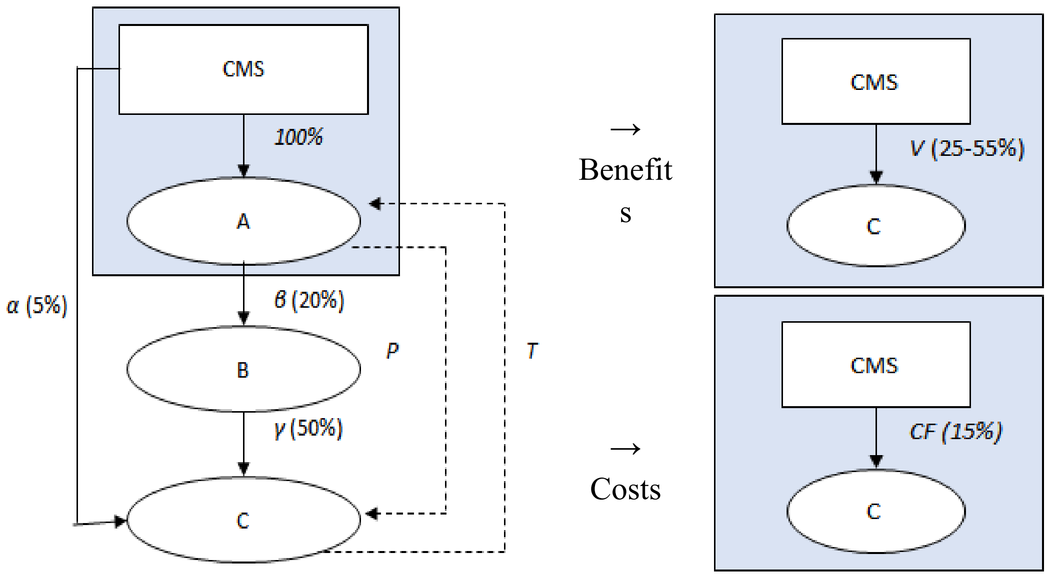
	Dependent variable = *Pr*(Accounting fraud)					
	(1)		(2)		(3)	
Model	Fraud	Detect | Fraud	Fraud	Detect | Fraud	Fraud	Detect | Fraud
Matching	GPSM		GPSM		GPSM	
X %			30%		70%	
Wedge ratio	0.688*					
	(0.382)					
Business group			-0.017		0.755***	
(X %)			(0.2255)		(0.284)	
Regulation	-2.018	0.924	-2.117***	0.367	-1.055**	-0.045
	(1.550)	(0.852)	(0.649)	(0.558)	(0.423)	(0.517)
Audit opinion		0.583		0.331		3.144***
		(1.832)		(0.582)		(0.413)
RPT	-0.005		0.014		0.024	
	(0.030)		(0.030)		(0.027)	
Dividend	-0.034		-0.037		-0.022	
	(0.081)		(0.081)		(0.062)	
ROA	-2.527***		-2.643***		-2.545***	
	(0.819)		(0.623)		(0.564)	
Leverage	0.754**		0.710**		0.730**	
	(0.379)		(0.359)		(0.355)	
Ln(Assets)	0.232**		0.232**		0.196**	
	(0.106)		(0.096)		(0.090)	
Working Capital	0.833**		0.810**		0.792**	
	(0.352)		(0.330)		(0.365)	
Tobin's Q	-0.148		-0.150		-0.146	
	(0.124)		(0.116)		(0.103)	
Largest=CEO	-0.332*	0.456	-0.447**	0.327	-0.409**	0.817**
	(0.197)	(0.701)	(0.185)	(0.303)	(0.192)	(0.342)
Outside directors	-3.581***	2.999	-3.622***	2.236*	-3.242***	4.907***
	(1.052)	(3.972)	(0.951)	(1.348)	(0.931)	(1.628)
Big*N* auditor	1.101	-5.892***	1.693**	-	0.121	-1.977***
	(2.307)	(1.211)	(0.789)	(.)	(0.250)	(0.348)
Stock market	2.490***	1.366***	2.506***	1.687***	2.597***	1.097***
	(0.355)	(1.296)	(0.344)	(0.373)	(0.291)	(0.364)
Ln (Firm year)	-0.355**	-0.219	-0.351**	-0.242	-0.361**	-0.243
	(0.169)	(0.272)	(0.151)	(0.180)	(0.140)	(0.164)
Government bank	0.544***	-0.277	0.479**	-0.141	0.656***	-0.789***
	(0.195)	(0.581)	(0.187)	(0.288)	(0.185)	(0.283)
Year dummy	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched	Yes & Matched
Industry dummy	Matched	Matched	Matched	Matched	Matched	Matched
Constant	-5.760**	5.648**	-4.865**	-	-4.865**	4.484***
	(2.397)	(2.818)	(2.038)	(.)	(2.038)	(0.522)
Observations	427		427		427	
Log likelihood	-172		-174		-173	

This table reports the bivariate probit estimation results between accounting fraud and *Wedge ratio*/*Business group(X%)*. Each column reports the probit estimation results by different matching methods: GPSM represents Generalized Propensity-Score Matching, while PM stands for partial matching. Numbers in parentheses are robust standard errors. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. Variables are defined in Appendix 4.B.

APPENDIX 4.A Controlling shareholders' motivational mechanism of control-ownership wedge

In Appendix 4.A, I provide additional analyses on controlling shareholders' motivational mechanisms by which they expropriate their firms and adjust their ownership structure. I illustrate the mechanisms using two hypothetical ownership structures.

Figure 4.2. Costs and benefits of control-ownership wedge



This figure illustrates the costs and benefits that wedge structure brings about for controlling minor shareholders (CMS). *A*, *B* and *C* represent firms directly and indirectly held by the CMS, and α, β and γ stand for the percentages of shares held by the CMS and its firms. *T* and *P* represent tunneling and propping respectively, while *V* and *CF* stand for voting and cash flow rights respectively. Numbers in the parentheses are hypothetical ones.

First, Figure 4.2. describes an exemplary mechanism through which controlling shareholders cause inefficiencies in firms through RPTs among affiliated firms. Increased control by control-ownership wedge provides an ideal condition for controlling shareholders to extract private benefits at the expense of outside investors (Grossman and Hart 1980; Burkart et al. 1998; Faccio and Lang 2002; La Porta et al.

2002; Joh 2003). Using control-ownership wedge, they can increase benefits without incurring proportional costs (Fan and Wong 2002).

In the LHS of Figure 4.2., controlling shareholders have cash flow rights (*CF*; 15 percent) amounting to the sum of α (5 percent) and β (20 percent) × γ (50 percent), where α, β, and γ represent the percentages of shares held by the controlling owners or their associated firms[87]. However, using a pyramiding structure, they can exercise voting rights (*V*; 55 percent or 25 percent) up to either the sum of α and γ – *the final link method* – or the sum of α and min(β, γ) – *the weakest link method* (see Ryu and Yoo 2011). According to *the final link method* (e.g., La Porta et al. 2002) and the KFTC regulation, control-ownership wedge (*W*; 40 percent) is defined as the difference between γ and $\beta \times \gamma$, which is simply the difference between *V* (55 percent) and *CF* (15 percent). Controlling shareholders benefit from this ownership structure by increasing the size of their expropriation and shift the costs of increased benefits on outside investors.

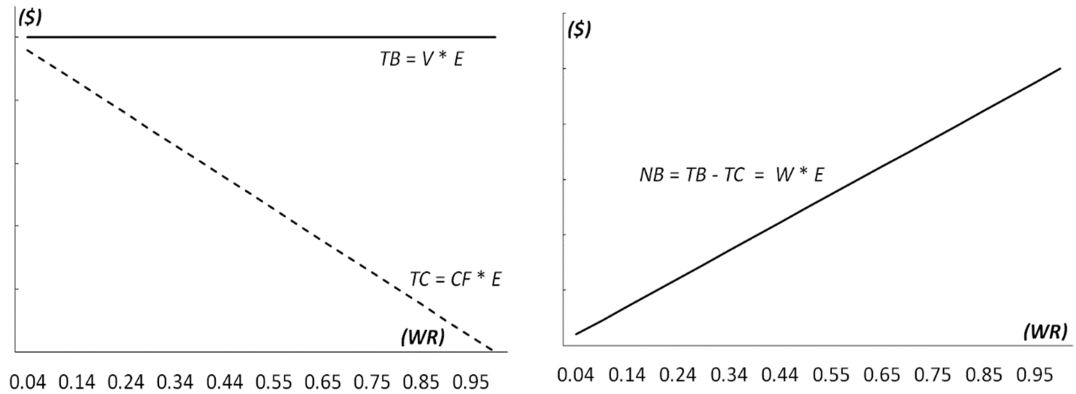
To begin, control-ownership wedge increases the maximum size of their potential expropriation (*E*)[88] exactly by *W* (40 percent) of firm *C*'s net assets ($\Delta E = NA \times W$). Without the ownership divergence, controlling shareholders could expropriate firm *C* only by *CF* (15 percent). Moreover, by transferring *E* from firm *C* to firm *A*, where the controlling owners have more direct cash flow rights (100 percent), the increased benefits (ΔE) can be materialised in firm *C*. In typical RPTs, firm *C* is expropriated by selling or purchasing products to and from firm *A* at lower and higher than market prices respectively (see Riyanto and Toolsema 2008). These effects are equivalent for

[87] Numbers in the parentheses are hypothetical ones.

[88] *E* is defined as the difference between tunneling (*T*) and propping (*P*) in this chapter. "Tunneling refers to a transfer of resources from a lower-level firm to a higher-level firm in the pyramidal chain, whereas propping concerns a transfer in the opposite direction intended to bail out the receiving firm from bankruptcy." (Riyanto and Toolsema 2008, p. 2178)

controlling shareholders to having V (55 percent) directly of firm C while bearing the costs of CF (15 percent) as is illustrated in the RHS of Figure 4.2. Through this process, controlling shareholders can increase their private benefits by ΔE, and it remains in firm C as economic distortions or inefficiencies.

Figure 4.3. Leverage effects of control-ownership wedge



This figure illustrates the analysis of the leverage effects of wedge using a hypothetical ownership structure: cash flow rights (*CF*) = [0, 0.25], wedge (*W*) = [0, 0.25], voting rights (*V*) = 0.25, expropriation (*E*) = $200 and wedge ratio (*WR*) = [0, 1]. *TB* stands for total benefits while *TC* represents total costs. Net benefits (*NB*) are the inefficiencies caused by increasing *WR*.

Second, Figure 4.3. further illustrates how controlling shareholders maximise their net benefits by adjusting the proportion of CF and W of their voting rights (*Wedge ratio*). In this setting, controlling shareholders can change both CF and W between 0 percent and 25 percent, and V is fixed at 25 percent. Accordingly, their *Wedge ratio* ($WR = W / V = (V - CF) / V$) changes between 0 and 1. As in Eq. (4.7) and Eq. (4.8) respectively, controlling shareholders' total benefits (TB) are the product of the dollar amount of E ($200) and V (25 percent), and the total costs (TC) are the product of E and adjustable CF. In the LHS of Figure 4.3., they acquire constant TB because E and V do not change in this setting, whereas they can decrease TC by adjusting their *Wedge ratio* because W does not incur additional costs to controlling shareholders as shown above. Therefore, their net benefits (NB) are ultimately proportional to the size of W

(Eq. (4.9)), which is exactly the costs borne by outside shareholders, not by controlling shareholders themselves. This illustration reveals that controlling shareholders can increase their net benefits of expropriation by adjusting *Wedge ratio* (RHS of Figure 4.3.).

$$\text{Total benefits } (TB) = E \times V \text{ (when } E = T - P\text{)} \tag{4.7}$$

$$\text{Total costs } (TC) = E \times CF \tag{4.8}$$

$$\text{Net benefits } (NB) = TB - TC = E \times W \tag{4.9}$$

where, E = the net dollar amount of expropriation ($200);

T = the dollar amount of tunneling;

P = the dollar amount of propping;

V = voting rights (25 percent);

CF = cash flow rights;

$W = V - CF$ = wedge.

APPENDIX 4.B Variable definitions

Variable	Definition
Dependent variable	
Accounting fraud	An indicator variable equal to 1 for firms for which the FSS published AAERs for alleged GAAP violations, and 0 otherwise.
Ownership structure	
Cash flow rights	Fraction of shares held directly or indirectly by the largest ultimate owners by investing their own cash flows in their firms (La Porta et al. 2002). The largest ultimate owners are individuals identified by tracing from the lowest to the highest firm along ownership chains of firms.
Direct cash flow rights	Direct portion of *Cash flow rights*.
Indirect cash flow rights	Indirect portion of *Cash flow rights* held through associated firms.
Control-ownership wedge	Fraction of shares held by the largest ultimate owners indirectly through associated firms without investing their own cash flows.
Voting rights	The sum of *Cash flow rights* and *Control-ownership wedge* (La Porta et al. 2002).
Wedge ratio	*Control-ownership wedge* over *Voting rights* (La Porta et al. 2002).
Business group (*X* %)	An indicator variable equal to 1 for firms which have both control-ownership wedge and controlling shareholders having more than *X*% of shares, and 0 otherwise. (see La Porta et al. 1999; Claessens et al. 2000; Faccio et al. 2001).
Regulation	An indicator variable equal to 1 for firms which are designated as *chaebol* by the KFTC, and 0 otherwise (Kim and Yi 2006; Byun et al. 2013). In DID analyses, it is an indicator variable equal to 1 for

	firms which are designated as *chaebol* at least once during the sample window, and 0 otherwise.
Post	An indicator variable equal to 1 for firm years from when they are designated as *chaebol*, and 0 otherwise. For non-*chaebol* firms, it is equal to 1 for firm years from when they are matched with *chaebol* firms, and 0 otherwise.
Immediate voting rights	Fraction of shares held by either individuals or institutions, who are the largest direct owners of firms.
CEO ownership	Fraction of shares held directly by a CEO.
Family ownership	Fraction of shares held by families of controlling shareholders. For missing data, I construct the variable whenever familial relationship is reasonably identified as below: a) A firm discloses the largest shareholder's familial relationships; b) The relationship is identified by news articles; c) Both the first and last names of major shareholders are the same.
Potential expropriations	
RPTs	Related party transactions (operating sales + operating purchase + non-operating transactions) / Book value of equity (Kang et al. 2014).
Dividend	The dividend per share (DPS) divided by the earnings per share (EPS) (see Faccio et al. 2001). If EPS is less than zero, I use the maximum *Dividend*.
Leverage	The ratio of total liability to total assets.
Financial ratios	
ROA	The ratio of income before tax expense to average assets.
Ln(Assets)	The natural logarithm of total assets.

Working Capital	The ratio of working capital (current asset – current liability) to total assets.
Controlling shareholders' power	
Largest=CEO	An indicator variable equal to 1 for firms in which a CEO is also the largest ultimate owner, and 0 otherwise (see Claessens et al. 2000).
Outside directors	The ratio of outsider directors on the board to the total number of directors.
Audit opinion	An indicator variable equal to 1 if the audit opinion in the first fraud year is not unqualified, and 0 otherwise.
Big *N* auditor	An indicator variable equal to 1 if a firm is audited by major auditors: Big *4* or Big *5* depending on fiscal years, and 0 otherwise (Kim and Yi 2006).
Political connectedness	
Government bank	An indicator variable equal to 1 if a firm's main creditor bank is owned by the government, and 0 otherwise (Byun et al. 2013).
Political connectedness	An indicator variable equal to 1 if any executive or director of a firms is a former member of parliament (MP) or minister (Byun et al. 2013). If a firm is not required to disclose its executives and directors, I assume no political connectedness.
Other controls	
Stock market	An indicator variable equal to 1 if a firm is listed on major stock markets such as KSE and KOSDAQ, and 0 otherwise (Kim and Yi 2006).
Ln(Firm age)	The number of years since the establishment of a firm.
Outside blockholder	The shares held by outside blockholders divided by total shares.
Industry	An indicator variable equal to 1 for seven two-digit SIC codes, which account for 53.3 percent of the

	total sample, and 0 otherwise. The ten industries are Wholesale trade (G46000), Manufacture of computer, electronic and optical products (C26000), Retail trade (G47000), Construction of buildings (F41000), Manufacture of other transport equipment (C30000), Real estate activities (L68000), Manufacture of motor vehicles, trailers and semi-trailers (C29000), Manufacture of chemical products (C20000), Manufacture of basic metals (C24000), and Libraries, archives, museums and other cultural activities (R91000).
Year dummy	An indicator variable equal to 1 for the Asian financial crisis (1997-1998) and the global financial crisis (2007-2009), and 0 otherwise (Mitton 2002). For DID analyses, it represents dummies for each year.

Chapter 5

Summary of Conclusions

5.1. Summary of findings

This thesis investigates the impacts of equity incentives on accounting fraud propensity both in and outside the U.S. context. As a prerequisite analysis, I also examine whether AAERs constitute a reliable database to analyse relatively intentional motivation to misreport.

First, Chapter 2 documents that AAERs are composed of firms that are more likely to represent material accounting irregularities than SCAL and AA firms, which are exclusively identified by capital market investors and firms' managers respectively. Further analyses indicate that the characteristics of AAERs may be explained by the SEC's strategic approaches in utilising constrained resources, in addition to AAERs' inherently egregious nature in that they involve accountants. Specifically, the SEC tends to focus more on high-risk and systematically important firms as enforcement targets and to allocate regional offices mainly where larger firms are more populated. Through this optimisation, the SEC may reduce inefficiencies inherent in its accounting fraud investigation process and mitigate the potential geographic bias.

Second, Chapter 3 shows that CEOs' stock option delta and stock ownership have differing non-linear associations with accounting fraud propensity. I interpret this finding as evidence that CEOs as option and stock holders drastically change their misreporting behaviours at certain critical levels of equity incentives. Once reaching these critical levels, CEOs as option holders are less likely to misreport, whereas owner-CEOs are more likely to misreport. Further analyses indicate that these changes in misreporting patterns may be driven by CEOs' disparate perceptions of the risks regarding accounting fraud commitment as two types of equity holders. At higher levels of equity incentives, CEOs as option holders are seriously concerned about the increased risk, whereas owner-CEOs underestimate it due to their enhanced control within firms.

Finally, Chapter 4 documents that controlling shareholders' control-ownership wedge is positively associated with accounting fraud propensity, but business group and *chaebol* affiliations are not. In particular, I report that firms' affiliation with *chaebols* is, in fact, negatively associated with accounting fraud propensity. These are novel findings suggesting that business groups and *chaebols*, which have long been considered as aggressive earnings manipulators (e.g., Kim and Yi 2006), are shrewd enough to actively manage their earnings without seriously crossing into GAAP violations. Further analyses suggest that the distinct effects of business groups and *chaebols* from those of control-ownership wedge may be explained by controlling shareholders' substantial cash flow rights in business groups and the tightened levels of monitoring over their expropriation in *chaebols*.

These results together suggest that accounting fraud context exposes CEOs and controlling shareholders with excessive equity incentives not only to the reward opportunities but also to the risk of bearing economic and legal costs. This exposure leads to variations in their misreporting behaviours at average incentive levels or in their earnings management strategies within GAAP. Accounting fraud allegations released by accounting regulators (e.g., the SEC) constitute a relatively reliable database for these analyses.

5.2. Contributions and implications

This thesis contributes to our understanding of the mechanisms through which accounting fraud is committed, in relation to equity incentives of CEOs and controlling shareholders, and provides several practical implications for both accounting regulators and researchers. First, Chapter 2 contradicts Karpoff et al. (2017)'s recent study arguing that each financial misreporting database has shortcomings, in that it covers only partial cases. Recognising this issue in current databases, I document that, despite the coverage issue, AAERs constitute a relatively reliable accounting fraud database that is more likely to represent material accounting irregularities rather than simple errors. The results should be of interest to researchers who use AAERs to proxy for material accounting irregularities and to investigate motivational determinants of accounting fraud.

Second, Chapter 3 adds to the extensive literature which has documented that options and stocks have diametrically linear opposite effects on financial misreporting propensity, and that stocks and options have non-linear impacts on various research focuses such as firm value and performance. I extend these two strands of studies by demonstrating that CEOs' financial misreporting patterns at average incentives levels are reversed at higher levels depending on how they perceive the risk of accounting fraud commitment. In particular, relying on the uniqueness of the accounting fraud context, I show that this non-linearity results mainly from an increase in risk effect rather than a decrease in reward effect. These findings are the first to report dual non-linearity of stocks and options *simultaneously* and provide empirical evidence for the differences in misreporting patterns of stock- and option holders based on their disparate risk tolerance as two equity holders. Practically, the results should be of interest to accounting regulators, who have a responsibility to detect accounting fraud.

Specifically, the findings suggest that regulators with constrained resources should consider targeting firms with CEOs holding average option delta or excessive stock ownership for investigation, since they are more likely to be incentivised to misreport in relation to equity incentives.

Finally, the findings of Chapter 4 contribute to the literature which has already shown congruent impacts of control-ownership wedge, business groups, and *chaebols* in the contexts of relatively indirect and less egregious earnings management strategies (i.e., accruals management). By contrast, I report that the detrimental effect of control-ownership wedge is curbed by the cost factors that accounting fraud context uniquely imposes on controlling shareholders: ownership concentration in business groups and government regulation in *chaebols*. Practically, this study suggests that regulators in other jurisdictions than Korea should consider adopting regulations for the potential risk of control-ownership wedge after sufficiently considering their institutional backgrounds. The findings also provide insights into the enduring popularity of large business groups and *chaebols* as investment targets, despite the concerns over their potential aggressiveness in earnings management.

5.3. Caveats

I acknowledge several limitations in this thesis. First, due to the non-random nature of accounting fraud cases, this thesis is inevitably exposed to sampling bias. To address this issue, I provide additional analysis results of matched samples (i.e., GPSM and PM) along with those of unmatched samples except in Chapter 2 where the adoption of a matching sample is not feasible. Second, this thesis is inherently exposed to the partial observability bias in that there could be accounting fraud cases that have not been detected by the SEC, capital market investors, and firms' managers. Even though there is no single and perfect solution for this issue, I have attempted to mitigate this bias by adopting the bivariate probit regression model and employing multiple proxies for financial misreporting instead of a single one. Third, Chapter 4 is particularly based on the assumption that controlling shareholders can influence firms' financial misreporting decisions even without holding key management positions. Even though this assumption is the one that is widely employed in this type of study, I further seek to provide empirical support for this assumption by showing that managerial ownership does not have a significant impact on firms' accounting fraud propensity in the Korean context. Finally, the analysis results of Chapter 2 should not be generalised to suggest that AAERs are superior to other databases or that the SEC's enforcement is effective in general. I acknowledge that the reliability of AAERs is valid only in a relative sense and the relative reliability of AAERs does not necessarily guarantee the effectiveness of SEC enforcement in general. A further study could evaluate the effectiveness or efficiency of SEC enforcement actions as a separate research topic.

5.4. Future studies

I identify two additional future areas of research that are not investigated in this thesis. First, in contrast with research on bankruptcy predictions (e.g., Shumway 2001), studies attempting to establish a better accounting fraud prediction model are relatively rare. Current models largely incorporate accounting ratios and stock market data (e.g., Beneish 1999; Jones et al. 2008; Dechow et al. 2012; Mingzi et al. 2016). However, if we could identify any alternative accounting fraud detector who has the independent ability to evaluate misreporting even before it is revealed by the SEC to the public (see e.g., Gao et al. 2016; Gao et al. 2017), the information produced by that accounting fraud detector (e.g., credit default swap traders as in Gao et al. (Gao et al. 2016)) would improve the predictive power of current models and therefore this research would have crucial implications for our current methods.

Second, with only some exceptions (e.g., Dechow et al. 1996; Beneish 1999; Dechow et al. 2011), the mechanisms by which firms are motivated to commit accounting fraud regarding their financing needs have not been fully investigated. There is, therefore, a definite need for investigation of firms' financing, refinancing, and investment patterns in the context of accounting fraud. In this thesis, I document that, after controlling for the financed levels in the first misreporting year, misreporting firms do not seem to invest significantly more than non-misreporting firms for the three years prior to the first misreporting year[89]. A much more comprehensive study would reveal specific conditions in which firms are more likely to misreport in relation to their financing and investment activities.

[89] Using matched samples, McNichols and Stubben (2008) also report that misreporting firms do not show significantly higher levels of investment prior to misreporting events. Instead, they find pronounced over-investment patterns in misreporting firms during manipulation periods.

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