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The Relation between CEO Compensation and Accounting Fraud
– The Role of CEOs' Proportion of Stock Options

Der Zusammenhang zwischen CEO-Vergütung und Bilanzbetrug
– Die Rolle des Anteils der Aktienoptionen der CEOs

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Abstract

Various scholars examine the relationship between CEOs’ stock options and accounting fraud. Unlike most previously published papers that use CEOs' option delta as incentive measure, I focus on CEOs’ proportion of options on their total compensation because I conjecture that other parts of their total compensation do not provide CEOs with powerful incentives to manipulate financial statements. To measure fraud, I use Accounting and Auditing Enforcement Releases against a firm in a consecutive five-year period without major changes in law enforcement. In the unmatched sample research design, I find evidence that CEOs with a higher proportion of options are more likely to commit accounting fraud. I also find other significant predictor variables that I use to control for financial performance. In the matched sample research design, I also find evidence that the proportion of options is positively associated with the tendency to accounting fraud. However, I do not find other significant predictors of accounting fraud. Thus, my overall findings suggest, that once industry and size are controlled for using a matched sample research design, the proportion of options is the only significant predictor of accounting fraud.

Verschiedene Wissenschaftler haben den Zusammenhang zwischen Aktienoptionen von CEOs und Bilanzbetrug untersucht. Im Gegensatz zu den meisten bisher veröffentlichten Arbeiten, die das Options-Delta des CEO als Anreizmaß verwenden, konzentriere ich mich auf den Anteil der Optionen an der Gesamtvergütung der CEOs. Denn ich vermute, dass andere Teile der Gesamtvergütung den CEOs keine starken Anreize zur Manipulation von Abschlüssen bieten. Zur Messung von Betrug verwende ich „Accounting and Auditing Enforcement Releases“ gegen ein Unternehmen in einem aufeinanderfolgenden Fünfjahreszeitraum ohne größere Veränderungen in der Verfolgung von Wirtschaftsstraftaten. Zuerst vergleiche ich die Betrugsfirmen mit allen zur Verfügung stehenden Unternehmen und finde Hinweise darauf, dass CEOs mit einem höheren Anteil an Optionen mit größerer Wahrscheinlichkeit Bilanzbetrug begehen. Ich finde auch andere signifikante Prädiktorvariablen, die für die finanzielle Performance kontrollieren. Wenn ich die Kontrollgruppe auf Unternehmen reduziere, die gleiche Eigenschaften wie die Betrugsfirmen aufweisen, finde ich ebenfalls Hinweise darauf, dass CEOs mit einem höheren Anteil an Optionen mit größerer Wahrscheinlichkeit Bilanzbetrug begehen. Allerdings finde ich keine anderen signifikanten Prädiktorvariablen für Bilanzfälschung. Insgesamt deuten meine Ergebnisse also darauf hin, dass der Anteil der Optionen der einzige signifikante Prädiktor für Bilanzfälschung ist, sobald für die Branche und Unternehmensgröße mittels einer Kontrollgruppe kontrolliert werden.

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List of Abbreviations

AAER	Accounting and Auditing Enforcement Releases
ACFE	The Association of Certified Fraud Examiners
CEO	Chief Executive Officer
CFRM	University of California-Berkeley Center for Financial Reporting and Management
EBIT	Earnings before Interest and Taxes
IAA	The Institute of Internal Auditors
SEC	Security and Exchange Commission
VIF	Variance Inflation Factor

1. Introduction

Accounting fraud causes serious harm to a firm's shareholders. Feroz, Park, and Pastena (1991, p. 127) reveal that on the first two days after an Accounting and Auditing Enforcement Release (AAER) is issued against a firm due to fraudulent financial statements, the stock price decreases, on average, by 13%. In the long run, Karpoff et al. (2008, p. 582) report that firms lose, on average, 38% of their market value due to unethical behavior. Thus, shareholders may lose a significant part of their wealth as a consequence of accounting fraud. For instance, the overall WorldCom accounting fraud scandal caused $180 billion in losses for shareholders (Bekiaris & Papachristou, 2017, p. 467). Also, accounting fraud often goes along with negative consequences for other stakeholders, e.g., employees and suppliers. For instance, Bekiaris & Papachristou (2017, p. 467) argue that 30,000 people lost their jobs as a direct consequence of the WorldCom accounting fraud scandal. Ultimately, major accounting fraud scandals may also affect the whole economic system (see, e.g., Harris and Bromiley, 2007, p. 5). The Association of Certified Fraud Examiners (ACFE, 2016, p. 8) estimates that accounting fraud costs the world economy $3.7 trillion per year. In summary, accounting fraud often causes massive consequences for shareholders, stakeholders, and the world economy and, thus, needs to be examined in detail.

On the other hand, firms increased Chief Executive Officers' (CEO) stock option compensation to align their wealth on the company's performance and solve the principal-agent problem between shareholders and managers during the 1980s (Murphy, 1999, p. 2515-2516; Conyon, 2006, p. 28-29, p. 32). Consistent with this, Demsetz and Lehn (1985), Core and Guay (1999), and Rajgopal and Shevlin (2002) document a positive relation between the value of options granted to the CEO and firm value maximization. On the other hand, other scholars argue that stock options may provide CEOs with powerful incentives to misreport (see, e.g., Conyon, 2006, p. 33; Goldman and Slezak, 2006, p. 604-605) because the manipulation of financial statements theoretically increases the stock price (see, e.g., Burns and Kedia, 2006). A higher stock price, in turn, increases the value of the CEO's stock options (see, e.g., Murphy, 1999, p. 2510). The value of an option at maturity is non-linear in the stock price: Option holders benefit from stock price increases unlimitedly. In contrast, when fraud is detected, the losses of options due to stock price declines are limited.

Various scholars test the relation between stock options and accounting fraud. Harris and Bromiley (2007) document a positive relation between the proportion of options and accounting fraud. Denis, Hanouna, and Sarina (2006) report a correlation between option intensity and the likelihood of fraud allegations. Burns and Kedia (2006) analyze the sensitivity of CEOs' option portfolios to stock price (option delta) to the tendency to misreport. They find a strong positive relation between option delta and the propensity to misreport. Chen, Wang, and Xing (2020) also state a strong positive relation between option delta and the tendency to misreport in a multi-year fraud period. In contrast, Erickson, Hanlon, and Maydew (2006) do not find consistent empirical evidence that executives with a higher option delta tend to commit accounting fraud. Johnson, Ryan, and Tian (2003) also find no relation between the propensity to fraud and stock options.

Unlike most previously published papers that use CEOs' option delta, I focus on the CEO's proportion of options as incentive measure. I conjecture that other parts of a CEO's total compensation, e.g., base salary, do not provide CEOs with powerful incentives to manipulate financial statements (see, e.g., Burns and Kedia, 2006; Murphy, 1999; Ryan and Wiggins, 2000). Thus, I infer that the proportion of options on the total compensation is crucial for incentives to manipulate: If managers receive only a small proportion of their compensation in options, the positive effect of increased stock prices through fraudulent statements on their wealth is smaller. This decreases, in turn, the incentives for manipulation (see Harris and Bromiley, 2007). If a large proportion of a CEO's compensation is paid in options, the positive effect of increased stock prices by fraudulent statements on their wealth is higher.

To construct a firm-year sample of fraud firms, I use the University of California-Berkeley Center for Financial Reporting and Management (CFRM) database. The database consists of Accounting and Auditing Enforcement Releases (AAER) that are issued by the Security and Exchange Commission (SEC) due to accusations of fraud against a company. Rakoff (2014, p. 6) argues that in 2001 the effectiveness of fraud law enforcement actions was poor because 1,000 federal agents were assigned from accounting fraud to antiterrorism units. These inconsistencies may lead to higher Type II (i.e., that firms applied fraudulent accounting techniques, however, were not detected by the SEC) error in the analysis of data including 2001 and dilute prior empirical results. To obtain a sample period without major changes in law enforcement, e.g., 9/11 or the Great Recession, I focus on AAERs issued between 2002 and 2006. If firms are accused of fraud in more than one year, I include only the firm-year with the first appearance of misreporting. I further exclude financial firms from the fraud sample leading to a final fraud sample size of 39 firm-years.

I use an unmatched sample and a matched sample research design. I build the unmatched sample by including all firms-years for which data are available on ExecuComp and Compustat, less firm-years of financial firms or firms accused of fraud. The final unmatched sample consists of 5,275 firm-years. To construct the matched sample, I match on size (i.e., total assets) and exact two-digit SIC codes. The matched sample consists of 39 firms. For the matched sample research design, I apply logistic regression. For the unmatched sample, I use conditional logit that takes the pairwise fixed-effects into account. In both research designs, fraud is the binary dependent variable that equals one if the firm of the underlying firm-year is accused of fraud.

I define the independent variable, the proportion of options, as the CEO's total value of stock options divided by the CEO's total compensation. I further use several control variables. First, I include total assets and the natural logarithm of sales to control for company size. Second, I include return on assets and the book-to-market ratio to control for financially low-performing firms. These firms may apply fraudulent accounting techniques to conceal their financial situation (see, e.g., Altman, 1968; Begley, Ming, and Watts, 1996; Erickson, Hanlon, and Maydew, 2006). Third, I include leverage to control for higher indebted firms. Fourth, I include CEO tenure because Core and Guay (1999, p. 158) argue that with growing years of service, the uncertainty about the capabilities of a CEO decreases. This may increase the confidence in CEO's actions and weaken stricter control mechanisms. In the unmatched sample research design, I also include an industry dummy to control for industries in which fraud is concentrated.

In the descriptive statistics, I reveal that fraud is highly concentrated in the manufacturing and business services industries. Regarding gender and age, I find that the average fraud firm's CEO is 55 years old and male. When comparing descriptive statistics of the independent variables, fraud firms' CEOs have a noticeably higher proportion of options than CEOs from the matched and unmatched sample. This indicates that accounting fraud coincides with a larger proportion of options. Fraud firms, on average, show a lower return on assets and a higher book-to-market ratio than the matched and the unmatched sample. These findings suggest that fraud firms' average financial performance is poorer compared to firms from the matched and unmatched sample.

In the unmatched sample regression design, the coefficient of the proportion of options is in all models significantly positive. Thus, for the unmatched sample, my results strongly support the hypothesis that CEOs with a higher proportion of options are more likely to commit accounting fraud. In all models, the coefficient of the return on assets is significantly negative and of the book-to-market ratio significantly positive. In addition, the industry dummy is significantly positive. In the matched sample research design, the coefficient of the proportion of options is, under the additional control for firm size, financial performance, leverage, and tenure, significantly positive. In contrast to the empirical results of the unmatched sample and the univariate tests, the coefficient of the return on assets and the book-to-market ratio are not significant. Thus, my overall findings suggest, that once industry and size are controlled for using a matched sample research design, the proportion of options is the only significant predictor of accounting fraud.

My work contributes to the literature in two aspects: First, I use the proportion of options on a CEO's total compensation instead of the CEO's option delta to consider that other parts of CEO's total compensation do not provide them with strong incentives to misreport. I find evidence that the proportion of options is positively associated with accounting fraud. Thus, given an equal amount of other compensation components, a higher value of options increases the likelihood of accounting fraud. Second, I add additional empirical evidence to previous work by using a consecutive sample period without major changes regarding law enforcement for fraudulent accounting. These inconsistencies may lead to higher Type II errors in the analysis of data including the year 2001 and dilute prior empirical results.

The rest proceeds as follows. In section 2, I provide background information on (accounting) fraud, discuss relevant literature, and construct the hypothesis. In section 3, I explain the sample construction and data acquisition process and the variable measurement. In section 4, I present the empirical results that I discuss in section 5. Section 6 contains the diagnostics and robustness checks. In section 7, I conclude this work.

2. Background, Literature, and Hypothesis

In the following section, I first provide background information on (accounting) fraud including definitional boundaries and common types of accounting fraud. Then, I present related work on the relation between CEO compensation and accounting fraud. I finish this section by constructing the hypothesis of the present paper.

2.1. Background: Definitional Boundaries and Common Types of Accounting Fraud

There is no generally acknowledged definition of fraud and attempts to define fraud differ among various countries and legal systems. The only definitional element that all definitions point to is that fraud requires a violation of the legal or regulatory framework (Jones, 2010). One widely spread definition of fraud is determined by the Institute of Internal Auditors (2013, p.1) that characterizes fraud as “any illegal act characterized by deceit, concealment or violation of trust”.

Figure 1

Classification of Fraud

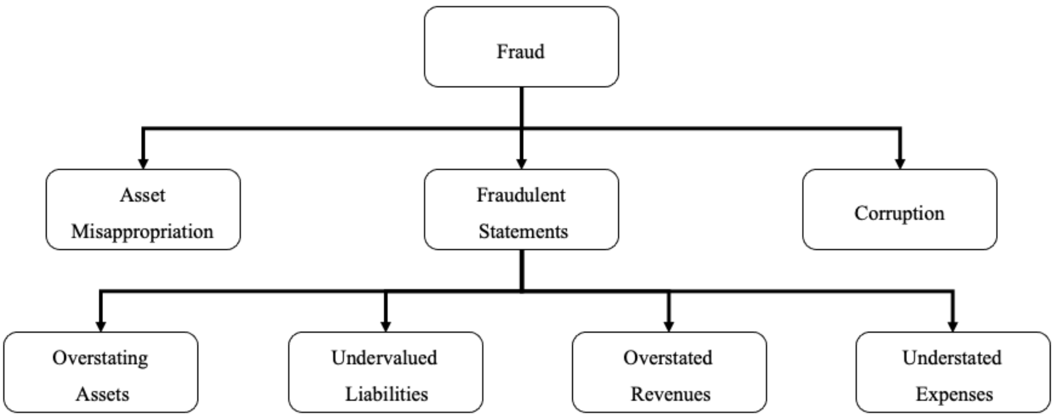

Figure 1 shows the different types of fraud in the economic sphere: The Association of Certified Fraud Examiners (ACFE, 2016, p. 4) categorizes fraud into corruption, asset misappropriation, and fraudulent statements *(i.e., accounting fraud)*. Within these categories, asset misappropriation (e.g., cash larceny or asset theft) is at a level of 83% the most common, fraudulent statements (10%) are by far the least common type of fraud. When it comes to the occupational impact, however, fraudulent statements are by far the most expensive category for firms: The median loss caused by the three types of fraud per affected company ranges from $125,000 (asset misappropriation) to $975,000 (fraudulent statements) (ACFE, 2016, p. 4).

Jones (2010) further divides fraudulent financial statements into overstated revenue recognition, understated expenses, overstated assets, and undervalued liabilities, or a combination of these. He argues that, so far, overstated revenue recognition, e.g., by inventing bills and costumers, and overstated assets are the most frequent types of accounting fraud. Nevertheless, the percentage of understated expenses or liabilities on total fraud cases almost doubled during the 1990s to 31% (Bao, 2020, p. 208). The perpetrators of fraud are on different hierarchical levels. The ACFE (2016, p. 5, p. 48) finds that most perpetrators are regular employees (41%), whereas executives represent only a small percentage (19%). However, the ACFE (2016, p. 5) also states that the median damage of fraud caused by executives is more than ten times higher than fraud caused by employees. In 2016, executive fraud caused on average a negative impact of $703,000 per affected company. In summary, executives are less-frequent perpetrators of accounting fraud but cause the greatest damage.

In literature, “earnings management”, “restatements” and “accounting fraud” are often used synonymously. Although these terms have certain properties in common, they are not interchangeable. The difference between accounting fraud and earnings management lays in the fact that earnings management can be within or outside the regulatory framework (Czakowska, 2020, p. 1-2). In contrast, accounting fraud is always outside the law. The distinction between fraud and restatements is that accounting fraud requires a primary purpose to deceive (Erickson, Hanlon, and Maydew, 2006, p. 117). Restatements are not necessarily caused by a primary intention to scam, companies may also restate due to normal processes (e.g., stock splits) (Harris & Bromiley, 2006, p. 6). For instance, Palmrose and Scholz (2004, p. 171-173) point out that only one-tenth of restatements lead to law enforcement actions. In the course of this work, I synonymously use the terms “(accounting) fraud”, “fraudulent statements”, “financial misrepresentation”, “misstatements”, and “fraudulent accounting techniques”.

2.2. Literature Review: CEO Compensation and Accounting Fraud

This subsection summarizes related work on the relation between four components of CEO compensation and their tendency to accounting fraud. First, I provide related literature on the relation of base salary and accounting-based short-term bonuses on the tendency to accounting fraud. Then, I present related work on the effects of stock options and restricted stock on the likelihood of accounting fraud.

2.2.1. Base Salary and Accounting-Based Short-Term Bonus

Base salary is the basic, cash-based component of a CEO's compensation (Murphy, 1999). Due to the non-direct performance-relatedness of base salary, Burns and Kedia (2006) find that higher salaries do not increase the likelihood to misreport. Accounting-based short-term bonuses are usually paid out to executives depending on a single fiscal-year's accounting performance often measured via earnings or EBIT (Frydman & Jenter, 2010, p. 76). Healy (1985, p. 95-96) assumes that, once executives have reached the bonus threshold, they may try to shift earnings – legally and illegally – to the next year to receive their bonus, again. Murphy (1999, p. 2507) suggests that if executives know that they will not reach the target agreement, they may provide special discounts to customers or even fraudulent accounting techniques to receive a bonus.

To add empirical evidence on the theory that accounting-based short-term bonus may increase the tendency to accounting fraud, Burns and Kedia (2006) and Harris and Bromiley (2007) test the relation between accounting-based short-term and accounting fraud. Using two different research designs, both papers do not find a statistically significant relation between short-term bonuses and the tendency to accounting fraud. Consequently, I assume that higher amounts of base salary and accounting-based short-term bonuses do not increase the likelihood of accounting fraud.

2.2.2. Stock Options

In the 1980s, companies introduced stock options to align risk-averse managers' wealth on company performance (Murphy, 1999). Demsetz and Lehn (1985), Core and Guay (1999), and Rajgopal and Shevlin (2002) document a positive relation between the value of options granted to the CEO and firm value maximization. On the other hand, other scholars argue that stock options may provide CEOs with powerful incentives to misreport (see, e.g., Conyon, 2006, p. 33; Goldman and Slezak, 2006, p. 604-605): The manipulation of financial statements theoretically increases the stock price (see, e.g., Burns and Kedia, 2006). A higher stock price, in turn, increases the value of the CEO's stock options (see, e.g., Murphy, 1999, p. 2510). The value of an option at maturity is non-linear in the stock price: Option holders benefit from stock price increases unlimitedly. In contrast, when fraud is detected, the losses of options due to stock price declines are limited.

Harris and Bromiley (2007) document a positive relation between the proportion of options (fraction of the total value of the CEO's options over CEO's total compensation) and accounting fraud. Under the control of governance aspects, size, and (relative) social performance, they find that the proportion of options significantly increases the likelihood of accounting fraud. Denis, Hanouna, and Sarina (2006) also report that there is a relation between a higher option intensity and the likelihood of fraud allegations. Burns and Kedia (2006) analyze the sensitivity of the CEOs' option portfolio to stock price (option delta) to the tendency to misreport. In all their different models, they find a strong positive relation between option delta and the propensity to misreport. Feng et al. (2011) also find that a higher CEO's option delta increases the likelihood of accounting fraud.

When dividing option sensitivity into the sensitivity of vested and unvested options, Burns and Kedia (2006) further report a strong relation between the sensitivity of vested options and the tendency to accounting fraud. Cheng, Wang, and Xing (2020) also state a strong positive relation between vested option delta and the tendency to misreport. They apply the logarithmic transformation on the option delta and specify fraud not only in the current but also in the next three fiscal years. Chen, Wang, and Xing (2020) argue that CEOs only profit from increased stock prices through accounting fraud if their options can be directly exercised.

In contrast to these findings, other scholars do not find empirical evidence for a relation between stock options and accounting fraud. Erickson, Hanlon, and Maydew (2006) test the relation between option delta and accusation of fraud by the Security and Exchange Commission (SEC). They do not find consistent empirical evidence that executives with a higher option delta tend to commit accounting fraud. Johnson, Ryan, and Tian (2005) also find no relation between the propensity to fraud and stock options. Armstrong et al. (2013) argue that a higher option delta does not necessarily lead to an increasing tendency to commit accounting fraud. However, they find that the sensitivity of managers to changes in risk (portfolio vega) provides executives with a strong positive incentive to misreport. In summary, empirical results on the effect of stock options on the likelihood of accounting fraud are mixed.

2.2.3. Restricted Stock

Like stock options, restricted stock also aligns the CEO's wealth to stock prices (see, e.g., Murphy, 1999). Therefore, one may argue that restricted stock also provides CEOs with incentives to increase stock prices by applying fraudulent accounting techniques. However, Burns and Kedia (2006) argue that, contrary to stock options, the payoff from restricted stock is symmetric to the underlying stock price. In turn, this exposes CEOs to price declines due to detected accounting fraud. Murphy (1999, p. 2510) argues that increased stock-price volatility through fraudulent statements leads to raising options values but not to an increase in the value of stock. He summarizes that the amount of restricted stock, in contrast to options, does not provide managers with higher incentives in riskier or fraudulent investments. Consistent with this, Burns and Kedia (2006) do not find empirical evidence that a higher amount of restricted stock is related to misreporting.

2.3. Hypothesis

Stock options, in contrast to base salary and short-term bonuses, directly tie CEOs' wealth to the underlying share price. The manipulation of financial statements theoretically increases the stock price (see, e.g., Burns and Kedia, 2006). A higher stock price, in turn, increases the value of the CEO's stock options (see, e.g., Murphy, 1999, p. 2510). The value of an option at maturity is non-linear in the stock price: Option holders benefit from stock price increases unlimitedly. In contrast, when fraud is detected, the losses of options due to stock price declines are limited. Thus, among other related work, I hypothesize that stock options provide managers with a meaningful incentive to apply fraudulent accounting techniques.

In contrast, I assume that other components of CEO compensation, for instance, base salary *(see 2.2.1. Base Salary and Accounting-Based Short-Term Bonus)* and restricted stock *(see 2.2.3. Restricted Stock)* do not provide managers with powerful incentives to manipulate financial statements. Thus, I conjecture that the proportion of options on the total compensation is crucial for incentives to manipulate. Harris and Bromiley (2007) also point out that undesired incentives through options are also based on the proportion of other components on the total compensation:

If managers receive only a small proportion of their compensation in options, the positive effect of increased stock prices through fraudulent statements on their wealth is smaller. This decreases, in turn, the incentives for manipulation (Harris and Bromiley, 2007). If a large proportion of a CEO's compensation is paid in options, the positive effect of increased stock prices by fraudulent statements on their wealth is higher. In addition, Erickson, Hanlon, and Maydew (2006) observe that the perceived rose in accounting fraud throughout the 1990s coincides with the relative increase in stock options. In summary, I hypothesize that a larger proportion of CEO compensation paid in stock options provides managers with more incentives to apply fraudulent accounting techniques.

Hypothesis: *CEOs with a higher proportion of stock options on their total compensation are more likely to commit accounting fraud associated with restatements.*

3. Research Design

In this section, I first explain the sample construction process and the data sources that I use. Then, I present the variable measurement including the dependent, independent, and additional control variables. I finish this section by establishing the different empirical models.

3.1. Sample and Data Collection

This subsection summarizes the sample construction and data collection process. First, I present data sources that I use to collect the dependent, independent, and additional control variables. Then, I describe the selection process for firms of the fraud sample, and the samples of matched and unmatched firms. *Table 1* provides an overview of the sampling method and data sources that were used by four previously published papers.

Table 1

Overview of Research Design Choices of Prior Literature

Paper	Incentive Measure	Measure of Fraud	Time Period	Sample Method
Burns and Kedia (2006)	Option Delta	GAO	1999 - 2001	Unmatched Sample
Erickson, Hanlon, and Maydew (2006)	Option Delta	AAER	1996 - 2003	Unmatched and Matched Sample
Harris and Bromiley (2007)	Proportion of Options	GAO	1997 - 2002	Matched Sample
Feng, Ge, Luo, and Shevlin (2011)	Option Delta	AAER	1982 - 2005	Matched Sample
Chen, Wang, and Xing (2020)	Option Delta	AA	2001 - 2015	Unmatched and Matched Sample

3.1.1. Data Sources

I use three different data sources to create a firm-year dataset. First, in line with other papers, for instance, Burns and Kedia (2006) and Chen, Wang, and Xing (2006), financial data comes from S&P Compustat. Second, I collect compensation data using ExecuComp. Again, this is in accordance with the above-mentioned, related work. In contrast, previous papers use different sources for the indicator of accounting fraud. *Table 1* indicates that both, Burns and Kedia (2006) and Harris and Bromiley (2007), use the United States Governmental Accountability Office (GAO) database. Chen, Wang, and Xing (2020) collect accounting fraud from Ives Group's Audit Analytics (AA). Both, GAO and AA, base data on the financial statement restatement announcements of companies in the United States.

Erickson, Hanlon, and Maydew (2006) and Feng et al. (2011) use Accounting and Auditing Enforcement Releases (AAER) issued by the Security and Exchange Commission (SEC). Since companies often restate due to normal reasons, e.g., stock splits and mergers, accusations of fraud must be manually extracted from the AAER database. Furthermore, the AAER database also contains enforcement releases against financial experts (e.g., lawyers and auditors) that must be also excluded (SEC, 2021). The University of California-Berkeley Center for Financial Reporting and Management (CFRM) compiles a final dataset of U.S. publicly traded companies that are accused of accounting fraud.[1]

Karpoff et al. (2017, p. 159) analyze the databases GAO, AA, and CFRM. They find that every database has advantages and disadvantages but are all suitable for accounting fraud research. However, they conclude that the CFRM database identifies fraud best and provides the highest overlap of fraud cases with the two other fraud databases. Thus, I decide to employ the CFRM database. Because there is limited access to the CFRM, I use the congruent firm-year dataset from Bao et al. (2020). They construct a fraud-prediction model using the CFRM database and make their dataset publicly available.[2] However, since the CFRM data is manual, hand-collected from the AAER database, Kedia and Rajgopal (2011, p. 265-267) and DeHaan et al. (2015, p. 87-88) argue that selection bias is an important disadvantage to consider.

3.1.2. Sample Construction

Table 1 indicates that prior literature primarily uses data from the late 1990s to the early 2000s. Due to several reasons, I decide to focus on the period between January 1, 2002, and December 31, 2006. First, I exclude data prior to 1990 as the SEC drastically increased its clout in the late 1980s (Atkins and Bondi, 2008, p. 395). Atkins and Bondi (2008) argue that this may have led to fraud firms changing their accounting practices and, in turn, makes data prior to 1991 hardly comparable. Second, I delete the period between 1990 and 1999 since Murphy (1999) finds that the percentage of stock options on the total compensation dramatically increased throughout the 1990s. This would make the proportion of options in a firm-year dataset inconsistent between the different years.

Rakoff (2014, p. 6) explains that 1,000 federal agents initially covering financial fraud were assigned to anti-terrorism units in 2001. He further argues that in 2008 and 2009 the SEC

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[1] See https://www.marshall.usc.edu/departments/leventhal-school-accounting/faculty/aaer-dataset

[2] See https://github.com/JarFraud/FraudDetection.

switched its focus from detecting accounting fraud to detecting Ponzi schemes. Thus, I exclude the years 2001, 2008, and 2009 in consequence of a significant shift in the law enforcement of accounting fraud. In addition, companies reduced their usage of stock options due to the introduction of FAS 123R after 2006 (Hayes, 2006, p. 1). To obtain a consecutive firm-year dataset without major changes in law enforcement and accounting practices, I decide to focus on the period between January 1st, 2002, and December 31st, 2006.

Table 2 summarizes the sample construction procedure. Between 2001 and 2006, the CFRM lists 131 firms accused of accounting fraud by the SEC. However, the actual number of Accounting and Auditing Enforcement Releases during that period is 282, because various firms were accused of fraud in more than one year. Consistent with Erickson, Hanlon, and Maydew (2006), I include only the firm-year with the first appearance of misreporting, leading to 131 fraudulent firm-years. For 86 of these firms, there are missing executive compensation data on Compustat or missing financial data on ExecuComp. I exclude all financial firms that operate in the fields of finance, insurance, and real estate. By nature, the leverage and market-to-book ratio, which I include as control variables, of these firms are difficult to compare with non-financial firms (see, e.g., Barber and Lyon, 1997). The final sample consists of 39 firm-years of companies accused of fraud.

Table 2 also shows information on the selection procedure of the two comparison samples. Following, for instance, Cheng and Warfield (2005), Burns and Kedia (2006), and Richardson and Tuna (2007), I first compile an unmatched sample. I start by including all firm-years from Compustat and ExecuComp between 2002 and 2006, leading to 8,548 firm-years. For many of the firm-years, however, there are financial data available but no compensation data, and vice versa. This reduces the unmatched sample by 1,669 firm-years. Again, I exclude 1,368 firm-years of companies operating in the field of finance, insurance, and real estate. In line with Erickson, Hanlon, and Maydew (2006), I exclude all firm-years that are either accused of fraud or firm-years of firms that are accused of fraud in another year. Less these 236 firms, the unmatched sample consists of 5,275 observations.

Table 2

Description of Sample Construction Process

Sample of firms accused of fraud by the SEC	
Firms accused of fraudulent statements in Accounting and Auditing Enforcement Releases (AAERs) issued from January 1, 2002, through December 31, 2006, from CFRM	131
– AAER firms for which data are not available (not on ExecuComp or Compustat)	86
– AAER firms which operate in the fields of finance, insurance, and real estate (SIC Code 60-67)	6
Sample of firms accused of fraud by the SEC	**39**
Sample of firm-years not accused of fraud by the SEC	
Unmatched Sample	
Total firm-years available on ExecuComp and Compustat from January 1, 2002, through December 31, 2006	8,548
– Firm-years for which data are not available (not on ExecuComp or Compustat)	1,669
– Firms-years of firms operating in the fields of finance, insurance, and real estate (SIC Code 60-67)	1,368
– Firm-years accused of fraud by the SEC or of firms also accused of fraud in other year	236
Unmatched sample of firm-years not accused of fraud by the SEC	**5,275**
Matched Sample	
Matched firms based on two-digit SIC codes and total assets	**39**

Following, for instance, Harris and Bromiley (2007), Erickson, Hanlon, and Maydew (2006) and Cheng, Wang, and Xing (2020), I also employ a matched sample design. For every firm-year of a company accused of fraud, I match one firm-year of a firm that is not accused of fraud. My matched sample consists only of firm-years of firms that were not accused of fraud in any year. In accordance with the above-mentioned papers, matching criteria are size (total assets) and industry (Standard Industrial Classification code). Regarding industry, I match on exact two-digit SIC codes. The matching procedure for the total assets is based on propensity scores and applies the nearest neighbor algorithm. The final matched sample consists of 39 firm-years.

Table 3

Fraud Firms and Matched Firms

1	**AFFILIATED COMPUTER SERVICES**
	CADENCE DESIGN SYSTEMS INC
2	**AMER ITALIAN PASTA CO**
	LANCASTER COLONY CORP
3	**APPLE INC**
	QUALCOMM INC
4	**APTIV PLC**
	GENERAL DYNAMICS CORP
5	**ARTHROCARE CORP**
	INFOCUS CORP
6	**ASPEN TECHNOLOGY INC**
	HENRY (JACK) & ASSOCIATES
7	**BLACK BOX CORP**
	RSA SECURITY INC
8	**BRISTOW GROUP INC**
	AIRTRAN HOLDINGS INC
9	**BROOKS AUTOMATION INC**
	AVOCENT CORP
10	**COMVERSE TECHNOLOGY INC**
	INTUIT INC
11	**CONAGRA BRANDS INC**
	HILLSHIRE BRANDS CO
12	**CUMMINS INC**
	DOVER CORP
13	**DANA INC**
	PACCAR INC
14	**DIEBOLD NIXDORF INC**
	LAM RESEARCH CORP
15	**FERRO CORP**
	CYTEC INDUSTRIES INC
16	**INTERPUBLIC GROUP OF COS**
	EBAY INC
17	**ITT INC**
	SPX CORP
18	**LSB INDUSTRIES INC**
	NOVEN PHARMACEUTICALS INC
19	**MAXIM INTEGRATED PRODUCTS**
	UTSTARCOM HOLDINGS CORP
20	**MEDQUIST INC**
	CROSS COUNTRY HEALTHCARE INC
21	**MERCURY INTERACTIVE CORP**
	TIBCO SOFTWARE INC

22	**MONSTER WORLDWIDE INC**
	DUN & BRADSTREET HOLDNGS INC
23	**NAVISTAR INTERNATIONAL CORP**
	VISTEON CORP
24	**NCO GROUP INC**
	ASCENTIAL SOFTWARE CORP
25	**NORTEL NETWORKS CORP**
	BB LIQUIDATING INC
26	**OM GROUP INC**
	COMMERCIAL METALS
27	**OVERSEAS SHIPHOLDING GROUP**
	MATSON INC
28	**SAKS INC**
	DILLARDS INC -CL A
29	**SOURCECORP INC**
	MANTECH INTL CORP
30	**STEWART ENTERPRISES**
	CINTAS CORP
31	**SYMBOL TECHNOLOGIES**
	MANITOWOC CO
32	**TENET HEALTHCARE CORP**
	DAVITA INC
33	**THOR INDUSTRIES INC**
	GENTEX CORP
34	**TIDEWATER INC**
	MATSON INC
35	**TIME WARNER INC**
	EXELON CORP
36	**TRIBUNE MEDIA CO**
	DIRECTV
37	**VERITAS SOFTWARE CORP**
	PEOPLESOFT INC
38	**VITESSE SEMICONDUCTOR CORP**
	SALTON INC
39	**ZALE CORP**
	PETSMART INC

Table 3 displays the matched pairs. The name of the fraud firm is in bold print and underneath is the name of the respective matched firm. As the list suggests, some of the fraud firms are well-known international companies (e.g., Apple, Thor Industries, or Time Warner). In contrast, there are also some smaller, less well-known firms (e.g., LSB Industries or Overseas Shipholding Group). This suggests that accounting fraud is a widely spread phenomenon occurring in both large, famous and smaller, less-familiar firms in the United States.

3.2. Variable Measurement

In this subsection, I first introduce the dependent variable (measure of accounting fraud). Then, I present the independent variable (measure of option incentives) and the additional control variables that I use to control for firm size, financial performance, leverage, and CEO tenure.

3.2.1. Dependent Variable

In line with all related previous papers, I use a binary variable as the measure of accounting fraud. The variable is one if the company is accused of accounting fraud by the SEC in the underlying fiscal year. The dependent variable is zero if the company was not explicitly accused of accounting fraud by the SEC. Very likely, the SEC does not detect all cases of accounting fraud leading to an unknown dark figure of accounting fraud. Thus, in both, matched and unmatched samples, there may be firms that applied fraudulent accounting techniques that the SEC was not able to detect. Therefore, as another important limitation to keep in mind, both samples have an unknown level of Type II error (see, e.g., Erickson, Hanlon, and Maydew, 2006).

3.2.2. Independent Variable

In contrast to various related papers, I use the *Proportion of Options* on the total compensation instead of option delta *(see Table 1)*. Following Harris and Bromiley (2007), I define the *Proportion of Options* as the CEO's total value of stock options divided by the CEO's total compensation in the year of the incident of accounting fraud *(Figure 2)*. The total value of CEO's stock options is the aggregate value of all stock options granted to the CEO during the year valued via Standard & Poor's Black-Scholes formula (ExecuComp Item: OPTION_AWARDS_BLK_VALUE). Wharton provides an overview on all concrete items that I use.[3] The total compensation consists of salary, bonus, other annual pay, the total value of restricted stock granted, the total value of stock options (also using the Black-Scholes formula), long-term incentive payouts, and all other types of compensation. The corresponding item in ExecuComp is TDC1. As the sample period starts in 2002 and ends in 2006, both ExecuComp items apply to the 1992 reporting format.

$$Proportion\ of\ Options = \frac{Total\ Value\ of\ Stock\ Options}{Total\ Compensation} \triangleq \frac{OPTION\_AWARDS\_BLK\_VALUE}{TDC1}$$

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[3] See https://wrds-www.wharton.upenn.edu/documents/960/Execucomp_Data_Definitions.pdf

3.2.3. Control Variables

Table 4 provides an overview of the eight additional control variables which I include in different logistic regression models. In general, I control for firm size, financial performance, leverage, industries that fraud is highly concentrated in, and CEO tenure.

Table 4

Overview of Additional Control Variables

Variable	Definition
Ln(Marketvalue)	Natural logarithm of the total market value
Return on Assets	Net income divided by total assets
Book-to-Market Ratio	Book value of the shareholders' equity divided by the total market value
Ln(Sales)	Natural logarithm of the net sales
Leverage	Total liabilities divided by total assets
Tenure	Number of the CEO's years of service
Industry Dummy	Binary variable equals one if SIC code is in highly concentrated industry

First, I include the *Natural Logarithm of the Total Market Value* at the end of the fiscal year. The corresponding Compustat item of total market value, MKVALT, includes the total market value of all stocks. I include total market value to control for company size (see, e.g., Erickson et al., 2006; Burns and Kedia, 2006). Because distributions of total market values are usually positively skewed, I calculate *Natural Logarithm of the Total Market Value*.

$$Ln(Market\ Value) \triangleq Ln(MKVALT)$$

The *Book-to-Market Ratio* is the total shareholders' equity (Compustat item: SEQ) divided by the total market value (Compustat item: MKVALT). Total shareholders' equity is the sum of common equity and preferred stock. Erickson, Hanlon, and Maydew (2006) include the book-to-market ratio as a performance metric to control for the effect of financially poorly performing or unstable firms. These firms may tend to commit accounting fraud to conceal their poor financial situation (see, e.g., Altman, 1968; Begley, Ming, and Watts, 1996). Chen, Wang, and Xing (2020) also state that the *Book-to-Market Ratio* is an important variable to control for poor financial performance.

$$Book-to-Market\ Ratio = \frac{Total\ Shareholders'Equity}{Total\ Market\ Value} \triangleq \frac{SEQ}{MKVALT}$$

In line with Erickson, Hanlon, and Maydew (2006), I also include *Return on Assets* as another proxy. This is again to control for financially poorly performing firms that may hide their true financial situations through fraudulent reporting. *Return on Assets* is calculated by dividing net income (Compustat item: NI) by total assets (Compustat item: AT).

$$Return\ on\ Assets = \frac{Net\ Income}{Total\ Assets} \triangleq \frac{NI}{AT}$$

I include the *Natural Logarithm of Net Sales* as another measure to control for company size. The corresponding Compustat item for net sales is SALE and consists of gross sales reduced by cash discounts, trade discounts, returned sales, excise taxes, and value-added taxes and allowances for which credit is given to customers. Again, net sales are usually strongly positively skewed. Thus, I use the *Natural Logarithm of Net Sales*. Harris and Bromiley (2007) also include the logarithm of sales.

$$Ln(Net\ Sales) \triangleq Ln(SALE)$$

Leverage is total liabilities (Compustat item: LT) divided by total assets (Compustat item: AT). Total liabilities are the sum of current liabilities, deferred taxes, other liabilities, and long-term debt. Altman (1968) and Begley, Ming, and Watts (1996) argue that highly indebted firms may show a higher tendency to fraudulent accounting techniques. Therefore, and following Erickson, Hanlon, and Maydew (2006), I also include *Leverage* to control for highly leveraged firms.

$$Leverage = \frac{Total\ Liabilities}{Total\ Assets} \triangleq \frac{LT}{AT}$$

CEO Tenure indicates the CEO's years of service. Following Erickson, Hanlon, and Maydew (2006), I calculate CEO tenure as the difference between the fiscal year (Compustat item: FYEAR) and the year the individual became CEO (Compustat item: BECAMECEO). Core and Guay (1999) argue that with growing years of service, the uncertainty about the capabilities of a CEO decreases. This may increase the confidence in CEO's actions and weaken stricter control mechanisms. Thus, I include CEO tenure to control for long-serving CEOs.

$$CEO\ Tenure \triangleq BECAMECEO - FYEAR$$

Burns and Kedia (2006) find that accounting fraud is highly concentrated in four industries and that their industry characteristics may also explain accounting fraud. Therefore, they include an industry dummy that is equal to one if the two-digit SIC code of the underlying firm-year is 35 (Industry Machinery & Equipment), 36 (Electronic & Other Equipment), 38 (Instruments & Related Projects), and 73 (Business Services). I also find that accounting fraud occurs in four industries more frequently *(see 4.1. Descriptive Statistics)*. Thus, I also include an industry dummy that is equal to one if the firm-year is related to the four most frequent fraudulent two-digit SIC code industries. In my sample, these industries are similar to those from Burns and Kedia (2006): Solely, 37 (Transportation Equipment) replaces SIC code 38 (Instruments & Related Projects).

3.3. Empirical Models

To test the relation between the proportion of options and accounting fraud, I use both – matched and unmatched – sample research designs. For the unmatched sample research design, I apply multivariate logistic regression. For the matched sample research design, I use McFadden's (1973) conditional logistic regression. Conditional logistic regression estimates fixed-effects logits for each matched pair (Hoffman and Duncan, 1988). In all empirical models, the independent and control variables are winsorized at the 1% and 99% levels.

Model 1 tests the relationship between accounting fraud and the proportion of options for firm *i* in year *t* without including additional control variables. I use *Model 1* in the matched and unmatched sample research design.

$$Fraud_{i,t} = \beta + \beta_1 * Proportion\_of\_Options_{i,t} + \varepsilon_{i,t} \tag{1}$$

Model 2 includes several additional control variables to control for firm size, performance metrics, leverage, and CEO tenure. I use *Model 2* in the matched and unmatched sample research design.

$$\begin{aligned} Fraud_{i,t} = \; & \beta + \beta_1 * Proportion\ of\ Options_{i,t} + \beta_2 * Ln(Market\ Value)_{i,t} + \beta_3 \\ & * \ Return\ on\ Assets_{i,t} + \beta_4 * \ Book - to - Market_{i,t} + \beta_5 \\ & * Ln(Sales)_{i,t} + \ \beta_6 * Leverage_{i,t} + \beta_7 * Tenure_{i,t} + \ \varepsilon_{i,t} \end{aligned} \tag{2}$$

Since fraud is concentrated in a few industries *(see 4.1. Descriptive Statistics)*, *Model 3* includes an industry dummy to additionally control for four industries with the highest proportion of accounting fraud. In the matched sample design, firms are exactly matched on two-digit SIC codes. Because the conditional logit calculates pairwise fixed-effects logits, the industry dummy becomes redundant. Thus, I apply *Model 3* only to the unmatched sample design.

$$\begin{aligned} Fraud_{i,t} = {} & \beta + \beta_1\, Proportion\ of\ Options_{i,t} + \beta_2\, Ln(Market\ Value)_{i,t} + \beta_3 \\ & * Return\ on\ Assets_{i,t} + \beta_4 * Book-to-Market_{i,t} + \beta_5 \\ & * Ln(Sales)_{i,t} + \beta_6 * Leverage_{i,t} + \beta_7 * Tenure_{i,t} + \beta_8 \\ & * Industry\ Dummy_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

4. Empirical Results

In the following section, I first provide statistics on fraud firms' industries and their executives' age and gender. Then, I present descriptive statistics of the independent variables for fraud firms, matched sample, and unmatched sample. I finish the chapter by providing the results of the multivariate analysis of the unmatched and matched sample research design.

4.1. Descriptive Statistics

In this subsection, I first present descriptive statistics on fraud firms' industry and division. Then, I provide descriptive statistics on the age and gender of fraud firms' executives. I finish the chapter by providing detailed descriptive statistics of the independent variables for the fraud firms, the matched sample, and the unmatched sample.

4.1.1. Distribution of Fraud Firms by Industry and Division

Table 5 shows the distribution of fraud firms and non-fraud firms from the unmatched sample by industry. As I set up the matched sample based on two-digit SIC codes and total assets, the industry distribution of the matched sample complies with the industry distribution of the fraud firms. The 39 incidents of accounting fraud are distributed over 16 industries. The first observation one can make is that in most industries, there are no or only one or two incidents of fraudulent statements. For their sample of 50 fraud firms, Erickson, Hanlon, and Maydew (2006) also find that in most industries there is no or little occurrence of accounting fraud. In their sample, fraudulent statements are spread over 22 industries.

In my sample, there are four industries in which accounting fraud occurs more frequently: By far, the highest number of accounting fraud cases (11 cases; 28.21% of total fraud cases) are in the Business Services Industry. Burns and Kedia (2006) and Erickson, Hanlon, and Maydew (2006) also find that the Business Service Industry records by far the highest number of fraud cases. However, both report a percentage of 'only' 20% of fraud firms. As their samples end in the early 2000s, the proportion of the Business Services Industry on fraudulent statements seems to have increased throughout the mid 2000s. In the unmatched sample, only 11.32% of the firms belong to the Business Services Industry. Thus, this industry is overrepresented in the fraud sample; firms are more than twice as likely as the average sample firm to be alleged of fraudulent statements.

The second-highest amount of fraud cases occurs in the Industrial and Commercial Machinery and Computer Equipment Industry (5 cases; 12.82% of total fraud cases). This is in line with Burns and Kedia (2006) and Erickson, Hanlon, and Maydew (2006). In their samples, the Industrial and Commercial Machinery and Computer Equipment Industry accounts for around 12% of the fraud sample. When comparing the fraud and non-fraud sample (7.20%), the Industrial and Commercial Machinery and Computer Equipment Industry is also overrepresented in the fraud sample.

In my fraud sample, the third-highest number (4 cases; 10.26% of total fraud cases) of fraudulent statements occurs in the Transportation Equipment Industry. This is contrary to the findings of Burns and Kedia (2006) and Erickson, Hanlon, and Maydew (2006). In their fraud samples, the Transportation Equipment Industry accounts for a single-digit percentage. Thus, the proportion of this industry on total fraud cases seems to have increased since the mid 2000s. In the unmatched sample, 2.92% of the firms manufacture Transportation Equipment. Consequently, this industry is highly overrepresented in the fraud sample. Companies belonging to the Transportation Equipment Industry are more than three times more likely to be involved in fraudulent accounting practices than the average sample firm.

Accounting for three cases (7.69%), Electronic & Other Electrical Equipment & Components represent the industry with the fourth-highest number of fraud cases. Burns and Kedia (2006) also find that there is an outstanding number (7.44%) of fraudulent statements belonging to the Electronic & Other Electrical Equipment & Components Industry. In contrast, Erickson, Hanlon, and Maydew (2006) report that only 4.00% of their fraud firms come from this industry. Regarding all other industries, there are either no incidents of accounting fraud or only one or two cases.

Three firms are underrepresented in the fraud sample. Although Electric, Gas, and Sanitary Services accounts for 6.65% of the unmatched sample, there is no incident of accounting fraud. Second, the Oil and Gas Extraction Industry accounts for 4.06% of the unmatched sample and does also not have an incident of accounting fraud. Third, 6.90% of the non-matched firms belong to the Measuring, Photographic, Medical, & Optical Goods, & Clocks Industry. However, there is only one firm (2.56%) of the fraud sample that is part of this industry.

Table 5

Distribution of Fraud Firms by Industry

SIC	Industry	Matched Sample			Unmatched Sample	
		Frequency	Percentage		Frequency	Percentage
01	Agricultural Production - Crops				9	0.17%
07	Agricultural Services				3	0.06%
10	Metal Mining				25	0.47%
12	Coal Mining				15	0.28%
13	Oil and Gas Extraction				214	4.06%
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels				16	0.30%
15	Construction - General Contractors & Operative Builders				48	0.91%
16	Heamy Construction, Except Building Construction, Contractor				29	0.55%
17	Construction - Special Trade Contractors				8	0.15%
20	Food and Kindred Products	2	5.13%		156	2.96%
21	Tobacco Products				11	0.21%
22	Textile Mill Products				26	0.49%
23	Apparel, Finished Products from Fabrics & Similar Materials				56	1.06%
24	Lumber and Wood Products, Except Furniture				36	0.68%
25	Furniture and Fixtures				44	0.83%
26	Paper and Allied Products				86	1.63%
27	Printing, Publishing and Allied Industries				77	1.46%
28	Chemicals and Allied Products	2	5.13%		411	7.79%
29	Petroleum Refining and Related Industries				34	0.64%
30	Rubber and Miscellaneous Plastic Products				44	0.83%
31	Leather and Leather Products				28	0.53%
32	Stone, Clay, Glass, and Concrete Products				29	0.55%
33	Primary Metal Industries	1	2.56%		111	2.10%
34	Fabricated Metal Products				87	1.65%
35	Industrial and Commercial Machinery and Computer Equipment	5	12.82%		380	7.20%
36	Electronic & Other Electrical Equipment & Components	3	7.69%		465	8.82%
37	Transportation Equipment	4	10.26%		154	2.92%
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	1	2.56%		364	6.90%
39	Miscellaneous Manufacturing Industries				50	0.95%
40	Railroad Transportation				18	0.34%
41	Local & Suburban Transit & Interurban Highway Transportation				8	0.15%
42	Motor Freight Transportation				48	0.91%
44	Water Transportation	2	5.13%		12	0.23%
45	Transportation by Air	1	2.56%		55	1.04%

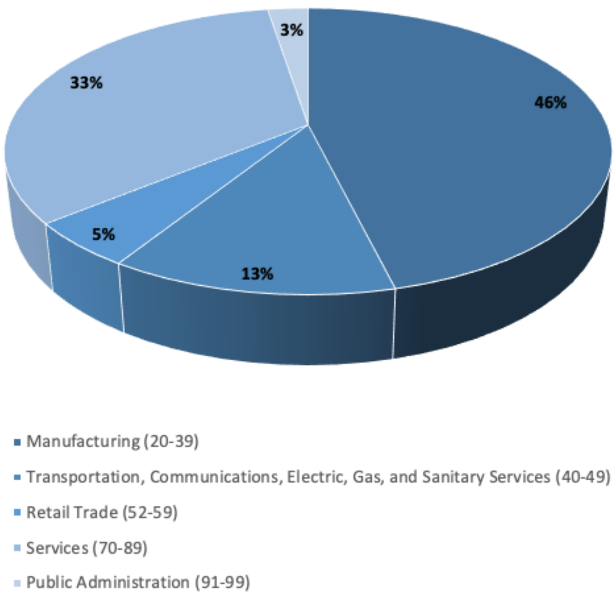
47	Transportation Services				13	0.25%
48	Communications	2	5.13%		122	2.31%
49	Electric, Gas and Sanitary Services				351	6.65%
50	Wholesale Trade - Durable Goods				137	2.60%
51	Wholesale Trade - Nondurable Goods				64	1.21%
52	Building Materials, Hardware, Garden Supplies & Mobile Homes				15	0.28%
53	General Merchandise Stores	1	2.56%		67	1.27%
54	Food Stores				28	0.53%
55	Automotive Dealers and Gasoline Service Stations				25	0.47%
56	Apparel and Accessory Stores				103	1.95%
57	Home Furniture, Furnishings and Equipment Stores				34	0.64%
58	Eating and Drinking Places				111	2.10%
59	Miscellaneous Retail	1	2.56%		88	1.67%
70	Hotels, Rooming Houses, Camps, and Other Lodging Places				16	0.30%
72	Personal Services	1	2.56%		32	0.61%
73	Business Services	11	28.21%		597	11.32%
75	Automotive Repair, Services and Parking				12	0.23%
78	Motion Pictures				11	0.21%
79	Amusement and Recreation Services				40	0.76%
80	Health Services	1	2.56%		104	1.97%
82	Educational Services				29	0.55%
83	Social Services				3	0.06%
87	Engineering, Accounting, Research, and Management Services				90	1.71%
99	Nonclassifiable Establishments	1	2.56%		26	0.49%
	SUM	**39**	**100.00%**		**5275**	**100.00%**

The United States Department of Labor suggests how to further aggregate SIC codes into divisions.[4] *Figure 2* shows the distribution of fraud cases by division. The first observation one can make is that accounting fraud is highly concentrated within two divisions: Manufacturing (SIC codes 20-39) and Services (70-89). There are also fraud cases in the Transportation, Communications, Electric, Gas, and Sanitary Service Division (40-49), the Retail Trade Division (52-59), and the Public Administration (91-99). In contrast, there is no occurrence of accounting fraud in Agriculture, Forestry, and Fishing (01-09), Mining (10-14), Construction (15-17), and Wholesale Trade (50-51).

[4] See https://www.osha.gov/data/sic-manual

Figure 2

Distribution of Fraud Firms by Division



In summary, data from *Table* 5 and *Figure 2* provide a first indication that firms in certain industries are more likely to commit accounting fraud than firms in other industries. I excluded six firms *(see Table 2)* from the fraud sample operating in Finance, Insurance, and Real Estate (SIC codes 60-67). When taking these firms into account and adding them to the fraud sample, they would account for 13.33% of fraud cases. Thus, accounting fraud also appears in financial firms more frequently. For the sake of completeness, *Appendix A* shows the number of fraud firms by year. Regarding firms that are accused of fraud for more than one year, I only include the first year of fraud occurrence. Therefore, *Appendix A* does not reflect the actual distribution of fraud cases in the period between 2002 and 2006.

4.1.2. Distribution of Fraud Firms' CEOs by Gender and Age

In *Table 6*, I present the gender distribution of the fraud sample's and the unmatched sample's CEOs. The first observation one can make is that only one perpetrator of accounting fraud is female (2.56%). The CEOs of the remaining 38 fraud firms are male (97.44%). In the unmatched sample, 97.80% of the CEOs are male whereas female CEOs account for only 2.20% of the sample. Thus, when comparing the fraud firms' CEOs with these of the unmatched sample, their gender is similarly distributed.

Table 6

Distribution of Fraud Firms' CEOs by Gender

Gender	Fraud Sample			Unmatched Sample	
	Frequency	Percentage		Frequency	Percentage
Female	1	2.56%		116	2.20%
Male	38	97.44%		5159	97.80%

Table 7

Distribution of Fraud Firms' CEOs by Age

Age		Fraud Sample	
		Frequency	Percentage
41		1	2.56%
42		3	7.69%
44		2	5.13%
46		1	2.56%
47		2	5.13%
49		1	2.56%
51		2	5.13%
52		1	2.56%
53		2	5.13%
54		4	10.26%
55		2	5.13%
56		4	10.26%
57		1	2.56%
58		1	2.56%
60		1	2.56%
61		1	2.56%
62		2	5.13%
63		2	5.13%
64		1	2.56%
65		1	2.56%
67		1	2.56%
68		2	5.13%
75		1	2.56%
SUM		39	100,00%
AVERAGE		55.05	

In *Table 7*, I present the age distribution of fraud firms' executives. The first observation one can make is that no CEO that is younger than 41 and only one that is older than 68. The ages between these two numbers seem to be approximately evenly split. Solely, there are in each case four CEOs that are 54 and 56. The average age of fraud firms' CEOs is 55.05; the average

age of the unmatched sample's CEOs is 55.27. Thus, fraud firms' CEOs do not seem, on average, to be younger or older than CEOs of the unmatched sample.

4.1.3. Independent Variables

In *Table* 8, I present descriptive statistics of the independent variables for the fraud firms, the matched sample, and the unmatched sample. For each variable, I indicate the mean, the minimum and maximum value, the median, and the lower and upper quartile. All variables are winsorized at the 1% and 99% levels. *Tenure* is measured in years; *Ln(Marketvalue)* and *Ln(Sales)* are shown in dollars.

The first observation one can make is that CEOs from fraud firms have, on average, a higher *Proportion of Options* than CEOs from their matched firms and the unmatched sample. On average, fraud firms' CEOs receive 46.6% of their compensation in stock options. In contrast, the *Proportion of Options* for matching firms' CEOs averages 38.2%, while for CEOs of the unmatched sample the average *Proportion of Options* is 33.1%. Thus, fraud firms' CEOs receive, on average, a *Proportion of Options* that is 1.2 (1.4) times higher than CEOs from the matched (unmatched) sample. This shows that accounting fraud coincides with instances when a firm's CEO has a higher *Proportion of Options*. The median differences are similar. In all three samples, the *Proportion of Options* ranges widely with low minimum and high maximum values: Some CEOs do not seem to receive options, while for other CEOs options account for over 90% of their total compensation.

Whereas firms from both matched and unmatched samples show an average *Return on Assets* of around 3%, fraud firms have an average *Return on Assets* of - 4.87%. This is a first indication that fraud firms perform, on average, financially worse. Because a firm's total assets cannot be negative, the fraud firms' negative average *Return on Assets* implies that fraud firms, on average, have a negative net income *(see 3.2.3. Control Variables)*. Regarding median values also reveals a noticeable difference between fraud firms and both matching samples. Erickson, Hanlon, and Maydew (2006) also find that fraud firms have, on average, a negative *Return on Assets*. When comparing the distribution of *Return on Assets*, the average lower quartiles of the matched firms are approximately 1% and their upper quartiles are 9%. In contrast, the lower (upper) quartile of the fraud firms is -2.86% (1.12%).

Table 8

Descriptive Statistics on the Independent Variables

VARIABLES		Observations	Mean	Min	Max	P25	P50	P75
Proportion of Options	Accused of fraud	39	0.466	0	0.940	0.174	0.471	0.765
	Matched Sample	39	0.382	0	0.863	0.120	0.359	0.731
	Unmatched Sample	5,275	0.331	0	0.940	0	0.311	0.554
Return on Assets	Accused of fraud	39	-0.0487	-0.710	0.131	-0.0286	0.0112	0.0610
	Matched Sample	39	0.0319	-0.302	0.205	0.0164	0.0544	0.0900
	Unmatched Sample	5,275	0.0280	-0.710	0.280	0.0130	0.0464	0.0854
Book-to-Market Ratio	Accused of fraud	39	0.696	0.0808	2.309	0.334	0.513	0.890
	Matched Sample	39	0.465	-0.0594	1.894	0.251	0.351	0.492
	Unmatched Sample	5,275	0.472	-1.731	2.309	0.265	0.429	0.624
Leverage	Accused of fraud	39	0.536	0.126	0.964	0.353	0.530	0.719
	Matched Sample	39	0.479	0.0770	0.972	0.314	0.466	0.631
	Unmatched Sample	5,275	0.521	0.0770	1.420	0.356	0.518	0.662
Ln(Sales)	Accused of fraud	39	21.28	18.91	24.44	20.00	21.13	22.49
	Matched Sample	39	21.34	17.58	23.78	20.55	21.19	22.24
	Unmatched Sample	5,275	20.99	10.40	26.47	19.97	20.93	22.01
Ln(Marketvalue)	Accused of fraud	39	21.23	18.46	24.79	20.20	21.03	22.44
	Matched Sample	39	21.70	18.88	24.83	20.78	21.53	22.65
	Unmatched Sample	5,275	21.15	11.98	26.68	20.15	21.06	22.16
Tenure	Accused of fraud	39	8.744	1	34	3	6	14
	Matched Sample	39	7.179	2	27	4	6	9
	Unmatched Sample	5,275	7.794	1	34	3	6	10
Industry Dummy	Accused of fraud	39	0.590	0	1	0	1	1
	Matched Sample	39	0.590	0	1	0	1	1
	Unmatched Sample	5,275	0.303	0	1	0	0	1

Note. The *Proportion of Options* CEO's total value of stock options divided by CEO's total compensation in the year of the incident of accounting fraud. *Return on Assets* is calculated by dividing net income by total assets. *Book-to-Market Ratio* is total shareholders' equity divided by the total market value. *Leverage* is total liabilities divided by total assets. *Ln(Sales)* is the natural logarithm of net sales. *Ln(Marketvalue)* is the natural logarithm of the total market value. *CEO Tenure* is the difference between the fiscal year and the year the individual became CEO. The *Industry Dummy* is a binary variable set to one if the two-digit SIC code of the underlying firm-year is 35 (Industry Machinery & Equipment), 36 (Electronic & Other Equipment), 38 (Instruments & Related Projects), and 73 (Business Services). All monetary amounts are measured in $ millions; *CEO Tenure* is measured in years. All variables are winsorized at the 1% and 99% levels.

The average *Book-to-Market Ratio* of the fraud firms is 0.696. In contrast, firms from the matched sample have, on average, a *Book-to-Market Ratio* of 0.465. Thus, on average, the market values fraud firms' equity to be more than 20% cheaper than their book value in comparison to the unmatched firms. This also holds when comparing fraud firms with the unmatched sample. When comparing median values, the difference between the fraud firms and their matching firms is 0.16. When comparing the distribution of the *Book-to-Market Value*, the upper quartile indicates that 25% of the fraud firms have a *Book-to-Market Value* higher than 0.890. In contrast, the upper quartile of the matching firms is 0.492. The higher average *Book-to-Market Ratio* is the second indicator that fraud firms show, on average, poorer financial performance. This is contrary to the findings of Erickson, Hanlon, and Maydew (2006). They report that their fraud sample has a lower average *Book-to-Market Ratio* (0.40)[5] than their matched (0.45) and unmatched sample (0.48).

When comparing the *Leverage* of the fraud sample (0.536) with the matched sample (0.479), the fraud firms have, on average, a higher *Leverage* than their matching firms. Given a relatively equal amount of total assets of a fraud firm to its matching firm, a higher amount of fraud firms' average total liabilities *(see 3.2.3. Control Variables)* seems to explain their higher *Leverage*. The average unmatched firm finances 52.1% of their total assets by debt leading to a difference of only 1.5% compared to the average fraud firm. The median values are similar to the mean values. Erickson, Hanlon, and Maydew (2006) also find that fraud firms, on average, have a higher (lower) *Leverage* than the matched (unmatched) sample. Thus, although of the same industry and size, fraud firms seem to be higher indebted than their matching firms.

The fraud firms, on average, have a *Ln(Sales)* of \$21.28. Firms from the matched sample have an average *Ln(Sales)* of \$21.34. In contrast, the average *Ln(Sales)* of the unmatched sample is, at a value of \$20.99, lower. Similarly, the median fraud firm and the median matched firm have a slightly higher *Ln(Sales)* compared to the median unmatched firm. Because I match on total assets, the relatively equal average *Ln(Sales)* of the matched and the fraud sample suggest that total assets may correlate with net sales.

[5] Actually, Erickson, Hanlon, and Maydew (2006) indicate a mean Market-to-Book Ratio of 0.040. From the context, however, I infer that this must be a literal because the lower quartile is 0.150 and the median is 0.325.

The average *Ln(Marketvalue)* of fraud firms is \$21.23; of the unmatched sample \$21.15. In contrast, firms from the matched sample have, on average, at several \$21.70 a higher *Ln(Marketvalue)*. Thus, given similar size and industry, the market seems to value, on average, fraud firms less than the matching firms. When comparing median values, the average *Ln(Marketvalue)* of fraud firms and unmatched firms is also lower than of the matched firms.

CEOs of fraud firms have an average *Tenure* of 8.7 years. Regarding the matched sample, the CEO's average *Tenure* is 7.1 years. Thus, fraud firms' CEOs, on average, seem to have already served longer than the CEOs of the matched sample. When comparing the average *Tenure* of the fraud sample with the unmatched sample (7.8 years), fraud firms' CEOs have already served, on average, almost one year longer. Regarding the upper quartile reveals that one-quarter of the fraud firms' CEOs has served for more than 14 years. In contrast, the upper quartile for the matched (unmatched) sample is 9 (10) years. In summary, this is an indication that accounting fraud coincides with instances when a firm's CEO has a higher *Tenure*.

The *Industry Dummy* is one if the firm operates in industries 35 (Industry Machinery & Equipment), 36 (Electronic & Other Equipment), 37 (Transportation Equipment), or 73 (Business Services). Because I exactly match on two-digit SIC codes, the *Industry Dummy* of the fraud sample equals the matched sample (0.590). Thus, 59.0% of the fraud firms, respectively, matching firms, operate in the above-mentioned areas. Regarding the unmatched sample reveals that only 30.3% of the unmatched firms operate in these industries. Thus, I conclude, that fraud is highly concentrated in four industries *(see 4.1. Descriptive Statistics)*.

In summary, fraud firms' CEOs have a noticeable higher *Proportion of Options* than CEOs from the matched and unmatched sample. Fraud firms, on average, show a lower *Return on* Assets and a higher *Book-to-Market Ratio* than the matched and the unmatched sample. These findings support the theory that accounting fraud coincides with instances when a firm's financial performance is poorer (see, e.g., Altman, 1968; Begley, Ming, and Watts, 1996). When comparing *Leverage* and *Ln(Marketvalue)*, firms from the matched sample perform, on average, better than firms from the fraud sample. These findings suggest that, although of the same size and industry, firms from the matched sample are also lower indebted and higher valued by the market than the fraud firms. Furthermore, I find that CEOs from fraud firms have a higher average *Tenure* than CEOs from the matched and unmatched sample.

4.2. Multivariate Tests

In this subsection, I present the empirical results of the unmatched sample research design and the matched sample research design. For the unmatched sample research design, I use a multivariate logistic regression. For the unmatched sample research design, I apply conditional logistic regression to take pairwise fixed-effects logits into account.

4.2.1. Unmatched Sample Results

In *Table 9*, I present the empirical results of the three different models using the unmatched sample research design. For all models, I can reject the hypothesis that the effect of the respective independent variables on the dependent variable equals zero (likelihood ratio chi-square coefficients of 8.46, 31.06, 43.47; $p<0.005$ in all models). McFadden's pseudo-R-square for my models is 0.018, 0.067, and 0.094. This is similar to Burns and Kedia (2006) that report pseudo-R-squares ranging from 0.017 to 0.0689.

The first observation one can make is that without any additional control variables *(Model 1)*, the coefficient of the *Proportions of Options* is positive and significant at the 1%-level. Thus, without additional control variables, *Model* 1 supports the hypothesis that CEOs' *Proportion of Options* is significantly positively associated with the likelihood of accounting fraud.

In *Model 2*, I add additional independent variables to control for size, financial performance, leverage, and CEO tenure. The coefficient of the *Proportions of Options* is significantly positive ($p<0.01$). Thus, with additional control for firm size, financial performance, and tenure, *Model 2* supports the hypothesis that CEOs' *Proportion of Options* is positively associated with the likelihood of accounting fraud.

Model 2 further reveals two statistically significant control variables that are associated with the tendency to fraudulent statements: First, the coefficient of the *Return on Assets* is negative and significant at the 1%-level. Second, the coefficient of the *Book-to-Market Ratio* is positive and significant at the 5%-level. Thus, a *higher Book-to-Market Ratio* and a *lower Return on Assets* are associated with the tendency to accounting fraud. This adds empirical evidence to the idea that financially poor-performing firms are associated with accounting fraud.

Table 9

Results of a Multivariate Logit Regression with an Unmatched Sample

	Fraud		
	Model 1	**Model 2**	**Model 3**
Proportions of Options	**1.610***** (0.56)	**1.590***** (0.60)	**1.309**** (0.60)
Ln(Marketvalue)		**0.073** (0.22)	**0.091** (0.23)
Return on Assets		**–2.777***** (0.95)	**–2.180**** (0.99)
Ln(Sales)		**0.167** (0.22)	**0.188** (0.24)
Book-to-Market-Ratio		**0.957**** (0.38)	**1.100***** (0.40)
Leverage		**0.337** (0.92)	**0.814** (0.94)
CEO Tenure		**0.032** (0.02)	**0.032** (0.02)
Industry Dummy			**1.235***** (0.35)
LR Chi2	8.455	31.059	43.476
P(Chi2)	0.004	0.000	0.000
Pseudo R2	0.018	0.067	0.094
Observations	5,314	5,314	5,314

Note. This table presents the results of a multivariate logistic regression where the dependent variable is a binary variable set to one if the firm of the underlying firm-year is accused of accounting fraud by the SEC and zero otherwise. The coefficients are in bold print and underneath are standard errors in parentheses. My sample consists of 39 fraud-firms and 5,275 unmatched firms from ExecuComp and Compustat. All variables are defined in subsection *3.2.3. Control Variables*. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

In contrast, the coefficient of *Leverage* is not statistically significant. Thus, *Model 2* does not provide empirical evidence that higher indebted firms are associated with accounting fraud. In *Model 2*, the coefficients *Ln(Marketvalue)* and *Ln(Sales)* are also not statistically significant. Therefore, *Model 2* does not provide empirical evidence that firm size is associated with accounting fraud. Because *CEO Tenure* is also not statistically significant, *Model 2* does not add empirical evidence to the idea that longer serving CEOs are more likely to commit accounting fraud.

In *Model 3*, I again control for firm size, financial performance, CEO tenure, and leverage. However, I now add an *Industry Dummy* that equals one if the firm of the underlying firm-year operates in the two-digit SIC code industry 35, 36, 37, or 73. As indicated in *Table 5*, fraud is highly concentrated in these industries. In *Model 3*, the coefficient of the *Proportion of Options* is significantly positive ($p<0.05$). Thus, under the additional control of fraud-concentrated industries, *Model 3* also provides empirical evidence for the hypothesis that there is a statistically positive association between the *Proportion of Options* and the tendency to accounting fraud.

Model 3 also reveals three statistically significant control variables. First, the coefficient of the *Return on Assets* is significantly negative ($p<0.05$). Second, the coefficient of the *Book-to-Market Ratio* is significantly positive at the 1%-level. Thus, *Model 3* also supports the idea that financially poor-performing firms are associated with accounting fraud. Third, *Model 3* reveals that the *Industry Dummy* is significantly positive ($p<0.001$). This finding suggests that industry characteristics of industries 35, 36, 36, and 73 may increase the tendency to accounting fraud.

In summary, the coefficient of the *Proportion of Options* is in all models significantly positive. Thus, for the unmatched sample, my results strongly support the hypothesis that CEOs with a higher *Proportion of Options* are more likely to commit accounting fraud. In all models, the coefficient of the *Return on Assets* is significantly negative. The models also reveal that the coefficients of the *Book-to-Market Ratio* are significantly positive. Consistent with the findings from the descriptive statistics, these findings provide empirical evidence that financially poor-performing firms are more likely to commit accounting fraud. In addition, the *Industry Dummy* is significantly positive. Thus, certain industry characteristics may also explain the propensity to fraudulent statements.

4.2.2. Matched Sample Results

In *Table 10*, I present the results of the two models using the matched sample research design. Because I apply conditional logistic regression that estimates pairwise fixed-effects logits and match exactly on two-digit SIC codes, I do not include an industry dummy *(Model 3)* in the matched sample research design. *Model 1* and *Model 2* remain the same as using the unmatched sample research design.

In *Model 1,* I exclude any additional control variable and only test for the relation between the *Proportion of Options* and accounting fraud. In contrast to the empirical results of the unmatched sample, the coefficient of the *Proportions of Options* is positive but not significant in *Model 1*. Thus, without additional control variables, the empirical results of *Model 1* do not support the hypothesis that a higher proportion of CEOs' *Proportion of Options* increases the likelihood of committing accounting fraud.

In *Model 2*, I again add additional control variables to control for firm size, financial performance, leverage, and tenure. The first observation one can make is that the coefficient of the *Proportion of Options* is significantly positive at the 10%-level. Thus, with additional control for firm size, financial performance, and tenure, *Model 2* supports the hypothesis that CEOs' *Proportion of Options* is positively associated with the likelihood of accounting fraud.

In contrast to the unmatched sample research design, *Model 2* does not reveal other significant control variables that are associated with the tendency to fraudulent statements: The coefficient of *Return on Assets* is again negative, however, not significant. The coefficient of the *Book-to-Market Ratio* is again positive, but not significant. Thus, *Model* 2 does not provide empirical evidence that a lower *Return on Assets* or a higher *Book-to-Market Ratio* are associated with the likelihood of committing accounting fraud. Therefore, *Model 2* does not support the idea that financially poor-performing firms are associated with accounting fraud.

In line with *Model 2* of the unmatched research design, the coefficient of *Leverage* is not statistically significant. Thus, *Model 2* does not provide empirical evidence that higher indebted firms are associated with accounting fraud. In the matched sample research design, the coefficients *Ln(Marketvalue)* and *Ln(Sales)* are again not statistically significant. Because *CEO Tenure* is also not statistically significant, *Model 2* does not add empirical evidence to the idea that longer serving CEOs are more likely to commit accounting fraud.

Table 10

Results of a Conditional Logit Regression with a Matched Sample

	Fraud	
	Model 1	**Model 2**
Proportions of Options	**0.926**	**2.063***
	(0.78)	(1.20)
Ln(Marketvalue)		**-0.714**
		(0.97)
Return on Assets		**-1.181**
		(2.41)
Ln(Sales)		**0.490**
		(0.65)
Book-to-Market-Ratio		**0.622**
		(1.66)
Leverage		**-0.184**
		(2.62)
CEO Tenure		**0.073**
		(0.06)
LR Chi2	1.492	13.255
P(Chi2)	0.222	0.066
Pseudo R2	0.028	0.245
Observations	78	78

Note. This table presents the results of the conditional logistic regression where the dependent variable is a binary variable set to one if the firm of the underlying firm-year is accused of accounting fraud by the SEC and zero otherwise. The coefficients are in bold print and underneath are standard errors in parentheses. My sample consists of 39 fraud-firms and their 39 matching firms matched on total assets and exact two-digit SIC codes. All variables are defined in subsection *3.2.3. Control Variables*. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

In summary, without additional control variables, the coefficient of the *Proportion of Options* in the matched sample research design is positive but not significant. However, under the additional control for firm size, financial performance, leverage, and tenure, I find that the coefficient of the *Proportion of Options* in the matched sample research design is significantly positive. Thus, although the coefficient in *Model 1* is not significant for the matched sample, my overall results support the hypothesis that CEOs with a higher *Proportion of Options* are more likely to commit accounting fraud.

In contrast to the empirical results of the unmatched sample and the univariate tests, the coefficient of the *Return on Assets* and *Book-to-Market Ratio* are not significant. Thus, my overall findings suggest, that once industry and size are controlled for using a matched sample research design, the *Proportion of Options* is the only significant predictor of accounting fraud.

5. Diagnostics and Robustness Checks

I apply several diagnostics that Stata recommends to validate that the models satisfy the assumptions of logistic regression.[6] First, I test every model for specification errors by rebuilding the model with the predicted value and the predicted value squared. In every test, the predicted value squared is not significant. Thus, my tests fail to reject the null hypothesis that there are specification errors are in the respective model. These results support the assumption that the logit of the dependent variable is a linear combination of the independent variables. Furthermore, these tests suggest to a certain extent that I choose meaningful independent variables. As an alternative link function, I also apply probit regression instead of logistic regression. Both regression designs lead to the same empirical results.

Second, I check for the goodness of fit of every model. I compare the log-likelihood chi-square and the pseudo-R-square with these of previously published papers that use similar empirical models and regression designs. For the models of the unmatched sample, I find that my pseudo-R-squares are similar to those from Chen, Wang, and Xing (2020) and Burns and Kedia (2006). For the models of the matched sample, my pseudo-R-squares correspond to those that Harris and Bromiley (2007) state. The same holds when comparing log-likelihood chi-squares.

For every empirical model of the unmatched sample research design, I apply the Pearson goodness-of-fit test with the hypothesis that there is no statistically significant difference of the observed values against the expected values (Smyth, 2003). For every Pearson goodness-of-fit test, I can reject this hypothesis. I also apply Hosmer and Lemeshow's goodness-of-fit test with ten groups. For every empirical model, this test returns large p-values. Thus, I can reject the hypothesis that the predicted frequencies and observed frequencies do not match closely. In summary, I conclude that my models fit the data well.

Third, I apply collinearity diagnostics to preclude that multicollinearity occurs in my empirical models. For every independent variable, I calculate the Variance Inflation Factor (VIF) that measures how much of the inflation of the variance could be explained by multicollinearity. For each independent variable, I find that the corresponding VIF is lower than five. These findings suggest that there is no indication for multicollinearity between the independent

[6] See https://stats.idre.ucla.edu/stata/webbooks/logistic/chapter3/lesson-3-logistic-regression-diagnostics-2/

variables. To reduce the influence of influential observations, I winsorize all variables at the 1% and 99% levels.

6. Discussion

In both, matched and unmatched sample research designs, I find evidence that CEOs' stock options are related to accounting fraud: CEOs with a higher proportion of options are more likely to commit accounting fraud. This is in line with the findings of Burns and Kedia (2006), Harris and Bromiley (2007), Feng et al. (2011), and Chen, Wang, and Xing (2020). However, my findings are contrary to these of Erickson, Hanlon, and Maydew (2006). They report that there is no consistent evidence that a firm's CEO with a higher option delta increases the tendency to accounting fraud.

Armstrong et al. (2013, p. 330) argue that mixed empirical results on the relation between CEO's stock options and accounting fraud may be due to differences in research design. In *Table 8*, I compare four important research design choices of related work (incentive measure, measure of fraud, period, and sampling method) that may explain different empirical results between my findings and these of Erickson, Hanlon, and Maydew (2006). When researchers use more than one sampling method (i.e., unmatched and matched sample), I report their findings separately.

Table 11

Detailed List of Research Design Choices and Findings of Prior Work

Paper	Incentive Measure	Measure of Fraud	Time Period	Sample	Findings
Burns and Kedia (2006)	Option Delta	GAO	1999 - 2001	Unmatched Sample	Positive Relation
Harris and Bromiley (2007)	Proportion of Options	GAO	1997 - 2002	Matched Sample	Positive Relation
Erickson, Hanlon, and Maydew (2006)	Option Delta	AAER	1996 - 2003	Unmatched Sample Matched Sample	Positive Relation No Relation
Feng, Ge, Luo, and Shevlin (2011)	Option Delta	AAER	1982 – 2005	Matched Sample	Positive Relation
Chen, Wang, and Xing (2020)	Option Delta	AA	2001 - 2015	Unmatched Sample Matched Sample	Positive Relation Positive Relation

Armstrong et al. (2013, p. 330) argue that different sampling methods may cause mixed empirical results on the relation between CEO's stock options and accounting fraud. They state that researchers that document a positive relation between CEO's stock options and fraudulent accounting techniques tend to apply an unmatched sample regression design; papers that find no relation tend to use a matched sample regression design. This holds for the findings of Erickson, Hanlon, and Maydew (2006). They document a positive relation between stock options and accounting fraud in the unmatched sample regression design. However, their overall results do not provide evidence that stock options are associated with accounting fraud.

In contrast, I find evidence that there is a link between stock options and accounting fraud in both – the unmatched and the matched sample regression design. Thus, my findings do not support the idea that empirical results depend on the sampling methods. In addition, Harris and Bromiley (2007), Feng et al. (2011), and Chen, Wang, and Xing (2020) also use a matched sample regression design and document a positive relation between option delta and accounting fraud. Thus, this suggests that a matched sample regression design is not the main reason for different empirical results.

Karpoff et al. (2017, p.1) find that different measures of fraud from different fraud databases (e.g., AAER and GAO) can cause different empirical results. Both, Erickson, Hanlon, and Maydew (2006) and I, use AAERs as a measure of fraud. Moreover, we exclude financial firms based on SIC codes 60 – 69. Feng et al. (2011) also use AAERs, exclude financial firms, and apply a matched sample regression design. They document a positive relation between option delta and accounting fraud. Thus, it seems that, in this case, the fraud database is not the main reason for different empirical results.

I use the proportion of options as incentive measure in contrast to most related work that uses option delta to consider that other parts of the total compensation do not provide executives with strong incentives to misreport. Although under the control of different independent variables, Harris and Bromiley (2007) also report a positive relation between the proportion of options and the tendency to accounting fraud. However, all other related papers (see, e.g., Burns and Kedia, 2006; Feng et al., 2011; Chen, Wang, and Xing, 2020) use option delta, similar other research design choices, and document a positive relation between stock options and accounting fraud.

Rakoff (2014, p. 5-7) reveals that there are large differences in the effectiveness of law enforcement actions throughout the 2000s. To obtain a sample period without major changes in law enforcement, e.g., 9/11 or Great Recession, I focus on AAERs issued between 2002 and 2006. In contrast to Erickson, Hanlon, and Maydew (2006) that use AAERs issued between

1996 and 2003. Rakoff (2014) argues that in 2001 the effectiveness of fraud law enforcement actions was poor because many federal agents were assigned from accounting fraud to antiterrorism units. These inconsistencies may lead to higher Type II errors (i.e., that firms applied fraudulent accounting techniques, however, are not detected by the SEC) in 2001 and dilute prior empirical results. In summary, despite the incentive measure and the sample period, my research design is like this of Erickson, Hanlon, and Maydew's (2006). Thus, these findings suggest that my research design with the proportion of options and a consecutive sample period without major changes in law enforcement seems to explain the different empirical results.

Previously published papers often find other significant predictors of accounting fraud in firms' characteristics and financial performance. For instance, Burns and Kedia (2006) report that firms with a higher market value of equity and higher leverage are more likely to commit accounting fraud. Erickson, Hanlon, and Maydew (2006) also state that a higher leverage is a significant predictor of accounting fraud. Harris and Bromiley (2007) find that firms with a lower negative social performance are related to accounting fraud. Chen, Wang, and Xing (2020) report that a higher book-to-market ratio is associated with accounting fraud. In contrast to these findings, I do not find constant empirical evidence for other significant predictors of accounting fraud. Thus, my overall findings do not support the theory that financially unstable or low-performing firms are more likely to apply fraudulent accounting techniques. Furthermore, I do not find empirical evidence that a longer CEO tenure is associated with accounting fraud. In conclusion, my findings suggest that once controlled for industry and size, the proportion of options is the only significant predictor for accounting fraud.

Most previous research finds that CEOs with a higher option delta are associated with accounting fraud. I advance prior literature in the way that I show that CEOs receiving a higher proportion of options are also more likely to commit accounting fraud. The proportion of options is the fraction of the value of options over total compensation. Thus, given an equal amount of other compensation components, a higher value of options increases the likelihood of accounting fraud. At this point, further research is needed on the proportion of other compensation components on the total compensation. For instance, further studies should control for the proportion of accounting based short-term bonus or the proportion of stock holdings. The generalizability of my results is, among other accounting fraud research, limited by the unknown Type II error. The dark figure of the number of fraudulent accounting techniques is presumably higher than the number of cases detected by the SEC.

7. Conclusion

The manipulation of financial statements often increases the stock price (see, e.g., Burns and Kedia, 2006). A higher stock price, in turn, increases the value of the CEO's stock options (see, e.g., Murphy, 1999, p. 2510). The value of an option at maturity is non-linear in the stock price: Option holders benefit from stock price increases unlimitedly. In contrast, when fraud is detected, the losses of options due to stock price declines are limited. To add empirical evidence on this theory, various scholars test the relation between stock options and accounting fraud. The majority finds a positive relation between a higher option delta and the tendency to accounting fraud (see, e.g., Burns and Kedia, 2006; Feng et al., 2011; Chen, Wang, and Xing, 2020).

Unlike most previously published papers that use CEOs' option delta, I focus on the CEO's proportion of options as incentive measure. I conjecture that other parts of a CEO's total compensation, e.g., base salary, do not provide CEOs with powerful incentives to manipulate financial statements (see, e.g., Burns and Kedia, 2006; Murphy, 1999; Ryan and Wiggins, 2000). Thus, I infer that the proportion of options on the total compensation is crucial for incentives to manipulate: If managers receive only a small proportion of their compensation in options, the positive effect of increased stock prices through fraudulent statements on their wealth is smaller. This decreases, in turn, the incentives for manipulation (see Harris and Bromiley, 2007). If a large proportion of a CEO's compensation is paid in options, the positive effect of increased stock prices by fraudulent statements on their wealth is higher.

To add empirical evidence on this hypothesis, I use an unmatched sample and a matched sample research design. The final unmatched sample consists of 5,275 firm-years for which data are available on ExecuComp and Compustat. To construct the matched sample, I match for every fraud firm another firm based on size (i.e., total assets) and exact two-digit SIC codes. In both research designs, fraud is the binary dependent variable that equals one if the firm of the underlying firm-year is accused of fraud. I define the independent variable, the proportion of options, as the CEO's total value of stock options divided by the CEO's total compensation. In both research designs, I include further independent variables to control for company size, financially low-performing firms, higher indebted firms, and CEO tenure. In the unmatched sample research design, I also include an industry dummy to control for industries in which fraud is concentrated.

My descriptive statistics reveal that fraud is highly concentrated in the manufacturing and business services industries. Regarding gender and age, I find that the average fraud firm's CEO is 55 years old and male. When comparing descriptive statistics of the independent variables, I find that fraud firms' CEOs have a noticeable higher proportion of options than CEOs from the matched and unmatched sample. This indicates that accounting fraud coincides with a larger proportion of options. Fraud firms, on average, have a lower return on assets and a higher book-to-market ratio than the matched and the unmatched sample. These findings suggest that fraud firms' average financial performance is poorer compared to the matched and unmatched sample.

In the unmatched sample regression design, the coefficient of the proportion of options is in all models significantly positive. Thus, for the unmatched sample, my results strongly support the hypothesis that CEOs with a higher proportion of options are more likely to commit accounting fraud. In the matched sample research design, without additional control variables, the coefficient of the proportion of options is, under the additional control for firm size, financial performance, leverage, and tenure, significantly positive. In contrast to the empirical results of the unmatched sample and the univariate tests, the coefficient of the return on assets and the book-to-market ratio are not significant. Thus, my overall findings suggest, that once industry and size are controlled for using a matched sample research design, the proportion of options is the only significant predictor of accounting fraud.

My results should be taken into account when firms and their respective board of directors consider how to compensate CEOs. Firms may aim to compensate managers in options to align their wealth on the company's performance and solve the principal-agent problem between shareholders and managers. On the other hand, companies should watch carefully because a high value of options relative to the total compensation increases the risk that CEOs apply fraudulent accounting practices to increase their personal wealth.

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Appendix

Appendix A

Distribution of Fraud Firms by Year

Fyear	Frequency	Percentage
2002	29	74.36%
2003	6	15.38%
2004	3	7.69%
2005	1	2.56%

Ehrenwörtliche Erklärung

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbstständig angefertigt habe. Die aus fremden Quellen direkt und indirekt übernommenen Gedanken sind als solche kenntlich gemacht.
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