FINANCIAL STATEMENT CONFORMANCE TO BENFORD'S LAW AND AUDIT FEES

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I certify that the substance of this thesis has not already been submitted for any degree and is not currently being submitted for any other degree or qualification. I certify that any help received in preparing this thesis and all sources used have been acknowledged in this thesis.

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Contents

Abstract

Auditors assure the fairness of financial statements for company stakeholders. Audit effort to minimise errors leads to higher audit fees. The reduced audit fees in the United State cause company stakeholders' concern on audit quality. A reliable method used in other fields, Benford's Law, may assist auditors to identify errors from data manipulation and accounting irregularities. This research investigates whether using Benford's Law can reduce audit risk and improve audit outcomes, using a sample of U.S. companies between 2000 and 2014. I empirically examine whether the FSD_Score based on the Kolmogorov-Smirnoff statistic (maximum deviation between empirical digit distribution and Benford's Law distribution) and the mean absolute deviation is an important determinant of audit fees. Validation tests are conducted to test the conformity with Benford's Law in my samples. Audit fee models are used to investigate the association between FSD_Score and audit fees. Evidence from validation tests indicates that numbers in financial statements closely conform to Benford's Law. I find a negative and significant association between FSD_Score and audit fees, inconsistent with the hypothesis that audit fees increase with FSD_Score because high FSD_Scores reflect high litigation risks. I also find that the association between FSD_Score is stronger in smaller firms than in larger firms. Results from audit fee models and additional tests suggest that FSD_Score can be used as a measure of audit quality instead of litigation risk.

1. Introduction

Accurate financial reporting contributes to the efficiency of capital markets and assets allocation (Bushman and Smith, 2003). The quality of financial data is always the concern of different market parties, such as companies, investors and regulators (Amiram et al., 2015). Another main player closely associated with the quality of financial report is the auditors. The auditor's primary responsibility is to obtain reasonable assurance about whether the financial statements are free of material misstatement (e.g. in the US: SAS, AU Sec 110, 1972).

Meanwhile, auditors are held liable for undetected material misstatement and for the losses of the client's stakeholders. In order to reduce such litigation risk, auditors need to undertake sufficient audit effort to maintain a high quality audit (Defond and Zhang, 2014). High audit effort is associated with high audit fees which are normally charged by the hour.

However, audit fees in the United States have experienced a decline due to the increase of market competition in the last decade and this causes wide concern among companies' stakeholders. There are tools via the internet for managers to search for lower audit fees and firms are willing to switch to the auditor that offers lower fees. Under the pressures of market competition, audit fees to clients' revenue ratio have decreased from $594 for audit fees per $1 million of revenue in year 2004 to $479 for audit fees per $1 million revenue in year 2013 (Audit Analytics, 2014).

In response to companies searching for audit services with low fees, regulators and members of the public have expressed concern about audit quality. A study (Christensen et al., 2014) shows that a 29% higher possibility of restatement occurs in firms associated with a relatively higher risk of accounting irregularities and lower audit fees. Furthermore, the number of restatements has decreased from the peak of 1842 in year 2006 to 831 in year 2014 (Audit Analytics, 2015). The SEC (U.S. Securities & Exchange Commission) considers that the decline of restatement cases may be due to lack of focus and reduction of detection ability. So the SEC announced in late 2013 that it would refocus on accounting fraud and created a Fraud Task Force to enforce the investigations (SEC, 2013).

Previous academic literature (Dechow et al., 2010; Owens et al., 2013; Defond and Zhang, 2014) highlights the limitations of current proxies of audit quality and measures of financial report errors, such as accruals-based models (e.g. Jones 1991; Dechow et al., 2011) and ratio models (e.g. Beneish, 1999). These measures are influenced by firm characteristics, rely on historical or forecasting data, do not capture subtle variations, and are inconsistent between different models (Dechow et al., 2010; Owens et al., 2013; Defond and Zhang, 2014). Amiram et al. (2015) have shown the advantages of the application of a mathematical theory, Benford's Law (1938), on financial report analysis. They introduce FSD_Score, which is the deviation between empirical distribution of the leading digit of the numbers in financial statements and Benford's distribution, to detect financial statement errors. As financial statements are a joint product of both company reporting and the audit process, the level of financial statement errors reflects the quality of auditing. Thus FSD_Score could be useful in audit research.

Audit quality is significantly associated with audit effort. Audit fees, as a direct measure of audit effort, are one of the frequently studied areas in audit research. Current audit fee models frequently use the measures of earnings quality to investigate the association between audit fees and litigation risk. However, most of these factors are influenced by a firm's business environment and financial performance. Furthermore, the measures of earnings quality focus on the misstatement of earnings and cash flow. They ignore other errors that appear in financial statements. As a result, current audit fee models may be incomplete.

In this study, I investigate the link between FSD_Score and audit fees and aim to reveal the association between audit quality, litigation risk and audit fees, and to improve current audit fee models. Furthermore, the study also aims to provide evidence on whether FSD_Score is a good alternative to existing measures of audit quality and litigation risk, and whether it can assist the SEC and auditors in evaluating audit effort and estimating litigation risk.

Audit quality, litigation risk and audit fees have been of great concern to academics, auditors and regulators. One unsolved problem is how to measure audit quality and litigation risk directly and accurately (DeFond and Zhang, 2013). Current research often uses different proxies to estimate the quality of auditing and the possibility of litigation risk (DeFond and Zhang, 2013). The measures of earnings quality are one of the important proxies of audit quality and litigation risk because the main responsibility of auditors is to ensure the quality of financial statements (United States General Accounting Office, 2012). Financial statements aim to report the performance of a company, and earnings is one of the most important indicators of a company's performance. Yet managers are found to manipulate the earnings numbers in financial reports to maintain earnings at close to market expectations (Hayn, 1995; Burgstahler and Dichev, 1997). While material misstatements remain in the audited financial statements, auditors are liable to be the subject of the litigation of such misstatement. Thus, earnings quality has been frequently used as a measurement of audit quality and litigation risk.

Earnings management models occupy one of the most important areas of earnings quality. Evidence shows that earnings management models are significantly related to earnings manipulation and business failure (Beneish, 1999; Jones et al., 2008). However, some researchers argue that the detection ability of earnings management models has been reduced due to design disadvantages in the models and the improvement of earnings management techniques (Amiram et al., 2015, Henselmann et al., 2015).

In order to improve earnings management models and the detection ability of existing tools, researchers tend to find alternative methods to measure the estimation of accounting irregularities and errors. In this respect, FSD_Score is an important breakthrough. FSD_Score calculates the deviation between the leading digit distribution of the numbers in financial statements and Benford's theoretical distribution (Amiram et al., 2015). Benford's distribution (1938) is a mathematical tool that has been used to detect data manipulation in different areas such as survey data, medical data and election data. Based on the analysis of large and various data sets, Benford (1938) establishes that a theoretical distribution of the first digit in random data will generally conform to, but made-up data do not follow, the distribution. When the distribution in a sample is significantly different from the theoretical distribution, there is a high possibility that the data are manipulated. Evidence further suggests that

Benford's Law is effective in examining the possibility of manipulation in financial data (Nigrini and Mittermaier 1997; Aono and Guan, 2008; Nigrini, 2012; Amiram et al., 2015).

FSD_Score calculates the deviation between the first digit's distribution of the numbers in financial statements and Benford's distribution. The greater the FSD_Score, the higher the possibility of accounting errors and irregularities occurring in the sample financial statements (Amiram et al., 2015). In addition, the results in Amiram's study (2015) reveal that FSD_Score is consistent with irregularity indicators and audit quality proxies. So FSD_Score could be used as an alternative tool to measure the level of accounting irregularities and auditing quality.

Accounting irregularity and error in financial statements reduce the quality of auditing and are important factors in evaluating litigation risk. This strongly influences audit effort and audit fees. The possibility of accounting irregularities and errors in financial statements also increases auditors' litigation risk. To reduce litigation risk, auditors will increase audit effort to collect sufficient evidence to support their audit opinions. Additional audit effort will increase audit fees. Consistent with this expectation, empirical evidence shows a positive and significant association between litigation risk and audit fees (Simunic, 1980; Houston et al., 1999; Bedard and Johnstone, 2004).

Even though large amounts of research have investigated litigation risk and audit fees, the factors related to litigation risk often fail to identify the influence of a firm's business environment and financial performance, which leads to misclassification of accounting irregularities and abnormal performance. Meanwhile, these factors ignore the errors that appear in financial statements other than in earnings numbers. Thus, a more accurate measure of litigation risk is needed to improve current audit fee models.

Furthermore, only a few studies analyze FSD_Score. Whether FSD_Score is an efficient and accurate measure of litigation risk and audit quality and whether FSD_Score is associated with audit fees are unknown. Thus, empirical studies are needed to enhance the evidence in the application of FSD_Score on the detection of accounting irregularities and errors as well as the relationship between FSD_Score and audit fees.

This study contributes to the literature in the following ways: First of all, this study is the first to analyze the association between FSD_Score and audit fees. The results of the study can also be used to improve existing audit fee models. Furthermore, the finding of this study will reveal whether auditors and regulators can use FSD_Score as an indicator of the level of litigation risk and the quality of auditing in practice. Thirdly, Amiram et al. (2015) only examine the FSD_Score between 2001 and 2011. This study provides empirical evidence of the application of FSD_Score in the financial data between 2000 and 2014 for further research.

Amiram et al., 2015, suggest FSD_Score measures the level of accounting errors and irregularities in financial statements. Higher levels of accounting errors and irregularities increase the litigation risk auditors are taking. Furthermore, auditors tend to put additional effort into their audit work, which will raise audit fees, to reduce litigation risk to an acceptable level. Thus, the greater the value of FSD_Score is expected to be associated with higher audit fees.

To test the association between FSD_Score and audit fee, I use the available data in WRDS (Wharton Research Data Services) between 2000 and 2014. I first calculate the FSD_Score based on KS (Kolmogorov-Smirnov, the maximum accumulative deviation) and MAD (mean absolute deviation) statistics, following Amiram's study (2015). FSD_Score based on the KS statistic is sample size sensitive with a critical value at a significant level of 5% which is decided by the sample size itself. FSD_Score based on the KS statistic is used to investigate whether the first digit's distribution of individual firm-year's financial statement numbers conforms to Benford's distribution. FSD_Score based on the MAD statistic is insensitive to size, so it can be used to compare observations. Therefore, FSD_Score based on the MAD statistic is applied in the audit fee models to test the association between FSD_Score and audit fees.

A validation test of Benford's Law is conducted before applying FSD_Score in the audit fee models. The validation test utilizes the FSD_Score based on the KS statistic to investigate whether individual firm-year observation conforms to Benford's Law at a 5% critical level. Only if the numbers in financial statements conform to Benford's Law in general, the further tests on FSD_Score would be useful.

The audit fee models used in this study follow prior audit fee models that use the natural log of audit fees as the dependent variable. FSD_Score based on the MAD statistic is the test variable. Other variables, such as client size, inherent risk, profitability and auditor size, all of which are found significant associations with audit fees, are included in the model to control other factors driving audit fees.

The results of the validation test show that 85.79% of individual firm-year observations conform to Benford's Law at a 5% significant level between fiscal year 2000 and 2014. All conformity rates in each fiscal year and each sector are over 85%. These results demonstrate that financial statements data follow Benford's Law closely.

However, the results of audit fee models are inconsistent with the hypothesis. I find a negative and significant, at 1% level, association between FSD_Score and audit fees. It indicates that the observations with higher FSD_Score are more likely to pay lower audit fees. One possible reason is FSD_Score measures the quality of audited financial statements instead of the litigation risk that auditors take. When auditors put more audit effort in audit procedures, less accounting errors and irregularities will remain in the audited financial statements. Financial statements with lower level of accounting errors and irregularities should conform to Benford's Law more closely, thus have lower FSD_Score. Therefore, lower FSD_Score is associated with higher audit fees due to higher audit effort. A high FSD_Score, in contrast, may indicate insufficient audit effort.

The remainder of the paper is structured as follows. Chapter 2 introduces the foundations and applications of Benford's Law and FSD_Score in the first section, and reviews the literature on audit fees research. In Chapter 3, I discuss the method to validate the conformity of Benford's Law and the models to investigate the association between FSD_Score and audit fees. Chapter 4 presents the samples used in the study and descriptive statistics. In Chapter 5, I report the results in this study and give a brief explanation of the results prior to the discussions and conclusions in Chapter 6.

2. Literature Review

2.1. Introduction

FSD_Score was introduced by Amiram et al. (2015) so recently that it has not received much attention yet and Benford's Law is also not widely used in audit research. However, the literature on auditors' litigation risk and audit fees is very extensive. An exhaustive review of the literature is thus beyond the scope of this work.

The aim of this chapter is to provide a detailed introduction to Benford's Law, FSD_Score and their applications to financial data in the existing literature. It further establishes, through selective reference to some of the literature, a clearer understanding of the associations between FSD_Score, litigation risk and audit fees. There is discussion on the disadvantages of current litigation risk measures that have been drawn from the empirical evidence. A hypothesis is developed based on the discussion of the prior literature.

The chapter is divided into three parts. The subject of the first is the introduction of Benford's Law, FSD_Score and their applications to financial data. The second part highlights the association between litigation risk and audit fees. The remainder of the chapter is devoted to the explanation of the hypothesis in this study.

2.2. Background

Auditing is the examination of the accounting information and documents of an organization to ensure the annual report of the organization follows the requirements of accounting standards and reflects the financial position of the organization in a fair view. It is an important process to protect outsiders from the damage of financial fraud and information risk.

In all public trading markets, listed companies are required to provide an audited annual report. Apart from the requirement for being listed in the market, high quality auditing is not just to detect the violation of accounting standards, but also to consider how well the annual report maps the financial position of the organization (DeFond and Zhang, 2014). For example, research has shown that auditing can affect the market value of an organization (Menon and Williams, 2010), reduce the cost of debt (Simunic et al., 2011) and increase forecast accuracy by managers of an organization (Clarkson, 2000), and that voluntary auditing would improve the credit ratings of an organization (Lennox and Pittman, 2011).

The main focus of audit quality is the quality of financial statements. The Government Accountability Office (2003) points out that "a high-quality audit is one performed in accordance with generally accepted auditing standards (GAAS) to provide reasonable assurance that the audited financial statements and related disclosures are (1) presented in accordance with generally accepted accounting principles (GAAP) and (2) are not materially misstated whether due to errors or fraud." Thus, it is the auditor's primary responsibility to ensure financial statements are reliable and free or material misstatements.

If auditors fail to detect material misstated information in financial statements, they are liable for fail to detect misstatement in their clients financial reporting. Thus, auditors face high risks by issuing low quality audit report. In an extreme case, failure could lead to the bankruptcy of even a very large audit firm, as happened with Arthur Andersen over Enron in 2001. Furthermore, during the period of the Enron scandal, other Andersen clients also suffered with negative market reactions mainly due to loss confidence by the market (Claney and Philipich, 2002; Cahan et al., 2009; DeFond and Zhang, 2014).

The main risks of such failures include the audit risk of undetected misstatements and the litigation risk of liability for the losses of a client's stakeholders. Audit risks are mainly accessed by field work evidence and audit risk models. In order to reduce audit risk to acceptable levels, auditors enforce audit procedures to test their clients' accounting systems and to apply professional judgment. Under the pressure of cost-effectiveness, auditors tend to apply minimum effort to meet GAAS (generally accepted auditing standards) (Brumfield et al., 1983). Thus, before planning an audit procedure, auditors will apply an audit risk model to access the audit risk of a specific client.

The audit risk model is used to estimate the audit risk based on client financial statement information and accounting systems. It includes inherent risk, control risk and detection risk. Inherent risk refers to material error in a client's accounting process; control risk refers to material error that has not been detected by a client's internal control system; detection risk refers to the material error that has not been detected by the audit procedure (Brumfield et al., 1983; Colbert, 1987). Audit risk mainly focuses on material error in client financial statements and accounting systems.

By contrast with audit risk, litigation risk associates with factors in client operational environments and is more difficult to measure. The main factors here include the economy, the industry, management philosophy, audit history, financial position and performance, existing litigation and public ownership (Brumfield et al., 1983). The decline of business environment or financial performance increases managers' intensity of irregular behaviours. This will further increase the probability that an audit firm is held liable for the loss of client stakeholders using inaccurate financial information (Brumfield et al., 1983; Houston et al., 1999).

Litigation risks are difficult to measure and foresee and have been a great concern for auditors and audit firms. Litigation risk refers to the damages claims against auditors for the proportion of their fault or up to the full amount of the stakeholders' losses, depending on the relevant damages award regime. This liability could lead to the failure of an audit firm, such as the Andersen collapse. Therefore, litigation risks are main considerations in audit planning.

In order to reduce risks to an acceptable level, auditors will put afford into audit process. The higher the estimated risk, more afford is needed in auditing, higher service fees will be charged. In recent years, audit fees has reduced in the American market, while there is no evidence shows audit risks have declined. Thus regulators and financial statement users are concerned about the quality of auditing due to the reduced audit fees.

2.3. Detection of Accounting Errors and Irregularities and FSD_Score

2.3.1. Reduced Detection Ability of Accounting Irregularities

Further to continue previous discussion, achieving high quality audits is important to audit firms because of the consequences of and possible liability for undetected material misstatement. Financial statements are the main product of the audit process, and the quality of audit relates mainly to the quality of financial statements. However, the quality of financial reporting is difficult to measure. Even though there are various proxies to measure audit quality, most of them are related to market perception, independence and auditor characteristics. Only a few proxies directly focus on the quality of financial statements, such as the measures of earning quality (DeFond and Zhang, 2014). The majority of these measures of earnings quality attempt to detect accounting irregularities and fraud, such as the Jones model (1991), the Dechow and Dichev model (2002) and the ratio model (Beneish, 1999).

Evidence shows that earnings quality measures have significant association with the manipulation and/or the failure of businesses. Beneish (1999) points out that the M-score based on the ratios of certain accounts between current year and prior years is significantly higher on earnings manipulators prior to public discovery. Dechow et al. (1996) reveal that discretionary accruals are associated with AAERs (Accounting and Auditing Enforcement Releases). Jones et al. (2008) provide evidence that the Jones model (1991), Dechow and Dichev model (2002), Beneish model (1999) and McNichols model (2002) are significantly associated with cases deemed fraudulent by the SEC.

However, researchers have argued that the detection ability of existing models has reduced over time (Amiram et al., 2015). First of all, the number of accounting restatement cases at the SEC has been reduced over time although Dichev et al.'s (2013) survey of 169 CFOs of public companies and in-depth interviews of 12 CFOs shows that an estimated 20% of companies still engage in earnings management (Dichev et al., 2013) and 65% of companies recognize accounting manipulation as an important risk (KPMG, 2009). One possible reason for the contrast between decreased restatement cases and a high percentage of earnings management activities is that current detection models have been studied for a long period of time. Accounting manipulation techniques are expected to improve in order to avoid detection by the various models. Another reason could be that some detection models, such as accruals-based models, are not accurate in measuring companies operating in a complex business environment, and they frequently misclassify those companies as having a high possibility of accounting manipulation.

2.3.2. FSD_Score and Benford's Law

Similar to other earnings quality measures, FSD_Score reflects the possibility of errors and irregularities in financial statements (Amiram et al., 2015). However, in contrast to other accounting irregularity detection models, Benford's Law does not build on the accounting concept behind financial statement numbers, but simply examines the frequency of the digits in the numbers. Benford (1938) examines the distribution of the digits in large numbers of samples of random numbers and weakly dependent numbers. Random numbers refers to randomly collected and independent numbers, such as numbers shown on the covers of magazines. Weakly dependent numbers may be collected from related areas or subjects, and for this reason there is a weak association between these numbers. An example is numbers in a table in an engineering handbook. Benford (1938) notes that the digit frequencies in a set of numbers follow a pattern—low digits appear more frequently than high digits.

To be specific, the frequencies of a number, in a random data set, which has a first digit, d_1, second digit, d_2 ... the nth digit, d_n is:

$P(d_1) = \log(1 + 1/d_1)$; $d_1 \in \{1, 2 \ldots 9\}$.

$P(d_2) = \sum \log(1 + 1/d_1 d_2)$; $d_1 = 1$, $d_2 \in \{1, 2 \ldots 9\}$

$P(d_1 d_2) = \log(1 + (1/d_1 d_2))$; $d_1 d_2 \in \{10, 11 \ldots 99\}$

where $P(d_1)$ is the frequencies of digits d_1 in the first place of the number, $P(d_2)$ is the frequencies of digits d_2 in the second place of the number, $P(d_1 d_2)$ is the frequencies of two digit $d_1 d_2$ in the first and second place of the number (Nigrini and Mittermaier, 1997, pp.54).

For example, the frequency of digit 1 appearing at the first place of a number is $P(1) = \log(1 + 1/1) = \log 2 = 0.3010$. The possibility that digit 2 appears at the first place of a number is $P(2) = \log(1 + 1/2) = \log 1.5 = 0.1761$. The theoretical distribution of $P(d_1)$ is shown in Table 2-1.

Table 2-1 Benford's Distribution

Digit	1	2	3	4	5	6	7	8	9
Theoretical Distribution	0.3010	0.1761	0.1249	0.0969	0.0792	0.0669	0.0580	0.0512	0.0458

Table 2-1 reported the theoretical distribution of Benford's Law.

2.3.3. The Applications of Benford's Law

Evidence shows that Benford's distribution applies to a wide variety of number sets. For example, numbers appear in newspapers, population statistics, addresses, area codes, cost data, electricity bills, engineer menus, stock prices and financial statements (e.g. Benford 1938; Nigrini and Mittermaier, 1997; Judge and Schechter 2009; Amiram et al., 2015). When the digit distribution of a sample is significantly different to Benford's Law, there is a high possibility that the data in the sample has been manipulated. Moreover, as a result of the development of computer science, most of the data are now available in digital format, so the distribution of the first digit of the numbers in a data set is easy to calculate by computer. Thus, the applications of Benford's Law in the detection of data manipulation have increased and have spread into different areas.

One significant application of Benford's Law is in analyzing survey data. Judge and Schechter (2009) apply Benford's Law to examine some survey data from Paraguay. The results show that when the crops are significant to the income of the family, the first digit distribution of the data follows Benford's Law closely. When the crops are not important to the family income, the data has greater deviation from Benford's Law. Judge and Schechter (2009) suggest that the data on the non-important crops are made up because the farmers who participated in the survey did not have clear information about the non-important crops. In addition, the data collected under the supervision of academic researchers appear to more closely match Benford's Law distribution than the data collected by government or international agencies. Furthermore, the data collected in the United States more closely follow Benford's Law than those collected in developing countries such as Mexico and Pakistan. Judge and Schechter (2009) conclude that Benford's Law is useful to validate raw survey data and that researchers should examine the quality of survey data before they spend time and effort on analyzing them.

More closely related to this study, Benford's Law has been increasingly used in recent years to examine manipulation of financial data. Even though financial data are not randomly collected, a logical explanation of this pattern is to consider sales starting with $100 having '1' as the first digit. The first digit will remain '1' until the sales grow 100% to $200. After that, in order to increase the first digit from '2' to '3', sales only need to increase 50% from $200 to $300. As the sales increase, a declining percentage is needed for the first digit to change from one to another. When sales reach $900, only 11.1% growth is needed for the first digit to change from '9' back to '1' when sales achieve $1,000 (Nigrini and Mittermaier, 1997). Benford's Law applies to numbers with similar circumstances, such as market value, expenses and net incomes.

One major application of Benford's Law on financial data is in assisting auditing procedures. Benford's Law has been used to assist internal auditors in discovering fraud (Nigrini, 2012) and to help external auditors plan auditing procedures (Nigrini and Mettermaier, 1997; Durtschi et al., 2004; da Silva and Carreira, 2013) and detect accounting irregularities (Carslaw, 1988; Aono and Guan, 2008).

Nigrini and Mittermaier (1997) suggest the application of Benford's Law to audit analytical procedures. In addition, prior evidence shows that invented numbers did not follow the distribution of Benford's Law on Chi-square and Kolmogorov-Smirnoff tests (Hill, 1988). Nigrini and Mittermaier (1997) further show that even if a bookkeeper is trying to create an authentic-looking number, it is extremely difficult to create accounting numbers following Benford's Law distribution. Thus, Nigrini and Mittermaier (1997) encourage auditors to test risky accounting data using the first digit, second digit, first two digits or last two digits in the planning stage of auditing to identify suspicious areas.

Following Nigrini and Mittermaier's (1997) study, Durtschi et al. (2004) reveal that 'transaction-level' data, such as receivable, payable, disbursements, sales or expenses, conform to Benford's Law. Examining the deviation of accounting data from Benford's Law can assist auditors in identifying fraud symptoms and highlighting suspicious areas instead of using randomly selected samples to apply auditing procedures. In recent years, da Silva and Carreira (2013) have advocated that auditors apply more complex techniques, such as Benford's Law, in selecting audit samples.

In addition to the audit planning process, Benford's Law is also applied to detect accounting irregularities. Based on the '1.99 pricing theory' in marketing, Carslaw (1988) and Aono and Guan (2008) argue that managers would round up the income as investors would consider \$200 million to be significantly higher than \$199 million. Carslaw (1988) reveals that, compared with Benford's distribution, there is a higher frequency of 0's, but a lower frequency of 9's in the second digit of net income in companies that reported losses. Similarly, Aono and Guan (2008) show that there are notably more 0's and fewer 9's in the second digit of net income in pre-SOX financial statements than in post-SOX financial statements.

Moreover, Aono and Guan (2008) discuss two advantages of using Benford's Law to examine earnings management. First, Benford's Law does not require the estimation of potential "noisy abnormal accruals" (Anon and Guan, 2008, p. 206). Secondly, Benford's Law is not based on different assumptions about managers' incentives and practical methods in earnings management. Thus, Benford's Law is easy to apply and efficient for testing large amounts of financial data.

2.3.4. Establish FSD_Score and Empirical Evidence

The detection ability of Benford's Law on the level of errors in financial statements has been brought to the attention of researchers in recent years. Similar to the discussion in Aono and Guan (2008), Amiram et al. (2015) highlight that Benford's Law does not depend on the economic and industrial baseline of a company's operational environment, and that it is unlikely that managers are able to alter the manipulated accounting numbers to follow Benford's distribution.

Amiram et al. (2015) also argue that the numbers in financial statements, as well as the cash flow from different parties involved in the business, are the result of high quantities of transactions within the current financial year and previous years. Thus, the first digit of the numbers can be considered to be randomly generated. Furthermore, the numbers in financial statements contain multiple orders of magnitude. These numbers are likely to satisfy the condition of using Benford's Law (Amiram et al., 2015).

Evidence shows that the first digit of all 10-K financial statements numbers in a 10-year period follows Benford's Law (Amiram et al., 2015). Amiram et al. (2015) further analyze the association between FSD_Score and other accounting irregularity indicators, such as information asymmetry, abnormal accruals predictability of fraud, and audit quality measures like restatement, loss and AAER. The results show that FSD_Score has a positive relation with information asymmetry and a negative association with earnings. In addition, significant differences in FSD_Score are captured between firms that announce restatement and that do not announce restatement, between firms having positive and negative net income, and between firms not identified by the SEC and identified by it as having material misstatement in financial statements (AAER indicator).

Similarly with Amiram et al. (2015), Henselmann et al. (2015) notice a higher degree of deviation between empirical distribution and Benford's distribution in the financial statements of companies around the earning benchmark. One argument highlighted by Henselmann et al. (2015) is the difficulty of manipulating accounting numbers to comply with Benford's Law due to the double entry system. Each manipulated number will influence at least two numbers in the financial statements. This argument is consistent with prior findings that show that manipulated accounting numbers do not follow Benford's Law distribution even if bookkeepers try to follow it (Nigrini and Mittermaier, 1997). Thus, firm level digit deviation is a useful indicator of accounting irregularities.

As the evidence suggests, the deviation between sample distribution and Benford's distribution reflects the possibility of manipulation and errors. The results apply to not only various random number sets, but also to financial data. The application of Benford's Law to financial data captures the possibility of accounting irregularities and the level of errors in financial statements. It can be used to assess the quality of financial information. Moreover, as FSD_Score includes all numbers in the financial statements instead of certain accounts, it is expected to capture not only the quality of earnings, but also the quality of the whole financial statement. Thus, compared with the measures of earnings quality, FSD_Score maybe a more appropriate proxy for audit quality.

2.4. Litigation Risk and Audit Fees

2.4.1. Litigation Risk

Following on from the foregoing discussion, FSD_Score reflects the possibility of manipulation and errors in financial statements. An auditor's main responsibility is to detect accounting irregularities. If financial statements include a high possibility of manipulation and misstatement, the risk of liability for future litigation costs will increase at the same time. Thus, FSD_Score can also be used as the measure of auditors' litigation risk.

In the process of audit pricing, litigation risk is a principle component (Simunic and Stein, 1996). In his seminal work, Simunic (1980) establishes a model to investigate the determinants of audit fees. The model is under the assumption that audit planning is driven by litigation liability because auditors are liable for the losses of their clients' stakeholders caused by using erroneous or misleading financial statements (Cassell et al., 2011).

Potential legal liabilities against auditors include both criminal and civil offences. Criminal offences occur when individuals or organizations breach a government imposed Law, for example against fraud and insider trading. Auditing is also subject to the legislation prescribed by the U.S. Companies Act 2006. The U.S. Companies Act 2006, Section 507 regulates "who can be an auditor, how auditors are appointed and removed", and the functions of auditing, including "any matter that is misleading, false or deceptive in a material particular" (s.507). Under the Law of Tort, auditors can be sued for negligence if they breach a duty of care towards their client's stakeholders who suffer financial loss due to undetected material misstatements.

Litigation risks associated with the future loss of a client's stakeholders from relying on misleading financial statements are difficult to estimate and foresee. The amount of such liability will also significantly affect auditors' wealth and operation in influencing cases, such as Enron's collapse. So, to reduce their litigation risk, auditors tend to put in more effort, based on professional judgment and audit risk assessment, than what is necessary to satisfy GAAS. The additional work due to litigation risk will increase audit investment, which will increase audit fees.

The underestimation of litigation liability could cause significant loss or even bankruptcy for an audit firm. Audit firms face uncertain profitability due to the increasing litigation risk. Since audit firms are fully or proportionally liable for the losses of financial statements users if they are misled by inaccurate financial information, such litigation liability may lead to bankruptcy for audit firms if auditors do not have sufficient assets and/or less risky clients to cover their losses (Simunic and Stein, 1999). Therefore, litigation risk significantly affect audit planning and pricing.

2.4.2. Litigation Risk and Audit Fees

Consistently with the assumption that audit planning is driven by litigation risk, prior audit literature reveals a positive association between litigation risk and audit fees. Simunic considers audit services as an economic good to both auditees and auditors. The prices of audit services are driven by the economic benefits "which are in the nature of liability avoidance" (Simunic, 1980, p. 162), and economic costs of auditors, which are in the form of auditing hours.

Building on Simunic (1980) and Simunic and Stein (1999)'s investigation, numerous studies examine the relationship between audit fees and various client characteristics in proxying for the auditors' litigation risk. Consistently, these studies present strong empirical evidence that audit fees are significantly associated with indicators of client risk such as the change of accounting choices (Houston et al., 1999), positive (income-increasing) abnormal accruals (Heninger, 2001) and annual restatements (Kinney et al., 2004).

Houston et al. (1999) investigate the conditions in which accounting choices influence the auditor's assessment of audit and litigation risk. They argue that material misstatements are caused by two different factors: errors and irregularities. Auditors not only face the risk of failing to detect unintentional misstatements caused by errors; but they are also responsible for the losses incurred by client stakeholders due to the use of intentional misstatements of irregularity. However, the audit risk model, which is used to estimate the audit risk based on clients' financial statement information and accounting systems, primarily examines the audit risk related to the errors made by clients, but departs from the factor of irregularities. Using an experimental design, Houston et al. (1999) point out that the existence of accounting choices indicates that higher risks of accounting irregularities are associated with higher litigation risk and audit fees.

Earnings management risk is also a consideration in auditors' risk assessment processes. Bedard and Johnstone (2004) examine whether auditors' assessments of earnings manipulation risk affect their planning and pricing decisions. They reveal insightful information by utilizing the risk assessments of a public accounting firm during its audit process of their clients. Evidence from the study shows that auditors increase audit effort and billing rates for clients with high earnings manipulation risk. Evidence also shows that with negative market reaction against alleged earnings manipulation (Feroz et al., 1991; Dechow et al., 1996), stakeholders would suffer loss due to the decline of share price. Thus earnings manipulation risk is closely related to litigation risk, and the increase of earnings manipulation risk is expected to increase audit effort and audit fees. Arthur Levitt, Chairman of the Securities and Exchange Commission (SEC), stated that earnings management created an "erosion in the quality of earnings, and therefore, the quality of financial reporting" (Levitt, 1998, p. 1).

Earnings management incentives are closely related to the factors of business risk and litigation risk that audit firms face. As discussed previously, the main factors affecting business risk and litigation risk are clients' economic environment, their industry, management philosophy, audit history, financial position and performance, existing litigation and public ownership (Brumfield et al., 1983). A change in these factors will change the performance of a company. In order to maintain company performance and reputation, managers will use earnings management techniques over time or even manipulate accounting information. For example, in order to meet and beat market expectations over time, managers may intentionally decrease earnings during the years that the company scores significantly above market expectations, and increase earnings during the years that the company does not perform well (Dechow et al., 2010). Secondly, when a company has financial difficulties, managers may manipulate accounting transactions or account balances to increase current assets or reduce current liability to improve the company's financial position. Such accounting irregularities increase the difficulty of auditing and increase the possibility of issuing unqualified accounting opinions, which may lead to future lawsuits and liability for the loss of the clients' stakeholders (Francis et al., 1996).

Prior research studies shows that accruals-based earnings management models have relatively high accuracy in detecting earnings management and accounting irregularities (Dechow et al., 1995; Dechow and Dichev, 2002; Jones et al., 2008). These models are also found associated with litigation risk in audit research. Heninger (2001) investigates the relationship between litigation risk and abnormal accruals. The increase in abnormal accruals reflects the increasing likelihood of earnings management. Heninger (2001) hypothesizes and finds that the increase in abnormal accruals is positively associated with audit litigation risk, as measured by whether the auditor is involved in a lawsuit.

Considering that managers have incentives to use accruals to modify performance or information (DeAngelo et al., 1994; Francis et al., 1996), such manipulation will mislead financial information users of the company's financial position and performance, and thus increase auditor litigation risk. Gul et al. (2003) examine the association between discretionary accruals and audit fees, using a sample of Australian companies. They argue that apart from auditor litigation risk, discretionary accruals are also associated with several accounts such as receivable, inventory and revenue. These accounts are used to access the inherent risk faced by auditors. Furthermore, in most fraud cases, the difference between earnings and operating cash flow is generally high. Thus, high discretionary accruals also indicate the possibility of manipulated financial statements. Discretionary accruals are closely related to different risks that auditors may be exposed to. In order to reduce the risk to an acceptable level, auditors are expected to increase audit effort or charge a risk premium, both of which result in higher audit fees. Their results indicate that discretionary accruals are positively associated with audit fees.

Similarly, using publicly available fee data, Abbott et al. (2006) find that a positive relationship between discretionary accruals and audit fees is more pronounced in greater litigation risk environments, as identified by 'high-growth' or high price-earnings (P/E) clients. Abbott et al. (2006) were the first to use publicly available fee data in the investigation of discretionary accruals and audit fees after the data became publicly available in 2000. The utilization of the data contributes to a larger sample size and more transparent and repeatable analysis. It also provides an example for future audit fee studies using publicly available fee data.

While previous studies show a relatively consistent association between litigation risk and audit fees, the value of the coefficient values are generally small, for example 0.18 in Abbot et al. (2004) and between 0.40 to 0.58 in Gul et al. (2003). The association may relate to the overall market or industrial performance instead of litigation risk. Furthermore, all factors included in audit fee models considered only the specific accounts related to earnings and cash flow in financial statements. They decided to capture the misstatement of earnings, but errors other than earnings misstatement have been ignored. Therefore, these measures do not reflect the overall level of audit quality and litigation risk, which may lead to mismatch between audit quality, litigation risk and audit fees.

As previous discussion in section 2.2 indicates, FSD_Score resolves some of the disadvantages of current earnings management models. Firstly, FSD_Score measures the overall level of accounting errors and irregularities in a company's entire financial statements instead of focusing on certain accounts. Secondly, FSD_Score does not take a company's financial performance into account so it will not be misclassified as an unusual performance and accounting irregularities. Therefore, investigating the association between FSD_Score and audit fees may reveal a clearer pattern between the level of accounting errors and the possibility of irregularities, litigation risk and audit fees.

2.5. Hypothesis

Audit fees are determined by auditors' assessed risk of clients, audit market competition, and negotiations between auditors and clients. Compared with market competition and negotiation, litigation risk is uncertain and difficult to foresee. For this reason, auditors generally put extra effort, such as increasing the level of evidence collected, to improve audit quality in order to prevent extreme litigation liability. This additional effort will increase the audit cost. The increased cost can be passed on to their clients, subject to the constraint from audit market competition and the balance in bargaining power between the auditor and their clients. Based on the assumption that auditors pass on this cost to clients, empirical literature (e.g. Simunic, 1980; Houston et al., 1999; Heninger, 2001; Kinney et al., 2004) demonstrates that auditors charge higher audit fees, because of additional audit effort and/or as a risk premium, when the risk of performing the audit is high.

Litigation risk increases with the level of accounting irregularities and errors. The level of financial reporting errors and accounting irregularities is one of the most important risk factors that affects audit pricing. Previous research finds that planned audit effort and billing rates increase with clients' earnings management risk (Bedard and Johnstone, 2004; Gul et al., 2003). Similarly, Charles et al. (2010) report that the relationship between audit fees and financial reporting risk more than doubled surrounding the passage of SOX, which is consistent with the legislation increasing auditors' costs associated with clients' financial reporting risk.

FSD_Score measures the possibility of financial reporting errors and accounting irregularities. The score increases with the deviation between the first digit distribution in the empirical sample and Benford's distribution. Prior studies (Nigrini and Mittermaier, 1997; Aono and Guan, 2008; Amiram et al., 2015) demonstrate that financial data free of manipulation closely follow Benford's distribution. The deviation of the distributions between the empirical sample and Benford's Law reflect the level of financial reporting errors and the possibility of irregularities.

The difference between the sample distribution and Benford's Law measures the financial reporting errors and irregularities which effects auditors' litigation risk and leads to a positive relation between audit fees and the deviation of empirical distribution and Benford's distribution. Thus, I have the following hypothesis:

H1. The deviation between empirical digit distribution and Benford's distribution is positively associated with audit fees.

2.6. Summary

The review of literature in this Chapter has concentrated largely on empirical research on FSD_Score, litigation risk and audit fees. Certain important concepts, such as Benford's distribution, FSD_Score and litigation risk, have been introduced and used to explain the expected association between FSD_Score and audit fees.

To investigate the association between FSD_Score and audit fees, it is necessary to design audit fee models for the test. Thus, this Chapter provides a basis for the next in which the development of audit fee models in this study is outlined.

3. Method

3.1. Introduction

This chapter discusses the sample source, the validation test and the specific method used in this study. The first section justifies the use of secondary data. The second part of this chapter establishes the validation test of Benford's Law and an example of the calculation of FSD_Score. The last section introduces audit fee models used in this study followed by the definitions of the independent variable, test variables and control variables in the models. The details of the method are explained in detail in this chapter.

3.2. Sample Sauce

Secondary data taken from data available in Compustat and WRDS is used in this study. In order to investigate the association between FSD_Score and audit fees, a large sample size is needed. The calculation of FSD_Score requires data in a well-organized digital format. Compustat provides data sets that meet such requirements from the 1960s.

Audit fees data, on the other hand, are only available to the public since 2000. Audit fee studies prior to 2006 (Simunic, 1980; Houston et al., 1999; Heninger, 2001) generally used primary data collected by researchers due to the limited available public audit fee data. The sample sizes in those studies are very small. For example, Simunic (1980) includes 397 firm-year observations in his study and Gul et al. (2003) uses a sample of 648 firm-years. Furthermore, results in those studies are difficult to compare due to the differences of firm-years used in different studies and various in the data collection methods. Abbott et al. (2006) are the first to use publicly available audit fee data in his research. Carrying on Abbott et al.'s (2006) research, the majority of current audit fee research studies (e.g. Charles et al., 2010; Cassell et al., 2011; Gul and Goodwin, 2010) uses publicly available audit fee data. These studies use accurate, comparable and replicable data sets. They also enjoy large samples that include thousands of observations. Therefore, I use secondary data in my study from fiscal year 2000 to 2014 in order to investigate a large sample size, over 20,000 firm-year observations, and compare my results with prior studies.

3.3. Validation of Benford's Law

In order to test whether the observations in the sample follow Benford's Law in general, FSD_Score based on Kolmogorov-Smirnoff (KS) statistic and FSD_Score based on Absolute Deviation (MAD) are used in this study. FSD_Score based on KS (FSD_KS) calculates the maximum deviation, the cumulative difference from digit value 1 to 9, between sample distribution and Benford's distribution. FSD_KS investigates the conformity of Benford's Law in an individual firm-year (small sample) at the 5% level, which is $1.36/\sqrt{P}$, where P is the total number of the first digits used. The measure is calculated as follows:

FSD_KS = max $|\sum_{i=1}^{i=K}(AD_i - ED_i)|$ =

$\max(|AD_1 - ED_1|, |(AD_1 + AD_2) - (ED_1 + ED_2)|, \dots, |(AD_1 + AD_2 + \cdots + AD_9) - (ED_1 + ED_2 + \cdots + ED_9)|)$, (1)

where AD (actual digit) is the frequency of a given sample, ED (expected digit) is the theoretical frequency in Benford's distribution, and K is the number of values of the leading digits being analyzed (Amiram et al., 2015, pp. 33).

FSD_Score based on the MAD statistic measures the absolute difference between a sample distribution and Benford's distribution of each digit. It is used to analyze a large sample as it does not consider sample size in the measurement. MAD is calculated by the following equation:

$FSD\_MAD = (\sum_{i=1}^{i=K}|AD_i - ED_i|)/K$, (2)

where, as for KS, AD (actual digit) is the frequency of a given sample, ED (expected digit) is theoretical frequency in Benford's distribution, K is the value of leading digits being analyzed (Amiram et al., 2015, pp. 33).

FSD_Score based on the MAD statistic is insensitive to sample size and useful for the larger pool of first digits used in the calculation. Furthermore, it is useful to compare results between observations to determine which firm-year conforms better with Benford's Law, as the MAD statistic is not related to sample size and critical values.

Following is an example of how to calculate the FSD_Score. Appendix 1 is an example of financial statements. To calculate the FSD_Score based on KS and MAD statistics, the actual distribution (AD) needs to be calculated. First of all, I take the first digit of each number (in bold), and calculate the frequency of the occurrences of each digit and present it in Table 3-1 (Occurrences). Secondly, I calculate the actual distribution (AD). In this example, there are 77 total numbers in all financial statements and 31 appearances of the number 1 as the first digit, so 1's frequency or actual distribution (AD) is 31/77=0.4026. This is the same as the other digits' frequency shown in Table 3-1 (AD). Then I compare the actual distribution (AD) of the sample Financial Statements to Benford's distribution (ED) ($P(d_1) = \log(1+1/d_1)$, section 2.2) and calculate the value of FSD_Score based on KS and MAD statistics.

Equation (1) displays how the FSD_Score based on KS equals the largest number in the last row of Table 3-1 ($|\sum_{i=1}^{i=K}(AD_i - ED_i)|$), which is 0.1463 (in bold), when K equals 2 in this example. The 5% critical value is $1.36/\sqrt{77} = 0.1550$. The KS statistic is lower than 0.1550, so the financial statements in this example do conform to Benford's Law. To calculate the FSD_Score based on the MAD statistic, I follow equation (2). The MAD statistic is the sum of |AD-ED| divided by K, which is 9 in the sample. The value of MAD statistic in this sample is 0.0356.

Table 3-1 Calculation of FSD_Score based on KS and MAD statistics

Digit (K)	1	2	3	4	5	6	7	8	9
Occurrences	31	17	8	4	4	3	4	5	1
Actual Distribution (AD)	0.4026	0.2208	0.1039	0.0519	0.0519	0.0390	0.0519	0.0649	0.0130
Expected Distribution (ED)	0.3010	0.1761	0.1249	0.0969	0.0792	0.0669	0.0580	0.0512	0.0458
AD-ED	0.1016	0.0447	(0.0210)	(0.0450)	(0.0273)	(0.0279)	(0.0061)	0.0137	(0.0328)
|AD-ED|	0.1016	0.0447	0.0210	0.0450	0.0273	0.0279	0.0061	0.0137	0.0328
$\|\sum_{i=1}^{i=K}(AD_i - ED_i)\|$	0.1016	**0.1463**	0.1253	0.0803	0.0531	0.0251	0.0191	0.0328	0.0000

Table 3-1 shows calculation of FSD_Score based on KS and MAD statistics. It reports the occurrences of each value of the first digits, and the distribution of the actual sample (AD) and Benford's Law (ED). Further reported are the difference, absolute difference and accumulated difference between actual distribution (AD) and expected distribution (ED).

3.4. Audit fee models

Existing audit fee models (e.g. Simunic 1980; Houston et al., 1999; Heninger 2001; Kinney et al., 2004; Duellman et al., 2015) include multiple determinants related to client and auditor attributes. To examine the association between the probability of accounting manipulation and audit fees, I introduce the accounting manipulation variable (FSD_MAD) to the audit fee models. The following regression model is used in this study:

$$LN\_AFEE=\beta_0+\beta_1 FSD\_MAD+\beta_2 LN\_ASSETS+\beta_3 FINCOME+\beta_4 ABS\_JONES\_RESID+\beta_5 INVREC+\beta_6 LEVERAGE+\beta_7 ROA+\beta_8 LOSS+\beta_9 INTERNAL\_CONTROL+\beta_{10} BIG4+\beta_{11} GOINGCON+\beta_{12} RESTATEMENT+\beta_{13} MB+\varepsilon \quad (3)$$

$$LN\_AFEE=\beta_0+\beta_1 FSD\_MAD+\beta_2 LN\_ASSETS+\beta_3 ABS\_JONES\_RESID+\beta_4 INVREC+\beta_5 LEVERAGE+\beta_6 ROA+\beta_7 LOSS+\beta_8 INTERNAL\_CONTROL+\beta_9 BIG4+\beta_{10} GOINGCON+\beta_{11} RESTATEMENT+\beta_{12} MB+\varepsilon \quad (4)$$

$$LN\_AFEE=\beta_0+\beta_1 FSD\_MAD+\beta_2 LN\_ASSETS+\beta_3 ABS\_RSST+\beta_4 INVREC+\beta_5 LEVERAGE+\beta_6 ROA+\beta_7 LOSS+\beta_8 INTERNAL\_CONTROL+\beta_9 BIG4+\beta_{10} GOINGCON+\beta_{11} RESTATEMENT+\beta_{12} MB+\varepsilon \quad (5)$$

Where the variables are defined in Table 3-2.

Table 3-2: Variable Definition

Variable	Definition
LNAFEE	The natural log of the audit fee (AUDIT_FEES)
FSD_MAD	FSD_Score based on the absolute deviation (MAD) between empirical distribution and Benford's distribution
FSD_KS	FSD_Score based on Kolmogorov-Smirnoff (KS) statistic between empirical distribution and Benford's distribution with 5% critical level, $1.36/\sqrt{P}$, based on sample size P.
LN_ASSETS	The natural log of year-end total assets (AT)
FINCOME	The foreign income before tax (PIFO) scaled by year-end total assets (AT)
ABS_JONES_RESID	The absolute value of the residual from the modified Jones model
ABS_RSST	The absolute value of working capital accruals
INVREC	The proportion of year-end total assets (AT) composed of inventory (INVT) and receivables (RECT)
LEVERAGE	Total debt (DLC) / year-end total assets (AT)
ROA	Income before extraordinary items (IB) / year-end total assets (AT)
LOSS	An indicator variable equal to '1' if the firm reports a loss in the current year and '0' otherwise
INTERNAL_CONTROL	Level of internal control (AUOPIC) in audit report (0 No audit report on internal control; 1 Effective - No material weakness; 2 Adverse - Material weakness exists; 3 Disclaimer - Unable to express opinion)
BIG4	An indicator variable equal to '1' if the firm is audited by a Big 4 audit firm and '0' otherwise (AUDITOR_FKEY=1-4);
GOINGCON	An indicator variable equal to '1' if the firm received a going concern modification (GOING_CONCERN) in the prior year and '0' otherwise
RESTATEMENT	An indicator variable equal to '1' if the firm restates their financial statement (RESTATEMENT) in the prior year and '0' otherwise
MB	Market to Stockholders' Equity (MKVALT/SEQ)
AT	Total assets at year-end
COUNT10	Total numbers in the financial statements used in the calculation of FSD_Score

Table 3-2 all the variables using in the analysis. The label of variables in original databases (Compustat and WRDS) is reported between brackets.

3.5. Variable measurement

3.5.1. Test Variable

The primary test variable used in this study is *FSD_Score based on the MAD statistic (FSD_MAD)* was chosen to assess accounting errors and irregularities in order to measure audit risk. FSD_Score measures the absolute deviation between the empirical distribution and Benford's Law distribution. It is insensitive to the size of the sample and is used in large sample sizes or to compare the level of deviation between observations.

As discussed in section 4.1, equation (2), FSD_Score based on the MAD statistic is calculated in the following equation:

$$FSD\_MAD = (\Sigma_{i=1}^{i=K} |AD_i - ED_i|) / K,$$

where AD (actual digit) is the frequency of a sample and ED (expected digit) is the theoretical frequency in Benford's distribution. K is the value of leading digits being analyzed (Amiram et al., 2015, pp. 33). In this study, K equals to 9 as I calculate the first non-zero digit from 1 to 9.

To calculate FSD_Score, I use the SAS program to convert all the numerical data in the financial statements used in the calculation to character data which can be read by each letter/number. Next, only digits from 1-9 are kept in the data as I calculate the non-zero first digits. After that, the function of recording the first number from the left will be used and each digit value from 1 to 9 is recorded separately in count1 to count9 to summarize the occurrences of each digit in each firm-year. The sum of count1-count9 is stored in count10 as the total numbers used to calculate FSD_Score. The next step is to calculate the MAD and KS statistics which can be referred to the example in section 4.1.

3.5.2. Earnings management measures

Amiram et al. (2015) underline the associations between FSD_Score and *accruals_based earnings management measures*. In audit fee research, earnings management measures are also used as a control variable of *litigation risk* (Gul et al., 2003; Kothari et al., 2005). The increase of litigation risk may force auditors to increase audit effort to reduce risks to an acceptable level. Accruals variables indicate the level of management opportunism and the likelihood of fraudulent financial statements (Francis and Krishnan 1999) and, thus, as their evidence suggests, positively associate with audit fees (Gul et al., 2003). In order to examine how accruals variables influence the correlation between FSD_Score and audit fees. I choose two different accruals variables as alternative control variables in my models, namely, *the absolute value of the residual from the modified Jones model (ABS_JONES_RESID)* and *the absolute value of working capital accruals (ABS_RSST)*.

The absolute value of the residual from the modified Jones model (ABS_JONES_RESID) (Kothari et al., 2005) is used to calculate the possibility of earnings management. The modified Jones model and the Dechow-Dichev model both show superior results in detecting earnings management than other models in prior studies (Dechow et al., 2010; Jones et al., 2008). To simplify the calculation in this study, I used the absolute value of the residual from the modified Jones model. Evidence shows that the modified Jones model is significantly associated with audit fees because of its influence on litigation risk (e.g. Heninger 2001; Abbott et al., 2006). The modified Jones model is defined as: tca = Δsales (SALE) + net PPE (PPENT) + ROA, where tca = (Δcurrent assets (ACT) – Δcash (CH) – Δcurrent liabilities (LCT) + Δdebt in current liabilities (DLC) – depreciation and amortization (DP)), ROA = income before extraordinary items (IB) / total assets (AT). All variables are scaled by beginning-of-period total assets (Kothari et al., 2005).

The absolute value of working capital accruals (ABS_RSST) is used as a measure of unreliable financial information (Richardon et al., 2005) and found significant association with FSD_Score (Amiram, 2015). ABS_RSST is calculated as (ΔWC + ΔNCO + ΔFIN) scaled by average total assets, where WC = (current assets – cash and short-term investments) – (current liabilities – debt in current liabilities). NCO = (total assets – current liabilities – long-term debt). FIN = (short – term investments + long-term investments) – (long-term debt + debt in current liabilities + preferred stock) (Richardson et al. 2005).

3.5.3. Dependent variable

The dependent variable in this study is *LN_AFEES*, *the nature logistic value of audit fees*. Previous research on audit fees mostly uses the logistic technique to investigate the association between audit fees, firm size (LN_ASSETS) and other factors. One prior study, Picconi and Reynolds, 2013, shows that there is no obvious relation between audit fees and total assets, while a clear linear pattern is shown between the logistic value of audit fees and the logistic value of total assets. Thus, to investigate the association between the test variable, FSD_Score, and to compare the results with prior studies, the nature logistic value of audit fees will be used as a dependent variable in this study.

3.5.4. Control variables

I control for the following variables that have shown significant associations with audit fees in prior literature (e.g. Hay et al., 2006; Simunic, 1980; Gul et al., 2003; Bedard and Johnstone, 2004; Abbott et al., 2006; Duellman et al., 2015). The most dominant determinant of audit fees in the literature is *company size (LN_ASSETS)* (e.g. Hay et al., 2006; Simunic, 1980; Abbott et al., 2003; Duellman et al., 2015). The size of a company influences the number of transactions in its accounting system. The more transactions in an auditee's accounting system, the more effort auditors will put in during audit procedures. Furthermore, total assets are frequently involved in defective financial statements and it is a starting point of traditional audit procedure to verify reported incomes, so that total assets is a significant factor in audit fees estimation. Following the prior studies and the discussion in section 4.3.2, the size of an auditee is represented here by the natural logistic value of total assets at the year-end (LN_ASSETS).

Similarly, the *complexity* of an auditee's operations also increases the audit effort in audit procedures. The number of foreign subsidiaries is often used in prior studies as a measurement of complexity as the result of increasing internal transactions and the difficulty of producing consolidated financial statements (e.g. Simunic 1980; Hackenbrack and Knechel, 1997; Gul et al., 2003). However, in this study, the data of the number of foreign subsidiaries is not available. I therefore use *foreign income (FINCOME)* as an alternative measure of auditee complexity. Foreign income before tax is scaled by total assets to eliminate the influence of firm size.

In addition to firm size and complexity, *inherent risk* is closely related to audit effort. Receivables and inventories are considered as two difficult and risky components to auditors as they are easily modified. Prior studies (e.g. Hay et al., 2006; Duellman et al., 2015) provide evidence that the strongest relation between the inherent risk measure and audit fees is *the combination of inventory and receivables divided by total assets (INVREC)* which will be used in this study.

Furthermore, *leverage and profitability* also indicate a company's financial position and the risk of an auditee's failing. Simunic and Stein (1996) suggest that higher financial leverage relates to higher bankruptcy rates especially when companies are in poor financial position. In order to maintain company and manager reputations, companies with poor financial positions tend to involve themselves in more dishonest accounting activities which would expose their auditors to litigation risk and loss. Thus, *LEVERAGE, ROA,* and *LOSS* are generally found to be significantly associated with audit fees (e.g. Simunic, 1980; Gist, 1994b; Bedard and Johnstone, 2004). In this study, I calculate LEVERAGE and ROA as total debt divided by total assets and income before extraordinary items divided by total assets respectively. LOSS is an indicator variable which is equal to '1' if a firm has negative income and '0' otherwise.

Apart from the components in financial statements, the evaluation of *client's internal control* is also a major part of the audit process. Solid internal control can prevent and detect accounting irregularities and reduce the chance of misstatement, thus reducing audit risk. Auditors would increase their audit effort when they are not satisfied with the efficiency of clients' internal controls (Knechel and Payne, 2001). Hence, this study uses levels 0 to 3 of internal control efficiency in audit reporting as a control variable (*INTERNAL_CONTROL*).

Finally, *auditor size (BIG4)* and *previous audit opinions (GOINGCON and RESTATEMENT)* would also affect audit fees (e.g. Balachandran and Simon, 1993; Bell et al., 2001; Che-Ahmad and Houghton, 1996; Craswell et al., 1995; Blankley et al., 2012). First of all, BIG4 audit companies generally enjoy higher audit service charges due to their higher audit ability, better reputations and stronger competitive position in the audit market. In this study, variable BIG4 is an indicator. It equals '1' if the audit firm key in the data equals to 1, 2, 3 and 4, namely, Deloitte Touche Tohmatsu Limited, PricewaterhouseCoopers, Ernst & Young and KPMG. Moreover, previous audit opinions reflect the quality of client's financial reports and financial position in the past, which are a good indicator of audit risk in current year and how much effort auditors should put into the audit process. GOINGCON and RESTATEMENT are both indicator variables which are equal to '1' if a firm received a going concern opinion or needed to restate its financial statements respectively in the prior fiscal year, and '0' otherwise.

3.6. Summary

This chapter looked at the research method used in this research, justifications for the use of secondary data in this study, and the validation test and audit fee models are explained in detail. Variables used in the study are also well defined. A detailed explanation of the method used in the study should establish a good understanding of the results.

4. Sample Selection

4.1. Introduction

This chapter discusses the samples used in this study. The chapter is separated into two sections. The first section explains the sample collection and the reduction of sample size due to merger of data sets and missing variables. The second section describes the statistics in the samples with details in each variable in the audit fee models used in this study. A comparison of the sample statistics in this study and prior studies is also provided in the second section.

4.2. Sample Selection

My sample consists of all U.S. companies' annual data from Compustat for the period 2000-2014. All Compustat variables in the Balance Sheet, Income Statement and Statement of Cash Flow categories are included to calculate the FSD_scores based on the MAD and KS statistics. In order to compare the results with a prior study on these measures by Amiram et al. (2015), I corresponded with one of the authors, Dr Zahn Bozanic, by email and he provided the 250 variables using in their study to calculate the FSD_score. The 250 variables included all the variables in the Balance Sheet, Income Statement, and Statement of Cash Flow fields provided by Compustat but exclude data items that do not appear on Financial Statements. As shown in Table 4-1, I start with 131,304 firm-year observations from Compustat, then subtract 14,391 observations with negative total assets. For variables reported with an absolute value less than 1, I use the first non-zero digit. Missing value is excluded from the numbers using in calculation. As Benford's Law has higher accuracy in measuring larger data sets, 41,780 firm-years with less than 100 numbers used in the calculation of FSD_Score are removed from the sample to increase the power of the test statistics. I also remove any firm-year with a negative total. These steps yield a sample of 75,133 firm-year observations to calculate the sample distribution.

The audit fees data are collected from WRDS data base with selected variables, such as audit fees, restatement and audit opinions. Total firm-year observations included in the audit data set are 59,033.

To merge these two data sets, I match the CIK number and total assets from Compustat data and Audit Fees data. I match the two data sets with total assets instead of fiscal year because the fiscal year in two data sets tends to be one year apart, probably due to the time lag between producing Financial Statements and audit reports. Total assets are consistent in both data sets. Considering the total assets might be rounded to different places in the number, the total assets is matched within the difference of 0.1%. After matching the data sets and deleting firm-year observations without an audit fee value, there are 35,119 firm-year observations in the sample.

The next step is to remove observations with missing values in the regression model. There are 11,931 observations with non-missing value of all necessary variables in the audit fee models. The sharp reduction of sample size is due to the large number of firms that do not have foreign subsidiaries indicates that large amount of value is missing from the variable of foreign income (FINCOME). In order to generalize the study to its larger sample size, I exclude FINCOME in Sample 2 which includes 21,641 observations. All non-indicator control variables in the three samples are winsorised at the 1% and 99% levels to eliminate the influence of outliers.

Table 4-1 Sample Selection 2000-2014

	Sample 1 included FINCOME	Sample 2 excloded FINCOME
Firm-years in Compustat	131,304	131,304
Less: Firm-years with negative income	14,391	14,391
Firm-years with less than 100 numbers in financial statements	41,780	41,780
Final sample size of Compustat (Validation Test)	**75,133**	**75,133**
Firm-years in audit data from WRDS	59,033	59,033
Combined Compustat and audit data	35,119	35,119
Less: Firm-years with missing value in regression model	23,185	13,478
Final sample size (Regression Models)	**11,931**	**21,641**

Table 4-1 shows the sample selection between 2000 and 2014. Total observations from Compustat are 131,304 firm-years. Less the firm-years with negative income and with less than 100 numbers in financial statements, 14,391 and 41,780 respectively. Final sample size of Compustat is 75,133 which will be use in validation test. After match data between Compustat data and audit data, sample size reduce to 35,119. Less observations without all the variables in the regression models, 23,185 in Sample 1 and 13,478 in Sample 2. The final sample size of regression models is 11,921 and 21,641 in Sample 1 and Sample 2 respectively.

4.3. Descriptive statistics

The descriptive statistics of final samples are presented in Table 4-2 and Table 4-3. First of all, I will discuss Sample 1 which includes the variable FINCOME and contains 11,931 firm-year observations, and then compare the statistics in the two samples. In Sample 1, the mean (median) of logarithm audit fees in dollars (LN_AFEES) is 14.32 (14.33). These statistics are similar to the mean (median) value of 14.24 (14.23) reported in the Duellman study which includes audit fees data in a similar period of time, between 2000 and 2010, with a sample of 7661 firm-year observations (Duellman et al., 2015). The mean (median) of the natural logarithm of total assets in millions of dollars (LN_AT) for my sample is 6.98 (6.97) with a standard deviation of 1.88, which reveals that the sample firms are generally large companies. Compared with the sample in Amiram's study (Amiram et al., 2015), which has a mean (median) of 6.20 (6.18) on total assets and a standard deviation of 2.12, my sample includes larger firms. This is also reflected in total assets (AT). The mean (median) value of total assets for my sample, in millions of dollars, is 6057.19 (1061.65), while the mean (median) value in

Amiram's study is 3228.28 (383.91) (Amiram et al., 2015). This may be the reason that the mean, 0.07, of ABS_JONES_RESID in my sample is significantly lower than the value of 0.18 in Amiram's study (Amiram et al., 2015). ABS_JONES_RESID measures the possibility of earnings management. Larger firms are expected to be more highly regulated and thus with lower value of earnings management measurement.

Moreover, the mean (median) value of the sum of inventory and receivables scaled by total assets (INVREC) in Sample 1 is 0.27 (0.25) with a standard deviation of 0.16. The mean (median) of the leverage (LEVERAGE) is 0.19 (0.16) with a standard deviation of 0.18. ROA scores 0.03 (0.05) for the mean (median) value with a standard deviation of 0.13 and 23.51% of firm-year reported LOSS. The mean (median) of the natural logarithm of market to book value (MB) is 2.92 (2.20) with a standard deviation of 3.58 and the mean (median) of foreign income scaled by total assets (FINCOME) is 0.03 (0.02) with a standard deviation of 0.05. Similarly with LN_AFEES, the statistics of INVREC, LEVERAGE, ROA and MB are highly comparable to the statistics reported in the Duellman study which also includes data for 2000 to 2010 (Duellman et al., 2015).

With respect to the test variable, the mean (median) of FSD_Score based on the MAD statistic is 0.0274 (0.0266) with a standard deviation of 0.0079. This statistic is highly consistent with the mean (median) of 0.0296 (0.0288) in Amiram et al. (2015) which showed a standard deviation of 0.0087.

Regarding indicator variables, 84.62% of firm-year observations audited by BIG4 audit firms, 11.45% firm-years stated the financial statements in prior year and 1.29% firm-years received going-concern audit opinions in the prior year. In all, 4.12% observations show material weakness in their internal control system.

Compared with Sample 1, Sample 2 includes slightly smaller firms with 6.63 (6.61) and 4898.19 (739.73) as the mean (median) value of LN_AT and AT respectively. Table 4-3 also shows that the observations in Sample 2 score lower mean values of LN_AFEE (13.94), INVREC (0.25) and MB (2.87), higher mean values of accounting error and irregularity measures, including MAD (0.0288) and ABS_JONES_RESID (0.0790), and a higher mean value of LEVERAGE (0.22). The firm-years in Sample 2 are slightly less profitable with a lower mean value of ROA (0.01) and higher percentage of LOSS

(25.68%). Furthermore, the percentage of observations audited by BIG4 (78.49%) is lower than Sample 1, while the percentage of restatement (11.90%) and going concern reports (1.88%) is higher. There is also a lower percentage of firm-years having material weakness in their internal control system. The absolute value of working capital (ABS_RSST) is also included in Sample 2 as an alternative control variable for the possibility of earnings management. This aims to test the influence of different accruals-based measures to the association between FSD_Score and audit fees. There are 17,793 observations including the value of ABS_RSST. The mean (median) value of ABS_RSST is 0.1167 (0.0660) with a standard deviation of 0.1531.

Table 4-2 Descriptive Statistics (Sample 1, n=11931)

Variable	Mean	Std Dev	Q1	Median	Q3
LN_AFEE	14.3170	1.1721	13.6292	14.3260	15.0867
MADs	0.0273	0.0079	0.0216	0.0265	0.0324
ABS_JONES_RESID	0.0711	0.0894	0.0182	0.0421	0.0854
LN_AT	6.9805	1.8836	5.6499	6.9675	8.2766
INVREC	0.2655	0.1600	0.1395	0.2494	0.3604
LEVERAGE	0.1927	0.1845	0.0176	0.1632	0.2967
ROA	0.0251	0.1276	0.0044	0.0478	0.0870
LOSS	0.2351	0.4240	0	0	1
MB	2.9184	3.5781	1.3592	2.1963	3.6094
INTERNAL_CONTROL	0.9078	0.4156	1	1	1
BIG4	0.8461	0.3607	1	1	1
GOINGCON	0.0129	0.1128	0	0	0
RESTATE	0.1144	0.3184	0	0	0
FINCOME	0.0262	0.0519	0.0011	0.0170	0.0479
AT	6057.18	18759.00	284.27	1061.64	3931.1

Table 4-2 reports descriptive statistics for all variables used in the regression model for Sample 1 with 11,931 firm-year observations. See Table 3-2 for variable definitions.

Table 4-3 Descriptive Statistics (Sample 2, n=21641)

Variable	Mean	Std Dev	Q1	Median	Q3
LN_AFEE	13.9436	1.2163	13.1635	13.9582	14.7346
MADs	0.0288	0.0085	0.02267	0.0279	0.03404
ABS_JONES_RESID	0.0790	0.1065	0.01893	0.0444	0.09170
ABS_RSST (n=17794)	0.1167	0.1530	0.02830	0.0659	0.13703
LN_AT	6.6310	1.9645	5.24959	6.6062	7.99474
INVREC	0.2454	0.1758	0.09805	0.2187	0.35378
LEVERAGE	0.2182	0.2088	0.02699	0.1822	0.33524
ROA	0.0082	0.1661	-0.0023	0.0420	0.08262
LOSS	0.2571	0.4370	0	0	1
MB	2.8737	3.9923	1.2800	2.0825	3.51136
INTERNAL_CONTROL	0.8610	0.4531	1	1	1
BIG4	0.7858	0.4102	1	1	1
GOINGCON	0.0187	0.1356	0	0	0
RESTATE	0.1195	0.3244	0	0	0
AT	4898.18	16168.00	190.48	739.73	2965.31

Table 4-3 reports descriptive statistics for all variables used in the regression model for Sample 2 with 21,641 firm-year observations, except ABS_RSST which appears in 17,794 observations in Sample 2. See Table 3-2 for variable definitions.

Table 4-4 presents the correlations between FSD_Score based on the MAD statistic, audit fees and the control variables for Sample 1. Pearson correlations are presented below the diagonal. I find a positive and significant, at the 0.01% level, relation between audit fees (LN_AFEES) and firm size (LN_AT), internal control inefficiency (INTERNAL_CONTROL), foreign income (FINCOME) and auditor size (BIG4), with correlation coefficient values 0.88, 0.43, 0.24 and 0.47 respectively. The correlations are consistent with the expectation that firms with larger size, weaker internal control or more complex operational environment tend to pay higher audit fees and larger auditors charge premium fees for their services.

FSD_Score based on the MAD statistic has a weak negative relationship with audit fees and (LN_AFEE) and firm size (LN_AT). This suggests that the bigger the firm or the higher the audit fees a firm pays, the lower the level of accounting errors and irregularities it has. Similarly with FSD_Score, the measurement of earnings management, ABS_JONES_RESID, is negatively related to audit fees and firm size.

Positive and significant, at the 0.01% level, associations are also found between firm size (LN_AT), profitability measures (ROA) and foreign income (FINCOME). This reveals that larger firms tend to have higher profitability and are more involved in foreign business. Furthermore, the correlation between ROA and FINCOME is 0.52 at the 0.01% level, meaning that firms with higher profitability are more likely to have foreign subsidiaries.

4.4. Summary

This chapter discusses the sample selection and the statistics in the samples. The detailed explanations of descriptive statistics should provide a full picture of the observations analyzed in this research. The comparison between the statistics in my samples and prior studies can also assist in the understanding of the differences in the results between this research and prior studies.

Table 4-4 Correlation Coefficient Matrix

	Pearson Correlation Coefficients, N = 11931 Prob > |r| under H0: Rho=0													
Column1	**LN_AFEE**	**MADs**	**ABS_JONES_RESID**	**LN_AT**	**INVREC**	**LEVERAGE**	**ROA**	**LOSS**	**MB**	**INTERNAL_CONTROL**	**BIG4**	**GOINGCON**	**RESTATE**	**FINCOME**
LN_AFEE	1													
MADs	-0.2709	1												
	<.0001													
ABS_JONES_RESID	-0.2024	0.1419	1											
	<.0001	<.0001												
LN_AT	0.8766	-0.2687	-0.2326	1										
	<.0001	<.0001	<.0001											
INVREC	-0.1222	-0.0177	-0.0898	-0.2268	1									
	<.0001	0.0538	<.0001	<.0001										
LEVERAGE	0.2322	-0.1410	-0.1147	0.2812	-0.1144	1								
	<.0001	<.0001	<.0001	<.0001	<.0001									
ROA	0.1810	-0.1164	-0.1434	0.3033	0.0173	-0.0810	1							
	<.0001	<.0001	<.0001	<.0001	0.0588	<.0001								
LOSS	-0.1861	0.1095	0.1499	-0.2932	-0.0358	0.0544	-0.7055	1						
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001							
MB	0.0619	0.0211	0.1133	0.0515	-0.0971	-0.0401	0.1062	-0.0782	1					
	<.0001	0.0214	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001						
INTERNAL_CONTROL	0.4325	-0.1306	-0.1209	0.3883	-0.1034	0.0377	0.1199	-0.1034	0.0242	1				
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0081					
BIG4	0.4694	-0.1262	-0.0862	0.4550	-0.1411	0.1110	0.1191	-0.1214	0.0737	0.3202	1			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
GOINGCON	-0.0522	0.0382	0.0576	-0.0965	0.0011	0.0503	-0.2064	0.1327	-0.0412	-0.0765	-0.0809	1		
	<.0001	<.0001	<.0001	<.0001	0.9018	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
RESTATE	-0.0033	-0.0047	-0.0041	-0.0239	0.0196	0.0091	0.0046	-0.0088	0.0013	0.0266	-0.0335	0.0079	1	
	0.7220	0.6066	0.6553	0.0091	0.0323	0.3189	0.6145	0.3374	0.8864	0.0037	0.0003	0.3909		
FINCOME	0.2355	-0.0852	-0.0685	0.2618	0.0112	-0.0792	0.5202	-0.4073	0.1362	0.1041	0.0852	-0.1090	-0.0081	1
	<.0001	<.0001	<.0001	<.0001	0.2210	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.3770	

Table 4-4 shows the correlation coefficient between each variable in Sample 1 and the significance level. See Table 3-2 for variable definitions.

5. Results

5.1. Introduction

This chapter reports the results and brief explanations of the validation test of Benford's Law and the results of the audit fee models. The validation test shows that financial statements data conform to Benford's Law in general. However, the results of audit fee models are inconsistent with the hypothesis. Following the results of audit fee models, additional tests are produced and explained in the last section of this chapter.

5.2. Validation test of Benford's Law

As evidenced by prior studies, financial statements data conforms to Benford's (Nigrini and Mittermaier, 1997; Durtschi et al., 2004; Aono and Guan, 2008). However, most studies test Benford's Law at individual account level with only a few exceptions, Amiram et al. (2015), for example, who tested it at financial statement level between 2001 and 2011. In order to extend and update the evidence on whether financial data conforms to Benford's Law at financial statement level and aggregate sample, I examine the final sample from Compustat with 75,133 firm-year observations between 2000 and 2014.

FSD_Score based on the KS statistic (FSD_KS) is used to test the conformity of individual firm-year financial data. The mean value of total numbers used to calculate FSD_KS in each firm-year is 122.96 with a standard deviation of 15.62. Table 5-1 shows the detail in each fiscal year (FYEAR) of the validation test. It includes the total firm-years, a count of firm-year observations that do not conform to Benford's Distribution at the 5% level based on FSD_KS, the percentage of conformity, the mean value the total numbers used to calculate FSD_Score and the mean value of FSD_Score based on the MAD statistic (FSD_MAD). As Table 5-1 reveals, the mean values of numbers in financial statements (count10) of each firm-year increases from 114.10 in year 2000 to 126.43 in 2014, which means the total numbers reported in financial statements have increased around 10% in the last 15 years. This suggests that more and more information is given in financial statements. In all, 85.79% of firm-years conform to Benford's Law at the 5% level or better based on FSD_KS in the whole period between 2000 and 2014. This result demonstrates that financial data follow Benford's Law closely. In an individual fiscal year, the percentage of conformity has been stable over the last 15 years at between 85.03% and 86.60%. The results are consistent with Amiram et al. (2015), who show that 86% of individual firm-years conform to Benford's Law at the 5% level or better based on the FSD_KS with a sample of 43,332 firm-years between 2001 and 2011. FSD_MAD is slightly reduced from 0.0308 to 0.0294. This shows that the deviation between empirical distribution and Benford's distribution decreases over time which reflects the slight improvement of the quality of financial statements.

Table 5-2 shows the results of the same variables as Table 5-1 but in each sector based on the Global Industry Classification Standard. The Materials sector has the highest mean values of the total numbers in financial statements of each firm-year observation (count10) at 129.79, followed by Consumer Staples and Industrials with mean values of 127.30 and 126.73 respectively. By contrast, Financials and Utilities have relatively low mean values, namely, 115.57 and 114.17 respectively, due to the differences in operational environment and the items reported in financial statements between these two sectors and other sectors. However, the Utilities sector achieves the highest percentage of conformity at 91.40% while Health Care has the lowest percentage at 82.24% and the highest mean value of FSD_MAD (0.0312). The results are also highly compatible with prior studies. Amiram et al. (2015) reveal that between 81.85% and 90.53% of firm-year observations conform to Benford's distribution in all industries based on the Fama-French 17-industry classification and between 84.96% and 86.96% in each fiscal year between 2001 and 2011.

Table 5-1 Conformity Test by Fiscal Year

Fyear	Total Firm-Year	KS Unconformed	KS Conformed %	Mean Count10	Mean FSD_MAD
2000-2014	75133	10675	85.79%	122.96	0.0298
2000	5298	732	86.18%	114.10	0.0308
2001	5619	780	86.12%	118.88	0.0302
2002	5536	753	86.40%	120.81	0.0297
2003	5397	808	85.03%	121.43	0.0299
2004	5462	817	85.04%	122.14	0.0300
2005	5372	780	85.48%	123.05	0.0297
2006	5163	771	85.07%	123.78	0.0299
2007	5012	714	85.75%	124.33	0.0297
2008	4916	667	86.43%	125.22	0.0294
2009	4751	655	86.21%	124.71	0.0295
2010	4618	641	86.12%	124.86	0.0295
2011	4539	608	86.60%	125.71	0.0294
2012	4557	647	85.80%	125.72	0.0295
2013	4513	673	85.09%	126.15	0.0295
2014	4380	629	85.64%	126.43	0.0294

Table 5-1 computes the percentage of Banford's Law conformation, based on a 5% significant level of KS statistics, in each fiscal year. Table 5-1 further reports the mean values of total numbers (Count10) in individual observations, and the FSD_Score based on the MAD statistic in each fiscal year.

Table 5-2 Conformity Test by Industry

GIC Sectors	Total Firm-Year	KS Unconformed	KS Conformed %	Mean Count10	Mean FSD_MAD
10 Energy	4616	637	86.20%	121.94	0.0300
15 Materials	4906	662	86.51%	129.79	0.0286
20 Industrials	11327	1360	87.99%	126.73	0.0286
25 Consumer Discretionary	13394	1912	85.72%	123.81	0.0295
30 Consumer Staples	3921	566	85.56%	127.30	0.0289
35 Health Care	9307	1653	82.24%	121.32	0.0312
40 Financials	6880	1023	85.13%	115.57	0.0309
45 Information Technology	16202	2369	85.38%	121.92	0.0302
50 Telecommunication Services	2217	288	87.01%	124.66	0.0291
55 Utilities	2302	198	91.40%	114.17	0.0293

Table 5-2 computes the percentage of Banford's Law conformation, based on a 5% significant level of KS statistics, in each sector based on the Global Industry Classification Standard. Table 5-2 further reports the mean values of total numbers (Count10) in the financial statements in individual observations, and the FSD_Score based on the MAD statistic in each sector.

Figure 1 shows an example of the distributions of two firm-years: GRH-2007 and MCR-2010. The KS statistic of GRH-2007 does not conform to Benford's Law at the 5% level. The firm received a going concern audit opinion in year 2007 and year 2008 and restated its financial statement in year 2008. The KS statistic of AIR-2000 conforms to Benford's Law at the 5% level and the distribution line follows Benford's distribution closely.

Figure 1 Conformity to Benford's distribution, firm examples

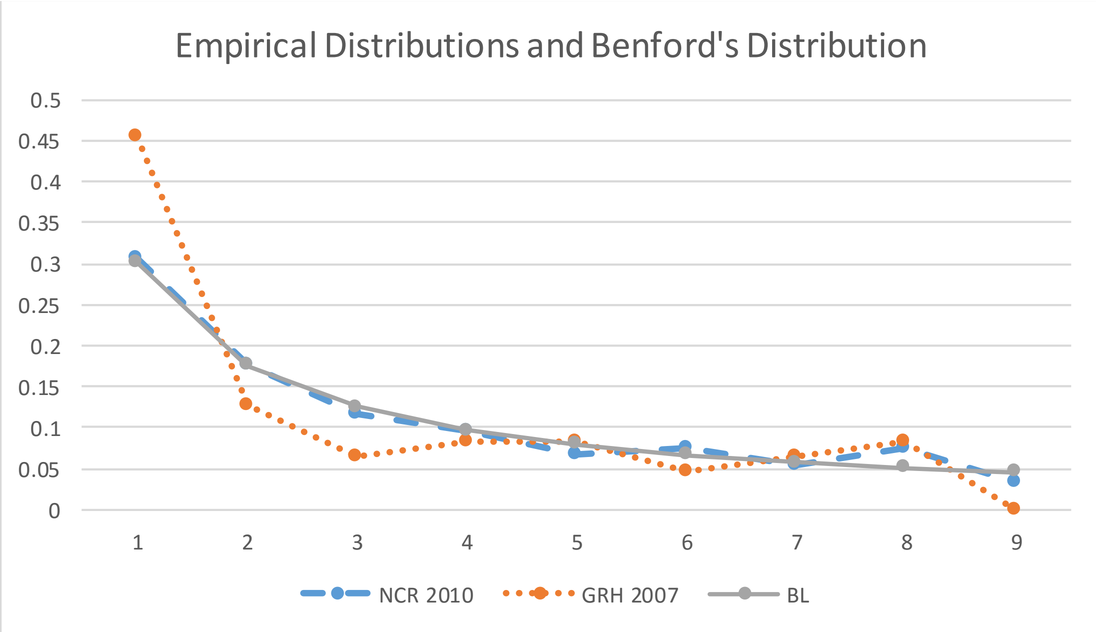

Figure 1 shows the conformity of Benford's distribution for two firm years, NCR 2010 and GRH 2007. NCR 2010 conforms to Benford's Law (FSD_Score based on the KS statistic = 0.046, FSD_Score based on the MAD statistic = 0.0098). GRH 2007, which restated its financial results for year 2007 and year 2008, does not conform to Benford's Law (FSD_Score based on the KS statistic = 0.079, FSD_Score based on the MAD statistic = 0.0402).

In the aggregate sample, there are over 9.35 million numbers generated from all firm-year observations in 15 fiscal years. FSD_MAD measures how close the sample distribution follows Benford's Law, the closer FSD_MAD is to zero, the less deviation between the sample distribution and Benford's distribution. The result of the FSD_MAD statistic in the sample is 0.0010 with 9.2 million numbers in the whole sample which shows that the numbers in the financial data follow Benford's Law very closely. For an individual firm-year, the mean value of FSD_MAD is 0.0298 with a standard deviation of 0.0088.

Table 5-3 compares means of the FSD_MAD and the total numbers in the financial statements between different firm sizes. FSD_MAD increases as firm sizes decrease, while total numbers in the financial statements decrease as firm sizes decrease. This indicates that larger firms have relatively fewer account errors or irregularities, have more accounting activities, and/or provide more information in their financial statements.

Table 5-3 FSD_Score by Firm Size

Firm size level	AT in Million	Firm-Year	FSD_MAD	Count10
90%-100%(Max)	12612.788<=AT<=3510975.059(Max)	7514	0.0273	132.70
75%-90%	2739.761<=AT<12612.788	11270	0.0277	131.01
50%-75%	530.063<=AT<2739.761	18783	0.0285	127.63
25%-50%	107.246<=AT<530.063	18783	0.0302	120.27
10%-25%	26.648<=AT<107.246	11270	0.0324	114.39
(Min)0%-10%	(Min)0.106<=AT<26.648	7513	0.0337	109.03

Table 5-3 segments firm-years by total assets (AT). Reported are the mean value of FSD_Score based on the MAD statistic and the mean value of total numbers in financial statements in each observations.

5.3. Regression model results

Table 5-4 provides the results of the regression models. To compare the results between samples and models, I test Model 1 and Model 2 on Sample 1 and test Model 2 and Model 3 on Sample 2. As reported in Table 5-4, the adjusted R-squares are 80.46% and 80.20% for Model 1 and Model 2 respectively tested on Sample 1, and 78.10% and 76.93% for Model 2 and Model 3 tested on Sample 2 separately. The high values of adjusted R-square suggest all models fit the data well.

I find negative and significant, at the 1% level, associations between the test variable, FSD_Score based on the MAD statistic (FSD_MAD), and audit fees in all models. These results are contrary to expectations. This suggests that the higher the audit fees, the lower the level of audit errors and irregularities. In addition, the high value of coefficients, between -5.09 and -8.05, demonstrate that FSD_Score has a strong association with the natural logarithm of audit fees.

Furthermore, the coefficients of FSD_MAD are around -5 for both models in Sample 1 and show a 60% increase in the absolute value in sample 2 where the coefficient reaches -8. The big difference between the coefficients may be due to the difference of firm size included in both samples. As discussed in section 5.2, Sample 1 includes larger firms than sample 2. The results show that audit fees of larger firms are less sensitive to FSD_Score than smaller firms.

On the other hand, within the sample, the coefficients of FSD_MAD are very similar, -5.09 and -5.14 in Sample 1 and -8.05 and -8.01 in Sample 2 when I exclude the valuable FINCOME or use different earnings management measures. Thus, an individual control variable seems to have little influence on the association between FSD_MAD and audit fees.

The results of control variables are consistent with prior studies. Both LN_AT and FINCOME are positively and significantly associated with the logistic value of audit fees as expected. This means the larger and/or more complex the firms, the higher audit fees they will pay.

Regarding the risk factors, the absolute value of the residual from the Jones model (ABS_JONES_RESID) is positively but not significantly related to audit fees in Sample 1 with both Model 1 and Model 2. However, in Sample 2 with Model 2, ABS_JONES_RESID is positively and significantly, at the 5% level, related to audit fees. Similarly, I also find a positive association between ABS_RSST and audit fees at a 1% significant level. In addition, INVREC, the measure of inherent risk, is at a relatively high value, between 0.68 and 0.72, and statistically significant. Consistent with prior research on audit fees suggesting that auditors charge higher audit fees for risky clients, all the risk factors in my samples are positively associated with audit fees. LEVERAGE, on the other hand, shows a negative and significant association to audit fees. The associations between leverage and audit fees in prior studies are mixed. Leverage is generally expected to be positively related to audit fees, but a large number of studies found non-significant association and some studies also reveal a negative and significant association between these two variables (Hay et al., 2006). The mixed results may be caused by the differences in sample size, sample period and the countries being studied.

The results of variables related to profitability, ROA and LOSS, are compatible with prior studies. ROA is negatively associated with audit fees while LOSS is positively associated with audit fees. This is consistent with the expectation that auditors consider firms with low or negative incomes have relatively higher risk. Thus auditors will spend additional audit effort in the audit process.

Internal control (INTERNAL_CONTROL) is an indicator variable, value 1 for effective internal control and value 2 for adverse internal control with material weakness. The results show internal control is positively related to audit fees. This suggests that the auditors charge high fees or spend more effort on firms with less effective internal controls. The same applies to firms that received a going concern opinion (GOINGCON). A firm-year observation with a going concern opinion in the prior year indicates that the firm-years have relatively higher risk, thus requiring additional audit effort. The auditor character variable, BIG4, is positively related to audit fees as indicated in prior studies, as big four auditors charge a premium fee on their services.

Furthermore, even though the coefficients of LEVERAGE, market to book value (MB) and restatement (RESTATE) are all statistically significant, the value is small, between 0.01 and 0.04, and they are not major factors driving audit fee values.

In addition to FSD_MAD, noticeable differences also appear in coefficients of LEVARAGE and ROA between the two samples. There are 70% to 120% increases, according to different models, in the coefficients of LEVERAGE between Sample 1 and Sample 2, compared with a 30% to 40% decrease in the coefficients of ROA. This reveals that in the sample with larger firms, Sample 1, ROA has stronger influence to audit fees than in the sample with smaller firms, Sample 2. By contrast with ROA, LEVERAGE has a weaker effect on audit fees in larger firms than smaller firms.

Table 5-4 Regression Results

Variable	Sample 1 Model 1	Model 2	Sample 2 Model 2	Model 3
Sample size	11,931	11,931	21,641	17,794
Intercept	10.0657***	10.0584***	10.1258***	10.1451***
FSD_MAD	**-5.0868*** **	**-5.1370*** **	**-8.0472*** **	**-8.0079*** **
	-8.1000	-8.1300	-16.7500	-15.3600
LN_AT	0.5310***	0.5372***	0.5116***	0.5028***
	154.9600	157.2800	181.6300	158.4700
FINCOME	1.3824***	N/A	N/A	N/A
	12.6900	N/A	N/A	N/A
ABS_JONES_RESID	0.0503	0.0676	0.1122**	N/A
	0.9000	1.2000	2.9300	N/A
ABS_RSST	N/A	N/A	N/A	0.1974***
	N/A	N/A	N/A	11.6300
INVREC	0.6877***	0.7032***	0.7262***	0.6844***
	22.0300	22.4000	30.6700	26.7100
LEVERAGE	-0.1247***	-0.1536***	-0.2730***	-0.2658***
	-4.5000	-5.5300	-13.5000	-12.0600
ROA	-0.9778***	-0.7395***	-0.5979***	-0.5039***
	-17.0800	-13.5800	-18.0700	-14.1400
LOSS	0.1084***	0.0987***	0.1437***	0.1598***
	6.7900	6.1400	11.9000	12.2100
MB	0.0085***	0.0101***	0.0097***	0.0105***
	6.2200	7.3700	10.0900	9.9100
INTERNAL_CONTROL	0.2675***	0.2682***	0.2419***	0.2488***
	21.1200	21.0400	24.6600	23.8400
BIG4	0.2439***	0.2363***	0.3265***	0.3361***
	16.1800	15.5900	28.6900	27.9600
GOINGCON	0.2681***	0.2711***	0.2023***	0.1596***
	6.2200	6.2400	6.7800	4.8600
RESTATE	0.0604***	0.0585***	0.0530***	0.0489***
	4.0400	3.8900	4.4100	3.6900
Adj R-Sq	0.8046	0.8020	0.7810	0.7693

Table 5-4 examines the association between audit fees and FSD_Score based on the MAD statistic, accruals-based earnings management measures, and other control variables. Reported are the OLS regression results of Model 1 and Model 2 on Sample 1, and Model 2 and Model 3 on Sample 2. T-statistics are reported in parentheses in the tables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Table 3-2 for variable definitions.

5.4. Additional test: FSD_Score based on the MAD statistic, Residual of modified Jones model and audit variables

The results of the regression models show that the direction of the FSD_MAD parameter estimate is different to expectations. Additional tests on the relationship between FSD_Score and other audit risk and quality variables are conducted. First of all, I compare the difference in FSD_Score between firm-years audited by BIG4/non-BIG4 auditors, that receive going concern/qualified opinions, and with/without restatement. Furthermore, I compare the value between FSD_Score and accrual measures, as both variables reflect the possibility of accounting errors and irregularities.

Table 5-5 shows the comparison of FSD_Score based on the MAD statistic (FSD_MAD) statistic and accrual measure based on the modified Jones Model and working capitals between the indicator variables related to auditor size (BIG4), audit opinions (GOING_CONCERN), profitability (LOSS) and regulation (RESTATE). Evidence in Table 5-5 shows that firm-years audited by BIG4 have lower FSD_MAD, 0.0269 in Sample 1 and 0.0281 in Sample 2, than the firm-year audited by a non-BIG4 auditor, 0.0297 in Sample 1 and 0.0310 in Sample 2. The results of the residual of the Jones model and working capital accruals are similar with FSD_MAD that BIG4 audited financial statements have lower values of ABS_JONES_RESID and ABS_RSST.

Firm-year observations that receive a going concern audit opinion have higher FSD_MAD and accruals-based measures (ABS_JONES_RESID and ABS_RSST) than the firm-years that received a qualified opinion. This reflects that firm-years that received a going concern opinion from auditors or were audited by non-BIG4 auditors have a relatively higher possibility of accounting errors and irregularities than the firm-years that received a qualified opinion. This difference is especially noticeable in the value of working capital accruals (ABS_RSST). The mean value of ABS_RSST is around 0.11 of observations with a qualified opinion in both samples but reach 0.30 and 0.50 of observations with a going concern opinion in Sample 1 and Sample 2 respectively.

Furthermore, firm-years that achieved positive net income contain fewer accounting errors or accounting irregularities in the financial statements than firm-years showing a loss. This shows that firms with good performance are less likely to manipulate their financial information.

However, the FSD_Score and accruals-based measures do not differ if the firm-years did or did not announce they would restate their financial statements. The reason for this is that when a firm announces it will restate their financial statements the restatement could be for the current or prior years and, thus, may not influence the current year's financial statements number.

Table 5-5 FSD_Score based on the MAD statistic and audit variables

Variables	Classification	Sample 1 Firm-year	FSD_MAD	ABS_JONES_RESID	ABS_RSST
BIG4	0	1835	0.0297	0.0893	0.1325
	1	10096	0.0269	0.0679	0.1085
Going Concern	0	11789	0.0273	0.0707	0.1102
	1	142	0.0296	0.1138	0.3021
Loss	0	9120	0.0269	0.0638	0.0909
	1	2805	0.0289	0.0954	0.1778
Restatement	0	10790	0.0274	0.0714	0.1124
	1	1141	0.0270	0.0687	0.1151
Variables	**Classification**	**Sample 2 Firm-year**	**FSD_MAD**	**ABS_JONES_RESID**	**ABS_RSST**
BIG4	0	4595	0.0310	0.1038	0.1617
	1	16767	0.0281	0.0725	0.1149
Going Concern	0	20917	0.0287	0.0778	0.1191
	1	369	0.0325	0.1509	0.5038
Loss	0	15875	0.0282	0.0682	0.0960
	1	5487	0.0303	0.1112	0.2069
Restatement	0	19190	0.0288	0.0790	0.1259
	1	2172	0.0286	0.0812	0.1277

Table 5-5 provides the comparison of the mean values of FSD_Score based on the MAD statistic, absolute value of residuals from the modified Jones Model and absolute value of working capital accruals between different indicator variables. BIG4 equals 1 for observations audited by BIG4 auditors and 0 otherwise. Going Concern equals 1 for observations that received a going concern audit opinion and 0 otherwise. Loss equals 1 for observations with negative net income and 0 otherwise. Restatement equals 1 for observations that announced that a firm restated its financial statements and 0 otherwise. See Table 3-2 for variable definitions.

5.5. Summary

This chapter presents the results of this study and a brief explanation of the differences between the results and the hypothesis. Additional tests are also produced to support the possible explanation of the difference. Further discussion will be continued in the next chapter.

6. Discussions and Conclusions

6.1. Discussions on Results

Consistent with prior studies, the results in my tests reveal that financial statement data follow Benford's Law. More than 85% of firm-year observations in all fiscal years and sectors conform to Benford's distribution. Furthermore, FSD_Score, the deviation between empirical distribution and Benford's distribution, is positively associated with accruals-based measures, which are often used to estimate the possibility of earnings management and accounting irregularities. This suggests that FSD_Score is useful to measure the level or possibility of accounting errors and irregularities.

The results of the regression models, however, are not consistent with the hypothesis. The evidence in Amiram et al. (2015) and the validation results in this study demonstrate that FSD_Score has a positive relationship with proxies of audit litigation risk, such as accruals-based measures and restatements, and these proxies are positively associated with audit fees. Thus, FSD_Score is expected to measure the litigation risk of auditors and have a positive relationship on audit fees. However, in this study, I find a negative and significant, at the 1% level, association between FSD_Score and audit fees.

One possible reason for the conflict between results and hypothesis is that FSD_Score measures the quality of audit outcomes instead of the risks that auditors take. Financial reporting is the outcome of auditing. Additional effort in audit procedures will lead to fewer errors being left in the audited financial statement.

Even though FSD_Score is positively associated with other measures of accounting irregularity, such as the accrual models, FSD_Score has its own advantages. One of the main differences between FSD_Score and accrual models, as prior discussion in section 2.2 suggests, is that FSD_Score is not affected by the underlying business environment and performance, while accrual models often miscalculate the possibility of accounting irregularities and abnormal business performance. This is also indicated by the value of correlations between different variables. Profitability and going concern opinions focus on the performance of a business, audit effort and auditor size are more related to the quality of financial information. The correlations between FSD_Score and profitability and going concern opinions are weaker than accruals-based measures, while the correlations between FSD_Score and audit effort and auditor size are stronger than the accruals-based measure used in this study. Thus FSD_Score may directly measure the accounting errors and irregularities in financial statements, which can be effectively corrected by auditors, while other risk factors may include risk in the clients' business, which cannot be controlled by auditors.

The other advantage FSD_Score has is that it assesses the level of accounting errors in whole financial statements, while accruals models only analysis certain areas related to earnings and cash flow. When accounting errors occur in the areas other than risky account, they may have strong influence on the quality of auditing but less effect on litigation risk.

The differences between the coefficients of FSD_Score in the two samples shows that the associations between FSD_Score and audit fees are stronger in smaller firms than in larger firms. The reason for this could be that auditors are not able to correct as many mistakes in larger firms as they can for smaller firms with the same effort due to large number of transactions in larger firms. Hence, when the same additional effort is applied in auditing, the FSD_Score of smaller firms will reduce more than the FSD_Score of larger firms.

Additional tests further show that FSD_Score is consistent with other audit quality measures, such as auditor size, going concern and profitability. The reason that FSD_Score is different between firm-years with good and bad performance is that firms with bad performance tend to manipulate their financial statements, which influences the input quality of financial data, thus affecting the output quality of the audit process (DeFond and Zhang, 2013). However, the more effort auditors put into auditing, the more errors and irregularities auditors will be found out, and the higher the quality of the financial report will be.

Therefore, based on the results of my study, FSD_Score is a significant measurement of audit quality. The high value of FSD_Score may be an important indicator of insufficient audit effort. On the assistance of digitally formatted financial statements and well developed software products, such as Excel, FSD_Score could be a highly practical tool without complicated calculations for auditors, investors and regulators to estimate the quality of information in the financial statements.

Regarding the accruals-based earnings management measures, the absolute value of the residuals from the modified Jones Model and the absolute value of working capital accruals, do not have a strong influence on the association between FSD_Score and audit fees. The measure of working capital accruals, ABS_RSST, has a stronger association with audit fees and audit quality proxies than the modified Jones Model in my study. For example, in Sample 2, the relation between ABS_RSST to audit fees is at the 1% significant level while the association between ABS_JONES_RESID and audit fees is at the 5% significant level. Furthermore, in the comparison of firms audited by BIG4/non-BIG4 auditors, and received qualified/going concern opinions, and with positive/negative income in additional tests, the differences of the mean value of ABS_RSST are more noticeable than the differences of the mean value of ABS_JONES_RESID.

6.2. Further Research

In order to test whether the FSD_Score measures audit quality accurately, additional tests are needed. One useful test would be to compare the FSD_Score of financial statements before and after auditing. The difficulty of such research is in gaining access to unpublished financial data. Furthermore, the investigation of the factors that influence FSD_Score is also important. In such research, academics can use the FSD_Score as a dependence variable and test its determinants.

In addition, the comparison of FSD_Scores in different countries has not been analyzed in existing studies. Accounting measures are often troubled by the differences in accounting standards and calculations across countries. FSD_Score is not influenced by accounting standards and calculations, so it is highly useful in comparing the quality of financial information in different counties.

Furthermore, this study does not include all the variables found significant correlation with audit fees in prior studies. Further research can investigate the influence of other control variables to the association between FSD_Score and audit fees.

Last but not least, determining a critical value of FSD_Score to identify firm-years with a significant level of accounting errors is highly useful in practice for auditors, investors, academics and regulators to assess individual firm-year observations early.

6.3. Limitations

There are certain limitations in this study. First of all, due to limited access to data, the audit fee models in my study do not include all the important variables in prior studies, such as corporate governance variables. However, the adjusted R-squares are around 0.80 in both models, which shows the models fit the sample in this study well. Secondly, sample size was reduced significantly due to a large amount of missing value, and the merger of audit fee data with financial statement data. The significant reduction of sample size may cause biases in the final data.

Thirdly, due to limited time, the sensitivities tests of FSD_Score with firms reporting fewer than 100 numbers are not provided in the study. Benford's Law is valid in larger sample size, but Amiram et al. (2015) point out that the firm-year with fewer than 100 numbers did not have a strong influence on their results. Thus, to generalize the application of FSD_Score, firm-year observations with fewer than 100 numbers in their financial statements should be further tested to find out if their FSD_Scores are significantly associated with audit fees.

All in all, this study investigates the data between 2000 and 2014 with a final sample size of 11,931 in Sample 1 and 21,641 in Sample 2. It is the first to provide empirical evidence on the association between audit fees and FSD_Score, and to suggest that FSD_Score can be a significant measurement of audit quality and an indicator of inefficient audit effort. The results are useful to regulators in estimating the level of accounting errors and irregularities in financial data. Auditors can apply FSD_Score to measure the outcome of auditing during audit procedures in order to determine whether additional audit effort is needed. The results can also be used by academics for further research, such as to compare different audit quality proxies and results from different countries.

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Appendix

Colgate Palmolive Co Fiscal Year 2015

Dollars in Millions Except Per Share Amounts

Consolidated Statements of Income		
For the years ended December 31, 2014		
Net sales	$	17,277
Cost of sales		7,168
Gross profit	$	10,109
Selling, general and administrative expenses		5,982
Other (income) expense, net		570
Operating profit		3,557
Interest expense, net		24
Income before income taxes		3,533
Provision for income taxes	$	1,194
Net income including noncontrolling interests		2,339
Less: Net income attributable to noncontrolling interests	$	159
Net income attributable to Colgate-Palmolive Company		2,180
Earnings per common share, basic		2
Earnings per common share, diluted		2

Consolidated Balance Sheets

As of December 31, 2014

Assets			
Current Assets			
Cash and cash equivalents	$ **1**,089		
Receivables (net of allowances of $54 and $67, respectively)	$ **1**,552		
Inventories	$ **1**,382		
Other current assets			**8**40
Total current assets			**4**,863
Property, plant and equipment, net			**4**,080
Goodwill			**2**,307
Other intangible assets, net	$ **1**,413		
Deferred income taxes			**7**6
Other assets			**7**20
Total assets		**1**3,459	
Liabilities and Shareholders' Equity			
Current Liabilities			
Notes and loans payable	$ **1**6		
Current portion of long-term debt			**4**88
Accounts payable	$ **1**,231		
Accrued income taxes			**2**94
Other accruals	$ **1**,917		
Total current liabilities			**3**,946
Long-term debt			**5**,644
Deferred income taxes			**2**61
Other liabilities			**2**,223
Total liabilities		**1**2,074	
Shareholders' Equity			
Common stock, $1 par value			
(2,000,000,000 shares authorized, 1,465,706,360 shares issued)	$ **1**,466		
Additional paid-in capital	$ **1**,236		
Retained earnings		**1**8,832	
Accumulated other comprehensive income (loss)			-**3**,507
Unearned compensation			-**2**0
Treasury stock, at cost		-**1**6,862	
Total Colgate-Palmolive Company shareholders' equity	$ **1**,145		
Non-controlling interests			**2**40
Total shareholders' equity	$ **1**,385		
Total liabilities and shareholder's equity		**1**3,459	

Consolidated Statements of Cash Flow		
For the years ended December 31, 2014		
Operating Activities		
Net income including noncontrolling interests		2,339
Adjustments to reconcile net income including noncontrolling interests		
to net cash provided by operations:		
Depreciation and amortization		442
Restructuring and termination benefits, net of cash		64
Venezuela remeasurement charges		327
Voluntary benefit plan contributions		-2
Charge for a foreign tax matter		66
Stock-based compensation expense	$	131
Deferred income taxes	$	18
Cash effects of changes in:		
Receivables	$	(109)
Inventories		-60
Accounts payable and other accruals		57
Other non-current assets and liabilities		25
Net cash provided by operations		3,298
Investing Activities		
Capital expenditures		-757
Sale of property and non-core product lines		24
Purchases of marketable securities and investments		-340
Proceeds from sale of marketable securities and investments		283
Payment for acquisitions, net of cash acquired		-87
Other	$	18
Net cash used in investing activities		-859
Financing Activities		
Principal payments on debt	$	(8,525)
Proceeds from issuance of debt		8,960
Dividends paid	$	(1,446)
Purchases of treasury shares	$	(1,530)
Proceeds from exercise of stock options and excess tax benefits		371
Net cash used in financing activities		-2,170
Effect of exchange rate changes on Cash and cash equivalents	$	(142)

Net increase (decrease) in Cash and cash equivalents	$	**1**27
Cash and cash equivalents at beginning of year		**9**62
Cash and cash equivalents at end of year	$	**1**,089
Supplemental Cash Flow Information		
Income taxes paid	$	**1**,009
Interest paid	$	**1**33