Benford's Law, earnings management, and accounting conservatism: The UK evidence

Tri Tri Nguyen[1]
School of Business and Law,
University of East London
London, United Kingdom
tri.tri.nguyen@uel.ac.uk

Chau Duong
School of Business and Law,
University of East London
London, United Kingdom
c.duong@uel.ac.uk

Nguyet Nguyen
University of Portsmouth
Portsmouth, United Kingdom
nguyet.nguyen@port.ac.uk

[1] *Corresponding author.*

Abstract

We apply Benford's Law to study first digits of financial statement items of UK listed companies. The evidence shows that the first digits conform to Benford' Law at the firm-specific level and market level. Further analysis shows that deviations of the first digits of income statement items from Benford's Law are larger that of balance sheet items and cash flow items, suggesting that income statements may contain more errors. The evidence also supports our hypothesis that, in addition to earnings management, accounting conservatism is a source of deviations of the first digits. We argue that accounting conservatism introduces biases to financial statements, which make accounting figures deviate from the law of digit distributions. The results have some implications for auditors.

1. Introduction

Accounting scandals normally begin with inflating earnings management up to four years prior to the collapse of corporations (García Lara *et al.*, 2009). A significant consequence is that investors may suffer some losses before accounting manipulations are detected. Therefore, building empirical models to identify earnings management in published financial statements attracts a lot of researchers (Dechow *et al.*, 2010).

One strand of research focuses on developing models to detect earnings management or predict accounting frauds. Some researchers use firm characteristics to estimate on abnormal accruals, which are viewed as earnings management (Jones, 1991, Dechow *et al.*, 1995, Dechow and Dichev, 2002, Kothari *et al.*, 2005). Other researchers use actual fraud cases to construct models to predict accounting frauds (Beneish, 1997, Beneish, 1999, Dechow *et al.*, 2011). A common feature of those models is that they use time-series or cross-sectional data to estimate earnings management or frauds. Although earnings management models are widely applied, previous studies indicate that those models may be misspecified (Dechow *et al.*, 2010).

Another line of accounting research relies on mathematics to examine risks of earnings management or frauds. Specifically, researchers apply Benford's Law, which is the "law" of distributions of digits of accounting numbers, to study errors which may be caused by intentional or unintentional acts. Benford's Law indicates that when there is an absence of errors in a dataset, every digit of numbers has a specific frequency of appearance. Thus, deviations from the expected frequencies are indications of the existence of errors in datasets. The research applying Benford's Law may overcome limitations of earnings management models because it relies on only mathematics. There is an emerging evidence on the application of Benford's Law to examine errors (Carslaw, 1988, Thomas, 1989, Nigrini, 1996, Van Caneghem, 2002, Van Caneghem, 2004, Amiram *et al.*, 2015, Nigrini, 2015).

In the contexts of UK, Van Caneghem (2002) and Van Caneghem (2004) provide evidence that deviations of second digits of earnings from Benford's Law are signals of earnings management. However, a major limitation of those studies is that they study only one item in financial statements (pre-tax income). Given that financial statements are prepared for various stakeholders, net income is not the only figure to be manipulated. This research expects to fulfil the gap in the literature by examining all numbers reported in financial statements. We adopt the methodology introduced by Amiram *et al.* (2015), which use firm-year data to calculate deviations of first digits of financial statement items. Amiram *et al.* (2015) show that first digits of financial statement items of US listed companies conform to

Benford's Law. In this study, we hypothesise that first digits of financial statement items of UK listed companies conform to Benford's Law.

Also, we expect to provide an alternative explanation for sources of deviations of first digits. The literature indicates that an introduction of earnings management or frauds in financial statements would lead to more divergence of digits of accounting numbers from Benford's Law (Van Caneghem, 2002, Amiram *et al.*, 2015). In addition to earnings management, we hypothesise that accounting conservatism is a source of deviations. The reason is that accounting conservatism also introduces biases to financial statements (Mora and Walker, 2015).

We test our hypotheses with a sample of UK listed companies from 2005 to 2012. We measure deviations of first digits from Benford' Law by using maximum cumulative absolute differences and mean absolute differences between expected frequencies and actual frequencies of first digits of financial statement items. The evidence shows that financial statements of UK listed companies conform to Benford's Law at the firm-specific level and market level. Further analysis shows that deviations of first digits of income statement items are larger than that of balance sheet items and cash flow items, suggesting that income statements may contain more errors. Also, the results from multivariate regressions show that deviations of first digits are positively correlated with discretionary accruals and timeliness of bad news over good news. The evidence implies that earnings management and accounting conservatism are sources of deviations of first digits.

The research makes significant contributions to literature and practice. First, we are the first to apply Benford's Law to analyse first digits of all items in financial statements of UK listed companies. Previous studies using UK data only examine second digits of a specific item such as pre-tax income (Van Caneghem, 2002, Van Caneghem, 2004). Thus the existing evidence can just suggest errors in earnings. By studying all figures reported in financial statements, this study allows the possibility that errors may exist anywhere in financial statements. Therefore, the findings may have more implications for practitioners. Second, we offer an alternative explanation for deviations of first digits. The existing literature explains that first digits deviate from Benford's Law because accounting data include frauds or biases such as earnings management. We hypothesise and find that accounting conservatism is also a source of deviations. The findings support recent improvements in accounting standards (International Accounting Standards Board, 2010), which remove the requirement that conservatism (prudence) is one the characteristics of financial statements.

The findings have some implications for auditors. We are proponents of the use of Benford's Law as an analytical procedure in an audit engagement because Benford's Law can indicate that there may be errors in accounting data. The findings of this research show that income statements have larger deviations of the first digits, suggesting that there may be more errors in income statements. Thus, auditors should be cautious when auditing income statement items such as revenues and expenses. Also, the findings indicate that deviations of the first digits may be caused by earnings management or accounting conservatism. Given that earnings management is more likely to be linked with material misstatements, the analytical procedure from applying Benford's Law may provide a false indication of accounting misstatements. Thus auditors should plan the audit engagement carefully to balance benefits and costs of using Benford's Law.

2. Literature review and hypothesis development:

2.1. Benford's Law in accounting research

Benford's Law refers to the distributional probability of the digits of numbers in a data set. The distributional probability of the first digits was discovered by astronomer Simon Newcomb in 1881 and was later tested on various data sets by physicist Frank Benford, therefore it is commonly known as Benford's Law (Amiram *et al.*, 2015).

The expected frequencies of the first digits of numbers in a data set are as follows (Amiram *et al.*, 2015, p. 1547) [2]:

First digit	1	2	3	4	5	6	7	8	9
Expected frequency	0.301	0.176	0.125	0.097	0.079	0.067	0.058	0.051	0.046

The intuition why the probability of the first digit one is the largest and the probability of the first digit nine is the smallest is as follows. As explained by Nigrini (1996), the number one needs 100% growth to change to the number two (e.g., the population of a city increases from 100,000 to 200,000 people), the number two needs 50% growth to change to number three (e.g., the population increases from 200,000 to 300,000 people), and so forth, finally the number nine needs only 11.1% growth to change to the number one (e.g., the population increases from 900,000 to 1,000,000 people). Therefore, a number starting with the digit one (nine) has the highest (smallest) probability of existence in a population.

Mathematically, the expected frequency of the first digit of a number following the Benford's Law is given by the equation (Nigrini, 1996, Amiram *et al.*, 2015, Nigrini, 2015)[3]:

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[2] *For expected frequencies of the second, third and fourth digits following Benford's Law, please read Nigrini, M.J., 1996. A Taxpayer Compliance Application of Benford's Law. The Journal of the American Taxation Association, 18, 72-91.*

[3] *Similarly, the probability of other digits can also be written in the mathematical formulas Carslaw, C.A., 1988. Anomalies in Income Numbers: Evidence of Goal Oriented Behavior. Accounting Review, 321-327, Thomas, J.K., 1989. Unusual Patterns in Reported Earnings. Ibid., 773-787, Da Silva, C.G. &*

$$P(D_1 = d_1) = \log_{10}\left(1 + \frac{1}{d_1}\right) = \log_{10}(d_1 + 1) - \log_{10}(d_1) \qquad (1)$$

Where D_1 is the first digit of a number, d_1 = 1, 2, 3, …, 9.

A common application of Benford's Law is to assess accounting numbers' conformity to Benford's Law in tabulated (actual) data. Nigrini (1994) indicates that non-conformity to Benford's Law may be a red flag for errors in data. From the practical perspective, Nigrini and Mittermaier (1997) propose that comparing actual and expected frequencies of a list of numbers can be used as an analytical procedure in an audit. Durtschi *et al.* (2004) also provide the guidance for auditors to apply Benford's Law to detect suspected accounts which may contain frauds. da Silva and Carreira (2013) uses predefined criteria based on Benford's Law to develop models which support auditors to construct auditing samples containing conformity and non-conformity transactions.

Early empirical studies apply Benford's Law to study earnings management. Examining interest received and interest paid on individual tax returns, Nigrini (1996) reports that interest received has higher (lower) than expected frequencies of smaller (larger) first digits. In contrast, interest paid has lower (higher) than expected frequencies of smaller (larger) first digits. The findings suggest that interest received (paid) has been understated (overstated), resulting from the tax evasion behaviour of taxpayers.

Carslaw (1988) studies the second digits of reported income in financial statements of New Zealand firms and finds that the actual frequencies of zeros (nines) are more (less) than

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*Carreira, P.M.R., 2013. Selecting Audit Samples Using Benford's Law. Auditing: A Journal of Practice & Theory, 32***,** *53-65, Nigrini, M.J., 2015. Persistent Patterns in Stock Returns, Stock Volumes, and Accounting Data in the U.S. Capital Markets. Journal of Accounting, Auditing & Finance, 30***,** *541-557.*

expected by Benford's Law. He interprets that this phenomenon is caused by the rounding up behaviour of managers to achieve earnings targets. For example, when the true earnings are 5,984 (or any number just below 6,000), managers are more likely to report the earnings as 6,004 (or any number just above 6,000) to meet or beat the earnings target of 6,000. Consequently, the frequency of the second digit zeros is abnormally higher than expected, while the frequency of the second digit nines is unusually low.

Consistent with Carslaw (1988), Thomas (1989) shows similar patterns in the US, but there is less deviation of earnings numbers from the expectations following Benford's Law. Thomas (1989) also reports that while loss firms have more second digit nines and fewer second digit zeros than expected, profit companies have abnormally high frequencies of zeros and fives in the second digits after the decimal points of earnings per share (EPS) numbers. Later studies provide further evidence supporting the notion that the second digits of earnings numbers do not follow Benford's Law as a result of the rounding-up behaviour (Niskanen and Keloharju, 2000, Van Caneghem, 2002, Van Caneghem, 2004).

Studying first digits rather than second digits, Amiram *et al.* (2015) prove that financial statement items follow Benford's Law. The finding of Amiram *et al.* (2015) is based on work of Hill (1995), Ray and Lindsay (2005), and Pimbley (2014). Ray and Lindsay (2005) indicate that a combination of normal distributions has a nearly exact normal distribution when their means are less than two standard deviations apart, therefore it conforms to Benford's Law. Hill (1995) proves that, under certain conditions, combined distributions follow Benford's Law if there is no error in data sets. While Pimbley (2014) shows that the Central Limit Theorem results in conformity to Benford's Law of data sets if data distributions tend to be smooth and symmetric in nature, Amiram *et al.* (2015) mathematically prove that the distribution of a mixture of estimations of cash flow realisations tends to be smooth and symmetric and therefore follows Benford's Law. Another significant of Amiram *et al.* (2015) is that they also develop an innovative score, namely FSD_SCORE, to capture the deviations of the first digits of figures reported in financial statements from Benford's Law. The FSD_SCORE is defined as the sum of deviations of the first digits from Benford's Law divided by nine, where deviations are absolute differences between observed (actual) frequencies of the first digits and the expected frequencies of all items in balance sheets, income statements, and cash flow statements. Amiram *et al.* (2015) prove that an introduction of errors in financial statements results in more divergence of first digits from Benford's Law. The FSD_SCORE is also found to be correlated with earnings management and is helpful to predict material accounting misstatements identified by the US Securities Exchange Commision (accounting and auditing enforcement releases, or AAER).

Similar to Amiram (2015)'s approach, Nigrini (2015) relies on the law of the first two digits to study the conformity to Benford's Law of accounting data, stock prices and trading volumes of US companies. To capture deviations of the first two digits, Nigrini (2015) also use the mean absolute deviations (MAD), which is the sum of absolute difference between expected frequencies and actual frequencies of the first two digits divided by 90 (which is the total first two digits from 10 to 99). Comparing MAD with predetermined ranges of conformity, the author shows that distributions of the first two digits of accounting data, stock prices, and trading volumes closely conform to Benford's Law.

2.2. Accounting research on Benford's Law in the UK

There are relatively few accounting studies applying Benford's Law in the UK. Van Caneghem (2002) and Van Caneghem (2004) find that there is an abnormal high (low) frequency of the second digit zero (nine) in income numbers and deviations of the second digit zero and nine from what are expected by Benford's Law are statistically significant. Highly abnormal distributions do not exist in other second digits. This evidence is consistent with previous studies on rounding-up behaviour (Carslaw, 1988, Thomas, 1989, Niskanen and Keloharju, 2000, Van Caneghem, 2002).

Van Caneghem (2002) attempt to explain causes of deviations from Benford's Law of earnings numbers. Using abnormal accruals as a proxy for earnings management, he indicates that firms which involve in rounding-up of earnings exhibit higher discretionary accruals. The evidence suggests that firms are likely to manage accruals to achieve targeted earnings and the introduction of earnings management results in large non-conformity of the second digits to Benford's Law. The notion that earnings management is related to deviations from Benford's Law is also supported by findings of Amiram *et al.* (2015). However, while Amiram *et al.* (2015) study the first digits of all figures reported in financial statements, Van Caneghem (2002) examine the distribution of the second digits of earnings numbers.

In another research, Van Caneghem (2004) study the effect of audit quality on deviation from Benford's Law which results from the rounding-up in the second digits of earnings figures. He uses deviations of the second digits zero and nine of pre-tax earnings as a proxy for earnings management. Contradict to evidence on the effect of audit quality on earnings management (Krishnan, 2003), he finds that the abnormal distributions of the second digits zero and nine are not statistically different between companies audited by Big Four and companies audited by Non-Big Four.

Although some studies apply Benford's Law to examine accounting practices of UK listed companies (Van Caneghem, 2002, Van Caneghem, 2004), there are still fruitful areas for further research. First, prior research only focuses on the second digits of a specific item (pre-tax income). This line of study provides evidence that deviations of the second digits from Benford's Law are related to rounding-up behaviours (Van Caneghem, 2002, Van Caneghem, 2004). In this study, we focus on the first digits of all numbers reported in financial statements. This is important because, under international financial reporting standards (IFRS), financial statements are prepared for general purposes (Financial Accounting Standards Board, 2010), meaning that there may be various stakeholders who use financial statements. Thus, earnings figures are not the only numbers to be manipulated. By studying all numbers reported in financial statements, our view is that any item in financial statements could be managed. Second, previous studies applying Benford's Law (Van Caneghem, 2002, Van Caneghem, 2004) require time series data or cross-sectional data for analyses which may can be costly for researchers. In this research, we use firm-year observations to calculate FSD_SCORE following Amiram *et al.* (2015), which capture deviations of first digits of financial statement items. In the context of UK, FSD_SCORE has even more potential because of the lack of data on earnings quality similar to which are available in the US (such as accounting restatements enforced by the US Government Accountability Office or Accounting and Auditing Enforcement Releases (AAER) from the US Securities and Exchange Commission).

2.3. Hypothesis

First of all, similar to Amiram *et al.* (2015) who find that first digits of financial statement items of US listed companies follow Benford's Law, we hypothesise that first digits of numbers in financial statements of UK companies conform to Benford's Law at the firm-specific level and market level.

H1: Distributions of first digits of figures reported in financial statements of UK listed companies follow Benford's Law.

In addition, previous studies show earnings management has an important implication for markets because earnings are used for equity valuation (Aharony *et al.*, 1993, Teoh *et al.*, 1998a, Teoh *et al.*, 1998b, DuCharme *et al.*, 2001, Kim and Park, 2005, Iqbal *et al.*, 2009, Kao *et al.*, 2009, Iqbal and Strong, 2010). The consequence is that items in income statements are more likely to be manipulated than other items because income and expense items affect net profit (earnings) directly. Therefore, it is reasonable to expect that deviations of the first digits of income statement items are larger than that of balance sheet items and cash flow items. This hypothesis is consistent with findings of Amiram *et al.* (2015) who also report larger deviations of income statement items than that of balance sheet items and cash flow items.

H2: Deviations of first digits of income statement items are larger than that of balance sheet items and cash flow items.

Furthermore, previous studies suggest that deviations from Benford's Law can signal red flags of earnings management (Van Caneghem, 2002, Durtschi *et al.*, 2004, Van Caneghem, 2004, Amiram *et al.*, 2015). Examining second digits, Van Caneghem (2002) indicates that firms which involve in rounding-up of earnings exhibit higher discretionary accruals. The evidence suggests that firms are likely to manage accruals to achieve targeted earnings and the introduction of earnings management results in large non-conformity of the second digits to Benford's Law. Amiram *et al.* (2015) also explain that an introduction of errors, frauds or bias (such as earnings management) leads to higher divergence of digits in financial statements (Amiram *et al.*, 2015). However, there is little attempt to provide an alternative explanation for deviations of digits from Benford's Law. Recently, Mora and Walker (2015) indicate that accounting conservatism leads to biased financial statements, such as downward earnings management by recognising too many losses to create reserves for future use. We also believe that accounting conservatism is a sort of deviations of first digits. Therefore, we hypothesise that both earnings management and accounting conservatism cause deviations of the first digits from Benford's Law.

H3: Earnings management leads to an increase in deviations of first digits of financial statement items

H4: Accounting conservatism leads to an increase in deviations of first digits of financial statement items.

3. Methodology:

3.1. Sample selection

This research uses data of all listed companies in London Stock Exchange from 2005 to 2012. We download all items in financial statements from Datastream database. Financial institutions and utility firms are removed. We replace missing values by zero when calculating distributions of first digits and this approach does not affect analysis because zero cannot be a leading digit of numbers. We extract the first digits of items financial statement (including, balance sheets, income statements and cash flows). For negative numbers, we obtain the first digits after the negative sign. For numbers from -1 to 1, we obtain the first non-zero digit. Finally, we delete observations with total first digits less than 50 because inclusion of firms with small number of total first digits may introduce bias to the sample[4]. As a result, we derive 10,048 firm-year observations from 2005 to 2012 (1,839 unique companies) with 721,027 first digits. This sample is used to calculate FSD_SCORE for firm-year observations and for the whole market to determine if financial statement data of listed companies in the UK conform to Benford's Law.

We test our hypotheses 3 and 4 based on a sample of 3,635 firm-year observations with sufficient data to calculate empirical measures. All continuous variables are winsorized the 1st and 99th percentiles.

3.2. Measuring conformity and deviations from Benford's Law

Previous studies document that conformity to Benford's Law can be tested for each digit or all digits. To test conformity of each digit, prior research uses the Chi-Squared (χ^2) test which uses Z-statistic as critical value (Carslaw, 1988, Thomas, 1989, Niskanen and Keloharju, 2000, Van Caneghem, 2002, Van Caneghem, 2004). To test conformity for all digits, the existing literature suggest two methods which are Kolmogorov–Smirnov (KS) test and mean absolute deviation (MAD) test (Nigrini and Mittermaier, 1997, Amiram *et al.*, 2015, Nigrini, 2015). For the purposes of this study, we use the KS test and MAD test to provide evidence for the hypothesis 1 and 2. The following part explains KS test and MAD test.

The KS test relies on a KS statistic which uses maximum deviation of digits from Benford's Law, where deviations are defined as absolute cumulative differences between observed and

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[4] Amiram, D., Bozanic, Z. & Rouen, E., 2015. Financial Statement Errors: Evidence from the Distributional Properties of Financial Statement Numbers. Review of Accounting Studies, 20, 1540-1593. Indicate that firms with less than 50 first digits may be too young or not in continuing operations, therefore inclusion of those firms may cause measurement errors.

expected probabilities of the digits. The calculation of KS statistic is as follows (Amiram *et al.*, 2015):

$$KS_{i,t} = max\{\left|OD_{1,i,t} - ED_1\right|, \left|\left(OD_{1,i,t} + OD_{2,i,t}\right) - (ED_1 + ED_2)\right|, \dots, \left|\left(OD_{1,i,t} + OD_{2,i,t} + \cdots + OD_{9,i,t}\right) - (ED_1 + ED_2 + \cdots + ED_9)\right|\} \quad (2)$$

Where $KS_{i,t}$ is maximum cumulative absolute deviation of the first digits of figures reported in financial statements from what are expected by Benford's Law of firm *i* in year *t;* $OD_{d,i,t}$ is the cumulative observed probability of the first digit *d* (*d* = 1, 2, …, 9) of firm *i* in year *t*; ED_d is the expected probability of the first digit *d* (*d* = 1, 2, …, 9) as defined by Benford's Law.

The critical value (test value) to test whether a data set conforms to Benford's Law at the 5% significant level is $1.36/\sqrt{\mathrm{P}}$, where P is the total number of the first digits. If the KS statistic is less than the test value, distribution of first digits conforms to Benford's Law.

Although KS test is used to test the conformity of digits to Benford's Law, it has a major disadvantage (Amiram 2015). When the total number of digits analysed (P) is large, KS test becomes sensitive because the test value is calculated based on P. Therefore, KS test is most appropriate to test the conformity to Benford's Law at the firm level. In this research, I only use KS test conformity for firm-year observations.

The second test for conformity to Benford's Law relies on the mean absolute deviation (MAD), where MAD is the sum of absolute differences between observed (actual) and expected frequencies of digits (Amiram *et al.*, 2015, Nigrini, 2015). Regarding the first digits, Amiram *et al.* (2015) develop an FSD_SCORE which is calculated based on MAD as follows:

$$FSD\_SCORE_{i,t} = \frac{\sum_{d=1}^{9}\left|OBSERVED_{d,i,t} - EXPECTED_d\right|}{9} \qquad (3)$$

Where: $FSD\_SCORE_{i,t}$ is the mean absolute deviation of the first digits of financial statement items from Benford's Law of firm *i* in year *t; $OBSERVED_{d,i,t}$* is the actual probability of the first digit *d* of firm *i* in year t; $EXPECTED_d$ is the expected probability of the first digit *d* following Benford's Law; and *d* = 1, 2, …, 9.

The construction of FSD_SCORE based on MAD statistic overcomes a major drawback of the KS statistic (Amiram *et al.*, 2015). When the population of the first digits are significant, compared with the KS statistic, the MAD statistic is more appropriate in comparing financial statements across firms, industries and times.

While there is no critical value for MAD, prior studies suggest ranges of MAD values which indicate levels of conformity to Benford's Law of the first digits (Drake and Nigrini, 2000, Nigrini, 2012). We also rely on suggested MAD range values to test conformity of first digits [5].

3.3. Main tests

To find evidence for hypothesis 3 and 4, we run regressions between FSD_SCORE and proxies for earnings management and accounting conservatism. The following section explains measures of earnings management and accounting conservatism.

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[5] *Drake, P.D. & Nigrini, M.J., 2000. Computer assisted analytical procedures using Benford's Law. Journal of Accounting Education, 18, 127-146. and Nigrini, M., 2012. Benford's Law: Applications for forensic accounting, auditing, and fraud detection: John Wiley & Sons. suggest four levels of conformity of first digits: close conformity (MAD values range from 0.000 to 0.004), acceptable conformity (MAD values range from 0.004 to 0.008), marginally acceptable conformity (MAD values range from 0.008 to 0.012), and non-conformity (MAD values are greater than 0.012).*

3.3.1. Earnings management proxy

There are various models to estimate earnings management (Dechow *et al.*, 2010). In this study, we apply the modified-Jones model (Jones, 1991, Dechow *et al.*, 1995) to estimate discretionary accruals (DAC) because Peasnell *et al.* (2000) find that it is the most effective model. We run the following regression with at least ten observations for each industry-year (Datastream level-six).

$$\frac{AC_{i,t}}{A_{i,t-1}} = \alpha + \beta_1\left(\frac{1}{A_{i,t-1}}\right) + \beta_2\left(\frac{\Delta REV_{i,t}}{A_{i,t-1}}\right) + \beta_3\left(\frac{PPE_{i,t}}{A_{i,t-1}}\right) + \varepsilon_{i,t} \qquad (4)$$

Where $AC_{i,t}$ is total accruals which equals to net income before extraordinary items minus net cash flows from operations; $A_{i,t-1}$ is total assets of firm *i* at the end of year *t–1;* $\Delta REV_{i,t}$ and $\Delta REC_{i,t}$ are change in sales and change in receivables from year *t–1* to year *t* of firm *i,* respectively; $PPE_{i,t}$ is gross plant, property and equipment of firm *i* at the end of year *t.*

Using $\hat{\alpha}, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$ estimated from equation (4), we calculate discretionary accruals as follows:

$$DAC_{i,t} = \left|\frac{AC_{i,t}}{A_{i,t-1}} - \left[\hat{\alpha} + \hat{\beta}_1\left(\frac{1}{A_{i,t-1}}\right) + \hat{\beta}_2\left(\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}}\right) + \hat{\beta}_3\left(\frac{PPE_{i,t}}{A_{i,t-1}}\right)\right]\right| \qquad (5)$$

In this research, we follow previous studies (e.g., Bergstresser and Philippon, 2006, Jiang *et al.*, 2010, Armstrong *et al.*, 2013, Hilary *et al.*, 2016) to use absolute values of earnings management regardless of directions (upward or downward). The reason is that both upward and downward earnings management introduce biases in financial statements, therefore lead to more divergence of first digits.

3.3.2. Accounting conservatism proxy

We follow Basu (1997) and Khan and Watts (2009) to estimate firm-year accounting conservatism. We firstly run the following regression for each year:

$$EARN_{i,t} = \beta_1 + \beta_2 D_{i,t} + \left(\mu_1 + \mu_2 SIZE_{i,t-1} + \mu_3 MTB_{i,t-1} + \mu_4 LEV_{i,t-1}\right) RET_{i,t} +$$

$$\left(\gamma_1 + \gamma_2 SIZE_{i,t-1} + \gamma_3 MTB_{i,t-1} + \gamma_4 LEV_{i,t-1}\right) D_{i,t} * RET_{i,t} +$$

$$(\delta_1 SIZE_{i,t-1} + \delta_2 MTB_{i,t-1} + \delta_3 LEV_{i,t-1} + \delta_4 D_{i,t} * SIZE_{i,t-1} + \delta_5 D_{i,t} * MTB_{i,t-1} + \delta_6 D_{i,t} * LEV_{i,t-1}) + \varepsilon_{i,t} \qquad (6)$$

$EARN_{i,t}$ is net income before extraordinary items in year t, scaled by market value of equity at the end of year t-1*;* $RET_{i,t}$ is buy-and-hold stock returns for the period from the beginning to the end of fiscal year t; $D_{i,t}$ is dummy variable which equals to one if $RET_{i,t}$ < 0, zero otherwise; $SIZE_{i,i-1}$ is natural log of market value of equity at the end of year t-1; $MTB_{i,i-1}$ is the market to book ratio at the end of year t-1; $LEV_{i,t-1}$ is the sum of long-term and short-term debts at the end of year t-1, scaled by the market value of equity at the end of year t-1.

Then we calculate empirical measures of the timeliness of good news (G_SCORE) and the incremental timeliness of bad news over good news (C_SCORE) based on firm characteristics as follows[6]:

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[6] *Khan, M. & Watts, R.L., 2009. Estimation and Empirical Properties of a Firm-year Measure of Accounting Conservatism. Journal of Accounting and Economics, 48, 132-150. use SIZE, MTB and LEV in year t to estimate G_SCORE and C_SCORE. In this paper, we use SIZE, MTB and LEV in year t-1. We argue that earnings are the incomes of the whole year so that firms may rely on the conditions (characterised by LEV, SIZE, MTB) in year t-1 to make decisions on how much accounting numbers should be conservative in year t. The idea of using firm characteristics in year t-1 is also stipulated by Ball, R., Kothari, S.P. & Nikolaev, V.V., 2013. On Estimating Conditional Conservatism. The Accounting Review, 88, 755-787.. An example of using the same approach to estimate G_SCORE and C_SCORE is the work of Banker, R.D., Basu, S., Byzalov, D. & Chen, J.Y.S., 2012. Direction of Sales Change and Asymmetric Timeliness of Earnings In T. University (ed.)..*

$$G\_SCORE_{i,t} = \beta_3 = \mu_1 + \mu_2 SIZE_{i,t-1} + \mu_3 MTB_{i,t-1} + \mu_4 LEV_{i,t-1} \quad (7)$$

$$C\_SCORE_{i,t} = \beta_4 = \gamma_1 + \gamma_2 SIZE_{i,t-1} + \gamma_3 MTB_{i,t-1} + \gamma_4 LEV_{i,t-1} \quad (8)$$

$CSCORE$ is the measure of accounting conservatism. After that, we calculate the average of $CSCORE$ across years t-2, t-1 and t. Then, we calculate the annual fractional rank of accounting conservatism, denoted CSCORE_RANK, by ranking average values of CSCORE of all observations by each year, and then dividing ranked values by N+1 (where N is total observations in each year). We use ranked values because they help to mitigate concerns about nonlinearity and measurement errors (García Lara *et al.*, 2016, Goh *et al.*, 2016).

3.3.3. Multivariate regression

To provide evidence for H3 and H4, we run the following regression

$$\begin{aligned} FSD\_SCORE_{i,t} \\ &= \alpha + \beta_1 DAC_{i,t} + \beta_2 CSCORE\_RANK_{i,t} + \beta_3 LOSS_{i,t} + \beta_4 FRAUD_{i,t} \\ &+ INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon \quad (9) \end{aligned}$$

In the model, we include two control variables, which is losses in previous years (LOSS) and risk of fraud (FRAUD) (Amiram *et al.*, 2015). $LOSS_{i,t}$ is equal to one if net incomes before extraordinary items in year t-2 and year t-1 are both negative, zero otherwise. $FRAUD_{i,t}$ is calculated based on FSCORE following Dechow *et al.* (2011) (Model 1, Table 7). $FRAUD_{i,t}$ is equal one if FSCORE is greater than one, zero otherwise; where FSCORE is calculated as follows:

$$Predicted\ Value = -7.893 + 0.790 * \text{ACC\_RSST} + 2.581 * \Delta\text{REC} + 1.191 * \Delta\text{INV} + 1.979 * \text{SOFTASSET} + 0.171 * \Delta\text{CASH} - 0.932 * \Delta\text{ROA} + 1.029 * \text{SEO}$$

$$Probability = \frac{e^{Predicted\ Value}}{1 + e^{Predicted\ Value}}$$

$$FSCORE = \frac{Probability}{0.0037}$$

Where: $e = 2.71828183$; ACC_RSST is change in non-cash net operating assets following Richardson *et al.* (2005)[7], scaled by total assets at the end of year t-1; ΔREC is changes in receivables from year t-1 to year t, scaled by total assets at the end of year t-1; ΔINV is changes in inventories from year t-1 to year t, scaled by total assets at the end of year t-1; SOFTASSET is soft assets in year t-1 (total assets minus cash and cash equivalent minus net property, plant and equipment, scaled by total assets at the end of year t-1); ΔCASH is changes in cash and cash equivalent scaled by total assets at the end of year t-1; ΔROA is return on assets in year t minus return on assets in year t-1, where return on assets are equal net income divided by total assets; SEO is actual equity issuance, which is equal one if change

[7] *ACC_RSST = (chWC + ChNCO + ChFIN)/AT_{t-1}; where:*

- *ChWC = WC_t – WC_{t-1}= [(ACT_t - CHE_t) - (LCT_t - DLC_t)] - [(ACT_{t-1} - CHE_{t-1}) - (LCT_{t-1} - DLC_{t-1})]; ACT is current assets, CHE is cash and cash equivalent, LCT is current liabilities, DLC is short term debts and current portions of long term debts.*
- *ChNCO = NCO_t - NCO_{t-1} = [(AT_t - ACT_t - $INVST_t$) - (LT_t - LCT_t - $DLTT_t$)] - [(AT_{t-1} - ACT_{t-1} - $INVST_{t-1}$) - (LT_{t-1} - LCT_{t-1} - $DLTT_{t-1}$)]; INVST is total investments; LT is total liabilities, DLTT is long term debts.*
- *ChFIN = FIN_t - FIN_{t-1} = [($STINVST_t$ + $LTINVST_t$) - (LT_t + $LTDEBTC_t$ + $PRESTOCK_t$)] - [($STINVST_{t-1}$ + $LTINVST_{t-1}$) - (LT_{t-1} + $LTDEBTC_{t-1}$ + $PRESTOCK_{t-1}$)]; STINVST is short-term investments, LTINVST is long-term investments, LTDEBTC is current portion of long term debts, PRESTOCK is preferred stock.*

in common share capital is greater than 5% and proceed from issuance is greater than 0, zero otherwise.

We expect that β_1 is positive and significant (Hypothesis H3), β_2 is positive and significant (hypothesis H4). β_3 and β_4 are also expected to be positive and significant because losses and high risk of fraud may cause an increase in FSD_SCORE (Amiram *et al.*, 2015).

4. FINDINGS AND DISCUSSIONS

4.1. Descriptive statistics and Correlations

Table 1 reports descriptive statistics of firm characteristics and selected variables. Firm characteristics are broadly similar to prior research which uses similar data (Goh and Gupta, 2016). At first glance, KS values are higher FSD_SCORE in all aspects (MEAN, STD, MEDIAN, MAX, MIN, P25 and P75). The reason is that while KS values are calculated based on maximum absolute cumulative differences between expected and actual distributions of first digits of financial statement items, while FSD_SCORE are calculated based on mean absolute differences. Also in table 1, mean of discretionary accruals is 0.080, indicating that on average, earnings are managed by 8% of opening total assets. The mean of CSCORE_RANK is 0.50 as expected because CSCORE is ranked values. The descriptive statistics also indicate that the sample has fewer firms with losses in two consecutive years (MEDIAN of LOSS is 0), and has fewer firms with a high risk of fraud (MEDIAN of FRAUD is 0).

[INSERT TABLE 1 ABOUT HERE]

Table 2 shows correlations of selected variables. The findings indicate that correlation coefficients between independent variables are very small (less than 0.2) and even insignificant (in italic), suggesting that multicollinearity is not a significant concern.

[INSERT TABLE 2 ABOUT HERE]

4.2. Evidence on conformity of first digits to Benford's Law

As discussed above, we have two tests for conformity of first digits of financial statement items to Benford's Law: KS test and MAD test. Table 3 reports findings of KS test of conformity at firm-specific level. In Panel A, we observe that the percentage of firm-year observations following Benford's Law is 90.86%. This conformity ratio is slightly higher than the conformity ratio of US companies for the period from 2001 to 2011, which is 85.63% (Amiram *et al.*, 2015, page 1584). In Panel B, the figures show that conformity rates level off around 91%, suggesting that financial statements of UK listed companies maintain high levels of conformity at least for eight years of the research period.

[INSERT TABLE 3 ABOUT HERE]

Table 4 and 5 report findings of MAD test. While Table 4 shows aggregate FSD_SCORE for the whole sample, Table 5 displays FSD_SCORE by income statements, balance sheets, and cash flow statements. Looking at Table 4, the aggregate FSD_SCORE for the entire market of listed companies in the UK from 2005 to 2012 is 0.0010, which is similar to that of companies listed in the US reported by Amiram *et al.* (2015)[8]. The small aggregate FSD_SCORE falls within the

[8] *In the US, Amiram, D., Bozanic, Z. & Rouen, E., 2015. Financial Statement Errors: Evidence from the Distributional Properties of Financial Statement Numbers. Review of Accounting*

first predetermined range (from 0.000 to 0.004) of conformity of the first digits to Benford's Law suggested by previous studies (Drake and Nigrini, 2000, Nigrini, 2012). The results indicate that distributions of first digits closely conform to Benford's Law. Turning to Table 5, FSD_SCORE of income statement items, balance sheet items, and cash flow items are 0.0014, 0.0009, and 0.0011, respectively. Those small figures also indicate that first digits of separate components of financial statements also closely conform to Benford's Law. In general, the findings of KS test and MAD tests support hypothesis 1 that first digits of financial statement items of UK listed companies follow Benford's Law.

[INSERT TABLE 4 ABOUT HERE]

[INSERT TABLE 5 ABOUT HERE]

Also in Table 5, we observe that FSD_SCORE of income statement items (0.0014) is larger than that of balance sheet items (0.0009) and cash flow items (0.0011). The evidence is consistent with expectation (hypothesis 2) and similar to findings of by Amiram *et al.* (2015). The reason for a larger FSD_SCORE of income statement items may be that managers are more likely to manipulate income statement items, such as revenues and expenses, because those items directly affect net profit of the year.

4.3. Multivariate regression results

Table 6 reports findings of regression (9), where independent variables include discretionary accruals (column a), accounting conservatism (column b) and both discretionary accruals and accounting conservatism (column c). Consistent with predictions, we find that FSD_SCORE is

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Studies, 20, 1540-1593. report that the aggregate FSD_SCORE of listed companies in US from 2001 to 2011 is 0.0009.

positively correlated with discretionary accruals (column a and c), which is a proxy for earnings management. The correlation is statistically significant at 1% level. The findings support hypothesis 3 that earnings management is a source of deviations of first digits. The findings are consistent with the notion that earnings management causes deviations of digits of accounting numbers from Benford's Law (Van Caneghem, 2002, Durtschi *et al.*, 2004, Van Caneghem, 2004, Amiram *et al.*, 2015). The reason may be that, when earnings are managed, first digits of financial statements deviate from expectations following Benford's Law. Thus, higher discretionary accruals are associated with larger FSD_SCORE. In column c, the evidence shows that one unit increase in discretionary accruals is associated with an increase of 0.0049 in FSD_SCORE. Given that the mean of FSD_SCORE is 0.032 (reported in Table 1), when discretionary accruals increase one unit, FSD_SCORE increases about 15.31% (=0.0049/0.032), which is non-trivial. Thus, the association between FSD_SCORE and discretionary accruals is significant in economic terms.

Also, we find that FSD_SCORE is positively correlated with the proxy for accounting conservatism (column b and c). The relationship is statistically significant at 1% level. The evidence supports the hypothesis that conservatism is a source of deviations of first digits. The findings are supported by the ideas of Mora and Walker (2015) that conservatism introduces biases in financial statements, which make first digits deviate from Benford's Law. In column c, we observe that one unit increase in accounting conservatism is associated with an increase of 0.0019 in FSD_SCORE, which accounts for 5.9% of FSD_SCORE (=0.0019/0.032). This relationship is also significant in economic terms.

Regarding control variables, we find that FSD_SCORE is higher for firms with two consecutive year losses (LOSS = 1) and firms with a higher risk of fraud (FRAUD = 1). The evidence is consistent with prior studies (e.g., Amiram *et al.*, 2015).

[INSERT TABLE 6 ABOUT HERE]

4.4. Robustness tests

To check whether our findings are robust, we replace FSD_SCORE by KS values in the regression 9. As discussed above, while FSD_SCORE is calculated based on the mean of absolute differences between actual frequencies and expected frequencies of first digits following Benford's Law, KS value is calculated based on maximum cumulative differences. We run following regressions:

$$KS_{i,t} = \alpha + \beta_1 DAC_{i,t} + \beta_2 CSCORE\_RANK_{i,t} + \beta_3 LOSS_{i,t} + \beta_4 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon \quad (10)$$

Table 7 reports findings of the regression (10). The evidence shows that KS values are also positively correlated with earnings management and accounting conservatism. The relationships are statistically significant. The findings are consistent with main results above, supporting hypothesis 3 and 4.

5. CONCLUSIONS

In this research, we apply Benford's Law to study distributions of first digits of financial statement items of UK listed companies. At firm-specific level, we find that the percentage of firm-year observations conforming to Benford's Law is 90.86%. At the market level, the evidence shows that the financial statements of all firms closely conform to Benford's Law.

First digits of separate components of financial statements (income statements, balance sheets, cash flow statements) also closely conform to Benford's Law. Further analysis shows that deviations of first digits of income statement items are larger than deviations of first digits of balance sheet items and cash flow items. Also consistent with our hypothesis, the results indicate that earnings management and accounting conservatism are two sources of deviations of first digits from Benford's Law.

This research makes significant contributions to the literature. First, this research is the first study which relies on the first digits of all items in financial statements of UK listed companies. Compared with previous studies in the UK which also apply Benford's Law (Van Caneghem, 2002, Van Caneghem, 2004), our study uses only firm-year observations and does not require time-series or cross-sectional data. Second, this research is the first study which provides an alternative explanation for deviations of digits from Benford's Law. Previous studies argue that digits of accounting numbers deviate from the law of distributions because of an introduction of frauds, errors or biases such as earnings management (Van Caneghem, 2004, Amiram *et al.*, 2015). Our findings show that accounting conservatism also increases deviations of first digits. The results have some implications for practitioners, especially auditors. First, auditors should be more cautious with income statement items, such as revenues and expenses, because the evidence shows that income statement items are more likely to deviate from Benford's Law. Second, auditors should consider benefits and costs of using Benford's Law as an analytical procedure, because the evidence shows that deviations of the first digits can be caused by both earnings management, which is more likely to be linked with material misstatements, and accounting conservatism.

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APPENDIX: VARIABLE DEFINITIONS

$CSCORE\_RANK_{i,t}$	Annual factional rank of accounting conservatism, based on Basu (1997) and Khan and Watts (2009).
$DAC_{i,t}$	$DAC_{i,t} = \left\lvert \frac{AC_{i,t}}{A_{i,t-1}} - \left[\hat{\alpha} + \hat{\beta}_1 \left(\frac{1}{A_{i,t-1}} \right) + \hat{\beta}_2 \left(\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} \right) + \hat{\beta}_3 \left(\frac{PPE_{i,t}}{A_{i,t-1}} \right) \right] \right\rvert$; Where $\hat{\alpha}, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$ are estimated from following equation with at least ten observations for each industry-year (Datastream level-six). $\frac{AC_{i,t}}{A_{i,t-1}} = \alpha + \beta_1 \left(\frac{1}{A_{i,t-1}} \right) + \beta_2 \left(\frac{\Delta REV_{i,t}}{A_{i,t-1}} \right) + \beta_3 \left(\frac{PPE_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t}$ Where $AC_{i,t}$ is total accruals which equals to net income before extraordinary items minus net cash flows from operations; $A_{i,t-1}$ is total assets of firm i at the end of year t–1; $\Delta REV_{i,t}$ and $\Delta REC_{i,t}$ are change in sales and change in receivables from year t–1 to year t of firm i, respectively; $PPE_{i,t}$ is gross plant, property and equipment of firm i at the end of year t.
$FSD\_SCORE_{i,t}$	$FSD\_SCORE_{i,t} = \frac{\sum_{d=1}^{9} \lvert OBSERVED_{d,i,t} - EXPECTED_d \rvert}{9}$ Where: $FSD\_SCORE_{i,t}$ is the mean absolute deviation of the first digits of financial statement items from Benford's Law of firm i in year t; $OBSERVED_{d,i,t}$ is the actual probability of the first digit d of firm i in year t; $EXPECTED_d$ is the expected probability of the first digit d following Benford's Law; and d = 1, 2, …, 9.
$FRAUD_{i,t}$	equal to one if FSCORE is greater than one, zero otherwise; where FSCORE is calculated as follows: $\text{Predicted Value} = -7.893 + 0.790 * ACC\_RSST + 2.581 * \Delta REC + 1.191 * \Delta INV + 1.979 * SOFTASSET + 0.171 * \Delta CASH - 0.932 * \Delta ROA + 1.029 * SEO$ $\text{Probability} = \frac{e^{\text{Predicted Value}}}{1 + e^{\text{Predicted Value}}}$ $FSCORE = \frac{\text{Probability}}{0.0037}$ Where: $e = 2.71828183$; ACC_RSST is change in non-cash net operating assets following Richardson et al. (2005), scaled by total assets at the end of year t-1; ACC_RSST = (chWC + ChNCO + ChFIN)/AT_{t-1}; where:

	$ChWC = WC_t - WC_{t-1} = [(ACT_t - CHE_t) - (LCT_t - DLC_t)] - [(ACT_{t-1} - CHE_{t-1}) - (LCT_{t-1} - DLC_{t-1})]$; ACT is current assets, CHE is cash and cash equivalent, LCT is current liabilities, DLC is short term debts and current portions of long term debts. $ChNCO = NCO_t - NCO_{t-1} = [(AT_t - ACT_t - INVST_t) - (LT_t - LCT_t - DLTT_t)] - [(AT_{t-1} - ACT_{t-1} - INVST_{t-1}) - (LT_{t-1} - LCT_{t-1} - DLTT_{t-1})]$; INVST is total investments; LT is total liabilities, DLTT is long term debts. $ChFIN = FIN_t - FIN_{t-1} = [(STINVST_t + LTINVST_t) - (LT_t + LTDEBTC_t + PRESTOCK_t)] - [(STINVST_{t-1} + LTINVST_{t-1}) - (LT_{t-1} + LTDEBTC_{t-1} + PRESTOCK_{t-1})]$; STINVST is short-term investments, LTINVST is long-term investments, LTDEBTC is current portion of long term debts, PRESTOCK is preferred stock. $\Delta\mathrm{REC}$ is changes in receivables from year t-1 to year t, scaled by total assets at the end of year t-1; $\Delta\mathrm{INV}$ is changes in inventories from year t-1 to year t, scaled by total assets at the end of year t-1; $\mathrm{SOFTASSET}$ is soft assets in year t-1 (total assets minus cash and cash equivalent minus net property, plant and equipment, scaled by total assets at the end of year t-1); $\Delta\mathrm{CASH}$ is changes in cash and cash equivalent scaled by total assets at the end of year t-1; $\Delta\mathrm{ROA}$ is return on assets in year t minus return on assets in year t-1, where return on assets are equal net income divided by total assets; SEO is actual equity issuance, which is equal one if change in common share capital is greater than 5% and proceed from issuance is greater than 0, zero otherwise.
$\mathrm{LOSS}_{\mathrm{i,t}}$	equal to one if net incomes before extraordinary items in year t-2 and year t-1 are both negative, zero otherwise.
$KS_{i,t}$	$\mathrm{KS}_{\mathrm{i,t}} = \max\{\lvert \mathrm{OD}_{1,\mathrm{i,t}} - \mathrm{ED}_1 \rvert, \lvert (\mathrm{OD}_{1,\mathrm{i,t}} + \mathrm{OD}_{2,\mathrm{i,t}}) - (\mathrm{ED}_1 + \mathrm{ED}_2) \rvert, \ldots, \lvert (\mathrm{OD}_{1,\mathrm{i,t}} + \mathrm{OD}_{2,\mathrm{i,t}} + \cdots + \mathrm{OD}_{9,\mathrm{i,t}}) - (\mathrm{ED}_1 + \mathrm{ED}_2 + \cdots + \mathrm{ED}_9) \rvert\}$ Where $\mathrm{KS}_{\mathrm{i,t}}$ is maximum cumulative absolute deviation of the first digits of figures reported in financial statements from what are expected by Benford's Law of firm i in year t; $\mathrm{OD}_{\mathrm{d,i,t}}$ is the cumulative observed probability of the first digit d (d = 1, 2, …, 9) of firm i in year t; ED_{d} is the expected probability of the first digit d (d = 1, 2, …, 9) as defined by Benford's Law.

Table 1: Descriptive statistics

Variables	N	MEAN	STD	MEDIAN	MIN	MAX	P25	P75
$AT_{i,t}$	3635	1,020,420	3,612,198	120,127	276	50,806,224	36,874	530,592
$Sale_{i,t}$	3635	818,674	2,559,972	121,071	0	41,591,430	26,067	549,600
Net income before extraordinary $items_{i,t}$	3635	71,504	403,825	4,677	- 1,425,847	6,893,275	491	28,200
Debt to assets $ratio_{i,t}$	3634	0.315	0.999	0.131	0.000	46.609	0.007	0.355
Market to book $ratio_{i,t}$	3634	4.039	20.544	2.084	0.083	1080.851	1.251	3.566
$FSD\_SCORE_{i,t}$	3635	0.032	0.010	0.031	0.009	0.088	0.025	0.037
$KS_{i,t}$	3635	0.089	0.039	0.082	0.012	0.307	0.061	0.111
$DAC_{i,t}$	3635	0.080	0.128	0.049	0.000	2.776	0.023	0.095
$CSCORE\_RANK_{i,t}$	3635	0.502	0.281	0.501	0.001	0.999	0.263	0.744
$LOSS_{i,t}$	3635	0.153	0.360	0.000	0.000	1.000	0.000	0.000
$FRAUD_{i,t}$	3635	0.102	0.303	0.000	0.000	1.000	0.000	0.000

Note: Table reports the number of observations (N), mean (MEAN), standard deviation (STD), median (MEDIAN), minimum (MIN), maximum (MAX), 25^{th} (P25), and 75^{th} (P75) percentiles of firm characteristics and selected variables. Definitions of variables are in the Appendix.

Table 2: Correlations

Variable		1	2	3	4	5	6
$FSD\_SCORE_{i,t}$	1	1.000					
$KS_{i,t}$	2	0.727	1.000				
$DAC_{i,t}$	3	0.127	0.091	1.000			
$CSCORE\_RANK_{i,t}$	4	0.065	0.058	*0.019*	1.000		
$LOSS_{i,t}$	5	0.238	0.197	0.192	0.059	1.000	
$FRAUD_{i,t}$	6	0.061	*0.031*	0.109	*0.042*	0.081	1.000

Note: The table reports the Pearson correlation coefficients between selected variables. The values reported in italic indicate the corresponding coefficients are not significant at 5% level. Definitions of variables are in the Appendix.

Table 3: Kolmogorov–Smirnov (KS) test of conformity to Benford's Law

Panel A: Aggregate conformity		
	Number of firm-year observations	*Percentage*
Conformity	9,130	90.86%
Non-Conformity	918	9.14%
Total	10,048	100.00%

Panel B: Conformity by year			
Year	*Number of firm-year observations*	*Number of conformity*	*Percentage*
2005	1544	1368	88.60%
2006	1535	1397	91.01%
2007	1447	1309	90.46%
2008	1311	1205	91.91%
2009	1182	1084	91.71%
2010	1086	999	91.99%
2011	1009	922	91.38%
2012	934	846	90.58%

Note: Table reports findings of KS tests for conformity to Benford's Law of first digits of financial statement items of UK listed companies from 2005 to 2012. Panel A report conformity of the whole sample, while Panel B reports conformity by year.

Table 4: Aggregate conformity to Benford's Law

Panel A: Aggregate deviations from Benford's Law				
First digit	Number of first digit	Expected frequency	Observed frequency	Deviation
(a)	(b)	(c)	(d)	(e)
1	218,700	0.3010	0.3033	0.0023
2	127,672	0.1761	0.1771	0.0010
3	90,719	0.1249	0.1258	0.0009
4	69,400	0.0969	0.0963	0.0007
5	57,485	0.0792	0.0797	0.0005
6	47,424	0.0670	0.0658	0.0012
7	41,411	0.0580	0.0574	0.0006
8	36,185	0.0512	0.0502	0.0010
9	32,031	0.0458	0.0444	0.0013
Total	721,027	1.0000	1.0000	0.0094
FDS_SCORE				0.0010

Note: the table reports the aggregate FSD_SCORE of UK listed companies for the period from 2005 to 2012. The table shows the first digits being analysed, expected frequencies of the first digits following Benford's Law, observed (actual) frequencies of the first digits, deviations of the first digits from Benford's Law, where deviations are defined as the absolute values of the observed frequencies minus the expected frequencies. FSD_SCORE is the sum of all deviations divided by nine. Definitions of variables are in the Appendix.

Table 5: Conformity to Benford's Law by statements

Panel A: Income statement

First digit	Number of first digit	Expected frequency	Observed frequency	Deviation
1	52,970	0.3010	0.3047	0.0037
2	30,657	0.1761	0.1764	0.0003
3	21,958	0.1249	0.1263	0.0014
4	16,610	0.0969	0.0956	0.0014
5	13,897	0.0792	0.0799	0.0008
6	11,425	0.0670	0.0657	0.0012
7	10,120	0.0580	0.0582	0.0002
8	8,639	0.0512	0.0497	0.0015
9	7,546	0.0458	0.0434	0.0023
Total	173,822	1	1	0.0127
FDS_SCORE				0.0014

Panel B: Balance sheet

First digit	Number of first digit	Expected frequency	Observed frequency	Deviation
1	101,811	0.3010	0.3032	0.0022
2	59,444	0.1761	0.1770	0.0010
3	42,247	0.1249	0.1258	0.0009
4	32,215	0.0969	0.0959	0.0010
5	26,590	0.0792	0.0792	0.0000
6	22,019	0.0670	0.0656	0.0014
7	19,404	0.0580	0.0578	0.0002
8	17,007	0.0512	0.0507	0.0005
9	15,013	0.0458	0.0447	0.0010
Total	335,750	1	1	0.0081
FDS_SCORE				0.0009

Panel C: Cash flow statement

First digit	Number of first digit	Expected frequency	Observed frequency	Deviation
1	63919	0.3010	0.3023	0.0013
2	37571	0.1761	0.1777	0.0016
3	26514	0.1249	0.1254	0.0004
4	20575	0.0969	0.0973	0.0004
5	16998	0.0792	0.0804	0.0012
6	13980	0.0670	0.0661	0.0008
7	11887	0.0580	0.0562	0.0018
8	10539	0.0512	0.0498	0.0013

9	9472	0.0458	0.0448	0.0010
Total	211,455	1	1	0.0098
FDS_SCORE				0.0011

Note: the table reports the aggregate FSD_SCORE of UK listed companies for the period from 2005 to 2012 by income statements (Panel A), balance sheets (Panel B), and cash flow statements (Panel C). The table shows the first digits being analysed, expected frequencies of the first digits following Benford's Law, observed (actual) frequencies of the first digits, deviations of the first digits from Benford's Law, where deviations are defined as the absolute values of the observed frequencies minus the expected frequencies. Definitions of variables are in the Appendix.

Table 6: Determinants of FSD_SCORE

Variable	*Expected sign*	*(a)*			*(b)*			*(c)*		
		Coefficient	*P-value*		*Coefficient*	*P-value*		*Coefficient*	*P-value*	
$DAC_{i,t}$	+	0.4953	0.0001	***				0.4886	0.0001	***
$CSCORE\_RANK_{i,t}$	+				0.1916	0.0006	***	0.1882	0.0008	***
$LOSS_{i,t}$	+	0.5149	0.0000	***	0.5282	0.0000	***	0.5032	0.0000	***
$FRAUD_{i,t}$	+	0.1040	0.0507	*	0.1122	0.0348	**	0.0976	0.0667	*
INDUSTRY FIXED EFFECTS		YES			YES			YES		
YEAR FIXED EFFECTS		YES			YES			YES		
Observations		3,635			3,635			3,635		
Adjusted R2		0.1023			0.1014			0.1051		

Note: Column (a) reports findings of the following regressions: $FSD\_SCORE_{i,t} = \alpha + \beta_1 DAC_{i,t} + \beta_2 LOSS_{i,t} + \beta_3 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon.$

Column (b) reports findings of the following regressions: $FSD\_SCORE_{i,t} = \alpha + \beta_1 CSCORE\_RANK_{i,t} + \beta_2 LOSS_{i,t} + \beta_3 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon.$

Column (c) reports findings of the following regressions: $FSD\_SCORE_{i,t} = \alpha + \beta_1 DAC_{i,t} + \beta_2 CSCORE\_RANK_{i,t} + \beta_3 LOSS_{i,t} + \beta_4 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon.$

All coefficients are multiplied by 100 for easy reading. Definitions of variables are in the Appendix. *, **, *** are significance at 10%, 5% and 1%, respectively.

Table 7: Determinants of KS values

Variable	Expected sign	(a) Coefficient	(a) P-value		(b) Coefficient	(b) P-value		(c) Coefficient	(c) P-value	
$DAC_{i,t}$	+	1.2067	0.0202	**				1.1815	0.0228	**
$CSCORE\_RANK_{i,t}$	+				0.7137	0.0018	***	0.7056	0.0020	***
$LOSS_{i,t}$	+	1.7082	0.0000	***	1.7247	0.0000	***	1.6643	0.0000	***
$FRAUD_{i,t}$	+	0.0593	0.7846		0.0706	0.7442		0.0351	0.8714	
INDUSTRY FIXED EFFECTS		YES			YES			YES		
YEAR FIXED EFFECTS		YES			YES			YES		
Observations		3,635			3,635			3,635		
Adjusted R2		0.0718			0.0729			0.0742		

Note: Column (a) reports findings of the following regressions: $KS_{i,t} = \alpha + \beta_1 DAC_{i,t} + \beta_2 LOSS_{i,t} + \beta_3 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon$.

Column (b) reports findings of the following regressions: $KS_{i,t} = \alpha + \beta_1 CSCORE\_RANK_{i,t} + \beta_2 LOSS_{i,t} + \beta_3 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon$.

Column (c) reports findings of the following regressions: $KS_{i,t} = \alpha + \beta_1 DAC_{i,t} + \beta_2 CSCORE\_RANK_{i,t} + \beta_3 LOSS_{i,t} + \beta_4 FRAUD_{i,t} + INDUSTRY\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon$.

All coefficients are multiplied by 100 for easy reading. Definitions of variables are in the Appendix. *, **, *** are significance at 10%, 5% and 1%, respectively.