Benford's Laws Analysis on Tax Irregularities in Banking and Investment Activities: The Case of the FTSE All-Share Index

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ABSTRACT

This paper examines financial data from FTSE all-share companies in the financial services sector using Benford's Laws to detect potential irregularities in accounting numbers that could indicate data manipulation and anomalies. The analysis is based on data sourced from REFINITIV EIKON, encompassing a sample of 63 companies in the banking and investments sector from 2008 to 2022. To address missing data, we implemented various adjustments to ensure the accuracy of the sample studied. The Benford's Laws test has been used to reject the null hypothesis for income and payable income tax distributions, with the most significant irregularities observed in both the first and second digits. Based on the numbers that adhere to Benford's law (the distribution of first digits), it is evident that companies tend to report lower income for tax purposes (as indicated by the prevalence of digits 1 to 3 as the first digit of income taxes), while they have higher tax obligations (as evidenced by the dominance of higher digits 5-7 as the first digits of payable income taxes). Non-compliance with Benford's Laws is a warning sign that the financial statement may be inconsistent or irregular.

Keywords: Benford’s Laws, FTSE all shares, Income Taxes, Payable Income Taxes.

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1. INTRODUCTION

There are several compelling reasons to focus on banks in this study. Firstly, banks play a crucial role in country economies, serving as potential sources of fiscal revenue that can significantly impact economic growth (Demirgüç-Kunt & Huizinga, 2001; Buch et al., 2016; Joshi et al., 2020). Therefore, any tax avoidance activities within banks could have adverse effects on the organization and the country's economy. Failure to pay the appropriate taxes can lead to reduced government revenue, increased public debt, and diminished investor confidence, thereby limiting investment opportunities and hindering economic growth. Additionally, banks are more opaque than nonfinancial firms (Furfine, 2001), which may lead them to engage in tax avoidance behaviour (Chen and Lin, 2017; Wang et al., 2020) due to the complexity of their financial transactions (Altawyan, 2022). This complexity increases the likelihood of engaging in tax avoidance activities.

Benford's laws are one method commonly used, especially in accounting. This method is capable of detecting anomalies in a set of financial data. A large number of situations and scientific contexts, such as finance (Clippe and Ausloos, 2012; Ausloos et al., 2016; Mir, 2016; Riccioni and Cerqueti, 2018) and accounting (Nigrini, 1999; Shi et al., 2018) are found to be valid under Benford’s Laws (BL). Exploring a set of numbers in greater detail is essential when it is inconsistent with BL. Since it is reasonable to assume that BL is valid, it might indicate that the data were manipulated if they are out of the BL. There are,

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of course, certain conditions under which this statement holds for the considered data, including having a wide range of variation and uniform distribution of several orders of magnitude, being the result of several random processes with varying probability distributions, or being a result of several multiplicative processes (Cerqueti and Maggi, 2021). Due to its association with fraud detection and data manipulation, BL is often associated with these functions (Kossovsky, 2014).

As a result, tax avoidance is an important and complex research topic that requires specialisation in the banking industry. Furthermore, it is necessary to examine the potential for tax avoidance in the banking industry using appropriate methodologies. This paper is organized as follows: Following a brief description, Section 2 presents the literature review, and Section 3 discusses methodology. Sections 4, 5, and 6 will provide data analysis with data, results, and conclusions.

2. LITERATURE REVIEW

Banking is a crucial component of the country's financial health, economic growth, and development, so it is imperative that banks are subjected to strict regulations (Joshi et al., 2020) and high supervision by regulatory agencies, including the central bank and deposit insurance corporations (Kanagaretnam et al., 2010). However, these regulations only partially eliminate manipulation in the banking industry. Previous studies have demonstrated that earnings management (Kanagaretnam et al., 2004, 2010) and tax avoidance practices exist in the banking industry (Mnif and Marwa, 2023). Banks can use several strategies to avoid taxes (Schandlbauer, 2017). It has also been demonstrated in previous studies that multinational banks use profit shifting to avoid paying taxes (Meeks and Meeks, 2014; Merz and Overesch, 2016; Schandlbauer, 2017)

Financial services have grown faster for much of the past one-and-half centuries than the rest of the UK economy. For the decade before the 2007-08 financial crisis, the financial sector grew at around 6 per cent annually, twice as fast as the overall economy. A significant proportion of the UK's GDP was accounted for by financial services by 2008, a figure that exceeded 9 percent (Meeks and Meeks, 2014). Banks alone (just one part of the financial sector) contributed a percentage of total UK corporation tax receipts in 2005-06. However, by 2011-12, the banks' contribution had fallen to just 4%. Compared with 2005-06, UK Corporation Tax (UKCT) revenue from the banking sector has decreased by only £1.3 billion in 2011-12 and £2.3 billion in 2012-13. It has been reported that Corporation Tax receipts from the banking industry were £7.0 billion in the financial year 2022-2023, an increase of £1.5 billion (28%) over the previous year, mainly due to the substantial increase in the profits of financial companies following the COVID-19 pandemic (Gov.UK, 2023).

As a result of these ups and downs, tax avoidance opportunities may arise, and HMRC describes the UK tax regime as 'relatively generous' in terms of its treatment of some deductions for tax purposes compared with other jurisdictions (Meeks and Meeks, 2014) and it may not be related to GDP (Mandigma and Gonzales, 2022). Morton (2019) relies on Benford's laws to detect the possibility of tax avoidance to improve tax transparency. It is based on Morton's research (2019) that this study seeks to detect tax irregularities in Banking & Investment services FTSE all shares by using three variables: (i) net income, (ii) income taxes, and (iii) payable income taxes. According to Othman and Ameer (2022), several methods for detecting fraud, including the Beneish model, Altman Z-score, and Benford's laws, can be applied. In Alali and Romero (2013), various accounting variables presented in the financial statements of US-listed companies were analysed using Benford’s Laws First Digit (BL1) and Benford’s Laws First-Second Digit (BL12).

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Benford's laws are tested by Nguyen et al. (2018) for companies listed on the UK capital markets, confirming the BL conformity findings of Amiram et al. (2015) concerning Fama-French Industry portfolios. Nguyen et al. (2018) analysed only the first digit of the financial statement numbers of UK-listed companies, concluding that "evidence" suggests income statement items deviate from Benford's Laws more often. According to Mora and Walker (2015), deviations in the first digits can be caused by both earnings management, which is more likely to be associated with material misstatements, as well as accounting conservatism, which can be manifested in the reporting of too many losses to generate reserves in the future by downward earnings management. In addition to the above, one may refer to Shi et al. (2018) paper, which evaluated whether the global FTSE price index contained error values (or irregularities).

In a recent study by Van Caneghem (2004), 1256 UK companies were examined with BL2 tests, finding results similar to those of Carslaw (1988). A deeper discussion of taxation considerations should have been provided in these later BL2-prone studies to detect the effects of rounding-up behaviour. In light of the purpose of debate, including potential limitations, I wish to point out that Mebane (2011) points out that Benford's law (BL2) does not detect every type of fraud successfully. This warning is backed by Ausloos et al. (2015) examination of long birth frequency and survival data series. When applied to birth records, Benford's laws are invalid based on Ausloos et al.'s findings (2015).

According to the conclusions of this literature review section, it appears that the majority of the studies mentioned are limited by the fact that they have only examined financial statements (pre-tax earnings) in conjunction with BL1 tests, with the exception, as noted, of a few authors who examined income items and BL2 from a behavioural perspective. Therefore, this study is expected to significantly contribute to the literature by studying several accounting and tax variables of financial statements on banking & investment services by examining not only BL1 but also BL2.

3. METHODOLOGY

3.1 BENFORD'S LAWS CHARACTERISTICS

This paper discusses the frequency of the first and second significant digits. As a result of Benford's laws, the following formula (known as Benford's Law for the first digit, BL1) is proposed for calculating the probability that a randomly generated number will have any digits other than zero as the first digit. The following is an adaptation of Ausloos et al. (2021):

$$P(d) = Log_{10}\left(1 + \frac{1}{d}\right) \tag{1}$$

As indicated in formula (1), "*d*" represents an integer between 1 and 9, and "*P*" represents a probability value between 1 and 9. The first digit, Benford's Laws (BL1), dictates that a randomly selected data set should usually contain a digit of 1 being the most frequently occurring first digit, while a digit of 9 is the least frequently occurring first digit (see Table 1). To assist in identifying a probability that the second digit, "d_2", equals 0 to 9, *BL1* has been advanced into the second digit Benford's Laws (*BL2*), which guides the second digit set of numbers.

$$P_2(d_2) = \sum_{k=0}^{9} Log_{10}\left(1 + \frac{1}{10_k + d_2}\right) \tag{2}$$

Table 1. Frequency ("Freq.") of the first, second, and first-second digit (*d*) in a set of data; *d*

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values ranging from 1 to 9 (for BL1), 0 to 9 (for BL2)

d	*BL*1	*BL*2
0		0.11968
1	0.301030	0.11389
2	0.176091	0.10882
3	0.124939	0.10433
4	0.096910	0.10031
5	0.079181	0.09668
6	0.066947	0.09337
7	0.057992	0.09035
8	0.051153	0.08757
9	0.045757	0.08500

3.2 STATISTICAL ANALYSIS

Z-statistics and MAD (Azevedo et al., 2021) are used as goodness-of-fit tests to determine if specific digit values conform to Benford's laws. The frequency of leading digits observed in sample data sets (P_k) is compared with the predicted frequency based on Benford's law (P_{Bk}) to determine whether the digits agree. χ^2 test is not preferable for this test as the results are affected by sample size, and it will produce inconsistent results with the MAD test (Cerqueti and Maggi, 2021). Equation (3) provides the mathematical formulation for MAD.

$$MAD = \frac{1}{9}\sum_{k=1}^{9} | P_k - P_{\mathrm{Bk}}| \tag{3}$$

A Z-test will be performed to determine if the first digit of data (d_1) correlates with the first digit of the *BL1* expected value. The deviation will be shown, i.e., dev = (data - BL1), and its absolute value, i.e.

$$z = \frac{P_{d1} - P_{Bd}}{\sqrt{P_{Bd}(1 - P_{Bd})/ N_{d1}}} \tag{4}$$

P_{d1} represents the observed proportion, i.e., "data". In contrast, P_{Bd} represents the expected proportion (by Benford's laws) for the d_1 digit, that is, in the *BL1* column frequency, and N_{d1} represents the number of observations for the d_1 digit. The second digit (d_2) data proportional occurrence, compare it to the *BL*2 expectation, provide the deviation, i.e., *dev* = (*data* - *BL*2), and its absolute value, i.e.

$$z = \frac{P_{d2} - P_{B2}}{\sqrt{P_{B2}(1 - P_{B2})/ N_{d2}}} \tag{5}$$

P_{d2} represents the observed proportion, i.e., "data". In contrast, P_{B2} represents the expected proportion (by Benford's laws) for the d_2 digit, that is, in the *BL2* column frequency, and N_{d2} represents the number of observations for the d_2 digit.

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Table 2. The Comparison of Conformity Level between BL1 and BL2 (Nigrini, 2012)

CONFORMITY RANGE	FIRST DIGIT	SECOND DIGIT
CLOSE CONFORMITY	0.000 - 0.006	0.000 - 0.008
ACCEPTABLE CONFORMITY	0.006 - 0.012	0.008 - 0.010
MARGINALLY ACCEPTABLE CONFORMITY	0.012 - 0.015	0.010 - 0.012
NON-CONFORMITY	Above 0.015	Above 0.012

4. DATA

Several tax variables are taken from financial data to detect potential irregularities in accounting numbers that may indicate data manipulation and anomalies. From 2008 to 2022, the company will be based on the FTSE all shares in the banking & investment services industry. Morton (2021) uses three variables to determine a company's tax transparency: net income, income taxes, and payable income taxes. Based on Morton's findings, this study aims to detect tax irregularities in the banking & investment services industry. The database used for this research is sourced from EIKON. The required financial data is extracted from the database using Microsoft Excel for data processing. The data is then sorted according to the company name and the type of industry that is being researched. It is then possible to eliminate "missing data" by filtering the data. Several standard Microsoft Excel functions were applied to obtain the first and second digits of the industry under study.

The process for extracting the first digit from Excel involved entering the column number of interest using the LEFT function in "text" and "1" in "num_chars" (for the first digit). To determine the frequency of each digit, 1 to 9, as the first digit, the COUNTIF function (range, criteria) must be utilised by specifying the range of cells and the digit of interest in "criteria". The first significant digit is determined by each digit, 1 through 9. For the calculation of the second digit, the Excel function MID is used with the parameters "start_num" = 2 and "num_chars" = 1 and the frequencies of numbers starting from 0 to 9.

Table 3. Statistical characteristics of the various variable value distributions for the respective *N-wide* data sets. N.B.: Data in rows 1-3 presented in GBP

FTSE ALL SHARES	Income Taxes	Payable Income Taxes	Net Income
Mean	420,396,175.81	186,253,242.88	1,357,609,812.09
Minimum	44,000.00	210,067.37	330,747.80
Maximum	3,813,576,200.00	1,397,000,000.00	25,691,000,000.00
Standard Deviation	777,961,363.63	273,374,939.56	3,079,388,410.76
Kurtosis	5.336	3.637	18.640
Skewness	2.376	1.962	3.913
N	210	165	345

5. RESULT

5.1 BL1 DISPLAY

Using the above formula, the first digit should be d, so that d = 1, …, 9. The visual observations distribution indicates that:

- Net income: This distribution is quite scatter, with d = 2 somewhat away from CI; below BL1 (-)

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- Income Taxes: This distribution is quite scatter, with *d* = 5 somewhat away from CI; below BL1 (-)
- Payable Income Taxes: This distribution is quite scattered, with *d* = 6 somewhat away from CI; above BL1 (+)

Table 4. Frequencies of the first digit (BL1) of the Banking & Investment Services industry. The corresponding calculated $\chi 2$ is to be compared with the theoretical one (15.5073) for the number of degrees of freedom is 8 at 0.05%. The null hypothesis is not verified for all tax variables except for revenue. $\chi 2$ with bold means the value is below the theoretical value.

	First Digit Banking & Investment Services									
Variable	1	2	3	4	5	6	7	8	9	$\chi 2$
Net Income*	0.33333	0.13333	0.11014	0.10145	0.09275	0.08116	0.07536	0.03768	0.03478	**11.2263**
Deviation	0.03230	-0.04276	-0.01480	0.00454	0.01357	0.01421	0.01737	-0.01347	-0.01098	
Z-Test	1.24936	2.01433	0.74969	0.19401	0.83401	0.94828	1.26541	1.01339	0.84692	
Income Taxes*	0.35238	0.21429	0.13810	0.10476	0.02381	0.03810	0.03810	0.03333	0.05714	18.0779
Deviation	0.05135	0.03820	0.01316	0.00785	-0.05537	-0.02885	-0.01989	-0.01782	0.01138	
Z-Test	1.54705	1.36259	0.47220	0.26799	2.84384	1.53496	1.08589	1.01535	0.62427	
Payable Income Taxes*	0.29091	0.15152	0.10303	0.09697	0.11515	0.10909	0.07879	0.03030	0.02424	**12.6312**
Deviation	-0.01012	-0.02457	-0.02191	0.00006	0.03597	0.04214	0.02080	-0.02085	-0.02152	
Z-Test	0.19856	0.72656	0.73343	0.00259	1.56706	2.01006	0.97649	1.03884	1.13643	
Benford's Set	0.30103	0.17609	0.12494	0.09691	0.07918	0.06695	0.05799	0.05115	0.04576	

Figure 1. The distribution of net income for the first digit (BL1) of the Banking & Investment Services industry.

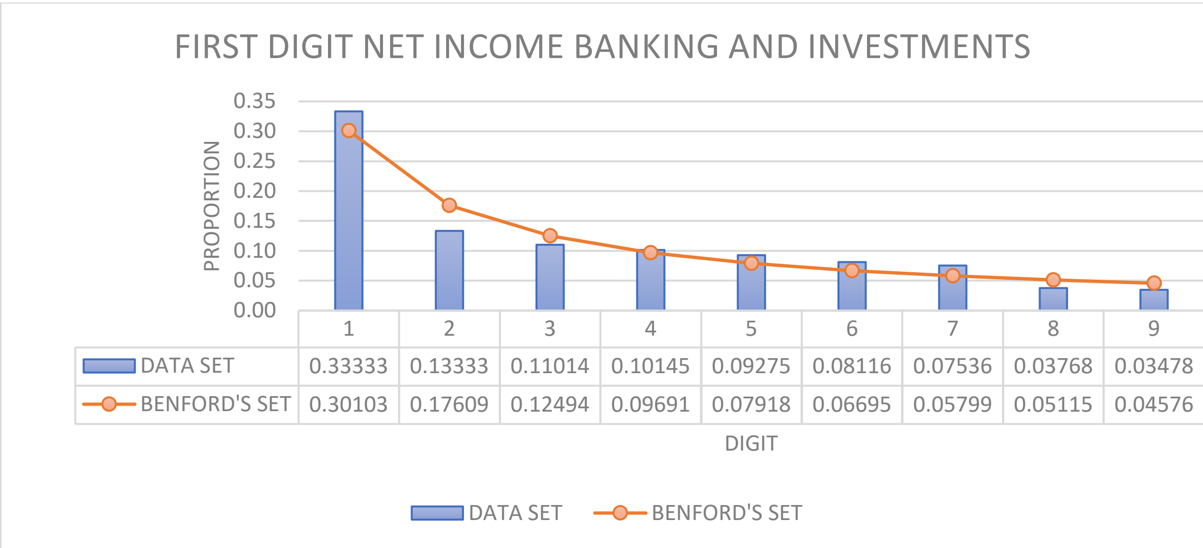

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Figure 2. The distribution of income taxes for the first digit (BL1) of the Banking & Investment Services industry.

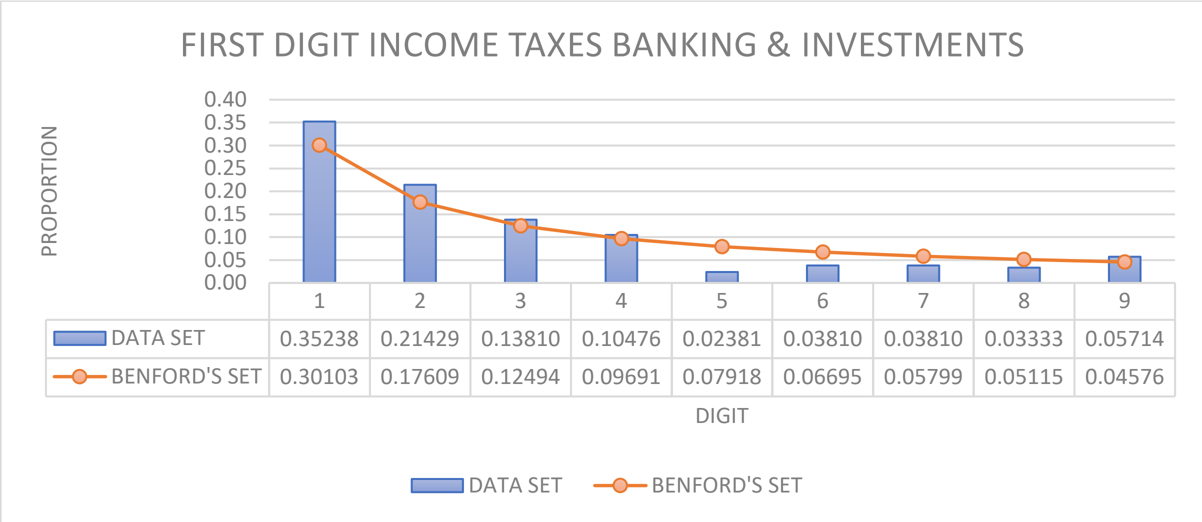
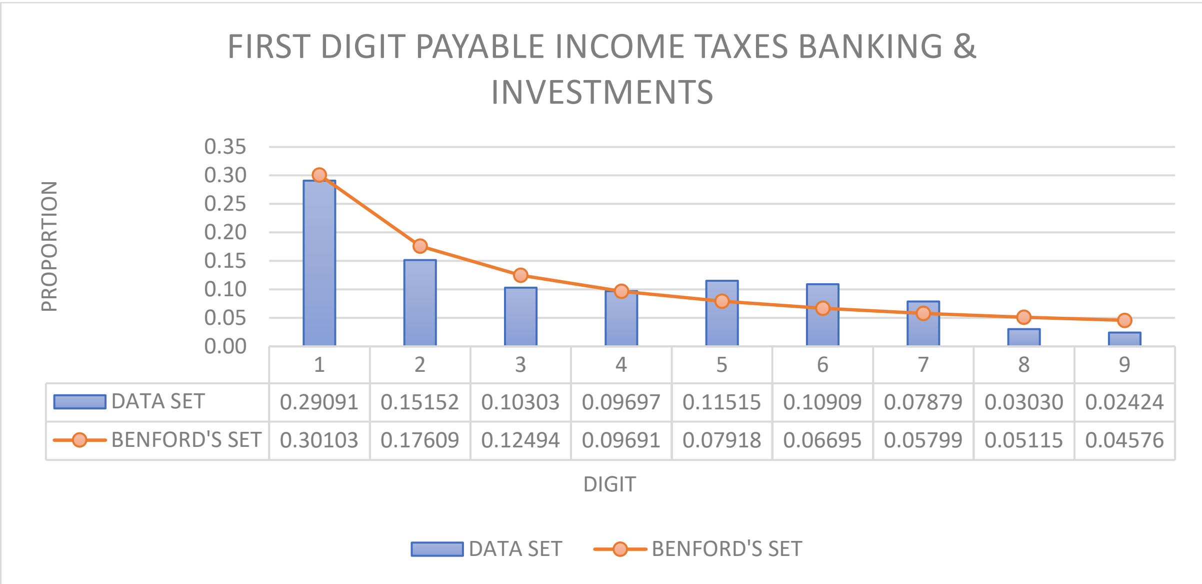


Figure 3. The distribution of payable income taxes for the first digit (BL1) of the Banking & Investment Services industry.



5.2 BL2 DISPLAY

The first digit should be d using the above formula, so $d = 1, \ldots, 9$. The visual observations distribution indicates that:

- Net income: This distribution is relatively smooth, not too far from the confidence interval (CI)
- Income Taxes: This distribution is quite scatter, with $d = 0, 1, 8$ somewhat away from CI; above BL1 (+) and $d = 2, 6, 7$ somewhat away from CI; below BL1 (-)
- Payable Income Taxes: This distribution is quite scattered, with $d = 0, 1, 2, 5, 8$ somewhat away from CI; above BL1 (+) and $d = 3, 4, 6, 7, 9$ somewhat away from CI; below BL1 (-)

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Figure 4. The distribution of net income for the second digit (BL2) of the Banking & Investment Services industry.

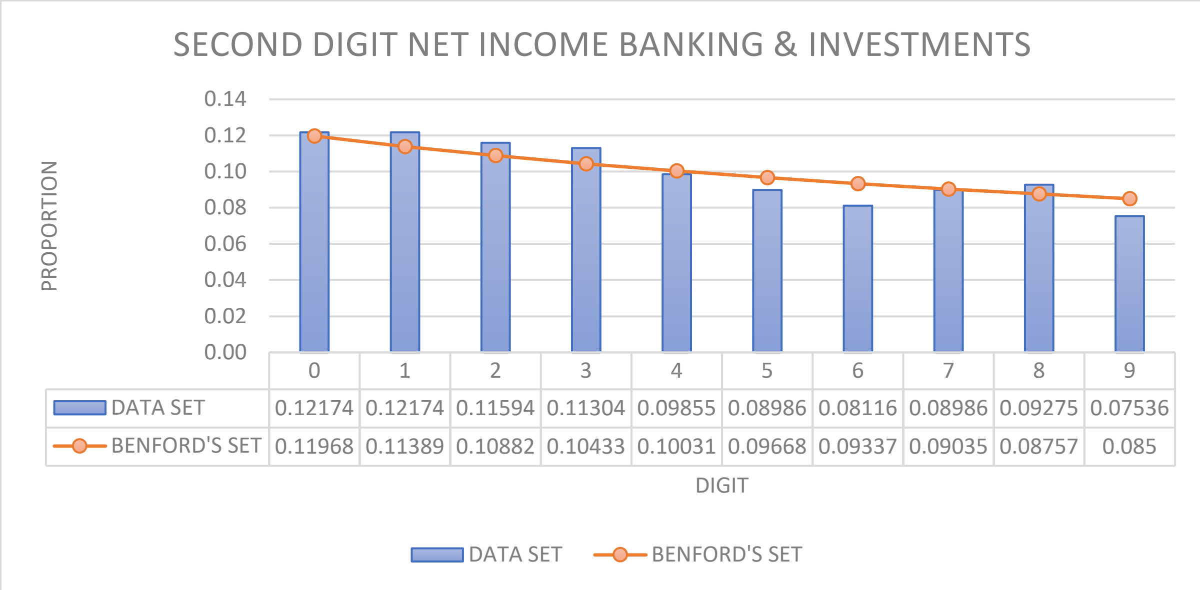
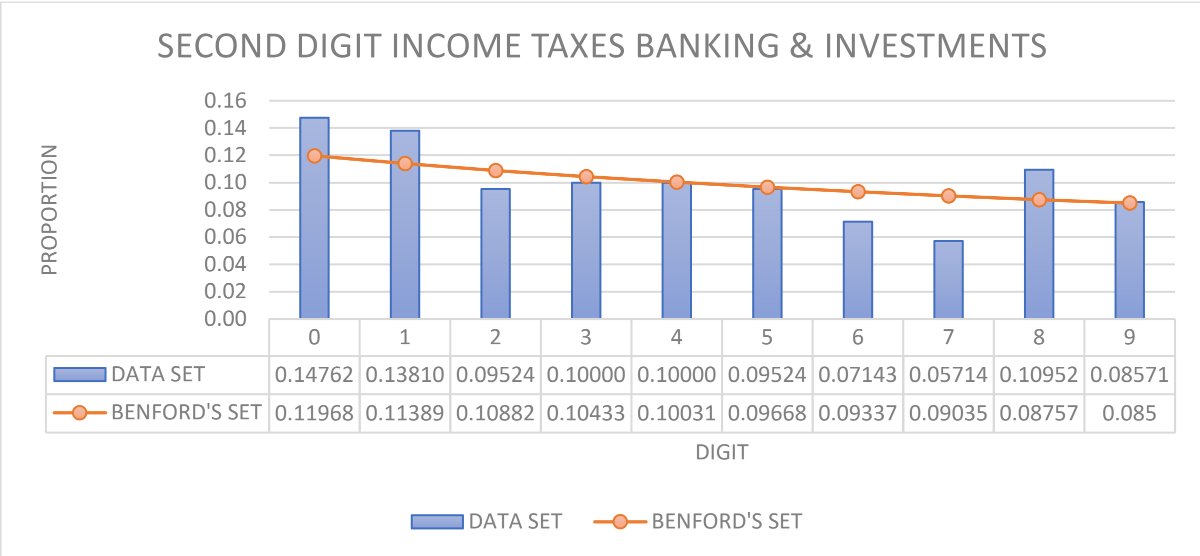


Figure 5. The distribution of income taxes for the second digit (BL2) of the Banking & Investment Services industry.



5.3 MAD VS χ2 RESULT

The results of MAD for the three variables tested are shown in Table 6. As seen, net income, income taxes, and payable income taxes do not obey BL1. As a result of the comparison between the standard number for BL1 and the number stated in the BL1 calculation results (> 0.015), the conformity level for the first digit does not comply with Benford's Laws. BL2 shows the same phenomenon. The results indicate that only net income follows Benford's laws for BL2, as indicated by the value for net income below the standard for the second digit of Benford's laws (below 0.08).

In Table 7, the red numbers indicate anomalies in the χ2 calculation. If Benford's laws are not followed, the χ2 results will be higher than the table χ2 results. Compared to the MAD

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results in Table 6, there are several oddities in the calculation results of net income, income taxes, and payable income taxes. For example, net income and payable income taxes do not follow BL1. Nevertheless, the $\chi 2$ income and payable income tax results are below the tables. Likewise, BL2 results also indicate that $\chi 2$ results are not recommended for determining conformity levels since the results differ from MAD and vary depending on the number of samples used (Cerqueti & Maggi, 2021).

Figure 6. The distribution of payable income taxes for the second digit (BL2) of the Banking & Investment Services industry.

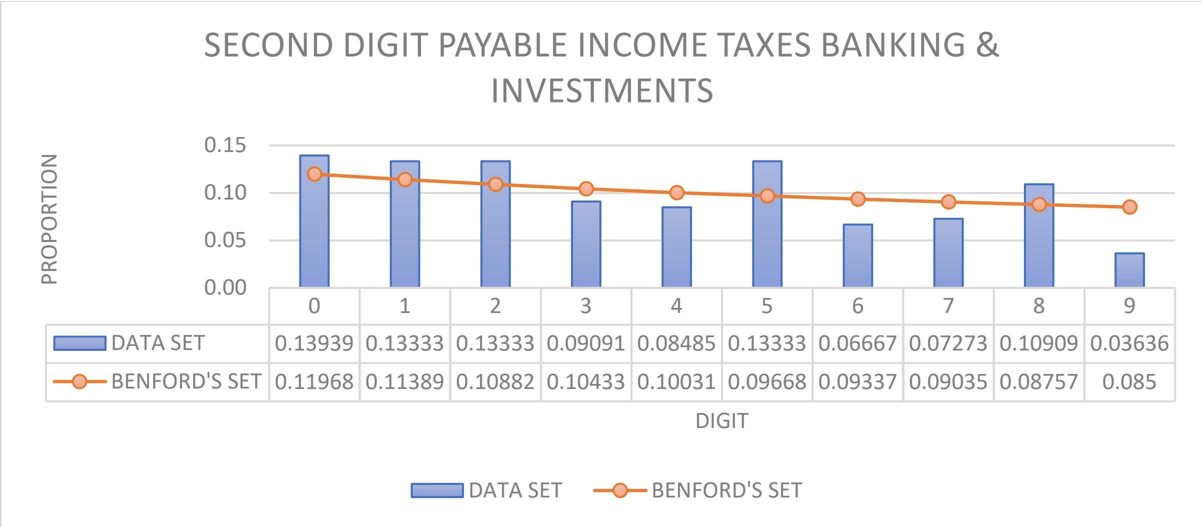

Table 5. Frequencies of the second digit (BL2) of the Banking & Investment Services industry. The corresponding calculated $\chi 2$ is to be compared with the theoretical one (16.919) for the number of degrees of freedom, which is 9 at 0.05%. The null hypothesis is not verified for all tax variables except for net income. $\chi 2$ with bold means the value is below the theoretical value. $\chi 2$ with bold means the value is below the theoretical value.

	Second Digit Banking & Investment Services										
Variable	0	1	2	3	4	5	6	7	8	9	$\chi 2$
Net Income	0.12174	0.12174	0.11594	0.11304	0.09855	0.08986	0.08116	0.08986	0.09275	0.07536	1.8223
Deviation	0.00206	0.00785	0.00712	0.00871	-0.00176	-0.00682	-0.01221	-0.00049	0.00518	-0.00964	
Z-Test	0.03490	0.37419	0.33835	0.44139	0.01917	0.33787	0.68700	0.03207	0.24538	0.54537	
Income Taxes*	0.14762	0.13810	0.09524	0.10000	0.10000	0.09524	0.07143	0.05714	0.10952	0.08571	**7.6513**
Deviation	0.02794	0.02421	-0.01358	-0.00433	-0.00031	-0.00144	-0.02194	-0.03321	0.02195	0.00071	
Z-Test	1.14106	0.99555	0.52123	0.09240	0.01495	0.07071	0.97425	1.55822	1.00343	0.03712	
Payable Income Taxes*	0.13939	0.13333	0.13333	0.09091	0.08485	0.13333	0.06667	0.07273	0.10909	0.03636	**12.2573**
Deviation	0.01971	0.01944	0.02451	-0.01342	-0.01546	0.03665	-0.02670	-0.01762	0.02152	-0.04864	
Z-Test	0.66024	0.66366	0.88614	0.43662	0.53154	1.46147	1.04515	0.65384	0.84026	2.10061	
Benford's Set	0.11968	0.11389	0.10882	0.10433	0.10031	0.09668	0.09337	0.09035	0.08757	0.085	

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Table 6. Results of MAD test of the conformity of d values with BL1 and BL2 (*d = d1, d2* respectively) for the 3 variables; the number N of firms (= number of data points/15) is indicated for each case.

N	Variables	BL1	Conformity	BL2	Conformity
23	Net Income	**0.0182**	Non-conformity	0.0062	Close Conf.
14	Income Taxes	**0.0271**	Non-Conformity	**0.0150**	Non-Conformity
11	Payable Income Taxes	**0.0220**	Non-Conformity	**0.0244**	Non-Conformity

Table 7. Results of χ2 test of the conformity of d values, with BL1 and BL2 (*d = d1, d2* respectively) for the 3 variables; the number N of firms (or data points) is indicated for each case. The number of degrees of freedom (*dof*) is easily derived from the number of relevant digits. The corresponding critical χ^2_c (p=0.05) is given for an immediate comparison for accepting or rejecting the null hypothesis.

		BL1	BL2
$\chi 2$	*dof*:	8	9
N	χ^2_c (0.05):	15.5073	16.9190
23	Net Income	**11.2263**	1.8223
14	Income Taxes	**18.0779**	**7.6513**
11	Payable Income Taxes	**12.6312**	**12.2573**

6. CONCLUSION

Benford's laws are routinely used by forensic analysts to detect errors, incompleteness, and suspected fraud in data (Ausloos et al., 2017). The test indicates that real data tend to have first digits closer to Benford’s Laws distribution than those who wish to play around with numbers but do not understand the law and attempt to place the digits uniformly. The data from the first digit is, therefore, varied, as can be seen (see Figure 1-6). As a result of the investigation, it can also be concluded that Benford's laws can be used to detect possible manipulation at the industry level.

The application of Benford's laws, which analyses the distribution of first digits in numerical data, reveals an interesting pattern in the realm of corporate taxation. The prevalence of digits 1 to 3 in the first digit of reported income taxes suggests that companies often report lower income taxes. Conversely, the dominance of higher digits 5 to 7 in the first digit of payable income taxes highlights the tendency for organizations to have higher tax obligations. This suggests a potential discrepancy between reported income taxes and payable income taxes for companies. However, the Benford's Laws graph shows no extreme numbers (both first and second digits). This could indicate that the company may have a reliable audit team to cover this issue, which is an interesting topic for further research.

The study concludes by suggesting the need for further exploration of potential violations of BL1 and BL2, which may indicate potential tax manipulation within the banking and investment services sector across all FTSE shares. However, this finding does not imply that companies are allowed to give up monitoring other variables, as supervision must still be carried out in every financial section periodically. BL can't be used exclusively

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to explain all findings: why do some tax indicators not have violators of BL1 and BL2 (Ausloos et al., 2017)? I do not make speculative statements. Nonetheless, this point supports the notion that a more in-depth analysis should be conducted to examine how financial data are typically collected and approved.

In this regard, pre-tax financial statements for banking and investment service companies listed on the FTSE all shares have not been examined within a larger Benford's laws framework to explore possible reasons for accounting fraud (or data manipulation) before. This paper examines Benford's Laws in detail to examine this issue for the first time.

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