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Manipulation in reported dividends: Empirical evidence from US banks

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Abstract

Based on a sample of US banks, and adopting Benford's law, regarding the distribution of digits of random numbers, I analyse reported dividends per share (DPS). I find uncommon patterns of significant digits of reported DPS that depart from the expected frequency based on Benford's law. I argue that the data may have been transformed to conceal the real financial conditions of the sample institutions. I show that the observed distribution of digits in the second place of DPS deviates significantly from Benford's law, especially for banks with high stock price volatility. I also find that banks report DPS with frequencies of second-place digits that deviate significantly from Benford's expected frequencies, regardless of whether they are large or small, and listed or not. Finally, I find no evidence that banks undertake less manipulation in the fourth quarter, which is audited, than in the previous three quarters. Misreporting dividends to conceal or improve true financial performance affects the decision-making of investors and financial analysts.

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1 Introduction

The importance of quality disclosed information in financial statements has been discussed in the literature (Watts and Zimmerman, 1986; Barth et al., 2008; Gros and Wallek, 2015; Knipp and Zimmermann, 2021). Considering that disclosure typifies a direct communication channel between firms and stakeholders, managers have a legal responsibility to prepare quality financial reports. Misreporting accounting data, such as earnings, loan loss provisions, and dividends, implies providing the market with poor quality information. This affects decision-making and may lead companies to financial distress. Therefore, demonstrating irregularities or possible manipulations in accounting data sets is important for financial markets and the quality of research conducted in this area (Varetto, 1998; Swicegood and Clark, 2001).

Herein, I analyse reported dividends per share (DPS) in the banking industry. I examine the differences in reporting between several bank groups and among quarters. Based on a 15-year period (2000–2015) for US banks, I compare the observed distribution of DPS digits with the theoretical distribution of digits, widely referred to as Benford's law. Benford (1938) shows that, in a large number of random data sets, the leading digit is often one and rarely nine, decreasing in frequency with the magnitude of digits. Additionally, the author formulates theoretical frequencies for the first-place, second-place, and higher-order digits. The literature suggests that managers often tend to round up accounting figures; for example, they overstate earnings per share and understate loan loss provisions (Ahmed et al., 1999; Nigrini, 2005; Cohen et al., 2014). Considering the economic significance of DPS, I also investigate whether managers tend to misreport DPS (Aerts et al., 2008). I compare the observed distribution of the digits in the second from the left place of the DPS (second-place digits) with the theoretical distribution based on Benford (1938). For example, consider a DPS figure of 1.98 and suppose a manager rounds it up to 2.00 because of psychological pricing. This will evidently, if repeated, result in an increased (decreased) frequency of small (large) second-place digits. This misreporting behaviour will be here defined as rounding-up or intentional transformation of reported figures.

Dividends are essentially a profit-sharing mechanism to distribute firm profits to the owners of the firm; thus, they are important to not only shareholders but also other stakeholders who use dividends as an indicator of a company's financial performance (Lintner, 1956; Modigliani and Miller, 1958; Miller and Modigliani, 1961; Porterfield, 1965; Lerner, 1971; Bhattacharya, 1979). Notably, DPS announcements often have an interim effect on market prices and investor behaviour (Aharony and Swary, 1980; Dong et al., 2005; Veit et al., 2010). For example, Jones and Aiken (1994) claim that most earnings manipulations are usually used to satisfy dividend requirements. Frankfurter and Wood (2002) suggest that behavioural and psychological managerial aspects increase in importance when examining dividend policy. Furthermore, prior literature shows that investors have a preference for dividends (Veit et al., 2010; Ainsworth et al., 2016). This affects how managers set and distribute dividends (Aerts et al., 2008; Jakob and Nam, 2020). Some important factors that affect investors' preference are firm's characteristics and information asymmetry, including clientele effects (Miller and Modigliani, 1961), agency costs (Akerlof, 1970; Easterbrook, 1984; Jensen, 1986), information signaling (Bhattacharya, 1979), and behavioural biases (Thaler and Shefrin, 1981). For example, loss aversion, i.e., the psychological difference observed between positive and negative gains, may explain the strong appetite of investors for cash dividends (Kahneman and Tversky, 1979). Another behavioural factor, numerical rounding or heaping towards the main divisors (ten, five and two) of the base ten numbering system, can also be used to understand corporate dividend policy (Turner, 1958; Nam et al., 2018; Castillo et al., 2020).

Misreporting dividends has thus implications for investors and firms' ability to raise capital (Farre-Mensa et al., 2014). Firms can use dividends to signal or communicate information to capital markets (Bhattacharya, 1979). Potential managerial intervention to conceal a firm's expected earnings affects investors' expectations about the firm's future dividend payouts, i.e., dividends become less informative (Hail et al., 2014). This may affect stocks' valuation and move prices away from their fundamental values. Dividends can also be used to reduce agency conflicts between managers and shareholders (Officer, 2011; Amberger, 2022). Managers that misreport dividends to gain private benefits, not only fail to mitigate agency problems through dividend payouts, but may also increase agency costs in the future. Hence, misreporting dividends has obvious implications not only for firms, but also for investors and the economy.

In this paper, I find significant deviations from the theoretical distribution of almost all second-place DPS digits regardless of if the banks are large and if they are highly volatile. More importantly, the magnitude of manipulation is significantly higher for the banks with high price volatility than for banks with low volatility. The manipulation pattern is also evident during the 2007-2009 financial crisis. Overall, the results indicate a strong managerial tendency to round up DPS. For instance, managers might round DPS upwards to meet analysts' forecasts, and this affects investors' expectations and decisions (Van Caneghem, 2004). Managers might also be inclined to round up DPS to sustain or improve historical performance or to meet behavioural thresholds and psychological cognitive reference points (Aerts et al., 2008). I also find that both listed and non-listed banks exhibit significant deviations between the observed and expected digit frequencies. Specifically, I find that DPS for listed and non-listed banks display more zeros and fives and less nines in the second-place DPS digits than would be expected based on Benford's law, with non-listed banks also displaying a higher proportion of digit two. This finding indicates possible upward rounding-up of DPS and suggests that both listed and non-listed banks are not Benford sets. Finally, I revisit the assertion that firms undertake less manipulation in the fourth quarter, which is audited, than in the previous three quarters (Guan et al., 2006). Interestingly, I find that the quarterly distributional differences between the observed and expected frequencies of the second-place DPS digits are insignificant. This suggests that auditing may not affect managerial rounding-up behaviour.

Overall, this study supports the findings of the existing literature that rounding-up DPS might be a management tactic to address behavioural and psychological triggers. Even though I provide evidence of managerial wrongdoing in reporting DPS, the empirical strategy applied here cannot be used to identify the characteristics (and reasons) of banks that tend to engage more in dividend misreporting (cf. Fama and French, 2010).[1] Nonetheless, I use several bank groups (i.e.,listed vs. non-listed banks, large vs. small banks, and high volatility vs. low volatility banks) and cross-sectional analysis to explore how dividend misreporting varies across banks.

The remainder of this paper is organised as follows: in Section 2, I present Benford's law and review the selected literature. In Section 3, I discuss the testable predictions based on Benford's law and present the data and statistical tools used to conduct the analysis. Section 4 presents the empirical results, while Section 5 concludes the paper.

2 A theoretical distribution of digits

2.1 Benford's law

Newcomb (1881) observes that the initial pages of a book of logarithmic tables are much more worn than the later pages. The author notices that numbers with a first digit of one occur more often than those starting with two, three, and so on, and calculates the probabilities of occurrence of each digit. Benford (1938) makes the same observation and shows that the leading significant digits of a number are not uniformly distributed but follow a logarithmic weak monotonic distribution. The author finds a logarithmic frequency of leading digits and formulates a general probability law that describes the frequency of digits in each place of a multi-digit random number. This distribution is known as Benford's law and holds with a large number of random data sets (Berger and Hill, 2011; Nigrini, 2012). Benford (1938) also proves that the expected frequency of a first-place digit of a random number follows a simple logarithmic function (see, also, Feller, 1966):

$$f_a = log_{10}(\frac{1+a}{a}), \text{ for } a = 1, 2, ..., 9, \tag{1}$$

where f_a, for $\sum_{a=1}^{9} f_a = 1$, is the frequency of a digit in the first place of a number. Additionally, if a is the first-place digit and b is the second-place digit of a number, then the frequency f_b of the second-place digit of a two-digit number ab is

$$f_b = \frac{log_{10}(\frac{1+ab}{ab})}{log_{10}(\frac{1+a}{a})}, \text{ for } a = 1, 2, ..., 9 \text{ and } b = 0, 1, 2, ..., 9, \tag{2}$$

[1] I would like to thank an anonymous referee for noticing a similarity of the empirical strategy used here with that in Fama and French (2010), in that I provide evidence of financial misconduct, but I do not identify the characteristics of banks with more tendency to misreport DPS; and for suggesting to explore more the cross-sectional heterogeneity of US banks.

where $\sum_{a=1}^{9} f_a = \sum_{b=0}^{9} f_b = 1$. Applying the same analysis, the frequency of a digit in the q^{th} place of a number, considering all the digits that precede it, that is, $[a, b, ..., q)$, can be derived. However, for a digit to occur in the third or higher-order q^{th}-place of a number, the probability of occurrence will approach a uniform distribution, that is, $f_q \approx 0.1$ for all digits 0 to 9 and $\sum_{q=0}^{9} f_q = 1$. Table I presents the expected frequencies for all digits in the first, second, third, and fourth places of a random number. It shows that digits one and two have a significantly higher likelihood of occurring in the first place of a number (30.103% and 17.609%, respectively) than that of other digits, and also that the frequency of a digit occurring in any of the first four places of a number decreases with the value of the digit.

Table I: Frequency of digits

Digit	First place	Second place	Third place	Fourth place
0	0.00000	0.11968	0.10178	0.10018
1	0.30103	0.11389	0.10138	0.10014
2	0.17609	0.10882	0.10097	0.10010
3	0.12494	0.10433	0.10057	0.10006
4	0.09691	0.10031	0.10018	0.10002
5	0.07918	0.09668	0.09979	0.09998
6	0.06695	0.09337	0.09940	0.09994
7	0.05799	0.09035	0.09902	0.09990
8	0.05115	0.08757	0.09864	0.09986
9	0.04576	0.08500	0.09827	0.09982

Table I gives the Benford's expected frequencies for digits 0 to 9 in the first four places of a multi-digit random number.

2.2 Related research

The existing literature uses Benford's law to investigate fraud in accounting and macroeconomic data sets (Durtschi et al., 2004; Nye and Moul, 2007). For example, Carslaw (1988) examines the frequency of second-place digits in the income figures of 220 listed firms in New Zealand. The author documents an abnormally high frequency of digit zero, an unusually low occurrence of digit nine, and argues that when income is below a particular psychological threshold, managers tend to round it upwards. Thomas (1989) observes that the reported losses of US listed firms exhibit a reverse pattern: fewer zeros and more nines. Nigrini (1996), utilising Benford's law, detects fraudulent information in accounting reports and tax-related transactions in the US. Degeorge et al. (1999) demonstrate that firms tend to round up earnings to meet analyst's forecasts, report positive profits, and sustain a targeted performance. Das and Zhang (2003) show that managers have a tendency to round up reported figures when they ex ante expect rounding-ups to meet forecasts, thresholds, and other benchmarks. In this context, Nigrini (2005) analyses earnings manipulation in a sample of listed US companies and shows a tendency of managers to overstate earnings with the aim of meeting behavioural thresholds.[2] Van Caneghem (2004) examines the impact of differences in audit quality on earnings management practices. Herrmann and Thomas (2005) analyse whether rounding behaviour is related to the level of information available to analysts. Aerts et al. (2008) use Benford's law to analyse the psychological determinants of dividend policy. The authors report that cognitive reference points, for example, the .99 psychological pricing that has an impact on sales, enhances rounding-up DPS to meet forecasts, and influences investors' preferences for dividends.

Abrantes-Metz et al. (2011) claim that Benford's law violation for the US Libor most likely indicates the exercise of fraudulent practices in the banking industry (see, also, Abrantes-Metz et al., 2006, 2012). The authors analyse Benford's frequency of the second-place digits of the daily US Libor from 2005 to 2008 and provide evidence of significant departures of the observed distribution from the expected distribution, indicating potential rate manipulation and collusion. Alali and Romero (2012) examine the characteristics of failed commercial banks relative to non-failed banks in the years leading to banks' failure for the period from 2000 to 2012. They find that both failed and non-failed banks in 2011 have frequencies of digits that are significantly lower than would be expected of data conforming to Benford's law. Ozer and Babacan (2013) analyse the effects of political interventions on the off-balance sheet disclosures of Turkish banks from 1990 to 2010 and suggest that the non-compliance of the reported off-balance sheet figures with Benford's distribution is a satisfactory first indicator of manipulation on governmental data sets. Tilden and Janes (2012) use Benford's law to investigate the occurrence of the intentional manipulation of financial statement numbers during recessionary times.

Nam et al. (2018) analyse behavioural biases that affect corporate dividend policy. The authors provide evidence of dividend heaping in Australian firms from 1976 to 2015. In a similar context, Jakob and Nam (2020) focus on heaping in dividend distributions and find that approximately 51% of the actual distributed dividends are heaped. Castillo et al. (2020) provide evidence that supports the abovementioned findings that dividend heaping depends primarily on information asymmetry (Turner, 1958) and firm-level characteristics (Nam et al., 2018). In a similar study, Jakob et al. (2021) examine whether switching currency affects dividend heaping and find pronounced dividend heaping activity.

3 Data and analysis

3.1 Testable predictions

I investigate three testable predictions based on managers' incentives to round up the actual performance of their banks to be attractive to investors and markets. If managers exhibit

[2] For other applications of Benford's law, refer also to Gonzalez-Garcia and Pastor (2009), Diekmann and Jann (2010), Jordan and Clark (2011), Michalski and Stoltz (2013), Lin and Wu (2014), and Lin et al. (2018).

a tendency to set DPS up to a break-even point to satisfy personal incentives, influence investors' expectations, or meet firm's performance thresholds, an uncommon distribution for second-place DPS digits would be observed. Moreover, I explore possible differences in reporting DPS between large and small banks, banks with high and low volatility, and particularly during the 2007-2009 financial crisis period. The first prediction to be tested is:

Prediction 1 *The observed frequencies of second-place DPS digits do not conform to Benford's expected frequencies.*

Second, considering that listed banks are scrutinised and supervised more than non-listed banks, I expect to observe distributional differences in second-place digits of DPS between listed and non-listed banks, with respect to Benford's conformity. For instance, higher quality audits and the public pressure of being listed might affect how managers report DPS. This is the second prediction to be considered.

Prediction 2 *The observed frequencies of second-place DPS digits differ from those of non-listed banks with respect to conformity to Benford's expected frequencies.*

Third, I analyse whether firms exhibit less rounding-up of DPS in the fourth quarter, which is audited, than in the previous three quarters. The extant literature suggests less manipulation in accounting figures prior to the publication of financial statements, which occurs during the fourth quarter (Guan et al., 2006; Liu et al., 2014). Therefore, I examine the distributional differences of the second-place DPS digits with respect to Benford's conformity among accounting quarters. The last prediction to be tested is presented as follows:

Prediction 3 *The observed frequencies of second-place DPS digits during the fourth quarter differ from those of the previous three quarters with respect to conformity to Benford's expected frequencies.*

3.2 Data

I use quarterly DPS of US listed and non-listed banks from the first quarter of 2000 to the last quarter of 2015, a total of 64 quarters, obtained from Thomson Reuters Datastream. I use US data because of the large impact of the US banking sector on the global banking industry and also because it is a heavily supervised sector. Put differently, the possible detection of misreporting in the US banking sector would be strong evidence of the effectiveness of Benford's law.

To investigate the theoretical propositions, I extract all equity US banks from Thomson Reuters Datastream. I exclude banks with significantly less than 15 years of available data and request quarterly DPS data for the remaining banks for 2000 to 2015. I also include quarterly accounting data that reflect bank's size such as total assets (TA), bank's assets quality such as loan loss provisions (LLP), bank's capital adequacy such as book equity value per share (BVS), bank's earnings quality such as total interest income (TII), bank's liquidity such as cash and due from other banks (Cash), bank's profitability such as return on equity (ROE) and return on assets (ROA), and bank's risk level such as stock price volatility (Volatility). I exclude erroneous entries, missing observations, banks that do not report DPS for each quarter, and DPS figures comprising only one digit from the sample.[3] I divide the sample into two main groups: listed and non-listed banks. The complete filtration procedure yields a final sample of 350 banks with a total of 17327 quarterly DPS observations; 12756 recorded observations of 219 listed banks and 4571 recorded observations of 131 non-listed banks. More specifically, Table II presents the summaries of the DPS and the other accounting variables for the final sample of banks, as well as for the listed and non-listed groups. It reports the means, medians, and standard deviations of quarterly DPS and other bank accounting variables, as well as the minimum and maximum values and the number of observations.

Table II shows that the observations of listed banks, for all variables, are considerably more than those of non-listed banks. The non-listed banks pay approximately three times as much DPS as listed banks do. The standard deviation of the DPS for non-listed banks is approximately fifteen times greater than that for listed banks. The range values of the DPS (i.e., Max − Min) also show that non-listed banks are considerably more dispersed than listed banks. Overall, the DPS distribution is heavily skewed. Additionally, the overall sample and both groups seem to satisfy Benford's law according to Wallace (2002) because they have DPS mean–median ratios of more than one and positive skewness values.[4] I also find that each quarter has a DPS mean–median ratio larger than one and a positive skewness value, implying conformity to Benford's law for listed, non-listed, and all banks for each quarter.

In addition, I observe that the means of total assets and loan loss provisions of listed banks are considerably higher than those of non-listed banks. This implies a higher average size of listed banks and also a higher variability of assets quality. Furthermore, the mean (and median) of book equity value of non-listed banks appears to be larger than that of listed banks, with a considerably high standard deviation (approximately 443 USD per share). I also find that the total interest income and cash reserves of listed banks are considerably higher, and also more dispersed, than those of non-listed banks. Table II shows also that, on average, the profitability of listed banks, as measured by the return on equity and return on assets, is higher than that of non-listed banks. Finally, the average stock price volatility of listed and non-listed banks is 21.95 and 21.48, respectively, however the non-listed banks show a considerably higher standard deviation of Volatility (13.24 vs. 6.59).

[3]Note that I require at least two-digit DPS figures because I focus on the frequency of second-place DPS digits.

[4]Wallace (2002) provides a simple screening test to check if a data set follows Benford's law: if the mean of a set of numbers is larger than the median and the series is positively skewed, then the data set is very likely to be a Benford set. It follows that, given positive skewness, the larger the mean–median ratio, the closer the sample will conform to Benford's law. This is because the figures following Benford's distribution have a predominance of small significant digits.

Table II: Descriptive statistics

Panel A: All banks								
Variable	N	Min	p25	Mean	p50	p75	Max	SD
TA *(000)*	17926	0	442.893	27500	982.632	3205.7	2580000	187000
Log TA	17924	1.386294	13.00111	14.16408	13.79813	14.98052	21.66995	1.787505
LLP *(000)*	17541	-543	0.09	44.58796	0.4	1.995	13400	435.9198
BVS	17814	-2355.834	8.205	29.06973	12.1385	17.685	6532.835	230.794
TII *(000)*	17815	0	5.737	273.674	12.213	38.315	33000	1773.323
Cash *(000)*	17675	0	10.021	1050.758	24.484	78.441	529000	12500
DPS	17327	0	0.043	0.2248469	0.11	0.19	150	2.441609
ROE *(%)*	17616	-33882.56	6.78	6.982781	9.85	13.255	4489.83	259.989
ROA *(%)*	16646	-308.97	0.86	1.060165	1.17	1.51	320.93	4.060949
Volatility	19068	4.15	16.43	21.8079	19.73	24.69	94.76	9.132024
Panel B: Listed banks								
TA *(000)*	13080	50.152	703.891	35700	1642.22	5168.234	2580000	219000
Log TA	13080	10.82281	13.46438	14.69212	14.31156	15.45804	21.66995	1.729599
LLP *(000)*	12859	-543	0.168	60.56167	0.75	3.167	13400	508.1729
BVS	13055	-57.318	8.141	16.79965	12.027	17.534	294.717	22.31324
TII *(000)*	13004	0.004	9.3335	372.1731	20.079	57.0185	33000	2066.925
Cash *(000)*	12982	0.009	16.171	1424.014	39.8515	118.191	529000	14500
DPS	12756	0	0.05	0.1565031	0.11	0.19	7.98	0.301419
ROE *(%)*	12964	-899.45	7.15	9.815538	10.26	13.77	4489.83	53.95883
ROA *(%)*	12422	-49.11	0.88	1.167164	1.2	1.54	320.93	3.083313
Volatility	13300	7.86	17.43	21.94945	20.74	24.97	67.96	6.595039
Panel C: Non-listed banks								
TA *(000)*	4846	0	194.052	570.3054	337.1405	581.126	9976.823	936.3193
Log TA	4844	1.386294	12.17674	12.73826	12.72847	13.27275	16.11578	0.979489
LLP *(000)*	4682	-8.349	0.03	0.7165649	0.11	0.3	493.493	8.245904
BVS	4759	-2355.834	8.542	62.72931	12.435	18.041	6532.835	443.2883
TII *(000)*	4811	0	2.707	7.433545	4.501	7.451	237.801	13.49922
Cash *(000)*	4693	0	4.658	18.23889	8.519	14.823	8929.258	134.1779
DPS	4571	0	0	0.4155697	0.109	0.18	150	4.722113
ROE *(%)*	4652	-33882.56	5.86	-0.9114273	8.87	11.745	457.8	497.7992
ROA *(%)*	4224	-308.97	0.79	0.7454995	1.12	1.41	43.24	6.075013
Volatility	5768	4.15	14.67	21.48151	17.46	23	94.76	13.23879

Table II reports the descriptive statistics on the US banks sample used in the analysis. The frequency of the data is quarterly and the sample period is from the first quarter of 2000 (Q1, 2000) to the last quarter of 2015 (Q4, 2015). More specifically, Table II reports the following summary statistics: mean, median (p50), and standard deviation, as well as the number of observations, other common percentiles (p25 and p75), and the minimum and maximum values per variable in the sample for the given period. The bank accounting variables are total assets (TA) reported in thousands USD, the logarithm of total assets (Log TA), loan loss provisions (LLP) reported in thousands USD, book equity value (BVS) at the bank's fiscal year end (i.e., proportioned common equity divided by outstanding shares), total interest income (TII) reported in thousands USD, cash and due to the bank from other banks (Cash) reported in thousands USD, dividends per share (DPS), return on equity (ROE) reported in percentage, return on assets (ROA) reported in percentage, and stock price volatility (Volatility).

3.3 Digital analysis

I rely on digital analysis to investigate possible discrepancies between the observed and expected frequency of the DPS digits; between listed and non-listed US banks, and among quarters; as well as between large and small banks, and high and low volatility banks. The most common approach in the existing literature is to test the first-, second-, or first-two-digit patterns of a data set (Nigrini and Mittermaier, 1997; Rejesus et al., 2006). I examine the distribution of the second-place DPS digits because of the stronger evidence of data intervention in the second-place digits than in the first-place digits (Van Caneghem, 2004; Nigrini, 2005; Diekmann, 2007). Managers have incentives to round reported DPS upwards, therefore observing more than expected zeros and ones and less than expected eights and nines, may indicate possible data transformation.

Considering that the DPS in the sample consist mostly of decimal numbers less than one, I multiply the observations by a factor of 1000 to facilitate numerical calculations (Pinkham, 1961).[5] I also use Hill (1995)'s theorem to assess the distributional differences of the first significant digits. Hill (1995) proves that combining various, biased or unbiased, individual distributions in an unbiased way may result in a Benford's distribution of first significant digits. It follows that the statistical significance of the deviation of the observed frequency from the expected frequency for each of the nine individual proportions can be assessed using a normalised z-statistic:

$$z_i = \frac{h_i - p_i}{\sqrt{p_i(1-p_i)/n}}, \tag{3}$$

where h_i and p_i denote the observed and expected proportions of the second-place digit i, for $i = 0, 1, ..., 9$, respectively, and n is the number of observations under assessment.[6] Note that to examine the distributional deviations between listed and non-listed banks, I use the normalised z-statistic for the mean comparison of two samples (see, Fleiss, 2003; Doane and Seward, 2011):

$$\bar{z}_i = \frac{h_i^l - h_i^{nl}}{\sqrt{\bar{h}_i(1-\bar{h}_i)(\frac{1}{n_l} + \frac{1}{n_{nl}})}}, \tag{4}$$

where h_i^l and h_i^{nl} denote the observed proportions of the second-place digit i, for $i = 0, 1, ..., 9$, for listed and non-listed banks, respectively; n_l and n_{nl} denote the number of observations for listed and non-listed banks, respectively; and $\bar{h}_i$ is a pooled proportion measure of the second-place digit i, for $i = 0, 1, ..., 9$, given by:

[5] Pinkham (1961) proves that multiplying a random set with a non-zero constant would not affect the distribution of the first significant digits.

[6] The 10%, 5% and 1% critical values correspond to 1.64, 1.96, and 2.57 z-values, respectively.

$$\bar{h}_i = (n_l h_i^l + n_{nl} h_i^{nl})/(n_l + n_{nl}). \tag{5}$$

I also apply the Pearson chi-square test to examine the overall data set's compliance to Benford's law, that is, [7]

$$\chi^2 = n \sum_{i=0}^{9} \frac{(h_i - p_i)^2}{p_i}. \tag{6}$$

If the chi-square test rejects the hypothesis that the probability of all digits conforms to Benford's distribution, I argue that the entire account of reported DPS warrants further examination. Small values of the chi-square statistic reinforce the null hypothesis that the data set conforms to Benford's law, while large values show non-conformity.[8]

I also employ the mean absolute deviation (MAD) test which is independent of the sample size. I use it as an alternative statistical measure to assess conformity to Benford's law. Precisely, the MAD test aggregates the results of comparing the observed frequency to Benford's expected frequency for every second-place digit into one single test statistic, that is,

$$MAD = \sum_{i=0}^{9} (|h_i - p_i|)/10, \tag{7}$$

where h_i denotes the observed frequency and p_i denotes the Benford's expected frequency of the second-place digit i, for $i = 0, 1, ..., 9$. Equation 7 indicates that, overall, larger absolute differences between proportions result to larger MAD values. Notice that there are no standard critical values to test the distribution of significant digits based on MAD test. However, it is common in the literature to use the critical values that Nigrini (2012) derives through numerical simulations, i.e., a MAD value for the second-place DPS digits in the range $[0, 0.008]$ indicates close conformity to Benford's law; a value above 0.012 indicates non-conformity; and intermediate values can be seen as quasi-conformity.

4 Results

4.1 The tendency of rounding-up dividends

Here, I present the results of the empirical analysis. Table III presents the deviations in percentage of each digit for all banks for the entire period, specifically for the 2007-2009

[7] The chi-square test is a goodness-of-fit statistical test that measures how well the data distribution from a sample matches a hypothetical distribution dictated by theory (see, for example, Gonzalez-Garcia and Pastor, 2009; Rauch et al., 2011).

[8] Note that there are a total of ten categories, thus the degrees of freedom are nine, that is, $\chi^2_{(9)}$. The 10%, 5% and 1% critical values correspond to 14.68, 16.92, and 21.67 chi-square values, respectively.

financial crisis period, for large and small banks, and for highly volatile and less volatile banks. I define large banks as if the bank's logarithm of total assets is greater than the mean total assets in the data. Similarly, I define banks with high volatility as if the bank's stock price volatility is greater than the mean volatility in the data.

Table III: Frequency of second-place DPS digits for US banks

	All	Financial crisis	Large banks		High vol. banks	
		2007-2009	Yes	No	Yes	No
Digit	Deviation (%)	Deviation (%)	Deviation (%)	Deviation (%)	Deviation (%)	Deviation (%)
0	16.529***	14.904***	18.494***	14.844***	32.482***	9.375***
1	-3.420***	-4.120***	-5.676***	-1.484***	-6.450***	-2.258 ***
2	-0.184	0.351	0.079	-0.410	-2.203***	0.570*
3	-1.637***	-0.705	-1.788***	-1.509***	-4.151***	-0.459
4	-2.374***	-1.147**	-1.867***	-2.809***	-3.701***	-1.525***
5	1.946***	-0.013	2.586***	1.398***	0.546	2.357***
6	-2.520***	-2.619***	-3.323***	-1.832***	-5.477***	-1.061***
7	-2.107***	-0.592	-2.269***	-1.968***	-3.449***	-1.706***
8	-1.905***	-1.195**	-1.705***	-2.077***	-1.636***	-1.834***
9	-4.328***	-4.865***	-4.530***	-4.154***	-5.958***	-3.461***
N	14405	2724	6651	7754	4171	9605
MAD	3.695	3.51	4.232	3.248	6.605	2.461
χ^2	4157.041	652.751	2477.713	1794.052	4351.156	1045.352

Table III presents the deviations in percentage of second-place DPS digits for all US banks for the entire period (Column 2), specifically for the 2007-2009 financial crisis period (Column 3), for large and small banks (Columns 4 and 5, respectively), and for banks with high and low volatility (Columns 6 and 7, respectively). The last three rows report the number of observations, the MAD values, and the chi-square tests for the overall conformity of the data set to Benford's law, respectively. The superscripts ***, **, and * indicate a p-value < 0.01, p-value < 0.05, and p-value < 0.1, respectively.

The analysis shows statistical significance at the 1% level for almost all second-place DPS digits of all banks, except for digit two. It also reveals a significantly 16.5% higher occurrence of zeros than the expected frequency of second-place DPS digits, and a significantly 4.3% lower than the expected occurrence of nines. The statistically significant high proportion of zeros and low proportion of nines might indicate possible upward rounding-up of DPS. Additionally, the MAD and chi-square tests (defined in Equations 7 and 6, respectively) reported in the last two rows of Table III, respectively, reject the prediction that the observed proportions of second-place DPS digits conform to Benford's proportions.

Additionally, Table III shows that the manipulation pattern is also evident during the 2007-2009 financial crisis and regardless of if the banks are large or small, and if they have high or low stock price volatility. More importantly, it shows that the magnitude of manipulation is significantly higher for the banks with high volatility, indicating a 168% higher MAD value compared to the low volatility banks (6.605 vs. 2.461). Overall, Table III seemingly indicates a strong managerial tendency to round up reported DPS, which is consistent with existing research (Carslaw, 1988; Thomas, 1989; Van Caneghem, 2004; Aerts et al., 2008). Interestingly, Table III shows an overall tendency of bank managers to use techniques that affect the distribution of all leading digits of the reported DPS.

4.2 The differences of rounding-up dividends between listed and non-listed banks

I apply the same analysis as presented above for listed and non-listed banks and report the results in Table IV. The analysis reveals patterns of second-place digits that deviate significantly from Benford's law.

Table IV: Frequency of second-place DPS digits for listed and non-listed banks

	Listed banks	Non-listed banks	Difference
Digit	Deviation (%)	Deviation (%)	Deviation (%)
0	18.395***	10.264***	8.131***
1	-3.812***	-2.103***	-1.709***
2	-1.314***	3.607***	-4.921***
3	-1.288***	-2.810***	1.522***
4	-2.607***	-1.592***	-1.015*
5	2.009***	1.736***	0.273
6	-2.517***	-2.532***	0.015
7	-2.611***	-0.415	-2.196***
8	-2.027***	-1.497***	-0.53
9	-4.229***	-4.658***	0.429
N	11099	3306	
MAD	4.081	3.121	2.074
χ^2	3881.132	503.216	202.848

Table IV presents the deviations in percentage of second-place DPS digits for listed and non-listed banks (Columns 2 and 3, respectively), and the deviations of the observed frequencies between listed and non-listed banks for all digits. The last rows report the number of observations, the MAD values, and the chi-square tests for the overall conformity of the data set to Benford's law, respectively. The superscripts ***, **, and * indicate a p-value < 0.01, p-value < 0.05, and p-value < 0.1, respectively.

Specifically, the DPS of listed banks display more zeros and fives and lower proportions of all the remaining digits than would be expected by Benford's distribution. The reported DPS of non-listed banks also exhibit more zeros and fives as well as more twos than the expected Benford's proportions. The proportions of the remaining digits in the second-place DPS of non-listed banks are significantly lower than Benford's proportions. Additionally, the chi-square tests reported in the last row of Table IV, reject the prediction that the frequencies of second-place DPS digits of listed and non-listed banks follow Benford's law at a 1% level of significance. The MAD result is also consistent with the chi-square. Specifically, the MAD values for the groups of listed banks and non-listed banks are 4.081% and 3.121%, respectively. These values are considerably larger than the critical value of 0.012, which indicates non-conformity to Benford's law. Overall, there are significant proportional violations of the second-place DPS digits from the expected proportions, regardless of whether a bank is listed or not.

Finally, the last column of Table IV reveals significant distributional differences between listed and non-listed banks at a 1% level of significance. Specifically, digits zero and three occur more frequently in the figures of listed banks than in those of non-listed banks; the reverse pattern is identified for digits one, two, and seven. The distributional deviations of second-place digits between listed and non-listed banks are not significant for large digits, that is, eights and nines. This might indicate that being listed or otherwise does not affect the managerial reporting of DPS. However, relying on the chi-square test reported in the last row of Table IV, the prediction that the observed proportions of the second-place DPS digits for listed banks conform to those for non-listed banks is rejected at a 1% level of significance. Moreover, the MAD value of the difference of deviations of the observed frequencies from the expected frequencies between listed and non-listed banks is 2.074%, i.e., larger than the threshold of conformity to Benford's law. This confirms the distributional differences between listed and non-listed banks shown by the chi-square tests.

4.3 The differences of rounding-up dividends among quarters

Prior research shows that potential managerial intervention in the fourth quarter is more difficult to conceal because of the auditing and regulatory pressure that usually occurs only during that quarter (Manry et al., 2003; Guan et al., 2006; Brown and Pinello, 2007; Liu et al., 2014). Table 5 shows significant discrepancies between the observed and expected proportions of the second-place DPS digits for most digits in each individual quarter. Specifically, the distribution of all digits, except digit two, appears to deviate significantly from Benford's distribution, at a 1% level of significance, regardless of the quarter. Interestingly, the magnitudes of deviation of digits zero and nine are, overall, larger than the magnitudes of deviation of the remaining digits. These results might indicate a managerial tendency of intentional rounding-up behaviour, that is, fewer nines and more zeros in the second place of reported DPS, irrespective of whether a specific quarter is audited or not.

Table 5: Frequency of second-place DPS digits for US banks per quarter

	Qrt 1	Qrt 2	Qrt 3	Qrt 4	Diff Q4-Q1	Diff Q4-Q2	Diff Q4-Q3
Digit	Dev (%)	Dev (%)	Dev (%)	Dev (%)	Dev (%)	Dev (%)	Dev (%)
0	16.550***	16.469***	16.689***	16.418***	-0.001	-0.001	-0.003
1	-3.653***	-3.384***	-3.103***	-3.534***	0.001	-0.002	-0.004
2	-0.091	-0.127	-0.311	-0.210	-0.001	-0.001	0.001
3	-1.298**	-1.592***	-1.947***	-1.711***	-0.004	-0.001	0.002
4	-2.409***	-2.349***	-2.402***	-2.339***	0.001	0.000	0.001
5	1.694***	2.084***	2.047***	1.952***	0.003	-0.001	-0.001
6	-2.458***	-2.734***	-2.366***	-2.512***	-0.001	0.002	-0.001
7	-2.298***	-2.135***	-2.092***	-1.912***	0.004	0.002	0.002
8	-1.706***	-1.695***	-2.157***	-2.067***	-0.004	-0.004	0.001
9	-4.332***	-4.537***	-4.357***	-4.085***	0.002	0.005	0.003
N	3503	3710	3500	3692			
MAD	3.649	3.711	3.747	3.674	0.216	0.1816	0.1884
χ^2	1011.201	4784.668	4527.080	4739.602	2.960	3.350	2.118

Table 5 presents the deviations in percentage of second-place DPS digits for all banks in quarters 1, 2, 3 and 4 (Columns 2, 3, 4 and 5, respectively). The last three columns of the table show the percentage deviations of the observed frequencies from the expected frequencies of the second-place DPS digits between quarter four and quarters 1, 2 and 3, respectively. The last three rows report the number of observations, the MAD values, and the chi-square tests for the overall conformity of the data set to Benford's law for each quarter, respectively; and the overall conformity of the proportional differences of the second-place DPS digits between quarter four and any previous quarter. The superscripts ***, **, and * indicate a p-value < 0.01, p-value < 0.05, and p-value < 0.1, respectively.

Additionally, the chi-square tests reported in the last row of Table 5 suggest significant deviations, at a 1% level of significance, of the observed frequencies from the expected frequencies of the second-place DPS digits for each quarter. The MAD statistic values confirm this result, i.e., the MAD value of each quarter is larger than the 0.012 critical value indicating non-conformity to Benford's law. Overall, the evidence does not seem to support the findings of earlier research that auditing might reduce the rounding-up or manipulation of accounting data.

Finally, the results, including the chi-square tests, indicate no significant distributional differences between the observed second-place digits of DPS for the fourth quarter and those for the previous three quarters. The MAD tests for the same distributional differences, also suggest that, overall, there are no distributional differences. Taken together, the analysis does not provide evidence of distributional differences between quarters, however it suggests that the proportions of the second-place DPS digits deviate significantly from Benford's expected proportions, regardless of the reporting quarter. This should be seen as a warrant for re-examination of the dividend data sets of US banks, if not as an indication of managerial intervention in reported DPS.

5 Conclusions

Based on a sample of quarterly accounting data of US banks for the 2000—2015 period, I use Benford (1938)'s distribution to analyse whether banks round up reported dividends to conceal or improve their true financial performance. I find significant deviations in the observed frequencies from the expected frequencies of almost all second-place DPS digits. The highest magnitudes of deviation are reported with regard to digits zero and nine; considerably fewer nines and more zeros than expected by Benford's law are observed. This result might indicate upward rounding up of DPS to meet forecasts, cognitive reference points, or investor's dividend expectations. More importantly, I find that highly volatile banks tend to engage more in dividend misreporting than banks with low stock price volatility (i,e., a 168% higher MAD value).

The results also suggest that all banks, regardless of whether they are listed or not, report significantly different proportions of second-place DPS digits than expected. Specifically, the reported DPS display more zeros and fives and less eights and nines in the second place of figures than would be expected by Benford's law, with non-listed banks also displaying a higher proportion of digit two. I also find significant deviations for each individual quarter, although the fourth quarter is audited. The proportions of all second-place digits deviate significantly from Benford's proportions, except for digit two, regardless of the accounting quarter. More specifically, the magnitudes of deviation of digits zero, five, and nine in the second place of DPS are larger than the magnitudes of deviation of the remaining digits. I find no significant distributional differences between the observed second-place DPS digits for the fourth quarter, which is audited, and those for the previous three quarters. Considering the chi-square statistic and MAD test, I confirm that the sample institutions are not Benford sets.

Overall, I find a stronger managerial tendency to round up DPS for banks with high stock price volatility than other banks. I also find significant distributional differences in specific second-place DPS digits between listed and non-listed banks, but not between quarter four and any previous quarters. Benford's law seems to be a suitable instrument for identifying accounting and financial data sets that deserve closer inspection. Further empirical analysis is needed to identify the characteristics of banks with more tendency to misreport accounting data.

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