LSF Research Working Paper Series

N°. 16 – 11

Date: November 2016

Title: Applying Benford's Law to Detect Accounting Data Manipulation in the Banking Industry

Author(s)*: Theoharry Grammatikos, Nikolaos I. Papanikolaou

Abstract: In this paper, we take a glimpse at the dark side of bank accounting statements by using a mathematical law which was established by Benford in 1938 to detect data manipulation. We shed the spotlight on the healthy, failed, and bailed out banks in the global financial crisis and test whether a set of balance sheet and income statement variables which are used by regulators to rate the performance and soundness of banks were manipulated in the years prior to and also during the crisis. We find that banks utilise loan loss provisions to manipulate earnings and income upwards throughout the examined periods. Together with loan loss provisions, problem banks resort to a downward manipulation of allowance for loan losses and non-performing loans with the purpose to tamper earnings upwards. We also provide evidence that manipulation is more prevalent in problem banks, which manage income and earnings to conceal their financial difficulties. Moreover, manipulation is found to be strengthened in the crisis period; it is also expanded to affect regulatory capital. Overall, banks utilise data manipulation without yet resorting to eye-catching manipulation strategies that may attract the scrutiny by regulators. Benford's Law appears to be a suitable tool for assessing the quality of accounting information and for discovering irregularities in bank accounting data.

Keywords: Financial crisis; banks; Benford's Law; financial accounting; data manipulation.

***Corresponding Author's Address:** Tel: +352 46 66 44 6939; Fax : 352 46 66 44 6835
E-mail address: theoharry.grammatikos@uni.lu

Applying Benford's Law to Detect Accounting Data Manipulation in the Banking Industry

Theoharry Grammatikos[a*], **Nikolaos I. Papanikolaou**[b♣]

[a] *Professor of Corporate Finance*
University of Luxembourg, Luxembourg School of Finance
4 rue Albert Borschette, L-1246 Luxembourg

[b] *Assistant Professor of Banking and Finance*
University of Sussex, School of Business, Management and Economics
Brighton, BN1 9SL, United Kingdom

ABSTRACT: In this paper, we take a glimpse at the dark side of bank accounting statements by using a mathematical law which was established by Benford in 1938 to detect data manipulation. We shed the spotlight on the healthy, failed, and bailed out banks in the global financial crisis and test whether a set of balance sheet and income statement variables which are used by regulators to rate the performance and soundness of banks were manipulated in the years prior to and also during the crisis. We find that banks utilise loan loss provisions to manipulate earnings and income upwards throughout the examined periods. Together with loan loss provisions, problem banks resort to a downward manipulation of allowance for loan losses and non-performing loans with the purpose to tamper earnings upwards. We also provide evidence that manipulation is more prevalent in problem banks, which manage income and earnings to conceal their financial difficulties. Moreover, manipulation is found to be strengthened in the crisis period; it is also expanded to affect regulatory capital. Overall, banks utilise data manipulation without yet resorting to eye-catching manipulation strategies that may attract the scrutiny by regulators. Benford's Law appears to be a suitable tool for assessing the quality of accounting information and for discovering irregularities in bank accounting data.

Keywords: *financial crisis; banks; Benford's Law; financial accounting; data manipulation.*

We thank the participants in the FMA European Meeting 2015 in Venice as well as the Scientific Committee of the aforementioned Meeting for nominating an earlier version of this paper for the Best Paper Award. We further thank the participants in the XXIV International Rome Conference on Money, Banking and Finance for their valuable comments and suggestions. The paper has been benefited from discussions with Claudio Giannotti, Iftekhar Hasan, Ranko Jelic, Marco Pagano, Piet Usselmann, and with colleagues at the University of Luxembourg and the University of Sussex. Also, we would like to thank Aineas Mallios and Mounir Shal for their help in data collection.

[*] Tel +352 4666446939; e-mail: theoharry.grammatikos@uni.lu
[♣] Tel: +44 (0) 1273678738; e-mail: n.papanikolaou@sussex.ac.uk

I. INTRODUCTION

Accounting standards and financial reporting systems are deemed as largely contributing to the transparency of the operation of the entire financial system by providing regulators, supervisors, equity holders, investors and other market participants with timely, accurate, and high-quality information on the financial condition of banking institutions. Bank managers, chief executives, and board members, however, have incentives to misrepresent the financial performance of their banks over time, covering losses or increasing earnings with the utmost purpose to convey a sounder picture of their companies' business to the public and to the regulatory and supervisory authorities than the actual one. The performance-based remuneration schemes that were widely adopted in the banking industry in the years running up to the late 2000s financial crisis provided officers and executives with additional incentives to implement data manipulation practices.

The crisis that began to unfold in the mid-to-late 2007 brought to light a number of financial accounting misreporting problems in the banking sector. The U.S. Securities and Exchange Commission (SEC)'s push to step up its policing of accounting fraud has lately led to a surge of cases and investigations, as officials again target cooking-the-books offenses that were once a staple of its workload. The upturn, the SEC's first year-over-year increase in such enforcement actions since 2007, came as the agency returned its focus to alleged financial reporting and disclosure cases that might have gone unpunished as crisis-era misconduct dominated its attention lately.

As of year-end 2009, the First National Community Bancorp (FNCB)'s investment portfolio included certain pooled trust preferred securities. Based on the Generally Accepted Accounting Principles (GAAP), FNCB was required to report in its financial statements the amount of impairment on the securities in its investment portfolio. FNCB's methodology for determining the amount of impairment did not comply with GAAP and, hence, the bank was caught understating the losses in 2009 and 2010.[1] To continue, as part of its acquisition of Merrill Lynch & Co., Inc. (hereafter, Merrill) on January 1, 2009, Bank of America Corp. (hereafter, BAC) assumed a $52.5 billion portfolio of structured notes and other relevant financial instruments that Merrill issued. At the time of acquisition, BAC recorded the notes at fair value, which was a $5.9 billion discount to the notes' par value due to an adverse change in Merrill's creditworthiness. By the early 2014, 87

[1] See: SEC Accounting and Auditing Enforcement, Release No. 3622/January 28, 2015.

percent of the notes had either matured or been repurchased by BAC. Because BAC recorded the notes at a discount to par when acquired, BAC realised losses on the notes upon their maturation. To calculate regulatory capital, BAC was required to deduct the realised losses on the notes as they occurred. From the early 2009 through the first quarter of 2014, however, BAC failed to deduct certain realised losses on the notes when it calculated and reported its regulatory capital, implying that capital was overstated in all regulatory filings that it made with SEC from 2009 to 2013.[2] In a similar vein, Fifth Third Bancorp. failed to record substantial losses during the crisis by not properly taking into account a portion of its commercial real estate loan portfolio. In the third quarter of 2008, the bank decided to sell large pools of non-performing commercial loans. When the bank board decided to sell the loans, GAAP required the firm to reclassify them from "held for investment" to "held for sale" and to carry them at fair value. Because the fair values of those loans were significantly below Fifth Third's carrying values, classifying them as "held for sale" would have resulted in a $169 million impairment. This would, in turn, have increased the pre-tax loss of the bank in the third quarter of 2008 by 132 percent.[3]

Auditors, on their side, have rather failed to raise the alarm to bank regulators in the years prior to and also during the crisis. FDIC sued PricewaterhouseCoopers (PwC) for $1 billion for not detecting a massive accounting fraud that brought down Colonial Bank in 2009. The FDIC lawsuit blamed PwC for missing huge holes in Colonial's balance sheet without ever detecting the multibillion-dollar fraud at Taylor Bean & Whitaker Mortgage Corp., which was Colonial's largest client. Furthermore, two KPMG auditors recently received suspensions for failing to scrutinise loan loss reserves at TierOne, which also failed during the crisis. Subsequently, TierOne reported $120 million in unforeseen losses after the real-estate collateral securing a vast portfolio of mortgages was found to be largely overvalued on the company's books. Moreover, just eight months prior to Lehman Brothers' demise, Ernst and Young's auditors remained silent about the repurchase transactions that disguised the bank's leverage.

In sum, numerous accounting violations have lately engulfed the U.S. banking system and several institutions are currently under investigation by regulators for these violations. Although they have received a little attention in the relevant literature so far, poor accounting data quality

[2] See: SEC Accounting and Auditing Enforcement, Release No. 3588/September 29, 2014.

[3] See: SEC Accounting and Auditing Enforcement, Release No. 3514/December 4, 2013.

and weak disclosure practices as combined with data manipulation in the financial services industry are considered to have contributed to the propagation and prolongation of the recent crisis. In this paper, we rely on a mathematical law which was established by Benford in 1938 to detect data tampering in bank accounting data. We test whether a set of fundamental balance sheet and income statement variables, which are widely used by regulators to rate the performance and the soundness of banks were manipulated in the years prior to the outbreak of the crisis and also during the crisis. The idea of detecting manipulation in accounting data by tests of conformity to Benford's Law has been mainly applied in the corporate finance literature and, more recently, in the economics literature as we discuss in Section II. Our study contains the first application of the Law on banking data. Moreover, it is the first study that identifies operational discrepancies and uncovers data manipulation practices amongst the failed, bailed out, and healthy banking firms in the recent crisis.

We report several interesting findings, which are robust to a variety of sensitivity tests we conduct. All banks utilise loan loss provisions to manipulate earnings and interest income upwards throughout the examined two periods. In the case of bailed out banks, non-interest income is also found to be manipulated upwards in both periods. Together with loan loss provisions, the set of problem (failed and bailed out) banks resorts to a downward manipulation of allowance for loan losses and non-performing loans with the purpose to tamper earnings upwards. Furthermore, our results provide comprehensive evidence that manipulation is more prevalent in problem banks, which manage income and earnings upwards by delaying loan loss provisions as well as loss allowances and non-performing loans in order to conceal their financial difficulties. Moreover, manipulation is found to be strengthened in the crisis period; it is also expanded during this period as banks are found to implement upward manipulation practices on their core regulatory capital.

Overall, we document that banks utilise data manipulation to disclose an artificially improved view of their performance to authorities, investors, and to the public without yet resorting to eye-catching manipulation strategies that may attract the scrutiny by regulators. Importantly, Benford’s Law appears to be a systematic tool, suitable for assessing the quality of accounting information and for discovering irregularities in bank accounting data.

The rest of this paper proceeds as follows. Section II describes Benford’s Law, whereas Section III presents the relevant literature. The empirical analysis and the discussion of the results of the application of Benford's Law to our data set follow in Section 4. Section 5 performs a series of robustness checks and, finally, Section 6 concludes.

II. THE BENFORD'S LAW

In 1881, Newcomb observed that the initial pages of a book of logarithmic tables were more worn than the latter pages. He also observed that numbers with first digit of 1 were observed more often than those starting with 2, 3 and so on. This led him to believe that, in practice, low numbers occur more frequently than high numbers. On that basis, he developed a set of mathematical theorems to determine the distributions of numbers appearing in different digital positions within naturally occurring figures. He discovered that low numbers possess a larger probability of appearing in the first two digital positions within a number compared to high numbers (Newcomb, 1881).

Almost fifty years later, Benford (1938) conducted a study that was focused on the expected distribution of digits in tabulated data from numerous natural data sets. More concretely, he formulated the expected frequencies for the first and second positions in a number together with their combinations and found that, when the data are ranked from smallest to largest, they form a geometric sequence. Basically, what Benford (1938) showed was that, in several naturally occurring data sets (i.e., data sets which are not contrived by man or machine), the distribution of digits do not follow a natural, regularly occurring pattern. This is to say, the leading significant digits (mostly those in the first two places of a number) are not uniformly distributed; instead, they follow a logarithmic weak monotonic distribution. The distribution of leading digits implied by Benford's Law is described by the following expressions:

$$f(i) = log_{10}(1 + i^{-1}), \quad (1)$$

and

$$\sum_{i=0}^{9} f(i) = 1, \quad (2)$$

where *f(i)* stands for the frequency of digit i implied by Benford's Law being the first or other leading digit; i=0, 1, 2,…, 9; and log_{10} is the base 10 logarithm. Note that the first digit cannot take the value of 0, unless the number under scrutiny is a decimal number. Table 1 shows the expected frequencies for the digits 0 through 9 to occur in each of the first four digital positions in any number. We note that digit 1 possesses a 30.10 percent likelihood of appearing in the first digital place within a number, while digit 9 has only a 4.58 percent likelihood of occurring in the first digital place. More generally, digit 1 occurs more often than any other number in the first position of a number, whereas the frequency of the remaining digits (i.e., from 2 to 9) decreases with respect to the value of the digits. Similarly, the probability of digit 0 appearing in the second place within a number is 11.97 percent, whereas digit 9 possesses only an 8.50 percent chance of occurring in the second place.

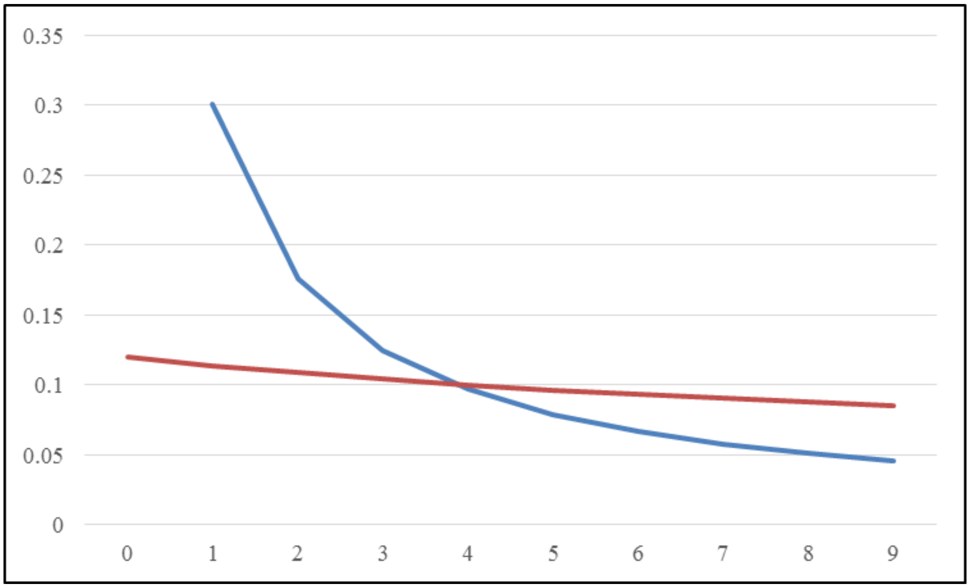
TABLE 1
Benford's Expected Digital Frequencies

Digit	1st place	2nd place	3rd place	4th place
0		.1197	.1018	.1002
1	.3010	.1139	.1014	.1001
2	.1761	.1088	.1010	.1001
3	.1249	.1043	.1006	.1001
4	.0969	.1003	.1002	.1000
5	.0792	.0967	.0998	.0999
6	.0670	.0934	.0994	.0999
7	.0580	.0904	.0990	.0999
8	.0512	.0876	.0986	.0999
9	.0458	.0850	.0983	.0998

This table presents the expected frequencies for the digits 0 through 9 in each of the first four places in any number based on Benford's Law distribution.

The expected digital frequencies for the first and second places based on the Benford distribution are graphically presented in Figure 1. The values on the vertical axis reflect the distribution probabilities of digits *i* as shown on the horizontal axis.

FIGURE 1
Benford's Law Expected Frequencies for the First and Second Digits



This Figure contains a graphical representation of the expected frequencies for the first digit (blue line) and the second digit (red line) based on the Benford distribution. The values on the vertical axis are the distribution probabilities of digit *i* as shown on the horizontal axis, where *i*=0, 1, 2,…, 9.

The Benford distribution is an empirically observable phenomenon, exactly like normal distribution. If distributions are selected at random and random samples are taken from each of these distributions, then the significant digital frequencies of the combined samplings are expected to converge to Benford's distribution, even though the individual distributions may not closely follow the Law. In the context of our research, this means that if the digital frequency in the bank accounting data we employ in our analysis departs from the expectations of Benford's Law, we can argue that data may have been manipulated. Or, in other words, that the data have been transformed to conceal the true financial condition of the banking institutions that comprise our sample.

III. APPLICATIONS OF BENFORD'S LAW IN THE LITERATURE

The first application of Benford's Law in the accounting literature is that of Carslaw (1988), which examines the frequency of the occurrence of second digits in income figures of a total of 220 listed corporate firms in New Zealand. He tests the hypothesis that when income is below some particular psychological threshold, managers have the tendency to round it up. His empirical findings provide support to his hypothesis since an abnormally high frequency of digit zero and an unusually low occurrence of digit nine are documented. Inspired by Carslaw (1988), Thomas

(1989) conducts a study to investigate if the reported earnings for U.S. firms follow similar patterns with those of New Zealand firms. His findings suggest similar, though considerably smaller, deviations from the expected frequencies for the latter firms, whereas an opposite pattern with fewer zeros and more nines than expected is reported for losses.

Further research on earnings management based on Benford's Law is conducted by Niskanen and Keloharju (2000), Van Caneghem (2002), and Skousen, Guean and Wetzel (2004) for the Finnish, U.K., and Japanese corporate companies, respectively. In this context, Das and Zhang (2003) rely on data from the I/B/E/S and the S&P's Compustat databases to show that firms tend to round up earnings per share so that they can meet analysts' forecasts and achieve their predetermined profitability goals. Tilden and Janes (2006) use the Law to investigate the occurrence of manipulation practices in corporate accounting data during the economic recessions that occurred from 1950 to 2006. They show that data conform to Benford's Law under normal economic and financial conditions. However, in periods surrounding recessions, some reported financial statement figures like the allowance for doubtful accounts and the net income fail to conform, which is an indication of manipulation.

In a somewhat different context, Nigrini (1996) resorts to Benford's Law to detect tax evasion. He investigates a number of tax declarations of American taxpayers and found that people lean towards the understatement of their real taxable income. In fact, low-income taxpayers are found to be more likely to invent numbers on their tax return. Similarly, Nigrini and Mittermaier (1997) detect fraudulent data in tax payments and accounting data, suggesting that auditors can test the authenticity of lists of numbers by comparing the actual and the expected digital frequencies by a recourse to Benford's Law. Durtschi, Hillison and Pacini (2004) provide further support to the importance of the Law in helping auditors to increase their ability to detect fraudulent practices. They show that digital analysis conducted on transaction level data rather than aggregated data, can assist auditors by identifying the specific accounts in which frauds might reside so that auditors can then investigate the relevant accounts in a more depth.

Benford's Law has been lately utilised in testing the quality of macroeconomic data. Gonzales-Garcia and Pastor (2009) argue that nonconformity with the Law should not necessarily imply poor quality of macroeconomic data. They argue that the rejection of the Law may result from marked structural shifts in the data series under scrutiny. Brahler, Engel, Gottsche, and Rauch (2011) also refer to Benford's Law to investigate the quality of macroeconomic data reported to

Eurostat by EU member states. Similarly, Michalski and Stoltz (2012) resort to the Law to examine whether a set of countries misquote the economic data they report to authorities in a strategic manner. Abrantes-Metz, Villas-Boas, and Judge (2011) use Benford's second digit reference distribution to track the daily Libor over the period 2005-2008 with the purpose to identify if Libor performs its intended price-signalling function. They provide evidence for significant deviations of the Libor's price most noticeably from January 1, 2007 through August 8, 2007.

Other studies that also resort to Benford's Law are those of Ashton and Hudson (2008), which examines various patterns of data streams to find instances of interest rate clustering in the UK financial services markets; Hales, Sridharan, Radhakrishnan, Chakravorty, and Samia (2008), which investigates the reliability of employee-reported operational data by testing the presence of the Law in these datasets; Diekmann (2007) that examines whether the first digits of regression coefficients published in scientific journals tend to be distributed according to the first digit-law; and, Diekmann and Jann (2010) that draws attention to difficulties in using the Law to detect fraud in scientific publications, pointing out that, in order to establish the validity of the relevant tests, it is required to demonstrate that real data are in agreement with the Benford distribution while manipulated data follow some different distribution.

IV. EMPIRICAL ANALYSIS

This section describes our data set and the accounting variables we employ in our analysis. The digital analysis of the conformity of Benford's Law to our data is also presented and discussed.

Data Period

Our data are of quarterly frequency and extend from the beginning of 2003 (2003q1) to the end of 2012 (2012q4) when the banking crisis in the U.S. literally came to a halt. We do not examine the years prior to 2003q1 for two main reasons. First, on 30 July 2002, the U.S. government signed the Sarbanes-Oxley Act (henceforth SOX) into law with the purpose to set new or enhanced disclosure standards for all U.S. public company boards including those of listed banking firms. The bill, which constituted a major regulatory reform, was mainly enacted as a reaction to the numerous financial accounting scandals in the years prior to and around 2000 like those of Enron, Tyco International, Qwest, HealthSouth, Adelphia, Peregrine Systems, and WorldCom. Under SOX, top management executives have to individually certify the accuracy of financial information, whereas penalties for fraudulent financial activity are severe. Additionally, SOX has increased both the independence of the outside auditors whose main task is to review the accuracy of corporate financial statements and the oversight role of boards of directors. The second reason for not examining the data prior to 2003q1 is because the two international financial crises which erupted in East Asia and in Russia towards the end of the '90s combined with the Long Term Capital Management (LTCM) crisis in late 1998 and the dot-com bubble crisis of the early 2000s all had a considerable destabilising impact on the operation of international financial markets and that of the U.S. banking system.

The entire data period is divided into two sub-periods: the earlier one (2003q1-2007q3) includes the years prior to the outbreak of the crisis, that is before September 2007 when the TED spread (i.e., the difference between the yield on the three-month Libor and the yield on three-month U.S. Treasury bills) which is one of the most widely-used indicators of credit risk, widened to almost 200 basis points relative to a historically stable range of 10-50 basis points. The pre-crisis years was characterised by stable financial conditions and strong economic expansion. The second period extends from 2007q3 to 2012q3 and refers to the crisis period in which financial turbulence, uncertainty, and distress prevailed in the economy. It has to be mentioned here that the former period follows the major accounting scandals occurring in early 2000s, which largely led to the development and implementation of SOX in mid-2002 and the increased scrutiny of financial reporting in the U.S. as earlier discussed. On the other hand, the latter period is the period when several financial reporting misstatements in the banking industry were revealed.

Data Set

We focus on U.S. commercial and savings banking institutions that file a Report on Condition and Income (also known as Call Report) and make a clear distinction between non-problem and problem banks.[4] The former group consists of all the banks that stayed afloat in that they neither failed, nor received some financial aid, nor merged with or acquired by some other institution during the recent financial meltdown. The banks which failed at some later point in time that is

[4] Thrifts -i.e., savings and loans associations- are excluded from our empirical analysis because they file a different report (the Thrift Financial Report). With the implementation of Dodd-Frank Act and the establishment of the Office of Thrift Supervision in July 2011, all thrifts were required to file and submit a Call Report from March 2012.

not covered in our data period -that is, from 2013q1 to 2015q4- are also excluded from our set of non-problem banks. Further, the latter group does not contain any institutions that were merged with or acquired by some other institution from the onset of the crisis onwards.

Problem banks, on the other hand, are those which either failed during the crisis or received TARP assistance. Failed banks are defined as the insured commercial and savings banks that were closed requiring disbursements by FDIC from the outbreak of the crisis in 2007q4 through the end of our data period. In general, a bank is closed when the regulatory authorities determine that it is critically undercapitalised and deem it unable to meet its obligations to depositors and other creditors. The key attribute determining undercapitalisation is insolvency, which occurs when the bank's assets are worth less than its liabilities according to either book or market values. Another fundamental reason for bank closure is liquidity shortages, which occur when a bank is unable to meet its current obligations as they come due. For instance, when depositors expect that a bank is very likely to fail, they may withdraw their deposits and precipitate a liquidity crisis at the bank.

In the event of a bank failure, the institution's charter is terminated and some or all of the failed bank's assets and liabilities are transferred to a successor charter. The FDIC acts as a receiver and is in charge of the failure resolution process. There are mainly two failure resolution mechanisms: the 'purchase-and-assumption' and the 'deposit pay out'. Under the former mechanism, the failed banking institution's insured deposits are transferred to a successor institution, and its charter is closed. In most of the purchase-and-assumption transactions, additional liabilities (e.g., part or all of its uninsured deposits) are assumed by and some or all of its assets are transferred to the acquiring bank. The FDIC usually provides assistance to the acquirer most often in the form of loan loss sharing agreements. In the case of remaining assets and liabilities, these are liquidated and the liquidation costs are internalised. In several purchase-and-assumption resolution cases, the acquiring bank compensates the FDIC for the franchise value from the failed bank's established customer relationships, which helps reduce the insurer's resolution cost. In a deposit payout transaction, on the other hand, the FDIC pays the failed bank's depositors the full amount of their insured deposits, the failed bank's charter is closed, and there is no successor institution. Typically, deposit payouts are observed when no other bank is interested in assuming the assets and liabilities of the failed bank.

In total, for the period starting from 2007q4 and extending to 2012q4, there have been recorded 449 failures of commercial and savings banks in the U.S. and FDIC has been appointed receiver of all the bankrupt institutions based on the relevant data collected from the FDIC web site.[5] To give the broad picture of the extent of bank failures in the recent crisis, we indicate that only 30 banks went bankrupt in the U.S. from 2000q1 through 2007q3.

To construct the sample of bailed out banks, we identify all TARP recipients. TARP has been the largest U.S. government bailout programme in history. It authorised the Treasury to inject loads of capital into banks by purchasing senior preferred shares. Those injections were intended to restore the health and increase the soundness of problem banks by helping them to address liquidity shortages and strengthen their capital base. Banks were scheduled to repay or redeem the preferred stock at an undetermined time, but the programme required them to pay an established dividend rate and interest rate to the Treasury as long as the securities were outstanding.

We refer to the complete list of TARP recipients which is obtained from the U.S. Department of the Treasury. This list discloses the financial institutions that received TARP funds via the Capital Purchase Program (CPP) which was the key component of TARP together with the respective transaction dates and investment amounts. We trace all commercial and savings banks which participated in the programme either directly, or through their parent (bank holding) companies. In total, we identify 736 TARP investment transactions excluding any multiple transactions, i.e., transactions in which a bank is involved in more than once. Out of these 736 institutions that received capital injections, 47 were thrifts which, as earlier mentioned, are excluded from our analysis. This leaves 689 institutions in our sample, out of which 596 are Bank Holding Companies (BHCs) and 93 are commercial and savings banks. We realistically assume that if a BHC was approved to participate in TARP, its subsidiary banks would have received some fraction of TARP funds. Out of 596 BHCs that participated in TARP, 56 were multi-BHCs, while the remaining 540 were mono-BHCs. We match all BHCs to their subsidiary commercial and savings banks by hand-matching the relevant information found in the Consolidated Financial Statements for Bank Holding Company Report (FR Y9-C Report) to the 'higher-holder' codes of the examined banks found in Call Reports. By doing so, we obtain a total of 731 FDIC-insured banks that received TARP funds via their parent holding companies. We add to this figure the 93

[5] The names of the banks, their distribution across the U.S. states and cities, the date that every failed institution ceased to exist as a privately-held going concern entity, the estimated assets and deposits of each institution at the time of failure, and the cost of every individual failure for FDIC are all available upon request.

commercial and savings banks which are not linked to a BHC to construct the final sample of 824 banks that received TARP support, either directly or through their parent companies.[6]

In sum, we begin with a total number of 8,722 active commercial and savings banking institutions that filed a Call Report in 2003q1. We then exclude the 46 banks that went bankrupt over the 2013q1-2015q4 period as well as those that were merged with or acquired from some other institution through some market deal and not through one of the two failure resolution mechanisms described above. We also check the data for reporting errors and other inconsistencies and we end up with 7,575 banks of which 449 went bankrupt, 824 were bailed out, and the remaining 6,302 stayed alive during the crisis. It is important to mention here that, from the statistical perspective, the sets of failed and bailed out banks do not intersect with each other in the sense that none of the sample banks which received financial assistance did later fail. Apparently, this also holds true for the set of non-problem banks with those of failed and bailed out banks.

The Bank Accounting Variables

To choose the bank accounting variables to utilise in our empirical analysis, we resort to the Uniform Financial Rating System, informally known as CAMEL. CAMEL is a vector of five different -yet interrelated- measures capturing Capital adequacy, Asset quality, Management expertise, Earnings strength, and Liquidity. It was introduced by the U.S. authorities in November 1979 to conduct on-site examinations in order to evaluate the individual performance and the soundness of banks and to monitor the conditions in the industry. In 1996, CAMEL evolved into CAMELS, with the addition of a sixth component ('S') that summarises the Sensitivity to market risk.

We construct five sets of accounting variables, each corresponding to the key variables used by regulators to construct the CAMEL components. We do not account for Sensitivity to market risk because this component is proxied by market (and not accounting) variables like the slope of the yield curve or the spread in the market interest rates. To measure Capital adequacy, we rely on the book equity capital (*EQUITY*) and the core regulatory capital (*TIER 1*); for Asset quality, we refer to non-performing loans (*NPL*), allowances for loan losses (*LOSSALLOW*), and loan loss provisions (*LLP*); Management expertise in measured by total loans and leases (*LOANS*), total

[6] The detailed list of these banks is available upon request.

deposits (*DEPOSITS*), and total earning assets (*EARNASETS*); the measurement of Earnings strength is based on total interest income (*INTINC*), and total non-interest income (*NONINTIC*); and, lastly, Liquidity is captured by cash and balances due from depository institutions (*CASH*), and by federal funds purchased and securities sold under agreements to repurchase (*REPOS*). All variables, which are shown in Table 2, are based on balance sheet and income statement data of quarterly frequency, and are collected from the Call Reports as found in the website of the Federal Reserve Bank of Chicago and that of the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution.

TABLE 2
Accounting Variables and Data Sources

CAMEL components	**Variables**	**Abbreviation**	**Data Source**
Capital adequacy	Book equity capital	*EQUITY*	Call Reports & Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution
	Core regulatory capital	*TIER1*	
Asset quality	Non-performing loans	*NPL*	
	Allowances for loan losses	*ALLOW*	
	Loan loss provisions	*LLP*	
Management expertise	Total loans and leases	*LOANS*	
	Total deposits	*DEPOS*	
	Total earning assets	*EARNAS*	
Earnings strength	Total interest income	*INTINC*	
	Total non-interest income	*NINTINC*	

Liquidity	Cash and balances due from depository institutions	*CASH*
	Federal funds purchased and securities sold under agreements to repurchase	*REPOS*

This Table presents all the variables that we use in the empirical analysis and in robustness checks. The abbreviation of each variable and the sources we use to collect the data are also reported.

If manipulation occurs in the accounting variables that reflect Capital adequacy (*EQUITY* and *TIER1*), Management expertise (*LOANS*, *DEPOS*, and *EARNAS*), Earnings strength (*INTINC* and *NINTINC*), and Liquidity (*CASH* and *REPOS*), then this is expected to have an upward trend. That is, we anticipate that a bank that resorts to data tampering it does so in order to signal to regulators, investors, and to the public a more robust performance than the actual one in terms of capital, management, profitability, and liquidity. On the other hand, manipulation in the Asset quality variables is expected to be of downward nature in the sense that lower non-performing loans (*NPL*), loan loss allowances (*ALLOW*), or loan loss provisions (*LLP*) would convey the picture of a less risky and, hence, more sound banking institution to the public.

Digital Analysis

We conduct a digital analysis to compare the actual with the expected frequencies predicted by the Benford's Law of the digits zero through nine appearing in the second position of our variables of interest. We resort to the normally distributed *z*-statistics to examine the statistical significance of the deviations in the actual and expected proportions, which is computed as follows:

$$z_i = \frac{|p_0 - p_i| - (\frac{1}{2n})}{s_i}, \tag{3}$$

where z_i is the *z*-statistic for digit i where *i*=0, 1, 2,…, 9; p_0 denotes the actual (observed) proportion; p_i is the expected proportion based on Benford's Law; *n* is the number of observations of the examined variable; the term $\frac{1}{2n}$ is the Yates' continuity correction term that is applied only when its value is smaller than that of $|p_0 - p_i|$ to bring normal and binomial probability curves into close agreement; and s_i is the standard deviation of digit *i* given by:

$$s_i = [p_i\ ((1 - p_i)/n)\ ]^{1/2} \tag{4}$$

The *z*-statistic tests the null hypothesis that the actual proportion does not statistically differ from the expected proportion based on Benford's Law. As the difference between p_0 and p_i increases in Equation (3), the *z*-statistic becomes larger. A *z*-statistic of 2.57 indicates a *p*-value of 0.01, 1.96 indicates a *p*-value of 0.05, and 1.64 suggests a *p*-value of 0.10.

An extension of the *z*-statistic that tests one digit at a time is the chi-square test that is, in fact, a 'goodness-of-fit' test as it is conducted over all nine digits of the second position of the variables under scrutiny. The chi-square test investigates whether the observed distribution significantly differs from the expected distribution. In case the chi-square test rejects the null hypothesis that the probability of all digits conform to the expected distribution under Benford's Law, then this is a strong signal for data manipulation. The value of chi-square is determined through the following formula:

$$\chi^2_{(9)} = n \sum_{i=0}^{9} \frac{(\hat{\theta}_i - f(i))^2}{f(i)}, \tag{5}$$

where $\hat{\theta}_i$ is the observed frequency of digit *i*; *f(i)* stands for the frequency of digit *i* implied by Benford's Law as noted under Equations (1) and (2); and, *n* is the number of observations of the examined variable. The conformity of the entire distribution is tested, implying that the results are summed up for all digits *i*=0, 1, 2,…, 9. As we focus on the second position of each of the examined variables, we have nine degrees of freedom, *i.e.* $\chi^2_{(9)}$. The 10 percent, 5 percent, and 1 percent critical values for $\chi^2_{(9)}$ are 14.68, 16.92, and 21.97, respectively.

The digit-by-digit analysis based on *z*-statistics and the variable-by-variable chi-square test are complementary to each other. The former is more discriminatory than the latter analysis and spots on finding line items that contain possible red flags; in other words, attention is drawn to certain digits with peaks. The latter analysis investigates whether the entire behaviour of a variable warrants further examination. Hence, it allows statements of the goodness-of-fit for the variable under examination as a whole. *Z*-statistics is used as a supplement to a chi-square test in order to reduce the probability of Type I and II Errors. A Type I Error occurs when a variable is not manipulated, but it is signaled as it underlies a human intervention. A Type II Error, on the other hand, occurs when a variable that actually underlies some portion of human intervention is signaled as not being manipulated.

V. RESULTS AND DISCUSSION

The results of our digital analysis for the second position in each of the CAMEL components based on the *z*-statistic and the chi-square test for the sets of non-problem, failed and bailed out banks over the pre-crisis as well as the crisis periods are presented in Tables 3 through 8. If a variable does not conform to Benford's distribution, then the data is likely to have been manipulated. If a variable has been manipulated upwards to increase the digit in the first position by one, a higher than anticipated proportion of low numbers (mostly zeros or ones) and a lower than expected frequency of high numbers (mostly nines or eights) will occur in the second position. This describes an uncommon digital pattern that violates Benford's Law and indicates an upward data manipulation. If the reversal pattern holds -more high digits and fewer low digits than expected appear in the second position- then data are suspect for a downward manipulation. A positive deviation implies that the actual proportions exceed the expected ones, while a negative deviation shows that the converse is true.

The Pre-crisis Period

We start our discussion by focusing on Tables 3 through 5 that contain the results of the digital analysis based on pre-crisis data. The results for non-problem banks as presented in Table 3 show that the actual proportion of zeros appearing in the second position of total earning assets (*EARNAS*) and total interest income (*INTINC*) exceeds the expected proportion by 4.88 percent and 5.56 percent, respectively. The reported deviations are both statistically significant at the 5 percent level. Along the same lines, the actual proportion of ones significantly exceeds the expected proportion by 3.74 percent and 3.95 percent, respectively. If we apply the same procedure to the remaining numbers (i.e., two through nine) appearing in the second position of *EARNAS* and *INTINC*, we find that eights and nines produce actual proportions that are significantly lower from the anticipated proportions. Deviations for *EARNAS* are equal to -2.64 percent and -6.08 percent for eights and nines, respectively, whereas for *INTINC* deviations are -2.56 percent and -7.18 percent, respectively. The goodness-of-fit chi-square test suggests a rejection of the hypothesis that the *EARNAS* and *INTINC* data are generated by the Benford's distribution. Taken together, the aforementioned results demonstrate a clear evidence of data manipulation. In specific, results show that the banks which remained afloat in the recent crisis, rounded up both *EARNAS* and *INTINC* in the years preceding the crisis in order to signal to regulators, market participants, and other economic agents a more efficient managerial performance and a higher profitability. These banks are also found to manipulate loan loss provisions downwards as actual proportions of *LLP* are lower by 4.14 percent compared to the expected proportions for zeros and higher by 4.52 percent for nines. For the remaining nine CAMEL components we employ in our analysis, all digits zero through nine appear in the second position at rates which approximate their expected frequencies. In addition, no statistical significant deviations based on *z*-statistic are reported. Consistently, the chi-square test does not provide us with any signal for data manipulation for these variables.

We now turn to shed the spotlight on the set of failed banks. The results in Table 4 reveal the occurrence of large positive (negative) and significant proportional deviations in digits zero and one (eight and nine) of *EARNAS* and *INTINC*. The magnitude of the reported deviations is larger as compared to the relevant deviations observed for the set of non-problem banking firms. Hence, a stronger upward manipulation for the Management expertise and the Earnings components of CAMEL ratings system for the set of failed banks in the years prior to outbreak of the crisis is documented. Importantly, a downward bias is reported for allowances for loan losses (*ALLOW*) as there are more nines (5.74 percent) and fewer zeros (6.82 percent) than anticipated in the second digit. The reported deviations are found to be significant at the 5 percent level. In a similar vein, loan loss provisions are manipulated downwards since the actual proportion of zeros appearing in the second position of *LLP* is significantly smaller than the expected proportion by 5.71 percent and that of nines significantly exceeds the expected proportion by 4.89 percent. We can thus argue that the banks that went down during the crisis were inclined to present lower loss allowances and loss loan provisions prior to their failure. Both the reported upward manipulation in *EARNAS* and *INTINC* and the downward manipulation in *ALLOW* and *LLP* described above are confirmed by the chi-square test. Neither large, nor statistically significant discrepancies between the actual and the expected frequencies are reported for any of the remaining CAMEL components.

The upward data manipulation practices of *EARNAS* and *INTINC* are also confirmed for the set of bailed out banks in the pre-crisis era as displayed in Table 5. More specifically, results indicate that the actual proportion of zeros appearing in the second position of *EARNAS* and *INTINC* exceeds the expected proportion by 6.71 percent and 7.32 percent, respectively, whereas the actual proportion of ones exceeds the expected proportion by 3.91 percent and 3.90 percent, respectively. As regards eights and nines, these are linked to actual proportions which are significantly lower from the anticipated proportions: deviations for *EARNAS* are -2.61 percent and -8.58 percent for eights and nines, respectively, while for *INTINC* deviations are equal to -3.42 percent and -9.16 percent, respectively. Interestingly, bailed out banks are found to also apply manipulation practices on *NINTINC* since the actual proportion of zeros exceeds the expected proportion by 8.20 percent. Conversely, the actual proportion of nines are less by 7.82 percent compared to the expected proportion. Both deviations are significant at the 5 percent level. Moreover, the pre-crisis downward manipulation of loan loss allowances documented for the failed banks is also found to hold true for the assisted banks since there are fewer zeros (-6.62 percent) and more nines (6.20 percent) than expected in the second position of *ALLOW* and the reported discrepancies are statistically significant at the 5 percent level. Bailed out banks are further found to manipulate loan loss provisions downwards as actual proportions of loan loss provisions (*LLP*) are lower by 7.93 percent compared to the expected proportions for zeros and higher by 7.38 percent for nines. Deviations are found to be significant at the 5 percent level for both zeros and nines. The goodness-of-fit test carried out produce statistically significant results for all the manipulated variables (*EARNAS*, *INTINC*, *NINTINC*, *ALLOW*, *LLP*).

The Crisis Period

The digital analysis performed on the pre-crisis sample is replicated on the crisis sample and the relevant results are displayed in Tables 6 through 8. We provide evidence of an upward data manipulation of both earning assets (*EARNAS*) and interest income (*INTINC*) for all three examined clusters of banks. The manipulation levels are found to be higher compared to those we document prior to the crisis. Indeed, the incidence of zeros and ones in the second position of the aforementioned variables increased after the outbreak of the crisis, whereas, at the same time, the occurrence of eights and nines is decreased. Moreover, problem banks appear to manipulate *EARNAS* and *INTINC* to a greater extent compared to non-problem banks. To continue, bailed out institutions are found to exert an upward manipulative influence on total non-interest income (*NINTINC*). Manipulation is found to be stronger compared to the manipulation reported in the pre-crisis period. The chi-square test is statistically significant at the 1 percent, 5 percent, and 10 percent levels for *EARNAS* and *INTINC* and significant at the 5 percent level for *NINTINC*, thus suggesting the rejection of the null of a Benford distribution.

As regards the Asset quality component of CAMEL ratings, *z*-statistic reveals significantly negative deviations in digit zero and positive deviations in digit nine for loan loss allowances (*ALLOW*) and non-performing loans (*NPL*) for both the bankrupt and saved banks. The same deviation scheme is reported for loan loss provisions (*LLP*) for all three banking groups. Importantly, the level of downward manipulation is found to be higher for all three Asset quality measures in the crisis era.

Remarkably, all sample banks are found to apply upward data manipulation practices on the core regulatory capital as an excess of zeros and a shortage of nines in the second digit of *TIER1* is reported. In particular, the actual proportion of zeros significantly exceeds the expected proportion by 4.98 percent for non-problem banks, 5.82 percent for failed banks, and by 5.32 percent for bailed out banks. On the other hand, digit nine is linked to actual proportions which are significantly lower from the expected proportions by 5.17 percent, 5.48 percent, and by 5.70 percent for the non-problem, failed, and bailed out banks, respectively. The chi-square test confirms the statistical validity of all the aforementioned deviations. Therefore, banks are found to signal a stronger capital base than the actual one to regulators and to market participants.

Discussion of the Results across the Two Periods

Our results suggest that all sample banks utilise loan loss provisions throughout the two time periods to manipulate earnings and interest income upwards. Interest income is by far the most important source of revenue for commercial banks; it mainly emerges from the interest that banks charge on loans and determines the degree of bank profitability to a considerable extent. In the case of bailed out banks the majority of which are large and universal institutions that are entangled with a very broad range of modern financial activities other than pure commercial banking activities like loan granting, the total non-interest income is also found to be manipulated upwards in both data periods.[7] Prior research (see, e.g., Kanagaretnam, Lobo, and Yang 2004) indicates that bank managers largely use loan loss provisions for earnings management mainly due to motives associated with income smoothing, achieving earnings targets, or meeting profitability benchmarks. Furthermore, the performance-based remuneration practices which prevail in the banking industry for many years now are widely considered as providing the managers and executives of banking institutions with strong incentives to manipulate the reported earnings and revenues.

Together with loan loss provisions, the set of problem banks is further found to resort to the downward manipulation of allowance for loan losses and non-performing loans with the purpose to manipulate earnings upwards. Under the Financial Accounting Standards No. 5 (FASB 1975) entitled 'Accounting for Contingencies', when credit losses on a loan or portfolio of loans are likely and can be reasonably estimated, an expense called loan loss provisions and a contra-asset (to earning assets outstanding) called loan loss allowances should be recorded on bank accounting books. This is to say, by manipulating loan loss provisions downwards, banks are inclined to follow the same or similar strategies with loan loss allowances, and, by doing so, are 'entitled' to artificially increase the volume of earning assets. Moreover, the reported downward manipulation of non-performing loans can be explained by the direct relation that holds between non-performing loans and loss provisions. In specific, higher levels of non-performing loans imply troubles in the bank loan portfolio and these troubles should be reflected in higher loss provisions (Kanagaretnam, Krishnan, and Lobo 2010).

In addition, we provide strong evidence that data manipulation is more prevalent in problem financial institutions. As regards income and earnings manipulation, it is established in the literature that this is more likely to occur when a bank's future prospects are rather bleak. Indeed, weak banks tend to manage income and earnings upwards by delaying loan loss provisions (Liu and Ryan 2006) and, in turn, loss allowances and non-performing loans, showing achievement of the relevant targets and, at the same time, concealing their financial difficulties. Along the same lines, distressed banks are more closely monitored by regulators and, hence, their managers are

[7] Fee-based activities are explicitly defined by the Gramm-Leach-Bliley Act of 1999 and include, amongst others, securities dealing and underwriting, financial and investment advisory services, merchant banking, derivatives trading, and issuing or selling securitised interests in bank-eligible assets.

more anxious in demonstrating to authorities that they can attain the imposed pre-specified performance thresholds. Moreover, a crucial prerequisite to obtain TARP assistance was viability, meaning that the applicant banks had to prove that they were viable. However, this viability criterion was rather loosely defined and was mostly linked to the level of profitability by many applicant banks, which they were incentivised to show to Federal assessors higher revenue streams and cash flows than the actual ones.

Our results reveal that manipulation is magnified after the eruption of the crisis. This is in accordance with Tilden and Janes (2012)'s findings of increased financial statement manipulation during economic recessionary times. Importantly, all sample banks are found to be involved in an upward manipulation of the core regulatory capital during the crisis era. By assumption, a bank has strong incentives to show it is not undercapitalised and that its capital is adequate to meet its obligations to depositors and other creditors. To the extent that the allowance for loan losses is included in regulatory capital, banks can manipulate allowances downwards with the purpose to show that a strong capital cushion has been set aside to absorb shocks due to the financial turbulence. Also, accounting discretion which is inherent in the current financial reporting rules allow banks to manipulate regulatory capital upwards by holding back on loan loss provisioning and by keeping their allowances for loan losses from ballooning. That is, in line with Huizinga and Laeven (2012), we suggest that banks manipulate their loan loss provisioning to manage their regulatory capital after the outbreak of the crisis.

Patterns of Data Manipulation Practices

We can now examine the pattern of data manipulation we have documented thus far. To this, we apply the Benford's Law to the first position of each of the manipulated variables, i.e., *EARNAS*, *INTINC*, *NINTINC*, *ALLOW*, *LLP*, *NPL*, and *TIER1*. Digital analysis is conducted for all the three sets of banks and for each of the two periods separately.[8] Results, which are very similar across the two periods and amongst the three bank clusters, indicate that the actual proportion of ones which occur in the first position of *EARNAS*, *INTINC*, *NINTINC*, and *TIER1* is

[8] For the sake of brevity, the relevant results are not presented and are available upon request.

higher than the anticipated and that eights and (mostly) nines are observed less often than expected. Conversely, for *ALLOW*, *LLP*, and *NPL* the actual proportion of ones is lower than anticipated, while that of nines is found to be higher. All the reported deviations are significant at the 1 percent level for digit one, and at the 5 percent level for digits eight and nine based on the values of *z*-statistic, whereas the values of the chi-square test reveal significance at the 1 percent and 5 percent levels.

Our results demonstrate that the reported data manipulation pattern is common amongst the examined CAMEL variables. In specific, the upward manipulation pattern suggests that when an accounting figure starts with either the digit eight or nine is more likely to be rounded up to a figure which has a one as the first digit. To give an example, a core regulatory capital (*TIER1*) of $894 million is likely to be rounded up to $1.012 billion. In the context of a downward manipulation, on the other hand, the reported pattern shows that banks tend to decrease the value of an accounting figure when its first digit is one to a figure which starts with the digit nine. For instance, loan loss provisions (*LLP*) of $1.085 million are manipulated downwards to $991,062. Interestingly, neither the level of soundness of banks under scrutiny (problem vs non-problem institutions) nor the occurrence of the crisis affect the documented manipulation pattern.

Our evidence suggests that banks exercise manipulation to increase the magnitude of balance sheet (*EARNAS* and *TIER1*) and income statement variables (*INTINC* and *NINTINC*) when the level of these variables is only slightly below a round number. By the same token, banks manipulate the balance sheet variables that reflect Asset quality (*ALLOW*, *LLP*, and *NPL*) downwards when the level of these variables is slightly above a round number. We can, therefore, claim that, in general, banks utilise data manipulation to present an artificially improved view of their performance to authorities, investors, and the public, without yet resorting to eye-catching manipulation strategies that may attract the scrutiny by regulators, the SEC, or auditors. Still, however, manipulation practices transmit noise in the operation of the entire banking sector. On the one hand, they distort the expectations of shareholders, investors, and the public about individual bank valuations but also about financial conditions in the sector as they provide false signals; on the other hand, they mislead regulatory and supervisory authorities in their tasks to identify and address any problems in the operation of banks and of the sector as a whole.

VI. ROBUSTNESS ANALYSIS

Our digital analysis based on the *z*-statistic and the chi-square tests has indicated that manipulation is likely to occur to some of the bank accounting variables we scrutinise. As a robustness test, we resort to Nigrini (1996)'s Distortion Factor (DF) model which indicates whether or not data are overstated or understated and also estimates the extent of manipulation (or distortion). The DF model compares the mean of the actual numbers in a data set and the mean of the expected numbers based on Benford's Law. Since there is no unique mean for the numbers contained in a data set which closely approximates the Law because such a data set consists of relatively large or relatively small numbers, Nigrini (1996) suggests to move the decimal point of each actual number so that each number would fall into the interval [10,100). More concretely, each number that is below 10 is expanded to a number within the range [10,100). Similarly, each number that is larger than 100 is collapsed to a number within the range [10,100). For example, the number 4.29 expands to 42.9, while the number 1040 collapses to 10.4. A comparison is then made between the mean of the set of actual numbers scaled to the [10,100) range and the mean of the set of expected numbers that conform to Benford's Law.

The Actual Mean (*AM*) of the *n* collapsed or expanded data is given by:

$$AM = \frac{\sum X}{n}, \tag{6}$$

where *X* stands for the collapsed or expanded data values, and *n* is the number of observations of the examined variable. Following Nigrini (1996), the Expected Mean (*EM*) of the Benford distribution is equal to:

$$EM = \frac{90}{n(10^{\frac{1}{n}} - 1)} \tag{7}$$

We can calculate *DF* as follows:

$$DF = \frac{(AM - EM)100}{EM} \tag{8}$$

Equation (8) gives the average percentage manipulation of the examined data. When *DF* is positive (negative), an upward (downward) manipulation is detected. Since *AM* and *EM* are the means of *n* random variables, the distribution of *DF* approaches the normal distribution according to the central limit theorem. Hence, the *z*-statistic that tests the null hypothesis that the *AM* equals the *EM* can be computed for relatively large *n*.[9]

In our robustness analysis, we also account for possible selection bias in our data. Towards this, we exclude from the group of bailed out banks all the institutions that regulators would never let them fail due to their systemic importance. Indeed, authorities injected loads of capital into nine U.S. banks under TARP at the very first instance, implying that those TARP recipients did not follow the formal assessment process like their peers did. These banks were Citigroup, Bank of America, JP Morgan Chase, Wells Fargo, Goldman Sachs Group, Morgan Stanley, Wachovia Corporation, State Street Corporation, and Merrill Lynch. By the same token, the biggest bank failure, that of Washington Mutual Bank with $307 billion assets, is treated as an outlier and is excluded from our set of failed institutions. Washington Mutual was the sixth largest U.S. commercial bank when it failed in September 2008. Bank of America, JP Morgan Chase, Wachovia Bank, Citibank, and Wells Fargo were those five institutions with more assets than Washington Mutual Bank. In fact, no other commercial or savings banking organisation with more than $100 billion of total assets went bankrupt during the crisis. On the other hand, the smallest failed bank held approximately $10 million of assets. By excluding the above ten banks from our analysis, we remove the impact of extreme values and outliers on our data. To further enhance the robustness of our results, we use the collapse of Lehmann Brothers on 15 September 2008 as a breakpoint in our whole data period. Hence, the crisis period commences in 2008q3 instead of 2007q4.

Table 9 presents the *DF* values in percentage terms for each of the CAMEL components for the non-problem, failed, and bailed out banks over the two examined periods. The signs and the magnitude of *DF* confirm the results obtained in our baseline digital analysis. Total earning assets (*EARNAS*) are significantly distorted upwards by 7.41 percent, 6.93 percent, and 6.53 percent for the non-problem, failed, and bailed out banks respectively in the pre-crisis era, and by 7.82 percent,

---

[9] To calculate the *z*-statistic, we obtain the standard deviation of DF by following the computations found in Nigrini (1996)'s Appendix A.

9.30 percent, and 8.81 percent respectively in the crisis era. The same distortion scheme is documented for total interest income (*INTINC*) for all three bank types between the two examined periods. Further, a significant upward distortion of 7.42 percent in the pre-crisis period and 8.94 percent in the crisis period is documented for non-interest income (*NINTINC*) for the bailed out banks. The core regulatory capital (*TIER1*) is found to be significantly upward manipulated by all three groups of banks in the crisis period, where the extent of distortion is higher for the problem banks. Moreover, loss loan allowances (*ALLOW*) are significantly downward distorted by failed and bailed out banks in the pre-crisis period (-5.94 percent and -6.20 percent, respectively), whereas the magnitude of distortion is higher in the crisis period (-8.53 percent and -7.64 percent, respectively). Loan loss provisions (*LLP*) are found to be distorted downwards by all banks across the two time periods. The reported distortion is statistically significant at the 5 percent level and is higher in the second period. The only difference we indicate between the results of our robustness analysis and those of digital analysis is that non-performing loans (*NPL*) are found to be manipulated downwards by the set of problem banks not only in the crisis period, but also in the pre-crisis period.

VII. CONCLUDING REMARKS

Excess accounting discretion and data tampering appear to have played a key role in the propagation and prolongation of the global financial crisis. In this paper, we aim to identify operational discrepancies and uncover manipulation practices among the failed, bailed out, and healthy banks in the recent crisis. We test whether and to what extent a set of fundamental balance sheet and income statement data were manipulated prior to and also after onset of the crisis. Towards this, we resort to the Benford's Law distribution according to which low digits possess a greater probability of appearing in the first two positions within a number than high digits. If the digital frequency in the bank accounting data under scrutiny departs from the expectations of the Law, then we receive a strong signal of data manipulation.

Several interesting findings are reported in our baseline analysis and corroborated by the robustness checks we conduct. Our sample banks utilise loan loss provisions to manipulate earnings and interest income upwards throughout the examined two periods. In the case of bailed out banks, non-interest income, which is a key income component for this group of banks, is also found to be manipulated upwards in both time periods. Furthermore, together with loan loss provisions, the set of problem banks resorts to the downward manipulation of allowance for loan losses and non-performing loans with the purpose to tamper earnings upwards. By manipulating loan loss provisions downwards, banks are inclined to follow the same or similar strategies with loan loss allowances in line with Financial Accounting Standards No. 5 (FASB 1975), and, this provides them with the necessary ground to artificially increase the volume of earning assets they report on their balance sheets.

Our results provide evidence that manipulation is more prevalent in problem financial institutions. Weak banks manage income and earnings upwards by delaying loan loss provisions and, in turn, loss allowances and non-performing loans in order to conceal their financial difficulties. Managers of distressed banks are more anxious in demonstrating to authorities that they can attain the pre-specified performance thresholds. Moreover, a crucial prerequisite to obtain TARP assistance was viability. However, viability criterion was rather loosely defined and was related to profitability by many applicant banks. As a result, banks were incentivised to present to application reviewers higher revenue streams and cash flows than the actual ones.

We additionally find that manipulation is strengthened in the crisis period; it is also expanded during the crisis to affect bank regulatory capital. Admittedly, a bank has strong incentives to signal that it is not undercapitalised and that its capital is adequate to meet its obligations. To the extent that the allowance for loan losses is included in regulatory capital, banks can manipulate allowances downwards with the purpose to show that a strong capital cushion has been set aside to absorb shocks due to the financial turmoil. Also, accounting discretion which is inherent in the current financial reporting rules allow banks to manipulate regulatory capital upwards by holding back on loan loss provisioning and by keeping their allowances for losses from ballooning. In sum, accounting discretion enables banking firms with impaired assets to satisfy the capital adequacy requirements, but renders the assessment of the true health of banks problematic.

Empirical results suggests that banks manipulate balance sheet and income statement variables upwards when their level is slightly below a round number. In a similar vein, banks exercise a downward manipulation when the level of the relevant variables is slightly above a round number. That is, banks utilise data manipulation to disclose an artificially improved view of their performance to authorities and investors without yet resorting to eye-catching manipulation strategies that may attract the scrutiny by regulators. Nevertheless, accounting data manipulation yields a distorted view of the financial conditions and the health of banks, providing evidence of regulatory forbearance and non-compliance with the accounting rules and standards.

In sum, manipulation decreases the reliability of bank accounting information, erodes confidence, and, in turn, has a devastating effect on the credibility of financial institutions. It is, therefore, crucial for regulatory and supervisory authorities to find ways to reduce data manipulation. Our results call for a more in-depth evaluation of the quality of the bank accounting information by applying a Benford's Law-based analysis to detect manipulation in the banking industry. The proposed empirical analysis appears to be a systematic method suitable for assessing the quality of accounting information and for discovering irregularities in the data of financial statements. It can thus assist the authorities in mitigating the phenomenon of data manipulation both under normal economic and financial conditions, but also during financial debacles when the phenomenon is exaggerated.

REFERENCES

Abrantes-Metz, R., S. Villas-Boas, and G. Judge. 2011. Tracking the Libor rate. *Applied Economics Letters* 18: 1-7.

Ashton, J. K., and R. S. Hudson. 2008. Interest rate clustering in UK financial services markets. *Journal of Banking and Finance* 32: 1393-1403.

Benford, F. 1938. The law of anomalous numbers. *Proceedings of the American Philosophical Society*: 78, 551-572.

Brahler, G., S. Engel, M. Gottsche, and B. Rauch. 2011. Fact and fiction in EU-governmental economic data. *German Economic Review* 12: 243-255.

Carslaw, C. 1988. Anomolies in the income numbers: Evidence of goal oriented behavior. *The Accounting Review* 63: 321-327.

Das, S., and H. Zhang. 2003. Rounding-up in reported EPS, behavioral thresholds, and earnings management. *Journal of Accounting and Economics* 35: 31-50.

Diekmann, A. 2007. Not the first digit! Using Benford's Law to detect fraudulent scientific data. *Journal of Applied Statistics* 34: 321-329.

Diekmann, A., and B. Jann. 2010. Benford's Law and fraud detection: Facts and legends. *German Economic Review* 11: 397-401.

Durtschi, C., W. Hillison, and C. Pacini. 2004. The effective use of Benford's Law to assist in detecting fraud in accounting data. *Journal of Forensic Accounting* 5: 17-34.

Gonzales-Garcia, J., and G. Pastor. 2009. *Benford's law and macroeconomic data quality*. Working Paper 09/10, International Monetary Fund.

Hales, D, V. Sridharan, A. Radhakrishnan, S. Chakravorty, and S. Samia. 2008. Testing the accuracy of employee-reported data: An inexpensive alternative approach to traditional methods. *European Journal of Operational Research* 189: 583-593.

Huizinga, H., and L. Laeven. 2012. Bank valuation and accounting discretion during a financial crisis. *Journal of Financial Economics* 106: 614-634.

Kanagaretnam, K., G. J. Lobo, and D. Yang. 2004. Joint tests of signaling and income smoothing through bank loan loss provisions. *Contemporary Accounting Research* 21: 843-884.

Kanagaretnam, K., G. V. Krishnan, and G. J. Lobo. 2010. An empirical analysis of auditor independence in the banking industry. *The Accounting Review* 85: 2011-2046.

Liu, C.-C., and S. G. Ryan. 2006. Income smoothing over the business cycle: Changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990 boom. *The Accounting Review* 81: 421-441.

Michalski, T., G. Stoltz. 2012. Do countries falsify economic data strategically? Some evidence that they might. *Review of Economics and Statistics* 94: 1-83.

Newcomb, S. 1881. Note on the frequency of use of the different digits in natural numbers. *American Journal of Mathematics* 4: 39-40.

Nigrini, M. J. 1996. A taxpayer compliance application of Benford's Law. *Journal of the American Taxation Association* 18: 72-91.

Nigrini, M. J., and L. J. Mittermaier. 1997. The use of Benford's Law as an aid in analytical procedures. *Auditing: A Journal of Practice and Theory* 16: 52-67.

Niskanen, J., and M. Keloharju. 2000. Earnings cosmetics in a tax-driven accounting environment: Evidence from Finnish public firms. *European Accounting Review* 9: 443-452.

Securities and Exchange Commission (SEC). 2013. Accounting and Auditing Enforcement, Release No. 3514/December 4. Washington, DC: SEC.

Securities and Exchange Commission (SEC). 2014. Accounting and Auditing Enforcement, Release No. 3588/September 29. Washington, DC: SEC.

Securities and Exchange Commission (SEC). 2015. Accounting and Auditing Enforcement, Release No. 3622/January 28. Washington, DC: SEC.

Skousen, C., L. Guean and S. Wetzel. 2004. Anomalies and unusual patterns in reported earnings: Japanese managers round earnings. *Journal of International Financial Management and Accounting* 15: 212-234.

Thomas, J. K. 1989. Unusual patterns in reported earnings. *The Accounting Review* 64: 773-787.

Tilden, C., and T. Janes. 2006. Empirical evidence of financial statement manipulation during economic recessions. *Journal of Finance and Accountancy* 10: 1-15.

Van Caneghem, T. 2002. Earnings management induced by cognitive reference points. *British Accounting Review* 34: 167-178.

TABLE 3
Digital Frequencies of CAMEL Components for Non-problem Banks in the Pre-crisis Period

Non-problem banks (obs=6,302)													
		EQUITY *n*=118,939	***TIER1*** *n*=118,801	***NPL*** *n*=117,592	***ALLOW*** *n*=118,671	***LLP*** *n*=116,805	***LOANS*** *n*=119,362	***DEPOS*** *n*=119,430	***EARNAS*** *n*=119,265	***INTINC*** *n*=119,382	***NINTINC*** *n*=119,270	***CASH*** *n*=119,320	***REPOS*** *n*=116,846
Digit	**Expected**	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)
0	.1197	0.0031	0.0147	-0.0105	-0.0053	-0.0414	0.0082	0.0041	0.0488	0.0556	0.0281	-0.0032	0.0040
		0.44	1.33	-1.28	-0.85	-1.87*	0.73	0.85	2.08**	2.30**	1.39	-0.84	0.49
1	.1139	0.0021	0.0115	-0.0074	0.0046	-0.0208	-0.0048	0.0039	0.0374	0.0395	0.0216	0.0029	-0.0038
		0.49	0.92	-1.12	0.94	-1.30	-0.94	0.67	1.98**	1.74*	1.30	0.41	-0.62
2	.1088	0.0014	-0.0028	0.0079	0.0037	0.0122	-0.0049	0.0032	0.0137	-0.0192	0.0142	0.0010	-0.0022
		0.36	-1.10	1.18	1.05	0.95	-1.08	0.84	1.39	-1.10	1.14	0.23	-0.48
3	.1043	-0.0052	0.0023	0.0061	-0.0044	0.0109	0.0033	0.0018	-0.0125	0.0153	-0.0049	0.0004	0.0020
		-0.60	1.17	1.05	-1.08	0.67	0.40	0.57	-1.20	1.28	-0.95	0.49	0.93
4	.1003	-0.0023	0.0016	0.0053	-0.0035	-0.0075	-0.0031	-0.0019	-0.0108	0.0042	-0.0051	-0.0029	0.0014
		-0.37	0.68	0.95	-1.14	-1.26	-0.98	-0.70	-1.19	1.13	-0.99	-0.58	0.61
5	.0967	0.0019	0.0014	-0.0054	-0.0023	-0.0053	0.0020	-0.0011	0.0095	0.0039	-0.0004	0.0012	0.0008
		0.43	0.72	-1.02	-0.85	-1.18	0.97	-0.85	0.98	1.06	-1.17	0.92	0.42
6	.0934	0.0030	-0.0022	-0.0069	0.0057	0.0061	0.0019	-0.0006	0.0084	0.0044	0.0013	0.0020	0.0004
		0.61	-0.58	-0.93	1.11	1.04	1.08	-0.44	0.69	1.02	0.62	1.04	0.67
7	.0904	-0.0039	-0.0018	0.0089	0.0096	0.0116	0.0062	0.0017	-0.0083	0.0098	-0.0040	-0.0039	-0.0014
		-0.28	-0.69	1.05	1.08	1.17	0.83	0.87	-1.15	1.16	-1.16	-0.62	-1.02
8	.0876	-0.0045	-0.0130	0.0094	0.0129	0.00125	0.093	0.0030	-0.0264	-0.0256	-0.0032	-0.0040	-0.0027
		-0.44	-1.14	1.07	0.64	1.04	0.99	0.93	-1.76*	-2.05**	-1.03	-0.51	-0.94
9	.0850	0.0059	-0.0141	0.0101	0.0148	0.0452	0.0099	-0.0058	-0.0608	-0.0718	-0.0153	-0.0103	-0.0049
		0.33	-0.93	1.18	1.22	1.98**	0.56	-1.04	-2.31**	-2.26**	-1.40	-1.02	-0.88
$\chi^2_{(9)}$		2.49	5.18	4.93	6.09	15.19*	3.92	3.68	17.48**	18.19**	9.31	5.30	2.90

The first column of the Table lists all ten digits that are likely to appear in the second place of each of the examined CAMEL components, while the expected frequencies of appearance for each digit determined by the Benford's Law are presented in the second column. Columns 3 to 14 report the observed deviations between the actual and the expected frequencies for each of the examined variables for the non-problem banks over the pre-crisis era. The values of the *z*-statistic and the corresponding significance levels are presented below the observed deviation for each digit and for each variable under scrutiny. The value of the chi-square goodness-of-fit test is reported for each variable in the last row of the Table. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 4
Digital Frequencies of CAMEL Components for Failed Banks in the Pre-crisis Period

Failed banks (obs=449)													
		EQUITY *n*=8,190	***TIER1*** *n*=8,036	***NPL*** *n*=7,592	***ALLOW*** *n*=7,920	***LLP*** *n*=7,633	***LOANS*** *n*=8,394	***DEPOS*** *n*=8,402	***EARNAS*** *n*=8,328	***INTINC*** *n*=8,439	***NINTINC*** *n*=8,421	***CASH*** *n*=8,296	***REPOS*** *n*=7,146
Digit	**Expected**	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)
0	.1197	0.0163	0.0344	-0.0310	-0.0682	-0.0571	0.0043	-0.0069	0.0632	0.0730	0.0382	-0.0096	0.0184
		1.04	1.20	-1.33	-2.31**	-1.99**	0.65	-0.43	2.12**	2.41**	1.51	-1.20	1.03
1	.1139	0.0103	0.0219	-0.0206	-0.0201	0.0093	0.0034	-0.0043	0.0459	0.0476	-0.0403	-0.0042	0.0128
		1.11	1.43	-1.42	-1.44	1.28	0.70	-0.39	2.05**	2.18**	-0.96	-1.02	1.21
2	.1088	0.0053	-0.0226	-0.0131	-0.0130	0.0032	0.0032	0.0025	0.0208	0.0202	-0.0329	0.0053	-0.0094
		1.16	-1.03	-1.20	-1.39	1.17	0.27	0.93	1.43	1.49	-1.17	0.67	-0.52
3	.1043	0.0031	-0.0094	0.0127	0.0083	0.0014	0.0017	0.0021	0.0121	-0.0218	0.0102	0.0039	-0.0048
		0.94	-1.13	1.29	1.32	0.91	0.93	0.68	1.29	-1.10	0.54	0.78	-0.71
4	.1003	-0.0023	0.0048	0.0114	0.0057	-0.0010	-0.0011	0.0028	-0.0054	-0.0094	0.0065	0.0008	0.0016
		-0.99	0.99	0.69	1.20	-0.73	-1.10	0.44	-1.38	-1.29	0.70	0.45	0.34
5	.0967	-0.0014	0.0037	0.0086	-0.0021	0.0009	0.0007	0.0020	-0.0032	0.0048	0.0032	0.0004	0.0003
		-1.18	1.06	0.43	-0.95	1.05	1.04	0.59	-0.76	0.85	1.05	1.12	1.10
6	.0934	0.0020	0.0022	-0.0039	0.0019	-0.0018	-0.0011	-0.0039	0.0048	0.0032	0.0033	-0.0055	-0.0011
		0.43	0.38	-0.53	1.36	-0.63	-1.15	-1.05	1.02	1.18	0.64	-0.53	-0.74
7	.0904	0.0038	-0.0029	0.0140	0.0203	-0.0020	0.0028	-0.0032	-0.0105	-0.0097	0.0095	-0.0126	0.0040
		0.75	-1.15	1.18	1.16	-0.87	0.57	-1.18	-1.38	-1.39	1.18	-1.10	1.32
8	.0876	0.0096	-0.0174	0.0232	0.0241	0.0082	0.0039	0.0040	-0.0319	-0.0425	-0.0153	0.0153	0.0111
		1.09	-1.38	1.39	1.54	1.38	1.12	0.62	-1.84*	-2.28**	-1.02	0.83	1.29
9	.0850	-0.0149	-0.0351	0.0288	0.0574	0.0489	0.0045	0.0048	-0.0841	-0.0822	-0.0228	0.0188	0.0173
		-0.85	-1.49	1.51	2.45**	1.94*	1.04	1.04	-2.34**	-2.49**	-1.44	0.99	0.42
$\chi^2_{(9)}$		4.62	9.31	10.74	18.34**	17.19**	3.88	3.51	18.94**	19.88**	6.93	2.76	2.62

The first column of the Table lists all ten digits that are likely to appear in the second place each of the examined CAMEL components, while the expected frequencies of appearance for each digit determined by the Benford's Law are presented in the second column. Columns 3 to 14 report the observed deviations between the actual and the expected frequencies for each of the examined variables for the failed banks over the pre-crisis era. The values of the *z*-statistic and the corresponding significance levels are presented below the observed deviation for each digit and for each variable under scrutiny. The value of the chi-square goodness-of-fit test is reported for each variable in the last row of the Table. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 5
Digital Frequencies of CAMEL Components for Bailed Out Banks in the Pre-crisis Period

Bailed out banks (obs=824)													
		EQUITY *n*=14,830	***TIER1*** *n*=14,918	***NPL*** *n*=14,142	***ALLOW*** *n*=14,721	***LLP*** *n*=14,008	***LOANS*** *n*=15,210	***DEPOS*** *n*=15,328	***EARNAS*** *n*=15,275	***INTINC*** *n*=15,402	***NINTINC*** *n*=15,426	***CASH*** *n*=15,224	***REPOS*** *n*=13,951
Digit	**Expected**	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)
0	.1197	0.0176	0.0272	-0.0352	-0.0662	-0.0793	0.0132	-0.0105	0.0671	0.0732	0.0820	0.0103	0.0081
		1.34	1.41	-1.20	-2.14**	-2.09**	1.18	-0.86	2.39**	2.69***	2.34**	0.54	1.16
1	.1139	0.0098	0.0238	-0.0198	-0.0170	-0.0094	0.0087	-0.0094	0.0391	0.0390	0.0346	0.0087	0.0052
		1.17	1.32	-1.31	-1.38	-1.55	1.12	-0.94	1.73*	2.13**	1.69*	0.67	1.05
2	.1088	0.0072	0.0170	-0.0149	-0.0094	-0.0086	0.0034	-0.0053	0.0157	0.0136	-0.0125	-0.0094	0.0027
		1.23	1.21	-1.28	-1.56	-1.48	0.80	-1.12	1.31	1.22	-0.85	-1.05	0.43
3	.1043	-0.0041	-0.0115	-0.0102	-0.0062	0.0051	-0.0021	0.0068	-0.0059	-0.0067	-0.0062	-0.0060	-0.0034
		-0.84	-0.89	-0.95	-0.49	1.04	-0.56	1.24	-1.33	-0.93	-0.68	-1.21	-0.87
4	.1003	-0.0031	0.0102	0.0061	0.0027	0.0019	-0.0012	0.0023	-0.0038	-0.0051	0.0035	0.0039	-0.0028
		-0.99	1.18	0.86	0.83	0.88	-0.69	1.15	-0.61	-1.17	0.31	0.50	-1.16
5	.0967	-0.0022	-0.0008	0.0048	-0.0017	-0.0012	-0.0003	-0.0011	-0.0021	0.0021	0.0028	0.0021	0.0032
		-1.05	-0.48	0.22	-1.14	-0.76	-0.97	-0.38	-0.83	0.96	0.63	0.87	1.37
6	.0934	0.0084	0.0014	0.0031	-0.0011	-0.0009	0.0075	0.0076	0.0015	-0.0048	0.0022	-0.0009	0.0039
		0.59	1.07	1.05	-1.23	-0.97	0.62	1.27	1.25	-1.00	1.17	-1.04	1.41
7	.0904	0.0096	-0.0114	-0.0101	0.0119	0.0044	0.0086	0.0088	-0.0116	-0.0105	-0.0173	-0.0028	0.0047
		1.14	-1.22	-0.74	1.30	1.29	1.10	1.15	-1.30	-1.18	-1.29	-0.63	0.78
8	.0876	0.0101	-0.0249	0.0160	0.0284	0.0084	0.0104	0.0091	-0.0261	-0.0342	-0.0259	0.0070	-0.0109
		0.78	-1.41	1.41	1.27	1.40	1.21	1.22	-1.78*	-1.79*	-1.84*	1.38	-1.11
9	.0850	0.0126	-0.0308	0.0387	0.0620	0.0738	0.0132	-0.0094	-0.0858	-0.0916	-0.0782	0.0106	-0.0125
		1.30	-1.33	1.44	2.49**	2.32**	1.32	0.75	-2.36**	-2.55**	-2.41**	0.92	-0.94
$\chi^2_{(9)}$		3.19	10.83	9.17	17.55**	17.93**	3.05	3.48	17.27**	20.07**	18.05**	3.58	4.01

The first column of the Table lists all ten digits that are likely to appear in the second place each of the examined CAMEL components, while the expected frequencies of appearance for each digit determined by the Benford's Law are presented in the second column. Columns 3 to 14 report the observed deviations between the actual and the expected frequencies for each of the examined variables for the bailed out banks over the pre-crisis era. The values of the *z*-statistic and the corresponding significance levels are presented below the observed deviation for each digit and for each variable under scrutiny. The value of the chi-square goodness-of-fit test is reported for each variable in the last row of the Table. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 6
Digital Frequencies of CAMEL Components for Non-problem Banks in the Crisis Period

Non-problem banks
(obs=6,302)

		EQUITY	*TIER1*	*NPL*	*ALLOW*	*LLP*	*LOANS*	*DEPOS*	*EARNAS*	*INTINC*	*NINTINC*	*CASH*	*REPOS*
		n=130,948	*n*=130,924	*n*=130,271	*n*=130,751	*n*=130,337	*n*=131,284	*n*=131,382	*n*=131,208	*n*=131,527	*n*=131,534	*n*=131,429	*n*=129,892
Digit	**Expected**	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)	**Observed deviation** (*z*-statistic)
0	.1197	0.0053	0.0498	-0.0096	-0.0067	-0.0582	0.0079	0.0054	0.0592	0.0641	0.0305	-0.0041	0.0053
		0.49	1.93*	-1.13	-1.04	-2.12**	0.90	0.81	2.32**	2.69***	1.44	-1.05	0.61
1	.1139	0.0034	0.0162	-0.0083	0.0052	-0.0164	-0.0048	0.0042	0.0457	0.0438	0.0192	0.0037	-0.0059
		0.40	1.42	-1.07	0.81	-1.55	-0.61	0.93	2.01**	1.85*	1.40	0.56	-0.77
2	.1088	0.0022	-0.0034	0.0068	0.0037	0.0133	-0.0037	0.0030	0.0170	0.0203	0.0091	0.0048	-0.0041
		0.31	-1.03	1.10	0.93	1.14	-0.73	1.05	1.22	1.25	0.89	0.39	-0.55
3	.1043	-0.0062	0.0028	0.0032	-0.0024	0.0117	0.0034	0.0017	-0.0103	0.0102	-0.0074	0.0009	0.0018
		-0.78	0.95	0.94	-0.92	0.81	0.96	0.76	-1.12	0.97	-1.04	0.56	1.15
4	.1003	-0.0037	0.0014	0.0021	-0.0025	-0.0084	-0.0028	-0.0018	-0.0089	0.0056	-0.0042	-0.0017	0.0007
		-0.45	0.74	1.10	-1.03	-1.18	-1.01	-0.82	-0.93	1.28	-0.73	-0.70	0.59
5	.0967	0.0028	0.0010	-0.0034	-0.0010	-0.0041	0.0052	-0.0011	0.0063	0.0024	-0.0019	0.0008	0.0004
		0.46	0.83	-0.89	-1.01	-0.94	0.88	-1.10	1.16	1.10	-0.67	1.02	0.69
6	.0934	0.0021	-0.0020	-0.0047	0.0038	0.0072	0.0068	-0.0008	0.0042	0.0052	0.0010	0.0033	0.0012
		0.74	-0.65	-1.05	0.89	1.19	1.05	-0.59	1.04	0.79	0.77	0.87	0.84
7	.0904	-0.0052	-0.0031	0.0078	0.0076	0.0131	0.0082	0.0024	0.0067	0.0104	-0.0035	-0.0028	-0.0011
		-0.21	-0.88	1.16	1.17	0.94	0.88	0.76	0.91	0.83	-0.82	-0.54	-0.93
8	.0876	-0.0046	-0.0114	0.0107	0.0104	0.0133	0.0094	0.0041	-0.0305	-0.0278	-0.0168	-0.0052	-0.0020
		-0.35	-1.29	0.88	0.52	1.47	1.02	1.07	-1.84*	-1.76*	-1.16	-0.69	-1.03
9	.0850	0.0060	-0.0517	0.0136	0.0125	0.0569	0.0103	-0.0050	-0.0737	-0.0869	-0.0273	-0.0087	-0.0056
		0.32	-2.06**	1.24	1.33	2.01**	1.14	-0.96	-2.47**	-3.08***	-1.37	-1.16	-0.71
$\chi^2_{(9)}$		3.16	14.93*	5.27	5.82	17.56**	4.31	3.79	19.04**	19.95**	9.60	6.18	3.37

The first column of the Table lists all ten digits that are likely to appear in the second place each of the examined CAMEL components, while the expected frequencies of appearance for each digit determined by the Benford's Law are presented in the second column. Columns 3 to 14 report the observed deviations between the actual and the expected frequencies for each of the examined variables for the non-problem banks over the crisis era. The values of the *z*-statistic and the corresponding significance levels are presented below the observed deviation for each digit and for each variable under scrutiny. The value of the chi-square goodness-of-fit test is reported for each variable in the last row of the Table. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 7
Digital Frequencies of CAMEL Components for Failed Banks in the Crisis Period

Failed banks
(obs = 449)

Digit	Expected	***EQUITY*** *n*=9,115 Observed deviation (*z*-statistic)	***TIER1*** *n*=9,093 Observed deviation (*z*-statistic)	***NPL*** *n*=8,830 Observed deviation (*z*-statistic)	***ALLOW*** *n*=9,064 Observed deviation (*z*-statistic)	***LLP*** *n*=8,792 Observed deviation (*z*-statistic)	***LOANS*** *n*=9,306 Observed deviation (*z*-statistic)	***DEPOS*** *n*=9,328 Observed deviation (*z*-statistic)	***EARNAS*** *n*=9,293 Observed deviation (*z*-statistic)	***INTINC*** *n*=9,361 Observed deviation (*z*-statistic)	***NINTINC*** *n*=9,340 Observed deviation (*z*-statistic)	***CASH*** *n*=9,305 Observed deviation (*z*-statistic)	***REPOS*** *n*=8,603 Observed deviation (*z*-statistic)
0	.1197	0.0178	0.0582	-0.0704	-0.0894	-0.0692	0.0051	-0.0078	0.0829	0.0788	0.0274	-0.0082	-0.0143
		1.21	2.05**	-2.16**	-2.71***	-2.36**	0.77	-0.57	2.42**	3.29***	1.39	-0.78	-0.64
1	.1139	0.0096	0.0163	-0.0140	-0.0242	-0.0087	0.0042	-0.0060	0.0461	0.0502	0.0188	-0.0055	0.0111
		0,87	1.51	-1.36	-1.59	-0.96	1.04	-0.44	2.08**	2.31**	1.20	-0.89	0.96
2	.1088	0.0099	0.0098	-0.0084	-0.0096	0.0058	0.0030	-0.0039	0.0163	0.0173	-0.0204	0.0040	-0.0060
		1.10	0.65	-1.12	-1.27	0.89	0.20	-1.15	1.31	1.30	-0.96	1.04	-0.78
3	.1043	0.0048	-0.0104	-0.0102	0.0080	0.0023	0.0027	0.0046	0.0100	-0.0187	0.0163	0.0027	-0.0031
		1.23	-1.12	-0.47	0.97	1.02	1.12	0.71	0.99	-0.86	0.69	1.18	-1.04
4	.1003	-0.0056	0.0059	0.0021	0.0063	-0.0009	-0.0008	0.0038	-0.0067	0.0112	0.0078	0.0013	0.0019
		-1.04	0.75	0.77	0.81	-1.01	-0.89	0.79	-1.20	0.68	1.07	0.64	0.69
5	.0967	-0.0028	0.0020	0.0038	-0.0080	0.0012	0.0012	0.0020	-0.0019	0.0086	0.0049	0.0010	0.0012
		-0.89	0.97	1.13	-1.03	0.87	0.99	0.74	-0.80	1.03	0.61	0.89	0.98
6	.0934	0.0035	0.0009	-0.0059	0.0028	-0.0014	-0.0023	-0.0012	0.0058	0.0090	0.0028	-0.0101	0.0008
		0.62	0.59	-1.00	1.08	-1.09	-1.02	-0.86	0.81	0.78	0.99	-1.19	-1.26
7	.0904	0.0049	-0.0055	0.0104	0.0163	-0.0034	0.0034	-0.0041	-0.0096	-0.0102	0.0051	-0.0092	0.0031
		1.13	-1.01	1.27	0.86	-1.15	0.69	-1.10	-1.12	-1.24	0.52	-0.85	0.86
8	.0876	0.0111	-0.0198	0.0188	0.0199	0.0073	0.0036	0.0052	-0.0350	-0.0412	-0.0104	0.0122	0.0076
		0.92	-1.49	1.50	1.50	1.40	0.87	1.03	-1.75*	-2.36**	-1.21	1.06	0.64
9	.0850	-0.0158	-0.0548	0.0673	0.0914	0.0648	0.0056	0.0060	-0.0918	-0.0898	-0.0233	0.0124	0.0103
		-1.20	-2.36**	2.02**	2.49**	2.39**	0.91	0.88	-2.27**	-2.40**	-1.30	1.17	1.29
$\chi^2_{(9)}$		5.17	16.98**	17.20**	23.78**	19.25**	3.26	4.08	18.03**	24.39***	5.80	4.29	3.38

The first column of the Table lists all ten digits that are likely to appear in the second place each of the examined CAMEL components, while the expected frequencies of appearance for each digit determined by the Benford's Law are presented in the second column. Columns 3 to 14 report the observed deviations between the actual and the expected frequencies for each of the examined variables for the failed banks over the crisis era. The values of the *z*-statistic and the corresponding significance levels are presented below the observed deviation for each digit and for each variable under scrutiny. The value of the chi-square goodness-of-fit test is reported for each variable in the last row of the Table. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 8
Digital Frequencies for Bailed Out Banks in the Crisis Period

Bailed out banks
(obs = 824)

Digit	Expected	***EQUITY*** *n*=16,782 **Observed deviation** (*z*-statistic)	***TIER1*** *n*=16,690 **Observed deviation** (*z*-statistic)	***NPL*** *n*=15,984 **Observed deviation** (*z*-statistic)	***ALLOW*** *n*=16,572 **Observed deviation** (*z*-statistic)	***LLP*** *n*=15,793 **Observed deviation** (*z*-statistic)	***LOANS*** *n*=17,102 **Observed deviation** (*z*-statistic)	***DEPOS*** *n*=17,086 **Observed deviation** (*z*-statistic)	***EARNAS*** *n*=17,025 **Observed deviation** (*z*-statistic)	***INTINC*** *n*=17,190 **Observed deviation** (*z*-statistic)	***NINTINC*** *n*=17,118 **Observed deviation** (*z*-statistic)	***CASH*** *n*=12,345 **Observed deviation** (*z*-statistic)	***REPOS*** *n*=15,648 **Observed deviation** (*z*-statistic)
0	.1197	0.0196	0.0532	-0.0744	-0.0803	-0.0882	0.0080	0.0095	0.0794	0.0778	0.0873	0.0079	0.0102
		1.22	1.75*	-2.17**	-2.37**	-2.31**	1.25	1.22	3.19***	3.15***	2.41**	1.15	0.99
1	.1139	0.0102	0.0244	-0.0261	-0.0194	-0.0142	0.0056	-0.0102	0.0305	0.0376	0.0355	0.0053	0.0065
		1.08	1.41	-1.48	-1.50	-1.24	0.87	-1.04	1.99**	2.34**	2.06**	1.02	1.37
2	.1088	0.0051	0.0109	-0.0108	-0.0105	-0.0100	0.0023	-0.0104	0.0104	0.0083	-0.0089	-0.0067	0.0014
		1.06	0.94	-0.96	-1.26	-1.38	1.02	-0.85	1.20	1.36	-1.04	-0.38	0.38
3	.1043	-0.0064	0.0086	-0.082	-0.0093	-0.0065	-0.0038	0.0051	-0.0063	0.0050	-0.0058	-0.0050	-0.0026
		-1.11	1.23	-1.01	-1.02	0.78	-0.53	0.78	-0.85	0.31	-0.96	-0.59	-1.02
4	.1003	-0.0048	-0.0097	0.0096	0.0009	0.0023	-0.0026	0.0034	-0.0048	-0.0057	-0.0033	0.0018	-0.0017
		-0.82	-0.82	0.72	0.33	0.59	-0.70	0.96	-0.79	-0.71	-0.40	0.68	-0.48
5	.0967	-0.0019	-0.0021	0.0037	-0.0008	-0.0009	-0.0012	-0.0023	-0.0013	0.0007	0.0004	0.0010	0.0006
		-0.70	-0.33	1.17	-0.84	-1.03	-1.15	-0.67	-1.01	1.26	1.28	1.05	1.40
6	.0934	0.0059	0.0038	0.064	0.0043	-0.0014	0.0044	0.0052	0.0029	-0.0035	0.0035	-0.0006	0.0034
		0.64	0.70	1.26	-0.92	-1.12	0.51	1.12	0.97	-1.04	0.49	-0.82	0.87
7	.0904	0.0108	-0.0085	0.0108	0.0126	0.0068	0.0072	0.0074	-0.0090	-0.0087	-0.0104	-0.0021	0.0040
		1.30	-1.05	-0.99	1.12	1.17	0.87	1.02	-1.22	-0.96	-1.33	-0.78	0.61
8	.0876	0.0119	-0.0209	0.0192	0.0205	0.0138	0.0096	0.0088	-0.0278	-0.0382	-0.0280	0.0064	-0.0094
		0.82	-1.46	1.51	1.48	1.32	1.04	0.95	-2.15**	-1.97**	-2.24**	1.20	-0.78
9	.0850	0.0132	-0.0570	0.0787	0.0762	0.0894	0.0101	-0.0097	-0.0924	-0.0938	-0.0901	0.0091	-0.0103
		1.41	-1.99**	2.11**	3.04***	2.49**	0.99	1.26	-3.38***	-2.56**	-2.49**	1.35	-1.11
$\chi^2_{(9)}$		4.34	15.11*	17.16**	23.71***	19.81**	2.86	2.97	24.96**	23.17***	22.70***	5.07	4.55

The first column of the Table lists all ten digits that are likely to appear in the second place each of the examined CAMEL components, while the expected frequencies of appearance for each digit determined by the Benford's Law are presented in the second column. Columns 3 to 14 report the observed deviations between the actual and the expected frequencies for each of the examined variables for the bailed out banks over the crisis era. The values of the *z*-statistic and the corresponding significance levels are presented below the observed deviation for each digit and for each variable under scrutiny. The value of the chi-square goodness-of-fit test is reported for each variable in the last row of the Table. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 9
Distortion Factor Model Results

	EQUITY	*TIER1*	*NPL*	*ALLOW*	*LLP*	*LOANS*	*DEPOS*	*EARNAS*	*INTINC*	*NINTINC*	*CASH*	*REPOS*
	DF	***DF***	***DF***	***DF***	***DF***	***DF***	***DF***	***DF***	***DF***	***DF***	***DF***	***DF***
	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)	(*z*-statistic)
Panel A: Pre-crisis period												
Non-problem banks	1.61	1.33	-0.78	-2.38	-3.19	-1.42	0.73	7.41	5.31	-1.01	0.75	0.89
(obs = 6,302)	0.49	1.06	-0.50	-1.46	-1.72*	-1.08	1.17	1.78*	2.14**	-0.47	1.27	0.55
Failed banks	-1.05	2.11	-2.95	-5.94	-3.51	2.19	1.59	6.93	7.89	1.18	-1.08	1.64
(obs = 448)	-0.67	1.18	-1.80*	-2.27**	-1.96**	0.64	1.41	2.40**	2.35**	1.50	-0.79	1.30
Bailed out banks	1.89	1.97	-3.76	-6.20	-6.63	1.53	-2.08	6.53	6.21	7.42	-1.33	0.82
(obs = 815)	1.04	0.85	-1.93*	-1.91*	-2.38**	0.78	-0.75	2.68***	2.14**	1.86*	-1.10	1.25
Panel B: Crisis period												
Non-problem banks	1.90	5.89	-1.38	-3.58	-3.85	-2.37	1.64	7.82	5.12	-0.75	0.38	1.38
(obs = 6,302)	0.52	1.74*	-0.72	-1.60	-1.94*	-1.19	1.29	1.97**	2.08**	-0.50	1.45	1.06
Failed banks	-2.19	7.41	-6.44	-8.53	-4.98	1.42	2.06	9.30	8.75	1.39	-0.96	2.16
(obs = 448)	-0.58	1.85*	-1.91*	-2.42**	-2.31**	0.76	0.98	3.17***	2.48**	1.28	-0.59	1.48
Bailed out banks	2.30	8.09	-6.79	-7.64	-7.53	1.90	-1.50	8.81	6.93	8.94	-2.00	0.77
(obs = 815)	1.21	2.27**	-2.04**	-2.10**	-2.17**	0.92	-1.31	2.80***	3.61***	2.31**	-1.29	1.14

This Table displays the *DF* values in percentage terms for each of the examined CAMEL components for the non-problem, failed, and bailed out banks. The values of the *z*-statistic and the corresponding significance levels are presented below the *DF* values. The results in Panel A refer to the pre-crisis era, which extends from 2003q1 to 2008q2. The results in Panel B refer to the crisis era, which extends from 2008q3 to 2012q4. To account for possible selection bias in our data, we exclude all the outliers from the sets of failed and bailed out banks. All variables and their data sources are described in Table 2. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.