Applying Benford's Law to detect accounting data manipulation in the pre-and post-financial engineering periods

Etienne Harb

Essca School of Management, Angers, France

Email: etienne_harb@yahoo.fr

https://orcid.org/0000-0002-4222-1173

Nohade Nasrallah

Conservatoire National des Arts & Métiers (Le Cnam), France

Laboratoire interdisciplinaire de recherche en sciences de l'action (LIRSA)

Email: nohade.kassis@gmail.com

https://orcid.org/0000-0003-3396-7886

Rim El Khoury

Notre Dame University, Louaize, Lebanon

Email: rkhoury@ndu.edu.lb

https://orcid.org//0000-0003-4359-7591

Khaled Hussainey

Portsmouth University, United Kingdom

Email: Khaled.Hussainey@port.ac.uk

https://orcid.org/0000-0003-3641-1031

ABSTRACT

Purpose: Lebanon has faced one of the most severe financial and economic crises since the end of 2019. The practices of the Lebanese banks are blamed for dangerously exposing economic agents and precipitating the current financial collapse. This paper examines the patterns of manipulation of the 10 biggest banks before and after implementing the financial engineering mechanism.

Design/methodology/approach: We apply Benford Law for the first and second positions of the reports of condition and income and four out of the six aspects of the CAMELS rating system (Capital Adequacy, Assets Quality, Management expertise, Earnings Strength, Liquidity, and Sensitivity to the market) by excluding Management and Sensitivity. The deviations from BL frequencies are tested using Z-statistic and Chi-square tests.

Findings: Banks seem to have manipulated their Capital Adequacy, Liquidity, and Assets Quality in the pre-financial engineering and considerably in the post-financial engineering periods. Fraudulent manipulations in the banking sector can distort depositors, shareholders, and regulating authorities.

Originality: The study is the first to examine the patterns of fraudulent manipulation in the Lebanese banking industry using Benford Law (BL).

Research implications: This study has many implications for governmental authorities, commercial banks, depositors, businesses, accounting and auditing firms, and policymakers. The Lebanese government needs to implement corrective fiscal and monetary policies and apply amendments to the bank secrecy and capital control law. The central bank should revamp its organizational structure, improve its disclosure practices and significantly reduce its ties to the government and the political elite.

Keywords: Benford law; Frauds; Financial engineering; Reports of condition and income; CAMELS; Lebanon.

1. INTRODUCTION

Financial fraud has been attracting a great deal of attention since the beginning of the 21st century due to several consecutive scandals, including Enron, WorldCom, Lehman Brothers (US), Parmalat Spa (Italy), Vivendi, and BPN (Portugal). According to PricewaterhouseCoopers (PwC) 2018 Global Economic Crime and Fraud Survey, 49% of organizations reported being a victim of fraud, and the global impact of fraud is close to $US 3 trillion dollars[1].

The last global financial crisis (GFC) highlights several cases of financial accounting misreporting in the banking industry. For instance, the Bank of America Corp overstated its capital in its SEC filings from 2009 to 2013 (Securities and Exchange Commission (SEC) 2014). The Federal Deposit Insurance Corporation (FDIC) sued PwC for not detecting the accounting fraud in Colonial Bank in 2009. In recent years, forensic accounting was developed, including auditing accounting records and searching for evidence of fraud (Singleton, 2010). Some fraud symptoms include accounting anomalies, internal control weaknesses, or analytical anomalies (Linville, 2008). A common technique is to create fictitious accounting entries, such as recording bogus sales transactions or submitting false expense claims. If those entries were successfully blended with other accurate entries, it becomes difficult for auditors to detect fraud (Nigrini, 2019).

Despite several methods to detect fraud, they still suffer from many deficiencies that limit their usefulness. Although it was regarded as an anomaly, even a paradox, for an extended period (Szekely, 1990), BL has recently received increasing attention and appears superior to other traditional approaches (Benford, 1938). BL is the test of probability for the occurrence of the digits in the first, second, third, and fourth positions; it is based on logarithmic distribution and is applied to compare observed values with expected ones (Nigrini, 2017). The forensic accounting community generally accepts this methodology, referenced in the Fraud Examiners Manual. The Generalized Audit Software such as IDEA™ and ACL™ have also recognized BL as a technique for detecting fraud, and courts of law have confirmed its use in fraud cases (Nigrini, 2019). BL offers several advantages. The application of BL is not constrained by data type, geographical context, or time. First, it is independent of firm-level characteristics (Dechow *et al.*, 2010). It directly measures the quality of the data rather than using some variables correlated with the examined figures (Amiram *et al.*, 2015). Second, it is straightforward to calculate, scale-independent, and fits every currency (Amiram *et al.,* 2015). Third, it is not an econometric model, so its results cannot be biased by omitted variables or any changes in the underlying model parameters (Kothari *et al.*, 2005). Fourth, this law depends neither on expected figures nor on price information, leading to a selection bias (Amiram *et al.*, 2015). More specifically, this study highlights the superiority and suitability of BL in detecting fraud in the banking sector.

Commercial banks are financial intermediaries that have always played a decisive role in a country's economy by properly allocating or channeling capital from economic agents with excess funds to those with cash needs (Orth & Maçada, 2020). The technological and digital advances allowed banks to offer various attractive services like mobile and internet banking and debit and credit cards. On the one hand, these services smooth daily operations, which supports the growth of trade and commerce and boosts specific sectors that are an integral part of the economy, such as the agricultural sector. Nonetheless, these services increase banks' exposure to fraudulent acts or financial crimes as such innovations amplify the banking sector's fragility and may hinder economic growth and financial stability. On the other hand, banks may manipulate earnings to meet financial analysts' forecasts, gain shareholders' confidence, attract potential investors, and relax financial constraints to sufficiently fund projects (Linck *et al.*, 2007). Thus, the banking sector becomes one of the most heavily regulated sectors to protect the public's savings. Yet, to meet regulations during economic downturns,

[1] https://www.pwc.com/gx/en/news-room/docs/pwc-global-economic-crime-survey-report.pdf

banks in trouble have incentives to manipulate numbers by overstating equity to meet the regulatory capital requirements or the quality of assets to reduce the riskiness of their portfolios (Huizinga & Laeven, 2012). Banks are exposed to moral hazards and asymmetries of information. They are opaque in lending decisions (Morgan, 2002) based on private information about borrowers (Diamond, 1984) and might thus engage in a complex and broad range of non-interest income-producing activities (Laeven, 2013).

Lebanon provides a unique country context to investigate fraudulent manipulations in the financial statements of the banking sector. This was brought to light with the implementation of financial engineering schemes by the Central Bank to supposedly preserve the large stock of foreign reserves that are the foundation of currency stability. Despite the subdued performance of the Lebanese banking sector since the year 2019, it has been for decades the backbone of the economy (the total consolidated balance sheet of commercial banks / GDP ratio was 4.6[2] in August 2019 on the eve of the financial crisis outbreak). Lebanon is currently enduring a severe and prolonged economic depression. The latest World Bank Lebanon Economic Monitor (LEM), released on June 1st, 2021, ranked Lebanon's economic and financial crisis in the top 3 most severe global crises of modern times (since the mid-nineteenth century). The poor accounting data quality and weak disclosure practices combined with possible data manipulation in the Lebanese banking sector have planted the seeds of fraudulent schemes. Amid a noxious and voluntary abstention from divulging key financial reports, the central bank was accused of profoundly colluding with government and political parties, using depositors' funds as a vehicle to meet public debt interests and other non-income generating projects. The whole banking sector was implicated in financial engineering and claims to uncover the magnitude of such scheme are worth investigating. The main research question is derived from the recent Lebanese crisis that hardly hit the Lebanese economy and affected the savings of most Lebanese residents and emigrants. This crisis was ranked by the World Bank among the top 3 most severe crises in modern times. This was mainly due to the corruption and financial engineering scheme undertaken by the central bank and the Lebanese commercial banks. It is also worth mentioning that the Lebanese banking sector as a progressive agent of the economy, played an important role nationally and regionally. It was well positioned to manage the diaspora's money as well as regional and foreign capital well before the neighboring countries could embark on modern banking. An attractive element that could explain this dominance is the secrecy law that was promulgated in Lebanon in 1959. Unsurprisingly, this led deposits at Lebanese banks to inflate and reach over three times the country's GDP by the end of 2013[3].

Financial institutions and specifically banks ensure financial intermediation and proper capital allocation, which make them play the role of a lubricant for the real economy. Any shock in this sector may spill over to financial and economic sectors in Lebanon and neighboring countries. Thus, banks' fraud and financial engineering schemes can paralyze the financial system and lead to public distrust. Hence, banks need to stay honest and promote transparency to restore confidence, which is necessary to attract local and foreign investors to re-establish a healthier financial system and economic recovery. Accordingly, transparency and reliability of banks' financial statements are very important topics in regions described with weak legal and institutional frameworks.

At the beginning of the crisis, many scholars and political analysts were expecting the collapse of the whole banking sector. Many have also predicted that some banks will cease operations while other banks will acquire small ones. Yet, to date, not a single bank went bankrupt. Lebanese commercial banks are distributing losses among depositors who are the only ones to bear the cost of the financial engineering scheme and frauds orchestrated by the Central Bank and commercial banks through unofficial capital control and large haircuts on deposits. This affected the savings of millions of people inside and outside the country. It is then worth investigating how Lebanese commercial banks have survived such a severe financial crisis. How they were able to continue operating while the whole country went into a steep stagnation with alarming and devastating hyperinflation?

This paper aims to test for possible data manipulation before the outbreak of the crisis, mainly around the financial engineering mechanism implemented by the Central Bank (Banque du Liban - BDL) in 2016. Hence, it examines the period before the financial engineering scheme spanning from 2005 until 2015 and after the BDL financial engineering operations launched from 2016 until 2019 or 2020 based on data availability. The deviations from BL will be tested using Z-statistic and Chi-square goodness-of-fit test. Accordingly, the current

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[2] Source: Banque du Liban, Monthly bulletins: https://www.bdl.gov.lb/downloads/index/9/147/Monthly-Bulletins.html

[3] Mantash Maya (2014), The banking sector in Lebanon: Rising up to the challenges of a conflict zone, Global Banking and Financial Policy Review. https://blog.blominvestbank.com/wp-content/uploads/2014/10/The-banking-sector-in-Lebanon.pdf

paper seeks to make the following contributions to the existing literature. First, it shows that bank regulating authorities can also benefit from BL's power to uncover fraud in the banking industry and use it as a diagnostic tool to avoid banking crises and ensuing economic spillover. Second, it is the first to examine and highlight the patterns of manipulation in the Lebanese banking industry represented by a sample of the 10 biggest banks. Third, it draws attention to the existence of banks' doubtful manipulations and collusions with government and imminent political figures. Fourth, it consists of an alert to convene public scrutiny more specifically in similar political, economic, and social contexts. Fifth, it serves as a preliminary step to convoke further judicial and forensic investigations in the banking sector that holds the savings of individuals and the deposits of governments and organizations. Sixth, it contributes to the body of knowledge by reinforcing and justifying the use of BL by accountants, auditors, and forensic accounting as a starting point to conduct further audits. To the best of our knowledge, no previous studies investigated the fraudulent manipulation of the Lebanese banking sector or the banking industry in the MENA region. Only Grammatikos & Papanikolaou (2021) used BL to test if the balance sheet and income statement data of US commercial banks were manipulated before and during the global financial crisis.

We show that banks have noticeably manipulated their accounting data to conceal their financial difficulties and window-dress their report of condition accounts and performance. Specifically, they have manipulated their capital adequacy (TIER 1 and TE), Liquidity (CASH), and Assets Quality (LLR) ratios in the pre-and more considerably in the post-financial engineering mechanism period on the financial outbreak eve. Hence, as a preventive tool, BL helps national authorities and policymakers detect fraudulent manipulations, identify and address problems in the course of bank operations, preserve the stability of the national financial system, and ensure a more optimal allocation of capital and irrigation of the real economy.

The remainder of the paper is structured as follows. Section 2 reviews the Lebanese context and the BL applications and hypotheses development. Data and methodology are described in Section 3. Section 4 displays the results and discusses the main findings. Section 5 concludes and suggests recommendations and future research directions.

2. LITERATURE REVIEW

2.1. Lebanese Context

For decades, the Lebanese banking sector has played a crucial role in fueling the country's economic growth and ensuring relative stability in the financial sector. This was possible by maintaining steady earnings growth amid high liquidity levels. However, banks were operating in a weak local environment, vulnerable to political instability and high fiscal deficits. The banking industry has constantly developed thanks to its specific comparative advantages: the banking secrecy law, a skillful workforce, a relatively stable currency, and, more importantly, a strict regulatory framework and conservative policies thoroughly implemented by the Central Bank (BDL). Despite the high level of debt to GDP (163% by year-end 2008 with 49% of the net public debt being held by the commercial banks and currently debts represent 180% of GDP[4]), the sector amassed assets over 327% of Lebanon's GDP with customer deposits accounting for 82.5% of the total asset base by the end of the year 2008[5]. The oversized banking sector relative to Lebanon's economy is mainly due to continuous inflows from the Lebanese expatriate community, lured by the high yields earned on local and foreign currency deposits compared to peer countries and a positive perception of the conservative policy of the Central Bank amidst the GFC.

Moreover, Lebanon has experienced a rentier economy thanks to foreign funding plans (International Conferences for Support to Lebanon aka Paris 1, Paris 2, Paris 3, and Paris 4). These plans have contributed to the accumulation of large public debts, representing 180% of the country's GDP[6].

In addition, since 1992, Lebanon has adopted a fixed exchange rate regime. In 1997, a fixed parity was set within a fluctuation range of 1501 - 1514 and an average rate of 1507.5 Lebanese pounds against the US dollar[7].To maintain this peg, the Central Bank heavily relied on foreign currency reserves. An unprecedented

[4] Source: the website of the Ministry of Finance: http://www.finance.gov.lb/en-us/Finance/PublicDebt/Pages/default.aspx
[5] Source: The Lebanese Banking Sector, FFA Private Bank, July 2009
[6] Source: the website of the Ministry of Finance: http://www.finance.gov.lb/en-us/Finance/PublicDebt/Pages/default.aspx

measure was taken in 1993 and more massively in 1999: Lebanese Treasury bonds were issued in foreign currencies with remuneration at high rates (between 7% and 8% on 10-year Treasury bonds, the rates even reached 11.5% in 2019[8]). Dollar deposits in the Lebanese banking system were also remunerated at abnormally high rates (sometimes reaching 18%).

Given the historical financial soundness of the Lebanese banking sector, depositors did not suspect how dangerous the complex financial engineering mechanism launched by the BDL in 2016[9] was. Encouraged by abnormally high rates (reaching 20%), Lebanese commercial banks placed their customers' dollar deposits as excess reserves at the Central Bank.

On the other hand, the BDL drew upon these reserves to cover the public deficit and maintain the exchange rate.

This mechanism ended up hampering the optimal capital allocation and financial intermediation that are supposed to be the main missions of commercial banks to irrigate the real economy and boost economic growth. In January 2019, the American rating agency Moody's downgraded the Lebanese Treasury bonds called Eurobonds to poor-quality speculative securities to sanction the delay in forming the government and launching reforms[10]. This decision further weakened the financial system. According to the Ministry of Finance, the economic slowdown, the worsening of the public deficit ($ 1.751 billion in April 2020), the increase in the unemployment rate, and the high cost of living have further accelerated the financial collapse. A cascade of damaging events took place following public unrest and demonstrations (restriction of foreign exchange transactions, banks closure, gradual capital control, unequal treatment between large and small depositors, and led to an average implicit "haircut" of over 50% at the time (and currently almost 80%[11] a series of BDL circulars that led to an average implicit "haircut" of over 50% at the time (and currently almost 80%[12]. This amplified the banks' liquidity crisis and accelerated the shrink in the value of the Lebanese currency against the dollar on the black market. In addition, the strictly imposed confinement due to Covid-19 cases led to a monetary, financial, and economic crisis. The GDP contracted by 20.23% in 2020, and the Lebanese Pound lost more than 90% of its value, with inflation rates currently hitting a record high at more than 150% as food prices soared up to more than 441% in April 2021[13].

In light of the above, the struggling Lebanese commercial banks may have been tempted to window-dress their financial statements before and, more importantly, after the launching of the financial engineering operations by the BDL. For all the aforementioned reasons, this paper applies BL to detect potential fraud in the Lebanese banking system.

2.2 Benford Law

2.2.1 Background

Simon Newcomb, an astronomer, in 1881, and then Frank Benford, a physicist, independently in 1938, discovered what is known today as BL. Newcomb observed that (1) the initial pages of books with logarithm tables were worn faster than the last ones, and (2) numbers with the first digit of 1 were observed more frequently than other digits. Thus, he proposed a law of the probability of appearance of the first digit, which he

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[7] In 1997, the Lebanese pound was officially pegged to the US dollar at a rate of 1,507.5 LBP/ USD and it used to fluctuate marginally around this figure. However, the dollar was trading in the local economy at 1,500 LBP/USD (Source: https://bdl.gov.lb).

[8] Source: Banque du Liban (Rates on securities and deposits).

[9] National and international newspapers and media are talking about it: https://www.ft.com/content/0838e10c-5481-4d76-a013-ad607a19b7d8, https://www.lorientlejour.com/article/1196726/en-quoi -the-Lebanese-financial-system-is-a-ponzi-system-.html, etc.

[10] https://www.thenationalnews.com/business/economy/moody-s-downgrades-lebanon-s-credit-rating-to-junk-over-debt-default-concern-1.816468 (accessed on March 30, 2022).

[11] At the current parallel market rate (19,000 LBP / dollar on average at the end of July 2021), withdrawals in dollars at the rate of 3,900 LBP per dollar (according to circular 154) impose an "implicit haircut" of (19,000 - 3,900) / 19,000 = 79.47% on the withdrawn amount.

[12] At the current parallel market rate (19,000 LBP / dollar on average at the end of July 2021), withdrawals in dollars at the rate of 3,900 LBP per dollar (according to circular 154) impose an "implicit haircut" of (19,000 - 3,900) / 19,000 = 79.47% on the withdrawn amount.

[13] Blominvest Bank, The Research Blog, Lebanon's Inflation Hits Record High at 147.55% as Food Prices Soar 395%, January 2021 and World bank data – Lebanon's Economic Update – April 2021.

called the "Law of frequency" and the "Law of the probability of occurrence of numbers" (Newcomb, 1881, pp.39-40). His two-page article "Note on the Frequency of Use of the Different Digits in Natural Numbers" went unnoticed.
The Law was rediscovered 57 years by Benford (1938) in his article "The Law of Anomalous Numbers." Benford observed that the pages containing the logarithms of the low numbers 1 and 2 are apt to be more strained by use than those of the higher numbers 8 and 9. Benford, unlike Newcomb, stated the algebraic expression for the probability of the first digits after empirically examining the first digits of 20,000 entries from 20 various datasets such as geographic, scientific, and demographic data. Thus, the phenomenon came to be known as "BL," though Benford called the phenomenon "The Law of Anomalous Number" and "The Logarithmic Law" (1938, p. 551). Benford proved that the distribution of the leading digit, d, is given by the logarithmic formula (Stoessiger, 2013, p.29). While not universal, this logarithmic distribution is known as BL and attracts many mathematicians, statisticians, economists, engineers, and physicists (Raimi, 1976, p.522). Even though the general benefits of BL for detecting financial fraud were discovered a long time ago, it is still not widely known (Cho & Gaines, 2007, p.2). Its awareness has been accelerated lately (Nigrini, 2019).

2.2.2 Benford Law Application and Hypotheses development

A major threat bedeviling the banking institutions is the growing rate of financial crimes and the paucity of appropriate mechanisms to combat this menace (Mangala & Soni, 2022). Banking crises are devastating because, typically the shock waves affect the entire economy (Hellmann, Murdock, and Stiglitz, 2000). The moral hazard theory explains banks' failures. The problem of "gambling on resurrection" implies that banks choose a risky asset portfolio that pays out high profits or bonuses if the gamble succeeds but leaves depositors, or their insurers, with the losses if the gamble fails (Kane, 1995). In the same context, large interest-rate increases associated with financial-market liberalization can systematically lead to financial crises (Demirgüç-Kunt & Detragiache, 1997, 1998). There is a clear theoretical connection between liberalization and the degree of the moral-hazard problem. For instance, the liberalization and deregulation process in developed markets after the 1970s has altered banks' focus to a diverse range of activities, such as asset management, underwriting equity and debt issues, securitization, and insurance (Vives, 2016). Through securitization, banks could reduce capital requirements by off-balance-sheet financing (Acharya *et al.*, 2013). Banks' risk-taking and highly leveraged positions in securitized subprime mortgages led to increases in market stealing incentives and financial crises (Acharya *et al.*, 2010). Although banks' prudential regulations are a medium to avoid such scenarios, any Pareto-efficient outcome remains bearly impossible using one single tool of prudential regulations such as capital requirements or deposit-rate ceilings (Scott, 2012). Thus, the banking sector remains a fertile ground for fraud despite internal and external managerial controls.
The Association of Certified Fraud Examiners (2011) defines fraud as "Any illegal acts characterized by deceit, concealment or violation of trust." The fraud triangle theory, developed by the American criminologist, Donald Cressey, emphasizes three factors: non-sharable perceived financial pressure or incentive, perceived opportunity to commit fraud, and rationalization to justify offensive behavior (Cressey, 1953). Financial pressure is the main factor influencing bank employees' propensity to perpetrate fraudulent offenses *(Asmah et al.*, 2020; Avortri & Agbanyo, 2020). Hidajat (2020) studied Indonesian rural banks and found that greed is the chief motivating non-financial pressure for shareholders, commissioners, and directors. In contrast, employees often perpetrate fraud under financial pressure caused by insufficient remuneration. On the other hand, opportunities are circumstances generally due to weaknesses in the internal control system that allow fraudsters to commit fraud and escape without being captured. Rationalization will enable fraudsters to justify their fraudulent behavior as normal and morally acceptable (Asmah et al., 2020) and defend themselves from indulging in wrongful acts (Kazemian *et al.*, 2019). Rationalization is significantly and positively related to the occurrence of fraud among management staff in the banking sector (Avortri & Agbanyo, 2020). Specifically, frauds in the banking sector have three dimensions: insider fraud, outsider fraud, and collaborative fraud (Repousis *et al.*, 2019). Yet, the majority of frauds are perpetrated or facilitated by bank directors, executives, and loan officers (Hidajat, 2020).
BL is considered an appropriate tool for fraud detection for financial institutions and all other types of businesses (Durtschi & Rufus, 2017). It was used to examine fraud and other forms of data manipulation in accounting (Nigrini, 1996) and cosmetic earning management (Aono & Guan, 2008; Carslaw, 1988; Nigrini, 2005). For instance, Carslaw (1988) examines the frequency of occurrence of the second digits in the annual

reports of 220 New Zealand listed companies and finds an abnormally high frequency of the digit zero and an abnormally low occurrence of number nine. Thereafter, Nigrini (1996) was the first to show that BL could be applied in detecting accounting fraud. He proposed that many accounting variables like sales, purchases, price history, and assets follow BL. Nigrini and Mittermaier (1997) apply BL to discover unusual patterns in accounting transaction activities. Hürlimann (2009) lists 350 publications on BL between 1881 and 2006, out of which 166 are published between 2000 and 2006. Companies that manipulate their profits tend to inflate their profits by managing their digits upward, 1 or 5 and tend to deflate their profits by moving their digits downwards like 9 or 4 (Skousen *et al.*, 2009). The rounding up behavior was found for Finnish companies' net income (Niskanen & Keloharju, 2000) for the positive pre-tax income of British companies (Van Caneghem, 2004), for the earnings per share before extraordinary items, and net income per share in the US (Carlson, 2016), and earnings of Japanese firms (Skousen *et al.*, 2004). Guan *et al.* (2006) discovered an upward rounding of net profits and a reversed pattern of earnings management for net losses for almost 22,000 firms in 18 countries. Aono and Guan (2008) use BL to detect fraud in quarterly earnings reports of cosmetics firms for Thai and Japanese companies and observe that the less audited quarterly report is the one that shows less manipulation. Žgela (2011) analyzes the net income of 500 companies during 2007, 2008, and 2009 to confirm that data fits BL. Therefore, we propose the first hypothesis:

Hypothesis 1: the probability of all digits of the accounts of the report of condition (balance sheet) and report of income (income statement) in the pre-and post- financial engineering mechanism periods does not conform to the expected distribution under BL, indicating a strong signal for data manipulation.

Notwithstanding, the calculation of banking financial ratio analysis is based on building public trust and banking prudential principles (Ricketts & Stover, 1978), several changes have occurred, and a greater emphasis on monitoring banks' risk-management systems took place (Hellmann *et al*., 2000). Recently, the CAMELS rating system was created by federal banking regulators (Rose & Hudgins, 2010) to evaluate Banks' managerial and financial performances and soundness (Roman & Sargu, 2013) and predict the failure rate (Salhuteru & Wattimena, 2015).

The CAMELS approach is a Uniform Financial Rating System used internationally as a scoring system by bank supervisors when comparing tires with six factors: Capital adequacy, Asset quality, mainly the Loans portfolio, Management expertise, Earnings strength Liquidity, and Sensitivity to market risk. It is a medium that helps regulators carry out their supervisory functions (Sarker, 2005). A myriad of studies relies on CAMELS to evaluate the solvency and liquidity of commercial banks. For instance, Hirtle and Lopez (1999) examined the utility of past CAMELS ratings for evaluating banks' current conditions. Yet, the viability of information on CAMELS ratings is short-lived. Cole and Gunther (1998) analyzed a similar question and found that even if CAMELS ratings contain useful information, they depreciate quickly. Accordingly, we reiterate the importance of applying BL as a technique to detect fraud in the banking sector. Empirically, Nigrini (2005) analyzes Enron's revenue and earnings per share data between 1997 and 2000 and finds cosmetic earnings management based on a time series analysis of rounding behavior concerning positive income numbers of publicly traded companies before and after the Sarbanes Oxley. Archambault and Archambault (2011) explore the profit from regulated and unregulated Moody's companies and conclude that both kinds tend to manipulate results differently. Cunjak (2019) applied BL to analyze the annual financial reports of eight publicly owned companies in Croatia for two years and found seven annual reports deviate from BL. Much more, he examines the usage of BL in forensic accounting. They analyze 12 randomly chosen companies listed on the Zagreb Stock Exchange from 2011 to 2016 and find significant deviations from BL. Shi *et al.* (2018) test whether financial data from ten industrial sectors of the six developing countries (Brazil, China, India, Indonesia, Mexico, and Turkey) from 2000 to 2014 comply with BL. Omerzu *et al.* (2019) test digits distribution in companies' financial statements from the Ljubljana Stock Exchange in Slovenia. Finally, Grammatikos & Papanikolaou (2021) are the first to examine fraud detection in the banking sector using BL. They find that banks adjust loan loss provisions to manipulate earnings and income upwards. They show that such manipulation was amplified during the global financial crisis of 2008 and that distressed banks also manipulated loan loss allowances and non-performing loans downwards to disguise their financial difficulties.

Hypothesis2: the probability of all digits of CAMELS in the pre-and post- financial engineering mechanism periods does not conform to the expected distribution under BL, indicating a strong signal for data manipulation.

3. RESEARCH DESIGN

Sample and Data

We focus on a representative sample of the 10 biggest commercial banks among the 16 alpha banks (a ranking based on the size of customer deposits in dollars, see Table I). The sample of banks adopted for analysis is dictated by the representativity in terms of bank size and data availability. The studied banks are: Audi Bank, Banque du Liban et d'Outre-Mer (BLOM), Société Générale de Banque au Liban, Byblos Bank, Fransabank, Bankmed, Bank of Beirut (BOB), Banque Libano-Française (BLF), Credit Libanais, and Intercontinental Bank of Lebanon (IBL). We use yearly reports of condition and income (banks' financial statements) for the period extending from 2005 to 2020, collected from the BankFocus database (Bureau van Dijk). We choose 2005 as a starting year due to bank data availability. The sample period is divided into a pre-financial engineering mechanism period (spanning from 2005 until 2015) and a post-financial engineering period (from 2016 until 2020).

[Insert Table I hereafter]

Variables

Following previous literature (Bahnsen *et al.*, 2014; Grammatikos and Papanikolaou, 2021), we propose a set of variables based on CAMELS.
The present study focuses on 4 components of the CAMELS rating, excluding Management and Sensitivity since the first seems to be measured by regulators according to qualitative and subjective factors, and market data reflect the second component. All possible proxies for the 4 studied aspects of the CAMELS rating are described in Table II. However, due to data availability, we have chosen specific variables to test for each category (highlighted in bold in Table II).

[Insert Table II hereafter]

Methodology

BL is a mathematically proven technique to detect irregularities. Based on Benford (1938), it recently received increasing attention and appeared superior to other traditional approaches. In this study, we do not claim that based on BL, we can judge that those Lebanese banks have committed fraud. We propose BL as a preliminary tool that serves as an early warning system to draw attention to potential irregularities, manipulations, or fraud. A further and detailed audit process is needed to uncover the roots of manipulations. BL, also known as First Leading Digit (LD) or First Significant Digit, considers the frequency of occurrence of the first digits to follow a specified theoretical logarithm. LD is the first (non-zero) digit of a given number appearing on the leftmost side. For negative numbers, the sign is discarded. The observation is that the first LD is not equally likely to be any of the nine possible digits. The occurrence of low digits such as 1, 2, and 3 is higher than that of high digits. Ignoring leading zeros, the implied probability of the first digit d1 = (1, 2..., 9) is:

$$\textit{Probability [1st digit is d]} = LOG_{10}(1 + 1/d).$$

where log denotes base 10 logarithms.

One remarkable consequence of BL is that the probability of 1 as a first digit is not 11.1% under the uniform distribution but 30.10%, which is approximately sixfold the proportion assigned to digit 9. However, consideration is also given to second, third-leading digits, and so forth. It is noted that for the second and all higher orders, digit 0 is also included, and all 10 digits {0, 1, 2, 3, 4, 5, 6, 7, 8, 9} are in use. Second-order leading digits distribution shows that the proportion for the second order is not nearly as skewed in favor of low digits as is the case for the first order. The third-order digit distribution is even more equal than for the second order. For the fourth order and subsequently, there is almost total digital equality where distributions are uniform and equal for all practical purposes.

[Insert Table III hereafter]

This paper applies BL on the first- and second- digits of the accounts of the report of condition (balance sheet) and report of income (income statement). If manipulation is detected in the second position, its pattern will be identified by applying the Law to the first position (Van Caneghem, 2002).
Then, the paper proceeds to check if the second and first positions of the selected CAMELS that capture Capital adequacy, Assets quality, Earnings strength, and Liquidity conform to BL. The actual frequency of digit occurrence is compared with the expected frequency predicted by BL for digits zero through nine appearing in the second position of the variables of interest. If one manipulates a variable upwards to inflate the digit in the first position, a higher frequency of low numbers (mostly zeros or ones) and a lower frequency of high numbers (mostly nines or eights) in the second position compared to the expected proportion of low and high numbers will be obtained. This observation violates BL as it reveals an uncommon digital pattern indicating an upward data manipulation. An opposite occurs- higher frequency of high digits and lower frequency of low digits in the second position- also violates BL and indicates a downward manipulation. A positive deviation implies that the actual proportions exceed the expected ones, while a negative deviation shows that the reverse pattern occurs.
Following Nigrini (1996), Durtschi and Rufus (2017), and Grammatikos and Papanikolaou (2021), the normally distributed Z-statistic is applied to examine the statistical significance of the deviations in the actual and the expected proportions:

$$z_i = \frac{|p_o - p_i| - \frac{1}{2n}}{s_i} \quad \text{Eq (1)}$$

Where is the Z-statistic for digit i where i = 0, 1, 2,…, 9; p_o is the observed or actual proportion; p_i denotes the expected proportion based on BL; and n is the number of observations of the examined variable.
We account for the Yates' continuity correction term (1/2n) applied only when its value is smaller than that of the deviation in the actual and expected proportions to bring normal and binomial probability curves into a close agreement. Finally, s_i represents the standard deviation of digit i given by:

$$s_i = \left[p_i \left(\frac{(1-p_i)}{n}\right) \right]^{1/2} \quad \text{Eq (2)}$$

The Z-statistic tests the null hypothesis that the observed proportion does not statistically differ or deviate from the expected proportion based on BL. A Z-statistic value of 2.57, 1.96, and 1.64 indicate a *p-value* of 0.01, 0.05, and 0.10 respectively.
Furthermore, the Chi-square test is performed as a goodness-of-fit test to examine whether the actual distribution significantly differs from the expected distribution over all nine digits of the second position of the variables (Durtschi & Rufus, 2017). Rejecting the null hypothesis suggests that the probability of all digits does not conform to the expected distribution under BL, indicating a strong signal for data manipulation.
The value of Chi-square is computed as follows:

$$\chi^2_{(9)} = n \sum_{i=0}^{9} \frac{(O_i - E_i)^2}{E_i} \quad \text{Eq (3)}$$

Where O_i is the observed frequency of digit i; E_i is the expected frequency of digit i under BL; n is the number of observations for the examined variable. The results are summed up for all digits $i = 0,1,2,...9$ to test the conformity for the entire distribution. Given the possibility of having 10 digits possible in the second position, the degree of freedom is 9 $(10-1)$ so $\chi^2_{(9)}$. The 10%, 5%, and 1% critical values are 14.68, 16.92, and 21.97, respectively. The same analysis is repeated for the first digit position in the two sub-periods.
In the present paper, we split the studied period into two distinct periods to shed light on the imminent role of the banking sector before 2016 and draw attention to the period of the financial engineering scheme. We provide real arguments and evidence of the financial engineering scheme that took place in 2016 and onward. Our work is not an event analysis. It is simply an analysis conducted over two periods to validate the importance of the sector before 2016 and its role in the Lebanese crisis after 2016.

4. RESULTS AND FINDINGS

Reports of Condition and Income

First, Tables IV to VII report whether the reports of condition and income of the 10 selected alpha banks conform to BL. For ease of comprehension, we also present the results in Figures 1 to 4. The expected frequencies under BL are scattered on the orange line in all figures. The analysis of the first digit in reports of condition and income in the sub-periods does not conform to BL (Tables IV and VI and Figures 1 and 3), where the digits do not exactly follow BL in the pre-and post-financial engineering period. The curve slopes downward at digit 1 with some anomalies for digits 3, 4, and 5, mainly in the report of condition (more occurrences than expected for these digits). This finding is attributed to the poor accounting data quality and weak disclosure practices that describe the Lebanese banking sector. The BDL is known to disclose little about its assets and liabilities in its fortnightly balance sheet publication. The theory of moral hazard and asymmetries of information best explains such manipulative context as banks have to meet regulatory capital requirements or the quality of assets to reduce the riskiness of their portfolios (Huizinga & Laeven, 2012). Furthermore, the digital analysis of the second position (Tables V and VII and Figures 2 and 4) detects fraud as the numbers do not follow BL, and the charts show curves that no longer slope downward or look like a waterfall slide. This outcome suggests that accounting manipulation took place in both periods. Still, deviations are magnified in the post-financial engineering mechanism period, in both the report of condition and income accounts (Figures 2 & 4). The manipulation also occurred in the pre-financial engineering mechanism period as the first digits (mainly digits 1 and 3) occurrences exceeded BL's expected ones. These findings are in line with Archambault and Archambault (2011) and Grammatikos and Papanikolaou (2021).
The last digits (especially 7 and 8) frequencies are lower than BL expected. The deviations are randomly negative or positive in other digits showing that accounting data could be fabricated in the reports of condition and income. The second position digits simply do not conform to BL. These results support Hypothesis 1, which incites us to perform a deeper digital analysis of selected CAMELS accounting variables presented in the previous section, based on Z-statistic and Chi-Square tests (Tables XIII and IX).

[Insert Table IV hereafter]

Figure 1. Graphical distribution of the first digit in reports of condition: pre-& Post- financial engineering period

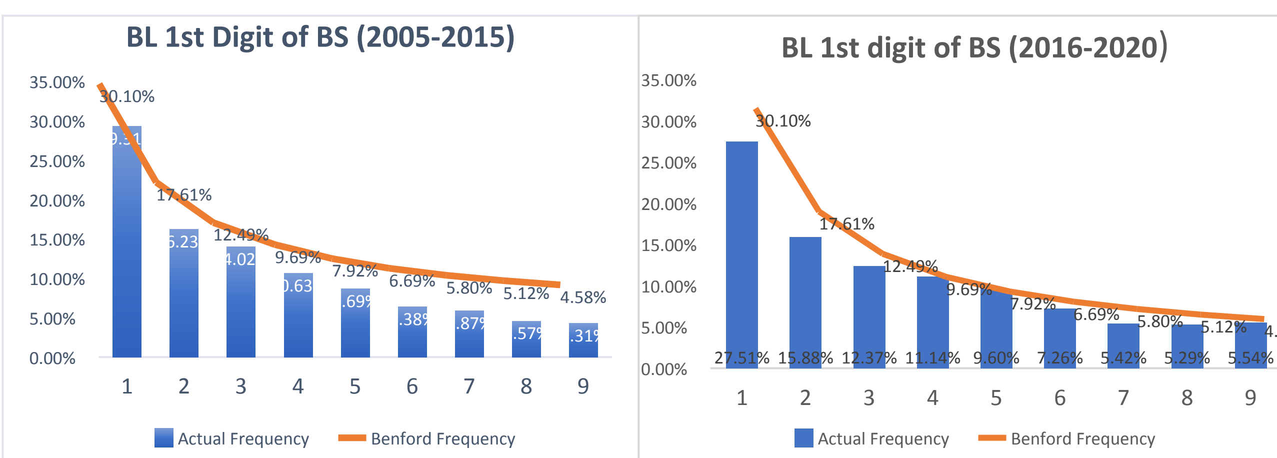


Table V and Figures 3 and 4 present the digital analysis of the second position in reports of condition. It shows some deviations occurring between the observed and expected proportions, which suggests that the numbers no longer follow BL. As BL predicted, the curve no longer slopes downward, even though the anomalies are still not pronounced. The deviations here are larger in the second sub-period. Banks seem to have manipulated their accounting data after launching financial engineering operations. The fraud triangle theory (Cressey, 1953) best explains the context of this latter deviation. The Lebanese banking sector has long faced financial and political pressure to lend to the Lebanese government and maintain the peg of the Lebanese pound to the US dollar.

Following the complex financial engineering mechanism launched by the BDL in 2016, commercial banks adopted a high differential between the interest rates of the Lebanese pound and the dollar to give incentives to local and foreign depositors, especially Lebanese emigrants, to deposit their savings in foreign currencies. The greed lured by abnormally high rates (reaching 20%) incentivized commercial banks to place their customers' dollar deposits as excess reserves at the Central Bank. Additionally, non-financial pressure such as meeting financial analysts' forecasts, gaining shareholders' confidence, attracting potential investors, and relaxing financial constraints to sufficiently fund innovative projects (Linck *et al.*, 2007) are important motives to commit fraud. The fraud opportunity is indeed based on the weak local environment, political instability, high fiscal deficits, banking secrecy law, and political affiliation, as many banks' shareholders are from the ruling parties. As for the rationalization, the banking sector can justify their fraudulent behavior as normal and morally acceptable (Asmah *et al.*, 2020) as a part of the BDL monetary policy is to maintain the peg and meet large public debts.

[Insert Table V hereafter]

Figure 2. Graphical distribution of the second digit in reports of condition: pre-& post financial engineering

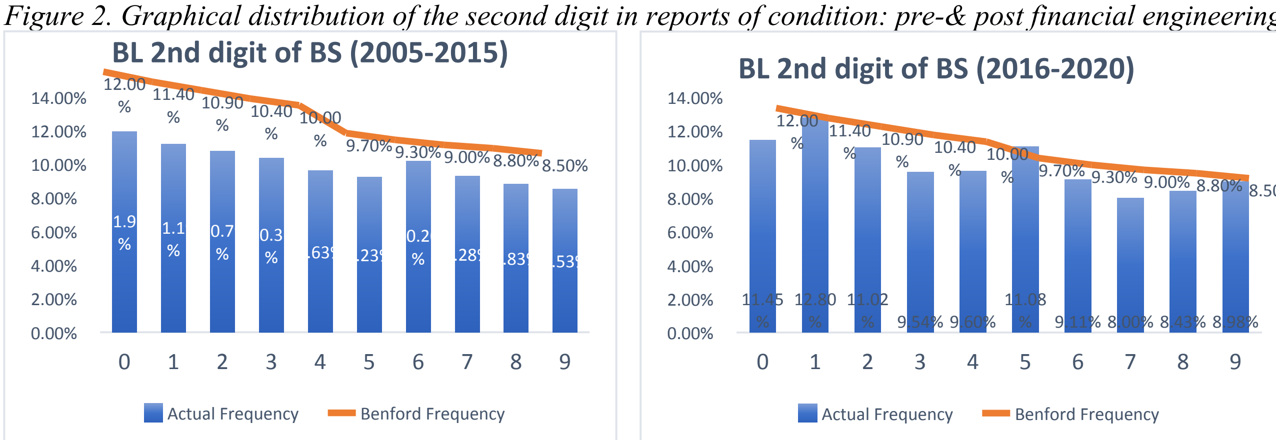


Table VI and Figure 3 present the digital analysis of the first position in reports of income which seems to slightly deviate from BL in both periods, especially for digits 2 and 3. Though the curve follows the BL waterfall slide, a further investigation of the second digit manipulation is worth exploring.

[Insert Table VI hereafter]

Figure 3. Graphical distribution of the first digit in reports of income: pre- & Post- financial engineering period

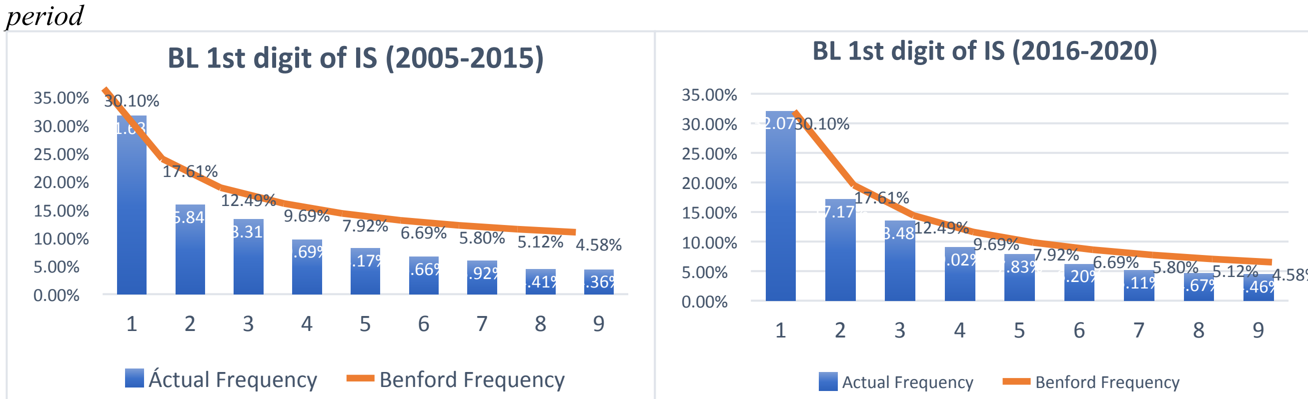
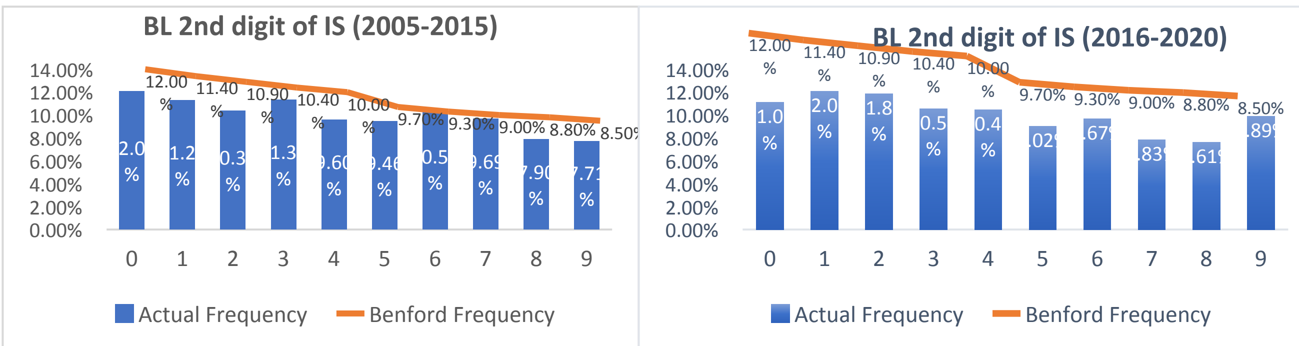


Table VII and Figure 4 present the digital analysis of the second position in reports of income. Similar to the second position digits of the reports of condition, those of the reports of income show deviations from expected proportions under BL, stipulating that frauds occur in the two sub-periods. The curves suggest without a doubt that accounting data manipulation took place in the Lebanese banking sector in the second sub-period.

[Insert Table VII hereafter]

Figure 4. Distribution of the second digit in reports of income: pre-& post financial engineering analysis



CAMELS

The results of the second-and first-digits analyses of CAMELS accounting variables based on the Z-statistic and chi-square tests for the pre-and post- financial engineering mechanism periods are reported in Tables VIII and IX, respectively.

The actual frequencies of the digits zero through nine appearing in the second position of the selected accounting variables are compared to the expected ones as predicted by BL. A variable is manipulated upwards (through an increase in the digit of the first position by one) when there is a positive deviation or higher than the expected proportion of low numbers (mostly zeros or ones) and a negative deviation or a lower than the anticipated frequency of high numbers (mostly nines or eights). This suggests an upward data manipulation, and the reverse pattern indicates a downward manipulation.

The second position results show that the actual proportions deviate from the expected BL frequencies in the pre-financial engineering period. There is a positive deviation in digit 3 (+22.38%) and a negative deviation in digit 8 (-7.20%) for Tier 1, significant at 1% and 10%, respectively; a positive deviation of digit 9 (+4.96%) for Equity, significant at 10%; and a negative deviation in digit 9 (-6.58%) for CASH significant at 5%. Furthermore, a downward manipulation is also detected in the LLR account where the zero digits' actual frequency deviates negatively from the anticipated one (by -6.14%) while the higher digits, mainly the 7^{th}, deviate positively from the expected frequency (by +5.52%), both with a significance level of 10%. The post-financial engineering mechanism period shows a reverse trend indicating a downward manipulation: a negative deviation in the first digits (2 for -10.88% and 0 for -11.97%) significant at 5% for Tier 1 and Equity, respectively. The middle digits (4 and 5) occurrences deviate positively from the BL expected frequencies at a significant level of 1% and 10%, respectively. It is important to note that the Chi-square for all examined variables is significant at a 1% level suggesting that fraudulent manipulations occurred in the accounting data of the 10 Lebanese alpha banks.

Banks seem to have overstated their capital adequacy variable (TIER 1) and Cash in the pre-financial engineering mechanism period while they understated TIER 1 in the post-financial engineering mechanism period. TE was manipulated downwards in both periods, while LLR was manipulated downwards in pre-financial engineering. Some of the study results are consistent with those obtained by Carslaw (1988), Van Caneghem (2002), and more recently by Grammatikos and Papanikolaou (2021). They suggest that banks exercise manipulation to increase the magnitude of the balance sheet (TIER1) when the level of these variables is slightly below a round number. Furthermore, banks manipulate loan loss provisions downwards when their level is slightly above a round number. In light of the above, banks seem to manipulate their accounting data to disguise their financial difficulties and window-dress their performance and their report of condition to outsiders.

We now apply BL to the first position of each of the relevant variables (TIER1, TE, LLR, INC, and CASH) to examine the patterns of manipulation. The results for the pre-and post-financial engineering mechanism periods are presented in Table IX. They show significant results only for TIER 1 (at a 1% confidence level in the two sub-periods) and TE and LLR (at 5% and 10%, respectively in the pre-financial engineering mechanism period). The first digit analysis shows that banks manipulated TIER 1 data (digit 1) upward before implementing the financial engineering operations and downward after it, confirming the second digit analysis results. The first digit analysis of TE and LLR variables shows an upward manipulation in both TE and the first sub-period for the second variable. In contrast, the second digit analysis for both variables reveals a downward manipulation in the first sub-period. Yet, the Chi-square test shows a larger significance (1% versus 10%) in the second position analysis. Lebanese banks seem to have mainly manipulated the data of capital adequacy and asset quality in the first or second sub-period or both. Our results support Hypothesis 2. They are in line with the findings of Carslaw (1988), Van Caneghem (2002), and, more recently Grammatikos and Papanikolaou (2021). From the other side, our findings are not in line with the findings of Omerzu et al.(2019). This latter study investigated BL's conformity for the financial statements of companies listed on the Ljubljana Stock Exchange over three years motivated by the fact that most Slovenian companies are using solutions accessible via the Internet (Oracle and SAP) and this would allow for greater accessibility of users and manipulation of data. In addition, although their study concluded with deviations in the third and fourth digits (0.526 % and 0.410 %, respectively) and the null assumption test indicated that the entire test data did not pass the first and second BL tests, they ended up stating that there was no suspected manipulation. We argue that our analysis is different from this latter study in many regards. Our study is extended over a longer period and motivated by critical instances that occurred in Lebanon. Moreover, it includes a longer period split into two critical ones. The CAMELS ratios are tested in addition to the financial statements to support and validate our findings. Finally, the need to conduct our analysis is well justified by offering a detailed view of the existing economic and financial situations and pinpointing the nurturing ground to commit fraud and financial engineering schemes.

In Lebanon, the three pillars of the fraud triangle: financial pressure, opportunity, and rationalization exist. The financial pressure is explained by the economic slowdown, the worsening of the public deficit, the increase in the unemployment rate, the high cost of living, and the imposed confinement due to Covid-19 which has aggravated the situation and led to a monetary, financial, and economic crisis. The opportunity factor stems from the existing collusion between the government and the banking sector. The majority of the banks' shareholders are political figures and are protected by the government. Besides, banks are operating in a weak local environment, vulnerable to political instability and high fiscal deficits. As a progressive agent of the economy, they are well positioned to manage the diaspora's money as well as regional and foreign capital due to the secrecy law that was promulgated in Lebanon in 1959. The rationalization factor relies on the fact that the BDL has long attempted to finance the deficit of the balance of payments, manoeuver the crisis, and spare the economy from collapse by supporting persistent governmental deficits. The banking system in Lebanon is well interconnected vertically and horizontally. This insinuates a collaborative fraud environment under the aegis of the central bank.

To conclude, fraudulent manipulations in the banking sector can distort depositors, shareholders, and regulating authorities to identify and address potential problems, which can seriously disrupt the whole financial industry and lead to economic crises. The subject's sensitivity has a ripple effect as a small initial shock can be amplified by the financial system and propagated to the whole economy. Furthermore, the weak legal environment, corruption, political bias, and entrenched economic and political crises in Lebanon are the roots of BDL's financial engineering plot that implicated the whole Lebanese banking sector and submerged the entire country in a steep economic recession. Accordingly, the study serves as a preliminary diagnostic tool to depict frauds and anomalies in the financial statements at the earliest possible moment. More specifically, the application of BL in the banking sector is very important as this sector is one of the main pillars of the Lebanese economy.

[Insert Table VIII hereafter]

[Insert Table IX hereafter]

5. CONCLUSION

This paper examined and highlighted the patterns of manipulation in the Lebanese banking industry represented by a sample of the 10 biggest alpha banks. Our focus on the Lebanese banking sector aims to address critical fraud issues in a sector that played a major role in supporting the national economy and promoting growth. It was considered the beating heart of the Lebanese economy for decades.

First, we show that BL can serve bank regulating authorities to detect fraud in the banking industry. Second, this study is the first to examine and highlight the patterns of manipulation in the Lebanese banking industry. To the best of our knowledge, no previous studies investigated the fraudulent manipulation of the Lebanese banking sector or the banking industry in the MENA region. Only Grammatikos and Papanikolaou (2021) employed BL to test if US commercial banks' balance sheet and income statement data were manipulated prior to and also during the global financial crisis.

Effectively, we show that banks have noticeably manipulated their capital adequacy (TIER 1 and TE), Liquidity (CASH), and Assets Quality (LLR) ratios in the pre-financial engineering mechanism period and more considerably after it, on the financial outbreak eve.

Banks manipulated accounting data to conceal their financial difficulties and window-dress their performance and report of condition accounts. These fraudulent manipulations biased the banking sector operations and misled depositors, shareholders, and, more importantly, regulating authorities in their task of identifying and addressing problems in the course of bank operations, which can seriously destabilize the financial industry and damage the national economy.

The paper has several implications. From a political perspective, it highlights the fragile political and legal environments in Lebanon. The existence of political ties with the banking sector constitutes a major threat to the Lebanese economy. From an economic perspective, the reliance on the banking sector proved very risky, as the collapse was well-tailored and bearishly orchestrated. Our paper defends the preliminary use of BL as a starting point to conduct further audits and forensic investigations. As a simple technique to detect potential fraud, BL could have prevented the launching of the financial engineering scheme in a country like Lebanon if the legal and judicial frameworks were stronger and more efficient. From a social perspective, it could have avoided the chaos and social unrest that led to instability, insecurity, and degrading social conditions that have reached the level of extreme poverty. We strongly believe that our paper serves as a lesson and offers tools to early detect risky or fraudulent manipulations in financial institutions' financial statements and prevent economic and financial collapse in the banking sector in countries with similar political, economic, and financial geographical contexts. The relevance of our paper is also justified from a scientific perspective. This constitutes additional evidence of the importance of BL as a preventive tool for possible irregularities in quantitative economic research. The work can be replicated in countries that have similar regimes and where the banking sector plays a dominant role in the economy. As the whole planet is inflicted by steep recession and high inflation and is on the verge of witnessing a severe economic crisis even worth than 2008, many scholars are encouraged to investigate and screen industries and companies to uncover suspicious manipulations and non-accidental human actions. Due to the fragile worldwide environment, this is expected to increase in many fields and many countries. Therefore, it is crucial for Lebanese banks and governmental authorities to restore confidence in the banking sector, promote and attract local and foreign investors to re-establish a healthier financial system and economic recovery. This can be done through a well-tailored government plan that can imminently cope with emergency bank resolution, a capital control law, amendments to the bank secrecy, and implement corrective fiscal and monetary policies, particularly by addressing the disastrous consequences of the hard currency peg. The central bank should revamp its organizational structure, improve its disclosure practices and significantly reduce its ties to the government and the political elite.

The study has some limitations. Although BL can serve as a fraud diagnostic tool, it cannot precisely indicate the source of the mistake or the manipulated account. Further, it is impossible to prove that a non-fraudulent dataset would follow a Benford distribution in a scientific or litigation sense. Hence, BL will be fruitful in some analyses, but it should be based on generalized common sense, curiosity, skepticism, models, and diverse automated and sophisticated techniques.

Future research may involve a more in-depth evaluation of the quality of accounting information in quantitative aspects not investigated in this study, such as the evolution of excess reserves maintained by banks at the central banks. We may also study the pattern of banks' exposure to Lebanese Eurobonds, CAMELs trend analysis, and their qualitative components, namely the Management performance. A future study might also be conducted based on event analysis in different geographical and economic contexts.

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Table I. Division of Lebanese banks

	Size
Alpha	>$2 billion
Beta	$500 million < Customer Deposits < $2 billion
Gamma	$200 million < Customer Deposits < $500 million
Delta	<$200 million

Source: (BANKDATA)

Table II. Bank accounting variables and data sources

CAMELS components	Variables	Abbreviation
Capital adequacy	**Core regulatory capital**	**TIER1**
	Total Equity	**TE**
Asset quality	**Loan loss reserves**	**LLR**
	Allowances for loan losses	ALL
	Non-performing loans	NPL
Earnings strength	**Total interest income**	**INC**
	Total non-interest income	NIC
	Total earning assets	TEA
Liquidity	**Cash and deposits in central banks**	**CASH**
	Reverse Repos; securities borrowed & cash collateral.	REPOS

Table II presents CAMELS rating proxies and variables used in the empirical analysis in bold with their abbreviation.

Table III. BL expected frequencies for digits coming in each of the first four positions

	1st Digit	**2nd Digit**	**3rd Digit**	**4th Digit**
0		12.0%	10.18%	10.02%
1	30.10%	11.4%	10.14%	10.01%
2	17.61%	10.9%	10.10%	10.01%
3	12.49%	10.4%	10.06%	10.01%
4	9.69%	10.0%	10.02%	10.00%
5	7.92%	9.7%	9.98%	9.99%
6	6.69%	9.3%	9.94%	9.99%
7	5.80%	9.0%	9.00%	9.99%
8	5.12%	8.8%	9.86%	9.99%
9	4.58%	8.5%	9.83%	9.98%

Table III presents the expected frequencies for digits 0 through 9 in each of the four places in any number based on Benford's Distribution.

Table IV. Distribution of the first digit in reports of condition: pre-and post-financial engineering period

Digit	*Count*	*Expected Proportion Under BL*	*Observed Proportion-Pre*	*Observed Proportion-Post*

1	*1089*	*30.10%*	*29.31%*	*27.51%*
2	*603*	*17.61%*	*16.23%*	15.88%
3	*521*	*12.49%*	*14.02%*	12.37%
4	*395*	*9.69%*	*10.63%*	11.14%
5	*323*	*7.92%*	*8.69%*	9.60%
6	*237*	*6.69%*	*6.38%*	7.26%
7	*218*	*5.80%*	*5.87%*	5.42%
8	*170*	*5.12%*	*4.57%*	5.29%
9	*160*	*4.58%*	*4.31%*	5.54%
Number of Observations			*3716*	*1625*

Table V. Distribution of the second digit in reports of condition: pre-and post-financial engineering period

Digit	Count	Expected Proportion Under BL	Observed Proportion-Pre	Observed Proportion-Post
0	444	12.00%	11.95%	11.45%
1	416	11.40%	11.19%	12.80%
2	401	10.90%	10.79%	11.02%
3	385	10.40%	10.36%	9.54%
4	358	10.00%	9.63%	9.60%
5	343	9.70%	9.23%	11.08%
6	379	9.30%	10.20%	9.11%
7	345	9.00%	9.28%	8.00%
8	328	8.80%	8.83%	8.43%
9	317	8.50%	8.53%	8.98%
Number of Observations			3716	1625

Table VI. Distribution of the first digit in reports of income: pre-and post-financial engineering period

Digit	*Count*	*Expected Proportion Under BL*	*Observed Proportion-Pre*	*Observed Proportion-Pro*
1	*1089*	*30.10%*	31.63%	32.07%
2	*603*	*17.61%*	15.84%	17.17%
3	*521*	*12.49%*	13.31%	13.48%
4	*395*	*9.69%*	9.69%	9.02%
5	*323*	*7.92%*	8.17%	7.83%
6	*237*	*6.69%*	6.66%	6.20%
7	*218*	*5.80%*	5.92%	5.11%
8	*170*	*5.12%*	4.41%	4.67%
9	*160*	*4.58%*	4.36%	4.46%
Number of Observations			*2178*	*920*

Table VII. Distribution of the second digit in reports of income: pre-and post- financial engineering period

Digit	Count	Expected Proportion Under BL	Observed Proportion-Pre	Observed Proportion-Post
0	444	12.00%	12.08%	11.09%

1	416	11.40%	11.29%	12.07%
2	401	10.90%	10.38%	11.85%
3	385	10.40%	11.34%	10.54%
4	358	10.00%	9.60%	10.43%
5	343	9.70%	9.46%	9.02%
6	379	9.30%	10.56%	9.67%
7	345	9.00%	9.69%	7.83%
8	328	8.80%	7.90%	7.61%
9	317	8.50%	7.71%	9.89%
Number of Observations			2178	920

Table VIII. Analysis of the second position of CAMELS accounting variables over the pre-and post-financial period

		Capital Adequacy								Asset Quality				Earnings Strength				Liquidity			
		TIER 1				EQUITY				TOTAL LOSS RESERVES				TOTAL INTEREST INCOME				CASH			
		2020-2016 (n= 42)		2015-2005 (n=70)		2020-2016 (n= 42)		2015-2005 (n=104)		2020-2016 (n= 42)		2015-2005 (n=103)		2020-2016 (n= 42)		2015-2005 (n=104)		2020-2016 (n= 42)		2015-2005 (n=104)	
Digits	BL Exp. Freq.	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic
0	0.1197	-0.0894	1.55	-0.0260	0.48	-0.1197	2.15**	0.0245	0.62	-0.0007	-0.22	-0.0614	1.77*	0.0708	1.18	0.0341	0.92	-0.0483	0.73	0.0438	1.22
1	0.1139	-0.0230	0.23	0.0580	1.34	-0.0901	1.59	-0.0177	0.42	-0.0425	0.62	-0.0168	0.38	-0.0425	0.62	-0.0466	1.34	0.0766	1.32	-0.0466	1.34
2	0.1088	-0.1088	2.02**	0.0006	-0.18	0.0102	-0.03	-0.0223	0.57	-0.0374	0.53	0.0077	0.09	-0.0136	0.03	0.0354	1.00	-0.0136	0.03	0.0547	1.63
3	0.1043	-0.0134	0.03	0.2238	5.93***	0.0624	1.07	-0.0274	0.75	0.0386	0.57	0.0025	-0.08	0.0147	0.06	-0.0178	0.43	0.0386	0.57	-0.0370	1.07
4	0.1003	0.2936	6.08***	0.0403	0.92	-0.0051	-0.15	0.0055	0.02	-0.0051	-0.15	0.0065	0.06	-0.0289	0.37	-0.0041	-0.02	0.0187	0.15	0.0055	0.02
5	0.0967	-0.0361	0.53	-0.0655	1.65*	0.0938	1.80*	0.0379	1.14	0.0700	1.27	-0.0190	0.49	0.0223	0.23	0.0091	0.15	-0.0491	0.82	0.0283	0.81
6	0.0934	0.0581	1.03	-0.0465	1.13	-0.0458	0.75	-0.0165	0.41	0.0018	-0.22	0.0328	0.98	0.0018	-0.22	-0.0069	0.07	0.0495	0.84	0.0220	0.60
7	0.0904	-0.0298	0.40	-0.0592	1.52	0.0286	0.38	-0.0327	0.99	-0.0190	0.16	0.0552	1.78*	0.0048	-0.16	-0.0327	0.99	0.0048	-0.16	-0.0135	0.31
8	0.0876	0.0033	-0.20	-0.0720	1.92*	0.0314	0.45	-0.0011	-0.14	-0.0162	0.10	-0.0099	0.18	-0.0162	0.10	0.0182	0.48	-0.0400	0.64	0.0086	0.14
9	0.0850	-0.0547	0.99	-0.0538	1.40	0.0340	0.51	0.0496	1.64*	0.0102	-0.04	0.0024	-0.09	-0.0136	0.04	0.0112	0.23	-0.0374	0.59	-0.0658	2.23**
X 2(9)		**82.84*** **		**111.45*** **		**38.20*** **		**81.13*** **		**29.98*** **		**92.64*** **		**34.39*** **		**86.13*** **		**43.077*** **		**90.27*** **	
P.value		**0.0000**		**0.0000**		**0.0000**		**0.0000**		**0.0004**		**0.0000**		**0.0001**		**0.0000**		**0.0000**		**0.0000**	

The first column of the Table lists the ten digits that are likely to appear in the second position of the examined CAMELS accounting variables, while the second column shows the expected frequencies of occurrence for each digit under BL. The observed deviations between the actual and the expected frequencies for each examined variable (TIER1, TE, LLR, INC, and CASH) and their z-statistic value for the two sub periods (pre-and post-financial engineering) are reported in the remaining columns. The values of the chi-square goodness-of-fit test are presented in the last row of the Table. All variables are described in Table II.

Table IX. Analysis of the first position of CAMELS accounting variables over the pre-and post-financial period

		Capital Adequacy								Asset Quality				Earnings Strength				Liquidity			
		TIER 1				EQUITY				TOTAL LOSS RESERVES				TOTAL INTEREST INCOME				CASH			
		2020-2016 (n= 42)		2015-2005 (n=70)		2020-2016 (n= 42)		2015-2005 (n=104)		2020-2016 (n= 42)		2015-2005 (n=103)		2020-2016 (n= 42)		2015-2005 (n=104)		2020-2016 (n= 42)		2015-2005 (n=104)	
Digits	BL Exp. Freq.	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic	Observed deviation	Observed Deviation Z-Statistic
1	0.3010	0.4847	6.68***	0.5561	10.01***	-0.0629	0.72	0.0452	0.90	-0.0629	0.72	-0.0680	1.40	0.1752	2.31**	0.0259	0.47	-0.0153	0.05	-0.0222	0.39
2	0.1761	-0.1761	2.79***	-0.1332	2.77***	0.1334	2.07**	0.0931	2.36**	-0.0332	0.36	0.1055	2.68***	0.0144	0.04	-0.0223	0.47	-0.0809	1.17	0.0354	0.82
3	0.1249	-0.1249	2.22**	-0.1106	2.62***	0.0180	0.12	-0.0480	1.33	0.0656	1.05	0.0304	0.79	-0.0297	0.35	-0.0576	1.63	-0.0297	0.35	-0.0191	0.44
4	0.0969	-0.0969	1.86*	-0.0826	2.13**	0.0698	1.27	-0.0296	0.85	0.0221	0.22	0.0196	0.51	-0.0017	-0.22	-0.0007	-0.14	-0.0017	-0.22	0.0089	0.14
5	0.0792	-0.0792	1.61	-0.0792	2.23**	-0.0316	0.47	0.0073	0.10	0.0160	0.10	-0.0404	1.33	-0.0792	1.61	0.0073	0.10	0.0637	1.24	-0.0023	-0.10
6	0.0670	-0.0670	1.43	-0.0670	2.00**	-0.0432	0.81	-0.0093	0.18	0.0044	-0.19	0.0495	1.81**	-0.0432	0.81	0.0003	-0.18	0.0282	0.42	0.0099	0.21
7	0.0580	0.0372	0.70	-0.0437	1.31	-0.0342	0.62	-0.0003	-0.20	-0.0104	-0.04	-0.0289	1.04	-0.0342	0.62	-0.0003	-0.20	0.0134	0.04	0.0093	0.20
8	0.0512	-0.0036	-0.24	-0.0369	1.13	-0.0274	0.46	-0.0127	0.37	-0.0274	0.46	-0.0318	1.24	-0.0274	0.46	0.0161	0.52	-0.0036	-0.24	-0.0320	1.26
9	0.0458	0.0256	0.43	-0.0029	-0.17	-0.0220	0.31	-0.0458	2.00**	0.0256	0.43	-0.0361	1.52	0.0256	0.43	0.0311	1.28	0.0256	0.43	0.0119	0.35
X 2(9)		57.25***		105.19***		10.6197		13.98*		3.9188		21.59**		11.1889		6.0847		5.2813		4.0126	
P.value		0.0000		0.0000		0.2242		0.0823		0.8644		0.0103		0.1912		0.6377		0.7271		0.8560	

The first column of the Table lists the ten digits that are likely to appear in the first position of the examined CAMELS accounting variables, while the second column shows the expected frequencies of occurrence for each digit under BL. The observed deviations between the actual and the expected frequencies for each examined variable (TIER1, TE, LLR, INC, and CASH) and their z-statistic value for the two sub periods (pre-and post-financial engineering) are listed in the remaining columns. The values of the chi-square goodness-of-fit test are reported in the last row of the Table. All variables are described in Table II.