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Hidden Risk: Detecting Fraud in Chinese Banks' Non-performing Loan Data[*]

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Abstract

Using self-reported data from banks in mainland China, I apply a technique used in forensic accounting based on Benford's Law to detect fraudulent manipulation of non-performing loan (NPL) figures. I find large data anomalies consistent with false reporting in mainland banks that do not appear in an identically structured survey of Hong Kong banks. A comparison of different types of data from mainland banks shows no statistically significant anomalies in data for total deposits from customers, operating expenses, net interest income, or non-interest income.

Keywords: *China; Banking; Non-performing loans; Fraud; Benford distribution*

JEL Classifications: *G21; G39; G28*

[*] This paper is an extension of my paper that is archived by the MPRA at https://mpra.ub.uni-muenchen.de/98435/

Introduction

A generation ago the Chinese financial system was not a significant factor in the world economy. This is clearly no longer true. As of 2013, the Chinese banking system reported assets of 147 trillion Yuan† or $23.5 trillion‡. This compares to assets held by U.S. banks of $13.8 trillion.§ If there were to be a large scale collapse of the Chinese banking sector, the repercussions would span the globe and have the potential to cause significant economic damage to other nations. The purpose of this paper is to determine if large volumes of undisclosed non-performing loans exist within the Chinese banking system that may pose a threat to the international financial system.

From the founding of the People's Republic in 1949 until 1978 China had only one bank, the People's Bank of China, which was an organ of the state. Starting in the late 1970's the government began a modernization of the banking system which included the creation of a series of special purpose banks. This process resulted in the "big four" special purpose banks being spun off into theoretically independent commercial banks, although still owned by the government. These were Bank of China (a separate entity from the similarly named People's Bank of China which functions as China's central bank), China Construction Bank, Industrial and Commercial Bank of China, and Agricultural Bank of China.

During the late 1980's and 1990's, Chinese banks began a dramatic increase in lending, primarily to various state owned enterprises. These enterprises were commonly not profitable and survived through continually refinancing their debt. Eventually, there were large scale defaults (Lardy, 1999). By the late 1990's, the largest state owned banks were estimated to have non-performing loan ratios of 30% (Huang, 2006). In response, in 1998 the Chinese government provided a capital injection of $32.5 billion (Okazaki, 2007) which constituted roughly 3% of China's GDP. In addition, four asset management companies were created to purchase non-performing loans at face value. This resulted in an additional $168 billion in capital for the banks (Turner, Tan and Sadeghian, 2012). This intervention succeeded in stabilizing the Chinese banking system such that as of 2005 the number of commercial banks had increased to 112.

Literature Review

Starting in the mid-2000's, there have been a series of anecdotal reports of unusual investment activity in China. Massive construction projects have been completed, but appear to sit unused. The New South China Mall is the largest shopping mall ever constructed. Completed in 2005, it spans 7 million square feet of leasable area and has a capacity of 2,000 stores. It includes an 80 foot tall replica of the Arc de Triomphe, a mile long canal (with gondolas), and full sized indoor roller coaster. The mall also has fewer than a dozen tenants, including four small retail shops and a few fast-food restaurants who are reported to be receiving free rent (Donohue, 2008). In Ordos Prefecture, west of Beijing, is the city of Kangbashi. Completed in 2008, Kangbashi was designed for a population of between 300,000 and 1 million at an estimated cost of 1.1 trillion Yuan, ($161 billion) (Hamlin, 2010). A recent estimate places the population of Kangbashi at below 30,000 (Peston, 2010). Multiple other nearly uninhabited "ghost cities" across China, have been documented (Krambeck, 2010).

The existence of such large projects that cannot plausibly be servicing their construction debt suggests the possibility that China has repeated the financial mistakes of the late 1980's and early 1990's. As majority shareholder, the Chinese government has the ability to direct banks' loans to politically beneficial projects that would not be able to obtain financing on the basis of financial soundness alone. But has this actually occurred? The People's Bank of China Annual Report 2013 states that the non-performing loan ratio (NPL) of major Chinese banks is 1% (People's Bank of China, 2013). This compares to 3.2% in the United States and 7.3% in the Euro area (International Monetary Fund, 2013). There is reason to suspect that the claim of a 1% NPL ratio may not be accurate. Multiple research papers have documented serious discrepancies in economic data reported by the Chinese government (Sinton, 2001), (Holz, 2004), (Mehrotra, 2011). According to a leaked U.S. diplomatic cable, in 2007 then Secretary General of Liaoning Province and current

† China Banking Regulatory Commission 2013 Annual Report
‡ At exchange rate of 1.00 USD = 6.13 CNY as of November 22, 2014
§ FRED Economic Data - Federal Reserve Bank of St. Louis as of January, 1 2014

Premier of China, Li Keqiang, admitted to U.S. ambassador Clark Randt that Chinese GDP statistics were "man-made" and "for reference only" (Minter, 2014).

Data

Self-reported financial data from mainland Chinese banks and Hong Kong banks was obtained from the KPMG Mainland China Banking Survey for the years 2003 through 2011 and the KPMG Hong Kong Banking Survey for the years 2006 through 2011.[**] In this paper I use the KPMG reports' definitions of mainland to be the People's Republic excluding Hong Kong and Macao, and Hong Kong to include Macao. KPMG is one of the "big four' international accounting firms, based in the Netherlands. KPMG Advisory (China) Limited describes itself as *"a wholly foreign owned enterprise in China and KPMG Huazhen (Special General Partnership), a special general partnership in China, are member firms of the KPMG network of independent member firms affiliated with KPMG International Cooperative ("KPMG International"), a Swiss entity."*

The banking surveys include data on 197 mainland Chinese banks and 142 Hong Kong banks, although not all banks are represented in each annual survey. Data is reported in local currency units, i.e. Yuan and Hong Kong Dollars respectively. The number of banks included in each report are shown in tables 1 and 2. The Hong Kong banking survey was not issued in 2010.

Table 1: Number of banks included in each KPMG Banking Survey

Year	*Mainland*	*Hong Kong*
2003	18	-
2004	20	-
2005	55	-
2006	66	139
2007	112	105
2008	121	136
2009	135	142
2010	111	-
2011	114	59

Methods

Six variables were chosen for analysis: Net Interest Income, Noninterest income, Operating expenses, Total assets, Total deposits from customers, and Gross NPLs. Having a survey available for both groups of banks using a common methodology is fortuitous in that it avoids the possible introduction of error due to differing definitions of each variable.

To defect fraudulent data manipulation, I compare the frequency of leading digits in banking data to the distribution predicted by Benford's Law. This is a technique suggested by Hal Varian (Varian 1972) and is currently used in forensic accounting (Nigrini and Mittermaier, 1997). Benford's Law is the observation that data produced by most processes, including most financial data, has a distribution of digits that is not uniform. For example, in a random sample of checking account balances the leading digit will be 1 about 30% of the time and 9 about 5% of the time. The distribution of leading digits predicted by Benford's Law is shown in figure 1.

[**] Data is available at https://sites.google.com/view/bobmayo/research

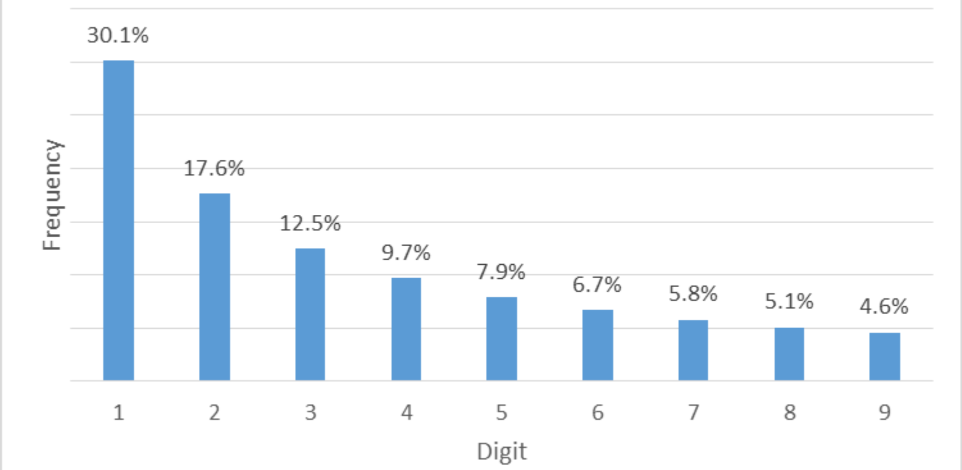

Figure 1: Leading digit frequency predicted by Benford's Law

In the late 19th century, astronomer Simon Newcomb noticed that the front pages of a book of logarithm tables was more worn than the back pages. The tables in the book were arranged in increasing numerical order so he concluded that lower digits like 1 or 2 were being looked up more frequently than higher digits like 8 or 9. Based on this observation, he published *"Note on the Frequency of Use of the Different Digits in Natural Numbers"* (Newcomb, 1881). The same observation was made half a century later by physicist Frank Benford who published an analysis of 20,000 numbers drawn from sources as varied as atomic weights of elements, surface areas of rivers, and figures appearing in Reader's Digest finding that they all conformed to a particular distribution (Benford, 1938). The probability of a digit d ∈ {1…9} being the leading digit in a group of numbers conforming to Benford's Law is

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

The use of Benford's Law as a tool for detecting fraud in forensic accounting is well established. In 1988, Charles Carslaw used deviations from the Benford distribution to detect anomalies in deposits by firms in New Zealand (Carslaw, 1998). One year later Jacob Thomas successfully applied the same technique to data on U.S. firms (Thomas, 1989). A standardized process for using Benford's Law in accounting fraud investigations was published by Mark Nigrini and Linda Mittermaeir (Nigrini and Mittermaier, 1997). The applicability of a Benford based analysis to public sector data was tested by Rauch, Göttsche, Brähler, and Engel in a study of fiscal data provided by the Greek government to the European Union. After the fraudulent nature of their fiscal reports was discovered in the wake of the Greek economic collapse, their data was observed to depart significantly from a Benford distribution (Rauch, et al., 2011).

The proof of the mechanism underlying Benford's Law was published by Theordore Hill (Hill, 1995) and provides insight on what types of data should follow a Benford distribution. Hill showed that when numbers are drawn randomly from multiple randomly selected distributions and are combined through common mathematical operations, the resulting distribution will approach the Benford's Law distribution as the sample size goes to infinity. Since most financial data is produced by combining numbers from different sources through common mathematical operations, the resulting data can be expected to display a Benford distribution.

Understanding the mechanism of the Benford distribution provides guidance on what types of financial data should not be expected to conform, as well as those that should. Numbers that have no interval meaning, such as phone numbers or zip codes, typically will not conform to a Benford distribution. In addition, data that is constrained by imposed maximums or minimums will not conform. Examples of this type of data are the heights of adults measured in feet, where numbers below 3 will be rare and 9 will not occur. Also, financial records that exclude transactions over $50 would under represent digits 6 through 9. In general, numbers that are assigned in part through the application of human judgment will deviate from a Benford distribution. Such a deviation can therefore only be interpreted as indicative of fraud within the context of the claimed data generating process.

Even if substantial fraudulent manipulation of a data set has occurred, there may not be a resultant deviation from Benford depending on the specific type of alteration. For example, if a fraction of transactions are deleted at random to reduce a total then the remaining transactions will not have an altered digit frequency. If the fraudulent entries are large in amount but few in number they will not introduce a distributional deviation proportional to their economic impact. Also, very small data sets or ones that do not span several orders of magnitude are not appropriate for a Benford based analysis (Singleton, 2011).

If a data set is judged an appropriate subject for a Benford based analysis, a statistical test must be selected. There are three main options: a z-test applied to each digit individually, a chi-square test applied to digits collectively, and a Bayesian approach. All three are described in detail by Durtsch, Hillison, and Pacini (Durtsch, Hillison and Pacini, 2004). Based on their assessment of relative merits, here I use a chi-square test because it has a lower false positive rate than a digit by digit analysis and requires less data than the Bayesian technique.

I analyze four groups of data in sequence. First, to determine if there is a deviation overall in the mainland NPL data, I create a sample consisting of the reported NPL volume for every mainland bank across all years in the KPMG mainland China surveys (2003 through 2011). I extract the leading digit of each value and define a null hypothesis that there is no statistically significant difference between the counts of digits in this sample and the counts predicted by a Benford distribution. I use a chi-square goodness of fit test to produce a p-value to test this hypothesis at the 5% significance level. Second, to exclude the possibility that the results of the initial test are a ubiquitous feature of banking data, I repeat this procedure using NPL volume data for every Hong Kong bank across all years in the KMPG Hong Kong surveys (2006 through 2011). Third, to exclude the possibility that the result of the mainland banks NPL data analysis is a general feature of all Chinese banking data, and based on the assumption that different categories of data will present different incentives for fraudulent manipulation, I chose five additional non-NPL variables across all years of the mainland surveys and repeated this procedure separately on each. Fourth, to detect any trend over time in fraudulent NPL reporting, I repeat the initial procedure separately by year on mainland banks NPL figures for the years 2006 through 2011. 2003 through 2005 are excluded from this fourth analysis on the basis that there are an insufficient number of banks surveyed in these years[††].

Results

The first test, which combines all mainland banks NPL figures shows a difference between the observed and predicted counts that is significant at α = 0.01. $\chi^2(8, N = 659) = 29.27, p = 0.0003$. The relative frequency of leading digits is displayed in figure 2. Summary statistics for all mainland NPL data is shown in table 2.

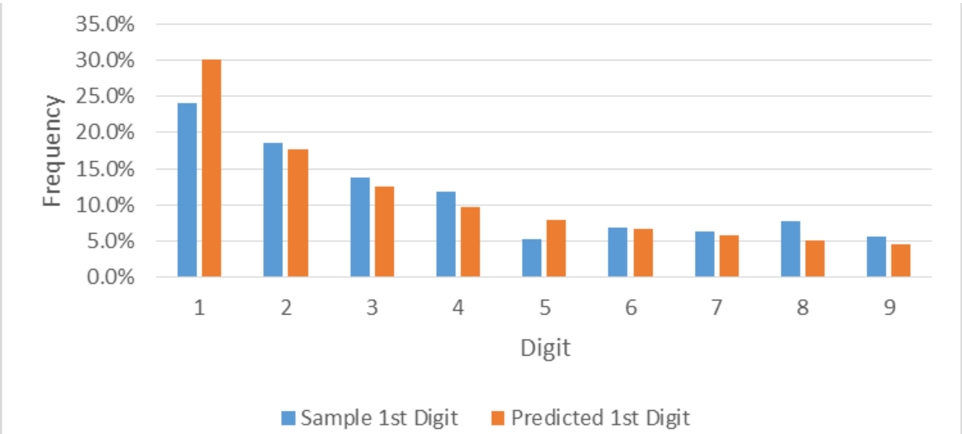

Figure 2: Mainland banks NPL vs. Benford distribution prediction 2003-2011

[††] For 2003, 2004, and 2005 n = 18, 20, and 55 respectively.

Table 2: Summary statistics for mainland NPL data

N	659
Mean	6141.19
Median	279
Standard Dev.	36166.94
Minimum	1
Maximum	818853

The second test repeats the first using Hong Kong banking NPL data for years 2006 through 2011. This analysis did not show a statistically significant difference between the counts of first digits in the sample and the counts predicted by a Benford distribution. $\chi^2(8, N = 256) = 7.07, p = 0.5291$. The relative frequency of leading digits is displayed in figure 3. Summary statistics for all Hong Kong NPL data is shown in table 3.

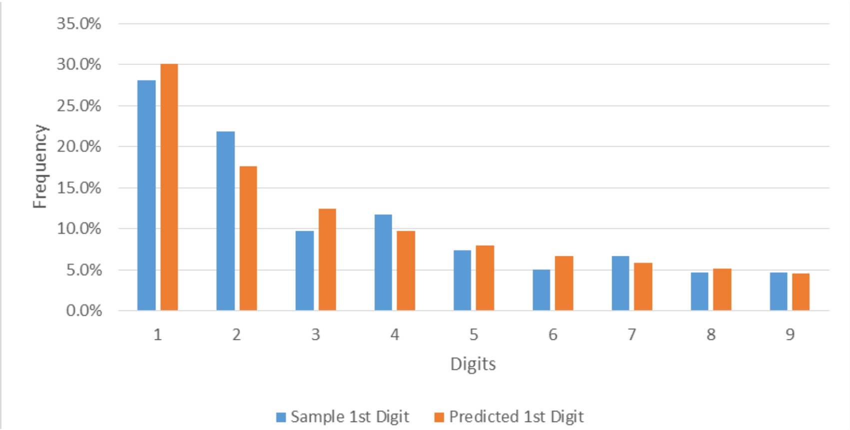

Figure 3: Hong Kong banks NPL vs. Benford distribution prediction 2006-2011

Table 3: Summary statistics for Hong Kong NPL data

N	256
Mean	999.63
Median	45.50
Standard Dev.	4285.09
Minimum	1
Maximum	22796

The third test compares mainland NPL deviations from deviations in four other mainland variables, for years 2003 through 2011. The results are shown in table 4.

Table 4: Comparison of mainland variables

Variable	*χ^2 statistic*	*P-value*
NPL	29.27	0.00
Total assets	18.38	0.02
Total deposits from customers	10.40	0.24
Operating expenses	6.71	0.57
Net Interest Income	6.61	0.58
Non-interest income	3.24	0.92

The fourth test calculates the deviation in mainland NPL data from the predicted distribution for each year individually. The χ^2 statistics and p-values are listed in table 5 and plotted in figure 4.

Table 5: Deviations of mainland NPL data over time

Year	*χ^2 statistic*	*P-value*
2007	8.70	0.3682
2008	20.45	0.0088
2009	9.58	0.2958
2010	12.60	0.1264
2011	14.86	0.0619

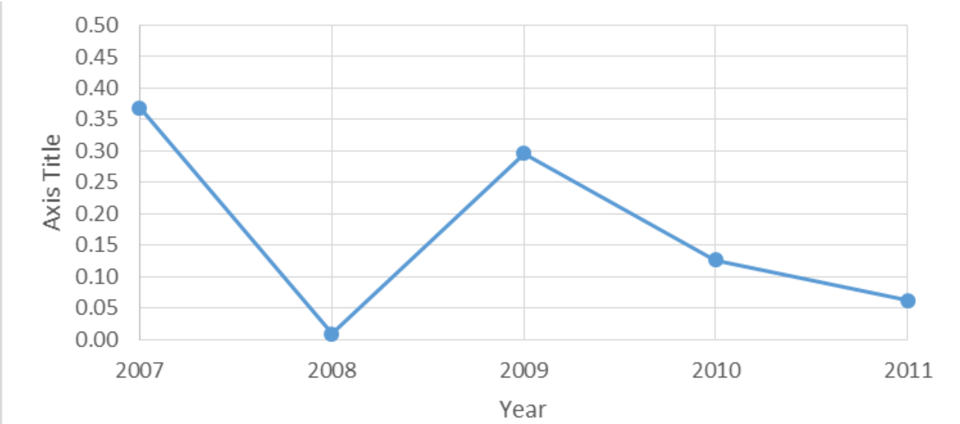

Figure 4: Chi-square p-value of mainland NPL data vs Benford distribution over time

Discussion

The test of NPL data for mainland banks across all years in the survey shows a very significant departure from the expected Benford distribution. In addition, the deviation manifests itself in a deficiency of 1's and an excess of 8's and 9's. This suggests that the data generating process avoids crossing the threshold where another digit would be added. An example would be recording a value of 1,000 as 900 or 800. A similar pattern, although less pronounced, is seen at the transition between 4 and 5 with more 4's and fewer 5's than predicted. An analogous example would be recording values of 500 as 400. The psychological significance of transitioning from a number of n digits in length to n+1 digits in length is obvious, as the routine practice of pricing consumer products at $9.99 rather than $10.00 will attest. A similar, and consistent with the results, lesser psychological barrier occurs between $4.99 and $5.00. Psychology, however is not the only explanation consistent with this data. Auditing or other bureaucratic triggers are more likely to be set at these round numbers than at others. Systematic avoidance of such trigger thresholds is also a reasonable explanation for the results.

The Hong Kong NPL data shows does not exhibit a statistically significant analogous pattern. This suggests that the anomalies found in the mainland banks' NPL figures is not a normal product of the accounting process. An internal comparison of mainland NPL figures to five additional mainland variables shows NPL data to have by far the largest deviation from the predicted distribution. However, while total deposits from customers, operating expenses, net interest income, and non-interest income did not show a statistically significant departure from Benford, data for total assets did. It is interesting to note that the p-values have an inverse relationship with what could reasonably be described as the political and financial sensitivity of the variable, i.e. non-performing loans show the highest deviation, total assets next highest, followed by deposits, interest income, and finally the mundane data on net operating expenses.

Charting the p-value of the χ^2 goodness of fit test for each year individually is hampered by the smaller number of observations than exists in the data across all years. Tests on 2003 through 2006 were not conducted because the number of mainland banks participating in the early years of the survey was so small.

Even with these limitations, an obvious pattern in evident. The first year of the great recession, 2008, shows a dramatic increase in deviation from predicted NPL values, represented by a sharp drop of the test p-values from 0.37 down to below 0.01. This is consistent with an increase in false financial reporting to compensate for a worsening of banks' balance sheets.

Conclusion

Using self-reported data from banks in mainland China, I apply a technique used in forensic accounting based on Benford's Law to detect fraudulent manipulation of non-performing loan (NPL) figures. I find large data anomalies consistent with false reporting in mainland banks that do not appear in an identically structured survey of Hong Kong banks. A comparison of different types of data from mainland banks shows no statistically significant anomalies in data for total deposits from customers, operating expenses, net interest income, or non-interest income, but total assets figures do show a significant anomaly although of smaller scale than that found in NPL data. Finally, an analysis of NPL data across the period 2007 through 2011 shows a sharp spike upwards in level of anomaly in 2008, the first year of the great recession.

Given that these anomalies appear in mainland Chinese banks, but not in Hong Kong banks, and that their magnitude corresponds to the political and financial sensitivity of the data type, it is difficult to imagine a plausible data generating mechanism other than deliberate fraud. Since human nature is such that people tend not to hide good news, it is reasonable to conclude that the volume of non-performing loans held on the balance sheets of mainland Chinese banks is significantly larger than claimed. Perhaps most troubling for the world economy is that the blind spot created by the attempt to conceal the true volume of NPL's is growing.

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