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Karlo Kauko

Benford's law and Chinese banks' non-performing loans



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Abstract

Benford's law states that the leading significant digits in real-world data sets, provided the data span several orders of magnitude, are not normally uniformly distributed. Deviations from this law may indicate human intervention, even fraud. The data on Chinese banks' non-performing loans has sometimes deviated from Benford's law. Up to 2012, the frequency of ones as leading significant digits was lower than predicted by Benford's law. Surprisingly, the number of ones well exceeded the expected level for large and government-owned banks during 2015–2018.

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1 Introduction

Newcomb-Benford's law (Newcomb, 1881; Benford, 1938), or Benford's law for short, states that the number 1 appears as the leading significant digit about 30.1% of the time in many data sets. Each number has a given frequency as the leading significant digit when the data follows this law. More precisely, the frequency of a as the leading significant digit is $\text{Log}_{10} [(1+a)/a]$, implying, for example, that the frequency of the number 9 as the leading significant digit is about 4.6%. (Benford, 1938). A somewhat similar regularity applies to second and third digits, although the frequencies are less skewed (Newcomb, 1881). This regularity applies to many, if not most, data sets consisting of measurements. As concluded by Fewster (2009), data from almost any distribution will follow the law as long as the distribution is reasonably smooth on the log-10 scale, and the distribution spans several orders of magnitude. The most notable exception to Benford's distribution, which applies to data generated by an astonishingly diverse range of processes, are data sets created by the human mind.

A fraudster would not necessarily be aware of this regularity, so numbers chosen at random by a person do not normally adhere to Benford's law. Therefore, as originally suggested by Varian (1972), deviations from Benford's law can be used to detect fraud. In a controlled experiment, it was found that the first digit of made-up numbers can be skewed even when the test subject is unaware of Benford's law; even if the frequency of ones in this experiment was significantly higher than 11.1%, the outcome grossly violated Benford's law (Hüngerbühler, 2007, p. 21). Deviations from Benford's law have been applied to detecting fraud in e.g. macroeconomic statistics (Rauch et al., 2011) and accounting data (Davydov and Swidler, 2016; Durtschi et al., 2004). The law has also been used to detect money laundering, because, unlike the values of genuine business transactions, the size of bogus transactions does not follow Benford's law (Badal-Valero et al., 2018).

Awareness on Benford's law is increasing. While Google access in China is limited, Google Trends data indicate a limited, yet increasing, interest in Benford's law since 2013. There were five searches with this term in 2012, 28 searches in 2013, 89 in 2014 and 165 in 2018. There was no comparable increase in overall Google searches from China in the mid-2010s.

Can Benford's law be applied to the data on the non-performing loans of Chinese banks? Taking the definition of the Basel Committee (2016) for a non-performing loan (NPL) as a loan that is at least 90 days overdue, had its value adjusted downwards or a loan on which the customer has defaulted,¹ it is realistic to assume that Benford's law applied even to NPLs, especially with a broad

¹ The existence of collateral should not affect this classification.

size distribution of banks, which is certainly the case in China. Moreover, Mayo (2015) concludes that the NPL data for Hong Kong banks do not significantly depart from Benford's distribution.

Chinese banks are sometimes accused of underreporting their NPLs or flouting international standards. A report of FitchRatings (2016) expresses such concerns, asserting that Chinese bankers do not always classify loans in arrears as non-performing, e.g. in cases where the loan had been granted to comply with government-issued guidelines or if the bank anticipates governmental support measures. The IMF's 2016 Financial Stability Report (IMF, 2016) presents estimates indicating that the amount of dubious loans in Chinese banks is much larger than officially reported. Mayo (2015) concludes that the official NPL numbers for Chinese banks do not follow Benford's law (the number one was the leading significant digit in less than 25% of cases). However, the data used in Mayo end in 2011, before the slow-down of the Chinese economy (see e.g. Kerola, 2019). The evolving macroeconomic situation has probably affected NPLs and the incentives not to openly disclose them in subsequent years. The following analyses test the validity of Benford's law with newer data, and tests hypotheses on the drivers of deviations.

As we will see in the following, an astonishing new pattern has emerged since economic growth began to slow in the mid-2010s. The number of ones as the leading significant digit has systematically exceeded 30.1% since 2015, especially in the case of large and government-owned banks.

2 The data and its distribution

The sample covers the period 2009–2018, with data collected from several sources. In total, there are 199 banks, and the maximum number of valid observations for one year is 155. There are very few observations for 2018. Data for several major banks are taken mainly from Bankscope and Fitch, but most of the data have been gathered manually from annual reports posted online.² About half of the banks of the sample in this unique data set are city commercial banks. Data are also available for rural commercial banks, joint stock banks, the “big five” state banks and numerous foreign banks. Policy banks and banks based in Hong Kong are excluded.

The most important variable is the yuan sum for NPLs disclosed in annual reports. Chinese banks come in many sizes, and their loan portfolios vary considerably in quality. The sum of NPLs in the sample range from CNY 300,000 to CNY 1.204 trillion. Here, however, the focus is simply on the leading significant digit. Tabulating the distribution of leading significant digits for each year

² The same database has been used by Fungáčová et al. (2020)

separately in Table 1, we see from the Chi-squared statistics that deviation from Benford's distribution is statistically significant at the 5% level in 2011, 2014 and 2015. Applying a simple statistical test such as chi-squared for a pooled sample would be misleading because the observations for consequent years are not independent of each other. In many banks, the NPL sums change rather slowly, and the leading significant digit remains constant.

Table 1 Distribution of leading significant digits

Leading significant digit, % of cases	1	2	3	4	5	6	7	8	9	Total banks	Chi-sq (relative to Benford's distribution)
2009	25.8	17.7	14.5	10.5	4.0	4.0	9.7	6.5	7.3	124	10.5
2010	25.2	23.0	9.6	6.7	5.2	10.4	6.7	8.1	5.2	135	12.2
2011	25.8	19.2	9.3	11.9	6.6	6.6	7.9	10.6	2.0	151	15.8**
2012	22.6	18.1	14.8	11.6	7.7	4.5	7.7	7.7	5.2	155	8.5
2013	28.4	13.5	17.0	11.3	9.9	3.5	8.5	5.7	2.1	141	10.8
2014	31.0	14.2	3.2	10.3	11.6	8.4	9.7	8.4	3.2	155	23.0***
2015	39.5	12.1	8.9	8.1	2.4	6.5	8.9	10.5	3.2	124	21.7***
2016	38.6	17.3	7.1	10.2	4.7	5.5	3.1	7.1	6.3	127	11.3
2017	39.2	20.8	10.0	5.8	4.2	4.2	3.3	9.2	3.3	120	15.2*
2018	60.0	40.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5	5.5
Total	30.4	17.4	10.4	9.7	6.5	6.0	7.4	8.2	4.1	1237	
Expected	30.1	17.6	12.5	9.7	7.9	6.7	5.8	5.1	4.6		
Euro area, latest obs.	30.2	18.0	12.4	9.6	8.1	6.5	5.9	4.7	4.5	2860	1.8

Recent data on Euro-area banks in the last row of Table 1 bolster the evidence on the tendency of NPLs to follow Benford's law. As of October 2019, the BankFocus database included 2,860 Euro-area banks with valid non-zero NPL numbers. The number one appeared as the leading significant digit in 865 banks (30.2% of cases) of the latest available NPL (mostly December 2018, for some banks 2017). If one evaluates the whole distribution of leading significant digits, Benford's law holds quite well for the Euro area.

In the whole sample of Chinese banks, the frequency of the number 8 is systematically higher than expected. It differs from the expected frequency by a larger margin than the frequency of any other number. For 2011 alone, the cumulative binomial distribution implies that the deviation from Benford's distribution is statistically significant at the 1% level. Be it a coincidence or not, the number 8 has traditionally been the lucky number in Chinese numerology, and it has reportedly affected economic decisions in the Chinese cultural sphere. Chau et al. (2001) found that in Hong Kong, flats with an 8 in the floor number sell for higher prices during property booms. The count of the number 8 boosts the price in auctions of vehicle license plates (Ng et al., 2010).

A surprising pattern can be seen in Column 1 of Table 1. The average value of NPL1 was less than 0.301 until 2013, which is consistent with what Mayo (2015) found for the period 2003–2011. A classic interpretation of deviations from Benford's law would suggest that some banks had reported NPL sums that people deliberately adjusted (and possibly fabricated) at the loan-portfolio level. However, this deviation is relatively minor, implying that most numbers likely reflect genuine observations and non-manipulated measurements.

For the years 2013 and 2014, the number of ones is about what one would expect. Even in 2014, when the overall distribution of leading significant digits grossly violates Benford's law (see Table 1), the number of ones is still close to what would be expected.

During 2015–2017, the number of ones climbs to almost 40%, deviating from the expected 30.1% statistically significantly at the 1% level for each year when the probability is assessed with the cumulative binomial distribution and if NPL numbers of different banks are independent of each other. There is no obvious explanation for this phenomenon. The previous literature does not address the overabundance-of-ones issue beyond the observation by Durtschi et al. (2004, p. 31), whereby, before initiating payments to regular payees, an employee accumulated payables until the sum exceeded a certain round threshold level. Even in this case, the deviation from Benford's law was a sign of human intervention. The data were not generated by a blind process.

3 The situation since 2015 – panel logit analyses

The most astonishing finding in Section 2 is the disproportionately large number of ones as the leading significant digit in the period 2015–2018. To study this anomaly in more detail, the leading significant digit of Chinese banks' NPL sums is converted into a binary variable such that NPL1 equals one if the leading significant digit equals +1, zero otherwise. Because the frequency of the number one is relatively high, it is relatively easy to study which background factors are statistically related to its occurrence.

If significant deviations from Benford's law, irrespective of the nature of the deviation, are signs of account manipulation, banks must have a reason to deliberately publish misleading numbers. Possible explanations for why a bank might do this include:

- Publicly listed banks seek to manipulate their share prices.
- Weakly capitalised banks resort to accounting fraud to maintain their credibility in the eyes of financiers. This is especially likely if the bank is dependent on interbank funding. A bank could also commit fraud to buy time in the face of impending illiquidity.
- Banks with shaky loan portfolio quality face strong incentives to underreport their NPLs.

- Managers attempt to hide their problems from the owners, even in the case of non-listed companies. Government-owned banks have an additional motivation to misrepresent their accounts if dishonest bank managers are striving to maintain good reputations in the eyes of government officials.

These potential explanations can be tested with logit analyses. As to the first potential explanation, the dummy variable *Listed* equals +1 if the bank is listed on a stock exchange. As to the second possibility, two explanatory variables are tested. *CAR* is the capital adequacy ratio. *IBF* is the ratio of interbank deposits (on the liability side) to the balance sheet total. The third hypothesis is tested by *RelatNPL*, the ratio of NPLs to total assets. This variable is problematic to the extent it does not properly measure the quality of the loan portfolio if a bank underreports its NPLs (an unlikely occurrence when loan quality is good). As to the fourth possibility, *GovOw* is the ownership share of public-sector owners among the ten biggest shareholders. To limit endogeneity issues, explained variables are lagged by one year. The panel logit analyses are presented in Table 2.

The logarithmic real equity capital [$LnEquity = \ln(\text{Equity capital}/\text{CPI})$] is used as a control variable. This is a less endogenous measure of bank size than balance sheet total, which is determined by e.g. the size of the loan portfolio, including non-performing loans. Due to missing explanatory variables in many cases, Table 2 has fewer observations than Table 1.

Table 2 Dependence of the number 1 as the leading significant digit on bank specific variables, 2015–2018, logit analysis

N	221	221	224	242	239
Banks	81	81	82	87	87
Years	2015-2018	2015-2018	2015-2018	2015-2018	2015-2017
Year dummies	Yes	No	Yes	Yes	Yes
GovOw (-1)	0.014 (2.6)***	0.014 (2.5)**	0.014 (2.6)***	0.012 (2.2)**	0.012 (2.2)**
IBF (-1)	-0.833 (-0.7)	-1.411 (-1.1)	-0.658 (-0.5)		
CAR (-1)	0.060 (0.7)	0.055 (0.7)	0.069 (0.7)		
Listed (-1)	-0.851 (-1.9)*	-0.943 (-2.1)**	-0.866 (-1.9)*	-0.809 (-1.9)*	-0.809 (-1.9)*
RelatNPL (-1)	28.715 (-0.9)	40.664 (-0.9)	-32.576 (-0.9)		
LnEquity (-1)	1.03E-03 (3.4)***	-8.71E-01 (2.9)***		1.25E-03 (6.3)***	1.25E-03 (6.4)***
Constant	-2.224 (-0.8)	-0.872 (-0.7)	-2.204 (-1.0)	-1.625 (-0.9)	-0.832 (-2.6)***
Wald Chi-sq	217.0***	179.0***	13.7*	712.6***	717.5***

Population averaged; robust std errors; within panel correlation autoregr order 1
Year dummies for 2015, 2016 and 2017 in eqs 1, 3 and 4; for 2015 and 26 in eq 5;
***, ** and * denote 1%, 5% and 10% significance, respectively; z stats in parentheses

Public listing does not appear to explain the anomalous abundance of ones. Instead of having too many ones, banks quoted on a stock exchange had fewer ones as the leading significant digit in 2015–2018 than other banks. About 27% of observations in the regression for 2015–2018 were for listed banks. In somewhat less than 30% of cases, NPL1 was 0 for listed banks. Capital adequacy and interbank funding seem irrelevant explanatory variables.

Government ownership has the opposite effect. In Table 2, government ownership is statistically significant in every equation. If we exclude cases where *GovOw* was less or equal to 50% or missing, there are 324 valid observations in the entire sample. In 133 cases (41.0%), the leading significant digit is 1. For the 52 cases where government ownership was less or equal to 50% among the ten biggest shareholders, the average of NPL1 was 0.288. Somewhat surprisingly, bank size seems to be the strongest explanatory factor. NPL1 equals one for large banks far more frequently than for small banks.

As to the “big five” group of massive government-owned banks, NPL=1 for nine of the 18 valid observations in 2015–2018. Testing the validity of Benford's law in this sub-group separately would not be meaningful due to the limited number of observations and the fact that their NPLs do not span several orders of magnitude. Interestingly, Bai et. al. (2019) found that moral hazard is particularly accentuated in Chinese state-owned banks and mitigated in listed banks; the explanatory power of *Listed* and *GovOw* may be primarily related to risk-taking incentives, not to incentives to hide problems.

4 Conclusions

This paper presented some observations on the frequency of different numbers as the leading significant digit in Chinese banks' non-performing loans, revealing that this distribution was not always consistent with Benford's law. Prior to 2013, the frequency of ones was systematically lower than 30.1%. This finding is consistent with the traditional explanation of manipulation of accounting data. Even the IMF has questioned the reliability of Chinese banks' NPL data.

More interestingly, however, the number of ones as the leading significant digit is abnormally large among government-owned banks in 2015–2018. This finding does not comport with any of the previous literature on deviations from Benford's law. Lacking any obvious explanation for this phenomenon, it may indicate that NPL data since the mid-2010s have been generated by a process that involves more human decisions that favour the number 1 rather than a mechanistic application of accounting rules at the loan level. The abnormally high frequency of ones is observed in large government-owned banks not listed on a stock exchange.

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