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Karlo Kauko

The vanishing interest income of Chinese banks

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Abstract

Chinese banks likely have more non-performing loans (NPLs) than officially reported. As hidden NPLs earn no interest income, loan quality problems may erode the gross interest income of banks. Using stochastic frontier analysis, we estimate the interest income of a hypothetical profit-maximising Chinese bank with no credit quality problems. Taking the deviation of actual interest income from the calculated efficient income, we then attempt to reveal the amount of hidden NPLs in Chinese banks. Our results uncover a substantial weakening in the quality of Chinese bank loan portfolios in 2016. Big banks are found to have the largest reservoirs of hidden NPLs. Dependence on interbank funding also seems to be a determinant in the size of hidden NPL portfolios.

JEL codes: G21, O53

Keywords: China, banks, non-performing loans, NPLs, impaired loans

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1 Introduction

China's banking system, the largest in the world, saw its balance sheet total surpass the euro area's banking sector in 2016 (Cerutti and Zhou, 2018). Statistics published by the China Banking and Insurance Regulatory Commission (CBIRC) show that China's aggregate balance sheet reached CNY 268 trillion (about EUR 34.7 trillion) as of December 2018. For comparison, the aggregate balance sheet total of euro area banks at that time was EUR 32.1 trillion.

Chronic loan quality issues are a pervasive feature of Chinese banking. Indeed, there seems to have been a kind of normalisation of arrears among Chinese corporate debtors in the previous decade, with companies following each other's example in deliberately postponing loan servicing (Li and Ng, 2013). More importantly, the ubiquity of poor risk management policies in lending seems to reflect structural and institutional specificities that repeatedly induce banks to grant loans to borrowers with abnormally high credit risks (Avgouleas and Xu, 2017). Data from 1999–2004 suggest that banks demonstrated no observable tendency to favour well-performing, creditworthy firms over sickly firms in their lending decisions (Bailey et al., 2011).

These long-lasting structural problems relate to bank ownership and bank objectives. Most banks in China are government owned, which means that public officials can use bank lending as a policy tool. "Window guidance" policies, i.e. explicit instructions on how banks should allocate credit and the amounts they should grant, are an essential part of the Chinese monetary policy toolkit (see Angrick and Yoshino, 2018). Banks were recently instructed, for example, to provide financing to small and medium-sized enterprises, or SMEs (PBoC, 2019, p. 9–10).

Banks with politically connected directors are more likely to have loan quality problems (Liang et al., 2013). Moreover, the tendency of banks to favour public enterprises is obvious and predictable to the extent that expectations on the continuance of these practices affect customer behaviour. Government-owned companies retain smaller cash buffers than privately-owned companies, presumably because they can always obtain credit from state-owned banks irrespective of their creditworthiness (Megginson et al., 2014). The privileged access to finance of state-owned enterprises (SOEs) even affects monetary policy transmission (Chen et al., 2019). Bank lending decisions can be used as a countercyclical policy tool. For example, the large state-owned banks responded to the outbreak of the 2008 global financial crisis by increasing lending, probably because of governmental guidelines (Zhang et al., 2020). While the degree to which these measures helped stabilise the economy can be debated, the impact on bank credit risk was indisputable.

The Basle Committee (2016, p. 8) defines a non-performing loan (NPL) as a loan that is at least 90 days overdue which has had its value has been adjusted downwards or otherwise "defaulted" under the Basel framework. Collateralisation of the loan is irrelevant to this classification. China's official ratio of NPLs to total loans is fairly unimpressive. Only about 1.8% of outstanding lending was classified as non-performing as of end-2018 (CBIRC, 2019). This is not the whole story, of course. While no precise statistics are available, Fitch Ratings (2016) posits that as much as 20% of loans could *de facto* be classed as non-performing. The IMF's 2016 Financial Stability Report (IMF, 2016) suggests the amount of doubtful loans was much larger than officially reported. Maliszewski et al. (2016), in their presentation of data on various categories of sub-standard loans in China such as "special mention loans" and "loans potentially at risk," note that the aggregate figures are much higher than official NPL ratios.

Auditors face minimal risk of litigation over malfeasance from private shareholders, so their main concern is potentially severe government sanctions (Lisic et al., 2015). Thus, it seems quite plausible that auditors do not always demand that claims on politically favoured, yet insolvent, state-owned companies be classified as NPLs. Outright accounting fraud is not deemed unusual in China (Lisic et al., 2015).

Unlike ratings agencies and policy-oriented international observers, who have questioned the official NPL data for Chinese banks, the face-value treatment of NPL data by academic researchers is somewhat puzzling. For example, Zhang et al. (2016) find that an increase in the NPL ratio raises riskier lending, presumably because of moral hazard. Wan (2018) studied the relationship between house prices and NPLs. Bian and Deng (2017) note that higher bank ownership dispersion reduces NPLs. This disparity in approaches may be due to the limitations of what is feasible in research. Econometric methods are necessarily based on available data, and by definition official data on undisclosed NPLs are unavailable. While it is conceivable that one could use purely theoretical models on incentives not to openly disclose NPLs in a government-owned, politically connected banking system, no such contributions appear to have been published yet. There are, however, several theoretical contributions on the potential benefits of opaque banking that do not directly address ownership issues (see e.g. Bouvard et al., 2015; Goncharenko et al., 2018).

Thus, the following analyses contributes to filling the gap between widespread scepticism towards official NPL figures and the tendency of econometric research to take official NPL data as given. We propose a novel method to identify hidden NPLs in order to test for the existence of hidden NPLs and shed light on bank decisions not to disclose their true amount. To our best knowledge, no previous contributions have addressed the drivers of hidden NPLs with econometric tools. By definition, the interest income of a bank diminishes when claims on customers become NPLs, so the existence of hidden NPLs is likely if a bank earns less interest revenue than comparable banks with ostensibly similar loan portfolios. To tease out hidden NPLs, we first estimate potential interest income using stochastic frontier analysis. The gap between actual and potential interest income is measured with available data, which, despite its imprecision and possible upwards bias, nevertheless reflects the state of the loan portfolio. As shown in section 4.2., the indicator covariates with disclosed NPLs in the expected way. Hidden NPLs are found to be particularly commonplace in banks that rely on interbank funding, presumably because banks want to appear sound to be able to renew funding from short-term financiers. Somewhat surprisingly, strongly capitalised banks appear to hide more NPLs on their balance sheets than weakly capitalised banks. Hidden NPLs seem particularly commonplace at China's large banks.

The rest of the paper is organised as follows. Section 2 describes the data. Section 3 presents hypotheses to be tested. Section 4 describes in detail how the proxy indicator of hidden NPLs is derived, and tests whether it is useful in assessing the NPL situation. Section 5 presents the empirical results on the drivers of hidden NPLs. Section 6 concludes and discusses the findings.

2 The data

The following analyses utilise a unique data set. The data have been collected from several sources. Some data on several of the major banks are taken from Bankscope and Fitch Ratings, i.e. sources frequently used in research on Chinese banks. As these agencies only cover a few major banks (i.e. an insufficient sample for the following analyses), the bulk of our data have been collected manually by Chinese trainees from annual reports posted online. This data set, also used by Fungáčová et al. (2020), is rich with information unavailable from most other sources. For instance, the data contain information on sectoral breakdowns of lending as reported in bank annual reports. As the publication of annual report is mandatory for listed banks, the coverage of publicly listed banks is likely quite high.

Because our intention here is to focus on relatively recent history, observations for the pre-2011 era are discarded. In most analyses, only 2013–2018 data are used. The strict lower limit for bank lending rates was not abolished before 2013, implying that interest rate data for earlier years should be analysed with different models. A form of "soft" interest rate regulation, which was based on prime rates set by the central bank, was in place during the sample period. Policy banks and banks based in Hong Kong are excluded. The sample is dominated by city commercial banks, i.e. banks with a license that are typically restricted geographically to a single city.

The largest number of banks that can be used in any of the following analyses is 131, but in many cases some variables are missing. The panel is unbalanced. Some banks may not have existed throughout the whole sample period. Very few banks had published annual reports for 2018 when the data were collected by early 2019. Some banks may not have published annual reports for each year, or the report had not been posted online.

Table 1 presents and defines the variables. No weighting is applied in the following analyses. Because listed banks are more likely to end up in the sample, averages of different variables may differ from those found in aggregate statistics. This is obvious when one looks at the data on government ownership. City commercial banks account for 52% of observations, rural commercial banks for 10%, joint stock banks for 10% and foreign banks for 23%. Also included are China's "big five" banks and a few banks not classified in any category.

Table 1 Definition and description of variables

Acronym	Interpretation & definition	Average value (arithm mean)	Std dev	Valid observ
CAR	Core capital adequacy ratio, end of December	13.7	10.4	730
Cash	(Cash and due from the central bank)/(Total assets), end December	0.128	0.050	726
CCB	Dummy variable for city commercial banks	0.521	0.500	722
ConstL	(Loans to construction companies)/(total loans), end Dec	0.052	0.039	730
CorpL	(Loans to the business sector in total)/(total loans), end December	0.785	0.308	730
CustDep	(Customer deposits)/(Balance sheet total), end December	0.651	0.121	730
GovOwn	Shareholdings of public sector entities, % of shareholdings of the 10 biggest shareholders	27.0	26.4	715
IBF	(Deposits from banks)/(Balance sheet total), end December	0.193	0.113	730
Listed	Dummy variable for banks listed on a stock exchange	0.175	0.380	725
LnEquity	Ln[(Equity capital/Consumer price index)], end December	7.663	1.743	730
LnRBalS	Ln[(Balance Sheet Total)/(Consumer price index)], end December	7.663	1.743	730
ManufL	(Loans to manufacturing companies)/(total loans), end Dec	0.239	0.153	730
NPL	(Published non-performing (impaired) loans)/(Total (gross) loans, end Dec)	0.015	0.050	580
PersL	(Loans to physical persons)/(total loans), end Dec	0.192	0.146	730
r	2*(Gross interest income on loans during the calendar year)/(Net loans end of year + Net loans end of previous year); If net lons for Dec of previous year not available, interest income/loans end of current year	0.064	0.018	730
RCB	Dummy variable for rural commercial banks	0.101	0.302	722
RealEL	(Loans to real estate companies)/(total loans), end Dec	0.078	0.058	730
ROE	Return on equity	0.232	0.447	730
Short	(Total Deposits, Money Market and Short-term Funding)/(Balance sheet total), end Dec	0.854	0.108	730
TradeL	(Loans to wholesale and retail companies)/(total loans), end Dec	0.163	0.087	730
y201x	Dummy variable for year 201x; separate variables for years 2012-2018			730

Cases where either year <2011, sectoral breakdown of lians is missing, CAR is missing or interest income on loans is either missing or obviously erroneous are excluded from this table and all the analyses.

The breakdown of loans by industry, which was based on information available in annual reports, was missing in some cases. Banks with missing data on the relative shares of borrower types and industries are excluded from the following analyses. The sum of corporate loans (CorpL) and loans to natural persons (PersL) is almost 100%, implying that loans have seldom been granted to private non-profit legal persons (such as associations) or public sector entities. Loans to mining, agriculture, utilities and services other than trade was included in CorpL, but did not show up in any of the industry categories.

Bank size is measured by two variables: real logarithmic balance sheet total (*LnRBalS)* and real logarithmic equity capital (*LnEquity)*. Equity capital is a less endogenous proxy for bank size than the balance sheet total, which depends on e.g. lending, including claims on insolvent customers. Because of capital adequacy requirements, equity capital has a direct impact on capacity constraints in lending. Interest income on loans is reported separately in annual reports and do not include interest income on assets such as bonds.

3 Hypotheses

We use the data to test a number of hypotheses. Our first hypothesis is simple, i.e.

H1) *Hidden NPLs exist.*

We also test several hypotheses on the determinants of hidden NPLs.

If a bank does not openly report its NPLs, there must be a reason for violating sound accounting principles. The two most obvious motivations for financial distortion are keeping financiers tranquil and avoiding bank runs. Financiers may even be aware that NPL data are not reliable and that such secrecy may have a rational basis. Jungherr (2018), for example, presents theoretical arguments for bank opacity such as the need to reduce the frequency of bank runs. Moreover, a bank is more likely to need opaque window-dressing when it is dependent on potentially unstable sources of funding or if there are factors that weaken the credibility of the debtor in the eyes of creditors prone to panic.

Pleasing select financier groups also seems relevant here. Retail depositors are unlikely to be the first in line to withdraw funding in reaction to accounting information, because they rarely follow information disclosures in any systematic way. China has had a deposit insurance scheme in place since 2015, and even before that retail depositors generally believed in the existence of an unofficial safety net that would protect them in the event of a bank failure. In contrast, counterparties in the interbank market are likely to move quickly withdraw short-term funding at the hint of bad news. This gives us our second hypothesis:

***H2)** Banks that rely heavily on interbank funding are more likely to have hidden NPLs.*

In some cases, banks may have access to insider information on each other through e.g. rumours or insider tip-offs, making it less worthwhile for banks to hide NPLs deliberately and potentially weakening this hypothetical effect.

The financial standing of the bank may also play a role, but two diametrically opposite hypotheses may be presented. Strong capital buffers and a steady income flow would maintain creditworthiness in the eyes of counterparties, even if the quantity of NPLs increases. In contrast, the credibility of a poorly capitalised bank may be unable to withstand additional adverse shocks. Therefore, weak banks have more incentive to hide problems in their loan portfolios. This gives us our third testable hypothesis:

***H3)** Banks with weak capital adequacy are more likely to have hidden NPLs.*

H3 may be valid as such, but there may be opposing effects. Strongly capitalised banks do not need to dispose of claims on customers by passing them on to the shadow-banking sector. Riskier borrowers, e.g. the real estate sector in China, are typically financed through off-balance-sheet arrangements (Allen et al., 2017: Chen et al., 2016). Thus, passing off loans to the shadow-banking sector probably improves the average quality of loans on the balance sheet. In the worst case, a high capital adequacy is a proxy for a general tendency to distort accounting figures. Thus, we offer a counter-hypothesis (CH) to H3:

***CH3)** Banks with strong capital adequacy are more likely to have hidden NPLs.*

Profitability may also affect hidden NPLs in two opposing ways. First, it can be hypothesised that high profitability improves the credibility of the bank in the eyes of any potential financier, reducing the incentive to hide NPLs, i.e.

***H4)** Banks with low ROEs are more likely to have hidden NPLs.*

While a bank's return on equity (ROE) could simply reflect its creditworthiness and financial strength, it could also be a proxy for risk appetite. Elementary economic theory tells us that abnormally high profits are not possible in a competitive market unless the company making high profits takes excessive risks or has a cost-efficiency advantage over its competitors. If high profitability is a sign of risk appetite, one would expect profitable banks to have substantial amounts of hidden NPLs.

***CH4)** Banks with high ROEs are more likely to have hidden NPLs.*

4 Constructing a hidden NPL indicator

4.1 Deriving the proxy indicator

By definition, there are no precise numbers on the quantity of undisclosed impaired loans (NPLs) in bank annual reports. Instead, the sum of performing or "healthy" loans (*L*), undisclosed "bad" loans (*M*) and disclosed NPLs are published as an aggregate, i.e. "gross loans." The amount of officially disclosed NPLs is also published. Thus, we start by determining difference between gross loans and NPLs (M+L = gross loans – impaired loans).

By construction, the gross interest income on loans is the quantity of claims on solvent and liquid debtors (*L*) multiplied by the average interest rate (*r**) of these loans. If there are undisclosed impaired loans, or loans that have been renegotiated because of customer insolvency (*M>0)*, their existence can be detected from the fact that they earn little or no interest revenue, unless the interest is otherwise continuously accrued in the P&L account (which is only possible for some temporary period).

Assuming that the income on *M* is zero, we write

$$(L + M)\, r = L\, \mathrm{r}^{*}, \tag{1}$$

where *r* is the average rate on the total loan stock excluding disclosed NPLs, but including loans to solvent customers and undisclosed impaired loans. A measure for the value of r in bank *i* year *t* is calculated with Equation 2 as

$$r_{it} = \frac{I_{it}}{(M_{it}+M_{i\,t-1}+L_{it}+L_{i\,t-1})/2}\,, \tag{2}$$

where *I* is the interest income on loans and the denominator is a proxy for the average size of the loan portfolio during the calendar year. Two abnormally high observations for one bank (r is several thousands of percent) are excluded from the data as obvious errors. By rearranging the terms in Equation 1, we calculate the relative share of loans with no interest revenue for bank *i* year *t* to obtain

$$\Omega_{it} = \frac{M_{it}}{M_{it}+L_{it}} = \frac{r^{*}{}_{it}-r_{it}}{r^{*}{}_{it}}\,. \tag{3}$$

If we can derive a proxy for r^*, we can also calculate the value of Equation 3. To do this, we re-purpose a well-known econometric method, stochastic frontier analysis (SFA), which traditionally has been used to estimate profit, production and cost efficiencies. In the case of profit efficiency, there is a maximum profit that can be achieved (efficient frontier), symmetrically distributed random variation around this level, as well as inefficiency-driven unidirectional deviations on the negative side. Maximal profit depends on such factors as prices of inputs and outputs.

The following analysis modifies this profit-efficiency concept to a narrow sub-component of bank net income, i.e. gross interest income on the loan portfolio. The explained variable is the average interest rate on loans of bank i year t (r_{it}). It is a function of a set of explanatory variables (x) and two error terms such that

$$r_{it} = \beta_0 + \sum_{j=1}^{k} \beta_i x_{jit} + \varepsilon_{it} + u_{it} \ . \qquad (4)$$

Our standard normally distributed error term ε_{it} consists of random variation, measurement errors and many symmetrically distributed unobserved bank specific factors. Notably, there may be forces that can cause only negative deviations from the level predicted by explanatory variables. The error term u consists of such inefficiencies. This inefficiency term is assumed to follow a truncated normal distribution so that only negative values are possible.

For the following analyses, the most interesting driver of u is the quantity of non-reported NPLs. If there are insolvent debtors not servicing their loans, and if the bank has not reported these loans as non-performing, a bank will earn less interest income on loans than banks with seemingly similar loan portfolios. Obviously, the quantity of non-reported NPLs cannot be negative, and this factor is asymmetrically distributed, causing income losses only.

A number of explanatory variables (x) are used. First, there are dummy variables for each year in the observation period (2012–2018). These variables capture e.g. variations in monetary policy and the macroeconomy. The rediscount rate used by the People’s Bank of China (PBoC) remained constant after December 2010, while the monetary policy stance was steered through such measures as adjusting the size of open-market operations and the rate of the standing lending facility (see e.g. Funke and Tsang, 2019). Second, Ln(Balance sheet total / Consumer Price Index) measures the size of operations. Bank size affects potential loan rates because it affects the set of corporate customers the bank can serve. A small credit institution would be unable to offer loans of the magnitude needed by a megacorporation. Third, there are dummy variables for banks with licenses to operate only within a given geographic area (e.g. city commercial banks or rural commercial banks). This restriction may affect bank behaviour by limiting opportunities for geographic diversification. Fourth, there are separate variables for the relative share of loans to different customer categories (real estate companies, construction, manufacturing, trading, corporate loans in total and natural persons).

SFA is used to estimate Equation 4. The first two columns of Table 2 present the results for the main estimation, the estimated beta coefficients and respective z-statistics. In the following sections, only the results of this first estimation are used. The other two estimations are provided here mainly for comparison. In estimation 2, we test whether restricting the sample to the period 2013–2018 (the years in our observation period after the abolition of interest-rate regulation) fundamentally changes the results. In estimation 3, two potential additional explanatory variables are tested.

Table 2 Panel stochastic frontier analysis on the determinants of r

	1		2		3	
	2011-2018		2013-2018		2011-2018	
	Coeff	z	Coeff	z	Coeff	z
CCB	0.0100	4.8***	0.0135	5.5***	0.010	4.8***
RCB	0.0138	4.2***	0.0184	5.3***	0.014	4.2***
RealEL	-0.0040	-0.4	-0.0029	-0.2	-0.004	-0.4
ConstL	0.0073	0.5	0.0207	1.1	0.007	0.5
ManufL	-0.0205	-3.6***	-0.0246	-3.7***	-0.020	-3.5***
TradeL	0.0144	2.3**	0.0079	1.1	0.014	2.3**
CorpL	0.0007	0.5	0.0003	0.3	0.001	0.5
PersL	0.0073	1.8*	0.0011	0.3	0.007	1.8
y2012	0.0028	2.4**			0.003	2.2**
y2013	-0.0028	-2.3**			-0.003	-2.3
y2014	-0.0021	-1.7*	0.0009	0.9	-0.002	-1.7
y2015	-0.0073	-5.9***	-0.0046	-4.3***	-0.007	-2.0**
y2016	-0.0173	-13.7***	-0.0144	-13.2***	-0.017	-4.2***
y2017	-0.0181	-13.5***	-0.0152	-13.1***	-0.018	-3.7***
y2018	-0.0181	-4.2***	-0.0152	-4.0***	-0.018	-2.7***
LnRBalS	-0.0007	-1.2	-0.0011	-1.7*	-0.001	-1.2
GovOwn					0.138	0.2
CorpL x Trend					0.000	-0.4
Constant	0.1380	0.2	0.1377	0.3	0.138	0.2
Sigma^2	1.91E-04		1.80E-04		1.91E-04	
Gamma	0.684		0.747		0.680	
Log Likelihood	2305.7		1735.2		2279.8	
Observations	722		533		715	
Banks	151		143		151	

As expected, year-specific effects seem extremely significant, while our regression coefficients are broadly consistent with the trend of the PBoC’s benchmark lending rate. The relative importance of various borrower categories is also important, especially in the case of manufacturing. Rural commercial banks and city commercial banks earn higher interest income than other banks in the sample. As can be seen in the second estimation, the results are not excessively sensitive to restricting sample length. Estimation 3 shows that ownership by governmental entities among the ten major shareholders and the interaction of the trend and the relative share of loans to corporate customers do not significantly affect the interest revenue at the efficient frontier.

Table 2 presents evidence on the existence of the unidirectional error term. The gamma value indicates that *u* accounts for about 68% of random variation in the explained variable *r*. While this percentage appears high and implies NPL ratios too high to be credible, it is significantly lower than the 0.95 reported by Jiang et al. (2013) for the interest-income efficiency of Chinese banks. Nevertheless, even if the estimates are upward-biased, the estimated values of Ω are a monotonically increasing function of the "true" underlying underperformance of the loan portfolio. If the true value of the efficient interest rate r^* is systematically lower or higher than its estimate, Equation 3 still classifies the levels of inefficiency correctly ($\partial\Omega/\partial r^* = r/(r^*)^2 > 0$) in the ordinal sense such that the conclusions in the following sections remain largely unaffected.

In the following sections, the proxy for the relative amount of non-performing loans in bank i year t is

$$\Omega_{i\,t} = \frac{r^*{}_{it} - r_{it}}{r^*{}_{it}} = \frac{[\beta_0 + \sum_{j=1}^{k} \beta_i x_{jit}] \ - r_{it}}{[\beta_0 + \sum_{j=1}^{k} \beta_i x_{jit}]}\ . \qquad (5)$$

In Equation 5, betas and x variables are from the first estimation of Table 2. If the analysis of Table 2 is carried out without data on the years 2011 and 2012, when the regulation of minimum lending rates was still enforced, estimated values of Ω would have been almost identical with those derived with the full sample. The simple correlation between the two proxies for hidden problem loans (*Ω*) is virtually perfect, about 0.998.

The average lending rate in the sample is about 6.4%, while the average interest rate at the efficient frontier is about 13.3%. The median value for Ω, about 52.4% over the sample period, seems high. The lowest median value (0.500) was reached in 2014 and the highest (0.576) in 2017. Because the actual interest rate can be higher than the one implied by the efficient frontier, there is no theoretical minimum value for omega, and the explained variable in the following analyses is not truncated, making following analyses technically slightly simpler. In fact, there are two negative values of omega in the sample. For 2013–2018, the average value of the indicator is about 0.49 for city commercial banks, about 0.50 for both rural commercial banks and joint stock banks and about 0.60 for other banks, indicating that foreign banks and the "big five" state banks are more likely to have underperforming loan portfolios, possibly because of frequent customer insolvencies.

The indicator is affected by other factors than mere customer insolvency, so it should not be seen as precise estimate of the quantity of hidden NPLs. Here are three possible additional reasons for a bank earning low interest income.

Market power: Some banks may have less market power than the average bank in the industry. The maximal market power prevails when the bank is a monopoly, but there is no banking monopoly in China. Thus, lack of market power should not cause unidirectional deviations on the negative side from a measurable and identifiable monopoly frontier. Variation of market power between banks would be included in ε, not in u in Equation 4. Thus, this factor cannot credibly explain why the values of Ω seem upwards biased.

High risk premia: A bank might lend to risky customers and charge a risk premium, even in a perfectly competitive market. There is no obvious upper limit for risk premia if the bank consciously chooses to go after high-risk customers. Thus, this is not a likely explanation for the existence of unidirectional deviations from the efficient frontier.

Non-profit objectives: Some banks may not seek to maximise revenue or profits. As is well-known in China, the government may encourage banks to supply funding to e.g. state-owned enterprises, small businesses or borrowers based in rural areas. A bank could ignore such guidelines and seek to maximise profits at the loan-decision level, which would set an efficient frontier for interest revenue. Unlike the two above-mentioned factors, non-profit objectives could also cause unidirectional deviations that would be included in u. Therefore, gamma in Table 2 could also capture intentions to grant funding under advantageous conditions to certain customer groups.

Thus, unidirectional deviations from the efficient frontier (u) are presumably driven mainly by two factors, namely hidden NPLs and non-profit objectives of banks. Other sources of variation are more likely to be reflected in the symmetrically distributed error term ε.

4.2 Testing the proxy indicator

The estimate of r^* derived from the results of Table 2 is likely imperfect and to be regarded with healthy scepticism. Does the indicator measure what it is supposed to measure? While the ratios it indicates are too high to be credible estimates of NPLs as such, the proxy should rank the quality of credit portfolios roughly correctly. As a side comment, it would be interesting to see the estimated Ω values of the Chinese banks bailed out in 2019. Unfortunately, these banks typically failed to release annual reports or their financial statements, making it impractical to assess the indicator.

The estimations of Table 3 focus solely on testing the usefulness of the indicator **Ω**. The idea behind these analyses is simple; NPLs cannot be simultaneously hidden and disclosed. If a bank with a given pool of overdue receivables discloses NPLs of CNY one million, the stock of non-disclosed bad debts instantly decreases by CNY one million as the hidden NPLs become disclosed NPLs. Thus, one must test whether the proxy for hidden NPLs typically diminishes when NPLs are disclosed. No hypothesised motives for non-disclosure are tested at this stage.

The sample has a relatively large number of cross-sections and a very limited number of time periods, creating a technical challenge for econometric analysis. Treating disclosed NPLs as a strictly exogenous variable would have little meaning, so panel OLS is not a well-suited method. Here, a dynamic two-step system GMM estimation is used instead to test whether the ratio of disclosed non-performing loans (*NPL*) to the sum of loans explains the development of Ω.

The analysis combines stock variables and flow variables. The variable Ω combines a flow measure cumulated during the calendar year with two end-year balance sheet figures. *NPL* reflects end-December data only. For instance, the value of *NPL* in 2016 refers to the situation as of December 2016, the value of Ω in 2016 depends on interest income between January 1 and December 31, 2016, and the loan stock assessment is taken from December 2015 and December 2016 (see Formulas 2 and 3). In order to cover roughly the same time period, the number of lags of a stock variable such as *NPL*, should preferably be one greater than the number of lags of the flow variable Ω. Thus, we test as potential control variables logarithmic equity capital, the relative shares of corporate and personal loans in December of the previous year and year-specific dummy variables as recommended by Roodman (2009). Because ambitious expansion often precedes bank difficulties (see e.g. Serrano-Cinca et al., 2014), an indicator of past growth is used as an instrument. The results are presented in Table 3.

As can be seen in each estimation, the immediate effect is statistically significant and relatively strong. If the bank openly discloses NPLs worth CNY one million , the estimated amount of hidden NPLs decreases by about CNY 450,000–550,000. This finding is consistent with the view that the indicator omega is driven to a large extent by decisions not to disclose NPLs.

Bank size does not seem to matter much. Interestingly, there was a positive shock to Ω in 2015 and again in 2016. Kerola (2019) asserts that these were particularly weak years for the Chinese macroeconomy. Although Ω can depend on several factors, these observations corroborate the view that it conveys a wealth of information about undisclosed NPLs.

Table 3 Two-step system GMM – dependence of hidden NPLs on disclosed NPLs

Explained variable = Ω	1	2	3
Observations	221	227	227
Banks	74	75	75
Instruments	44	40	62
Ω(-1)	0.86	0.833	0.703
	(12.1)***	(8.7)***	(6.2)***
NPL	-0.525	-0.448	-0.479
	(-3.5)***	(-3.5)***	(-2.2)**
NPL(-1)	2.359	0.206	0.863
	(1.8)*	(0.2)	(1.0)
NPL(-2)	-0.569		
	(-1.7)*		
LnEquity(-1)		-0.003	0.000
		(-0.7)	(0.0)
CorpL(-1)			-0.001
			(-0.2)
PersL(-1)			0.041
			(1.9)*
y2014		0.004	0.008
		(1.1)	(1.0)
y2015		0.017	0.017
		(2.7)***	(2.2)**
y2016		0.055	0.055
		(6.2)***	(6.7)***
y2017		0.017	0.019
		(1.6)	(1.6)
y2018		0.021	0.017
		(1.1)	(1.0)
Constant	0.074	0.111	0.138
	(2.2)**	(2.3)**	(2.7)***
AB Test for AR(2), z val	-0.21	1.55	1.50
P-value for AB test	0.83	0.12	0.13
Hansen test, Chi squared	49.49	35.36	55.10
P-value for Hansen test	0.12	0.23	0.29

Robust standard errors; z-stats in parentheses;
*, ** and *** denote significance at 10, 5 and 1 percent
Lagged regressors, CorpL and PersL as predetermined variables.
Year dummies and past growth (defined as
{LnRBAlS -1} - {LnRBalS -2}), RCB and CCB
as exogenous instruments;
2013-2018; collapsed instruments

5 Determinants of hidden NPLs

We presented several hypotheses in Section 3 on possible drivers of hidden NPLs. We now consider whether the potential drivers of hidden NPLs have any statistical connection to *Ω*. Partial correlation coefficients are used for this purpose. Both omega and its potential drivers are regressed on year-specific dummy variables, and the correlations of residuals are presented in Table 4. As an additional analysis, all variables are regressed on both year-specific and bank-type-specific dummy variables. Somewhat surprisingly, these findings strongly indicate that well-capitalised banks are more likely to have poorly performing receivables on their balance sheets. This may indicate that poorly capitalised banks passed their high-risk loans on to the shadow banking sector, a finding consistent with Counter-hypothesis 3 (CH3). Otherwise, these correlations seem weak.

Table 4 Partial correlation coefficients of Ω with both current and lagged values of hypothesised hidden NPL drivers

	Controlled for					
	year dummies			year dummies, CCB and RCB		
N=447	ROE	CAR	IBF	ROE	CAR	IBF
No lag	0.079	0.308***	0.022	0.054	0.216***	0.036
1 st lag	0.012	0.292***	0.058	0.003	0.191***	0.086
2nd lag	-0.060	0.280***	0.090	-0.046	0.178***	0.121**

*** = 1% significance; ** = 5% significance

We now test the hypotheses on drivers of hidden NPLs in a more systematic way. OLS analysis is not particularly well-suited to further analyses of data characterised by a very limited number of years, a large number of cross-sections and the potentially endogenous nature of the most interesting variables. There may be bidirectional causalities with unknown nature and complicated lag structures between *Ω* and its hypothesised drivers. Thus, as in Section 4.2, a two-step system GMM estimation is used. Both the suggested drivers and several control variables are tested as explanatory variables. The results for the various estimations are presented in Table 5.

Hypothesis 2 (H2) on the impact of interbank funding finds support in Estimations 1–6, although there is a lag before the effect can be observed. When one controls for openly reported NPLs in Equation 7 of Table 5, the effect of interbank funding disappears, which is consistent with the view that interbank funding affects hidden NPLs only to the extent that interbank funding affects NPL disclosures.

As to Hypothesis 3 (H3) and Hypothesis 4 (H4) on other drivers of hidden NPLs, the results defy expectations. There is no evidence that weak capitalisation would lead to large values of Ω. In

Estimation 5, a weak positive effect is found, which is consistent with the partial correlation coefficients presented in Table 4. While it is possible that the hypothesised signalling effect is there, strongly capitalised banks may not need to remove high-risk loans from their own balance sheets. In such case, the two effects would roughly offset each other.

In these estimations, the coefficient of the lagged value of Ω is surprisingly low in many estimations, indicating that the persistence of hidden NPLs is low. This is consistent with the view that non-disclosed NPLs are normally either reported openly or written off the books after a couple of years unless the customer recovers. It is also possible that banks are able to compensate for the lost interest revenue by charging higher rates for new loans.

Again, it appears that the quantity of hidden NPLs increases from 2016 onwards, the point at which the slowdown in Chinese economic growth gets underway (Kerola, 2019). The increase in hidden NPLs may also reflect China's tight monetary stance up to 2015, and the resulting transfer of high-risk loans from bank balance sheets to the shadow banking sector (see Chen et al., 2018). Most control variables seem insignificant. Surprisingly, even the overall amount of short-term funding (*Short*) seems irrelevant. Instead, the big banks have more hidden NPLs than small ones. This observation may be due to structural weaknesses that make big banks persistently cost-inefficient (see Fungáčová et al., 2020).

Table 5 Two-step system GMM on the determinants of hidden NPLs

	1	2	3	4	5	6		7
Observations	438	438	435	435	438	435		309
Banks	131	131	130	130	131	131		102
Instruments	49	76	93	93	76	38		58
Ω-1	0.668	0.498	0.349	0.249	0.420	0.733		0.489
	(8.2)***	(5.3)***	(3.5)***	(2.2)**	(3.7)***	(8.7)***		(3.8)
IBF		0.022	-0.186	-0.495	-0.062			
		(0.4)	(-0.8)	(-1.4)	(-0.7)			
IBF-1	0.170	0.191	0.193	0.157	0.132	0.126		0.030
	(2.8)***	(2.9)***	(2.3)**	(2.0)**	(2.0)**	(2.3)**		(0.4)
CAR		0.486	0.477	0.411	0.656			
		(1.4)	(1.1)	(0.9)	(1.9)*			
CAR-1	0.158	0.030	-0.04	0.029	0.018			
	(1.4)	(0.2)	(-0.1)	(0.1)	(0.1)			
ROE	0.222	0.005	-0.049	-0.035	0.002			
	(2.0)**	(0.8)	(-1.0)	(-0.9)	(0.3)			
LnEquity		0.009	0.015	0.015	0.009	0.009		0.008
		(1.9)*	(3.6)***	(2.7)***	(1.7)*	(1.8)*		(2.4)**
Cash			0.125	0.028			NPL	-0.444
			(1.5)	(0.3)				(-2.0)**
Short			-0.041	0.109			NPL (-1)	-0.292
			(-0.2)	(0.3)				(-0.3)
CorpL			0.007	0.006				
			(0.6)	(0.7)				
CustDep			-0.279	-0.458				
			(-1.2)	(-1.3)				
y2014				0.013	0.001	0.001		0.007
				(1.0)	(0.1)	(0.1)		(0.9)
y2015				0.013	0.019	0.017		0.023
				(1.0)	(1.6)	(1.7)*		(2.7)***
y2016				0.040	0.043	0.046		0.061
				(2.9)***	(3.9)***	(4.0)***		(5.6)***
y2017				0.031	0.030	0.346		0.498
				(2.2)**	(2.5)**	(3.0)		(3.0)***
y2018				0.024	0.056	0.020		0.039
				(1.4)	(3.2)***	(1.1)		(2.0)**
Constant	0.122	0.099	0.382	0.483	0.216	0.122		0.176
	(3.6)***	(2.1)**	(3.3)***	(3.8)***	(4.6)***	(2.3)**		(3.2)***
AB Test for AR(2), z val	-0.17	-0.47	0.01	0.00	0.11	-0.35		0.56
P-value for AB test	0.863	0.641	0.990	0.997	0.910	0.729		0.572
Hansen test, Chi squared	60.39	80.14	87.87	90.33	92.69	75.50		54.80
P-value for Hansen test	0.051*	0.149	0.282	0.125	0.176	0.134		0.203

Robust standard errors; z-stats in parentheses;
*, ** and *** denote significance at 10, 5 and 1 percent
Lagged regressors, LnEquity, Short, CorpL,
Cash and CustDep as predetermined variables.
Year dummies, RCB and CCB exogenous

6 Conclusions

This paper addressed the loan portfolio quality of Chinese banks. Given long-standing suspicions that Chinese banks hold substantial amounts of loans that should be classified as NPLs but are not, this is a challenging research topic.

While it is a tautology to say that the interest revenue of a loan portfolio is adversely affected when customers stop servicing their loans, the fact that a bank earns less interest revenue on its loan portfolio than other banks with apparently similar loan portfolios could indicate that not all debtors are servicing their loans as they should. Using stochastic frontier analysis (SFA), we calculated a bank's potential maximal interest income, then considered the gap between this level and the actual interest rate, which we assume to be indicative of loan quality problems. Given other potential explanations for weak interest revenue, our proxy indicator for missing interest income yields no precise statistics on the quantity of NPLs. Indeed, the estimates on the missing interest income appear too high to be credible NPL estimates as such. Granting funding at advantageous conditions because of objectives other than loan-level revenue maximisation is likely an additional factor that drives down gross interest revenue below the efficient frontier. Nevertheless, whenever a bank openly classifies loans as NPLs, the value of the indicator diminishes, indicating that secretive treatment of bad assets is almost certainly an essential driver of the indicator.

Perhaps surprisingly, the indicator for hidden NPLs is not characterised by high persistence. This may indicate that claims on insolvent customers are typically either written off the books or openly disclosed as non-performing within a couple of years delay after a customer has been given a chance to recover. It is also possible that banks react to debtor defaults by charging higher rates in new lending.

The results from testing the hypotheses presented in Section 3 can be briefly summarised as follows.

H1) *Hidden NPLs exist.* => Confirmed.

There is a substantial gap between actual and potential interest revenue. Estimations in Table 3 affirm the view that this difference is largely driven by the tendency of banks to avoid open disclosure of all NPLs.

An obvious reason not to disclose the poor state of the loan portfolio is the need to renew financing and obtain loans from risk-averse financiers. Hypotheses H2, H3 and H4 are based on this notion. The Counter-hypotheses CH3 and CH4 contradict Hypotheses H3 and H4. These results for the testing of these hypotheses can be briefly summarised as follows.

H2) *Banks that rely heavily on interbank funding are more likely to have hidden NPLs.* => Confirmed.

H3) *Banks with weak capital adequacy are more likely to have hidden NPLs.* => Strongly rejected.

CH3) *Banks with strong capital adequacy are more likely to have hidden NPLs.* => Confirmed (although the effect is a correlation rather than a causality).

H4) *Banks with low ROEs are more likely to have hidden NPLs.* => No evidence.

CH4) *Banks with high ROEs are more likely to have hidden NPLs.* => No evidence.

The most surprising finding is the strong evidence in favour of CH3. Strongly capitalised banks are less likely to hide non-performing loans, although the lack of significance in GMM estimations implies that this is a correlation rather than a straightforward causality. It is unlikely that strongly capitalised Chinese banks are mismanaged when their cost-efficiency is higher than weakly capitalised banks (Pessarossi and Weill, 2015).

Most of these testable hypotheses derive from the idea that banks try to minimise funding risks and keep providers of short-term capital tranquil by not disclosing the true extent of problems in their loan portfolios. There are other possible reasons for such secrecy, however. It is possible that banks try to prop up their own share prices. If listed banks try to boost the equity price by non-disclosure of NPLs, one could expect that hiding NPLs is particularly commonplace among listed banks. However, our preliminary results not reported in this paper found no evidence to suggest this was the case.

Another possibility relates to managerial career concerns and the need for managers to uphold their bank's good reputation. Feng and Johansson (2017) present evidence on the impact of firm performance on the career prospects of managers in Chinese state-owned enterprises. As starting point for hypotheses derived from this insight could be testable if individual-level data on managers and board members were available. For instance, we might hypothesise that managers approaching the age of retirement have no particular need for reputation-building, and thus might behave differently than their younger colleagues.

Although the results are tentative, they provide further evidence on the widespread existence of hidden NPLs. The existence of such loans has been acknowledged by Chinese authorities, and the government is about to take a tougher approach to solve the problem. In 2018, the Chinese Banking and Insurance Regulatory Commission required that by the end of 2019 city and rural commercial banks must classify all loans more than 90 days overdue as NPLs (see the article "Chinese Banks Face Tougher Rules for Declaring Nonperforming Assets" by Caixin News Agency, May 2, 2019). If properly enforced, this measure is a move in the right direction – at least from the point of view of the credibility of the accounting systems of Chinese banks.

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