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Non-performing loans, moral hazard and regulation of the Chinese commercial banking system

Dayong Zhang [a,*], Jing Cai [a], David G. Dickinson [b], Ali M. Kutan [c,d,e]

[a] Research Institute of Economics and Management, Southwestern University of Finance and Economics, China
[b] Department of Economics, University of Birmingham, UK
[c] Jiangxi University of Finance and Economics, China
[d] Southern Illinois University Edwardsville, USA
[e] The William Davidson Institute, University of Michigan, USA

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ABSTRACT

Non-performing loans (NPLs) represent a major obstacle to the development of banking sector. One of the key objectives of the banking sector reforms in China has therefore been to reduce the high level of NPLs. To do so, Chinese regulatory authorities have injected significant capital into the banking system and scrutinized NPLs since 2003. This paper examines the impact of NPLs on bank behavior in China. Using a threshold panel regression model and a dataset covering 60 city commercial banks, 16 state-owned banks and joint-stock banks, and 11 rural commercial banks during 2006–2012, we test whether lending decisions of Chinese banks exhibit moral hazard. The results support the moral hazard hypothesis, suggesting that an increase in the NPLs ratio raises riskier lending, potentially causing further deterioration of the loan quality and financial system instability. Policy implications of findings are evaluated.

1. Introduction

China has had a long-standing problem with non-performing loans (NPLs) as a major obstacle to the development of domestic banks. Previous work has identified that NPLs signal future financial problems for banks. Demirguc-Kunt (1989) and Barr et al. (1994) find that banks often have a high level of NPLs prior to their failure. Unlike other industries, in the banking sector the impact of failure of one bank can spread to others, causing a chain effect and likely shaking the stability of the entire system at home or even globally. The 2008 global financial crisis has shown how fragile the global financial system can be and that a financial crisis initiated in one country could affect not only the stability of the global banking system[1] but also be destructive to the real economy and financial system. Indeed, empirical evidence indicates that financial system development and banking reforms have significantly improved economic growth in China and promoted small banks (Hasan et al., 2009; Fang and Jiang, 2014; Peng et al., 2014; Lin et al., 2015).

Chinese policy makers have been moving forward with further financial sector reforms with the objective of building globally more competitive banks. As part of such efforts, Li Keqiang, the Chinese Prime Minister, signed the "Rules for Bank Deposit Insurance", effective on May 1, 2015. Attempts to reform the banking sector further requires a good understanding of non-performing loans and its implications for banking sector and financial stability. In addition, the nature of state ownership and associated soft budget constraints likely affect the moral hazard problem in the Chinese banking sector (Shi, 2004). China's banking sector has been relatively immune from financial crises due to strict government controls, which isolate the domestic financial sector from the developments in the global financial system. It is therefore timely to consider the extent of moral hazard issues in the Chinese banking sector and how it might be related to NPLs.

Since 2003, as part of the banking sector reforms, the Chinese government has injected significant amount of capital to the

* Corresponding author at: Research Institute of Economics and Management, Southwestern University of Finance and Economics, 555 Liutai Avenue, Wenjiang, Chengdu 611130, China. Tel.: +86 158 8113 9915.

E-mail address: dzhang@swufe.edu.cn (D. Zhang).

[1] For example, during the recent financial crisis of 2007–2008 period, Jo (2014) shows that U.S. financial shocks were transmitted to emerging market economies through the international lending activities of U.S. banks. Gang and Qian (2015) report that China's systemic risk increased in recent years since 2009 due to the contagion from the volatile global financial markets.

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banking sector (Jiang et al., 2013), which has resulted in declining NPLs ratios (defined here as the ratio of NPLs over total loans outstanding). According to the China Banking Regulatory Commission (CBRC), the recent average NPLs ratios are maintained within less than 2% across all banks. However, this does not necessarily imply that NPLs would not become a problem in the near future. Indeed, a sign of rebound in NPLs is observed in 2014 due to economic slowdown. The NPLs amounted to 842.6 billion RMB by the end of 2014, which is 255.5 billion RMB higher than the number at the beginning of the year. Although the average NPLs ratio is around 1.25%, troubled loans have had a ratio of NPLs reaching 3.11%, which corresponds to 4.36% of loans that are potentially in trouble. Another concern for policymakers is that the distribution of NPLs ratios is uneven across bank types. For example, at the end of 2013, the average NPLs ratio for rural commercial banks was 1.67%, but at the same year it was only 0.86% for joint-stock banks.

This paper aims to examine one particular aspect of China's banking sector, namely, the extent to which domestic banks face challenges in their lending relationships and engage in a risky behavior, which may further increase the moral hazard problem of the banking sector in the near future. Our contribution to the existing literature is twofold. First, we adopt a threshold approach to study the role of NPLs in signaling moral hazard problems. Second, we apply this model to the Chinese commercial banks in order to test the hypothesis in that troubled banks have incentives to take excessive risks, causing further losses and potential insolvency. Our proposed methodology and empirical findings have important implications for Chinese regulators facing high NPLs and potential moral hazard problems in the domestic banking sector.

Applying the threshold panel regression model to a dataset of 87 Chinese commercial banks from 2006 to 2012, we investigate whether banks' lending behavior is sensitive to reaching a particular threshold level of NPLs and, more importantly, whether banks with higher NPLs ratio tend to adopt a more aggressive and riskier lending strategy. We hypothesize that banks with higher NPLs ratio take more risks in order to offset the losses associated with NPLs and hence NPLs increase further as a result of higher loan growth. In addition to NPLs, this paper also considers the usefulness of the capital adequacy ratio (CAR) as an alternative regulatory measure, which is motivated by the recent major regulatory changes in China. In particular, the CBRC started considering the implementation of the Basel Accord in 2007 and subsequently adopted a stepwise strategy requiring banks that are concerned more with their international operations to apply the Basel Accord as early as 2011 but no later than 2013. Other commercial banks could choose to follow the Basel Accord voluntarily starting in 2011. The newer and stricter Basel III are to be implemented in 2015. The capital adequacy ratio required by the Basel Accord plays an important role in maintaining the stability of Chinese banks. Using the threshold approach we provide insights whether the use of both NPLs ratio and CAR together as regulatory tools can be of value to Chinese regulators seeking to understand the degree of bank risk and monitor it.

The structure of this paper is as follows. The next section briefly elaborates upon the background of our study and summarizes relevant studies in this area. Section 3 explains the methodology and empirical strategy. Section 4 describes the data used while Section 5 reports empirical results. Section 6 reports additional empirical results based on CAR measures and compares and contrasts the effectiveness of CAR and NPLs ratio as alternative regulatory measures. Section 7 provides some robustness analysis using data for different bank categories and also addresses the potential endogeneity bias problem by reporting estimates based on an instrumental variable approach. The last section concludes the paper with policy implications of the findings.

2. Background and literature review

2.1. Commercial banking system and regulations in China

Historically, the People's Bank of China (PBC) was the only bank in China, acting partly as the central bank and partly in the role of commercial banks ('mono-bank system', Lin and Zhang, 2009). As part of market economy reforms, initiated in 1979, the Bank of China, the China Construction Bank and the Agricultural Bank of China were established. In 1984, the Industrial and Commercial Bank of China was separated from the PBC and joined the others as one of the 'big four' state-owned banks. These banks now make up the foundation of the commercial banking system in China.

Alongside the introduction of the concept of a modern corporate system to the Chinese economy, banking reforms especially in terms of ownership structure have been taking place since the mid-1980s. The reforms are introduced in a series of joint-stock or joint-equity banks (Liang et al., 2013), such as the Bank of Communications, which was established in 1986 as the first countrywide joint-stock commercial bank; Shenzhen Development Bank Co., Ltd, which was established in 1987 as the first public listed bank; and the China Merchants Bank Co. Ltd., which was established in 1987 as the first enterprise-owned bank. In total, there are now 12 national joint-stock banks.

The reform of the commercial banking system in China has progressed further since 1994, including the establishment of policy banks and the promulgation of bank laws (i.e. the Central Bank Law and the Commercial Bank Law). Another exciting development has been the emerging of regional commercial banks with city and rural commercial banks as being the key components. By the end of 2012, there were 144 (337) city (rural) commercial banks operating in almost every province, with more than ten thousand branches across China. These banks have played quite an important role in China's regional economic development. In 2012, for example, the share of regional commercial banks in terms of asset values was around 14%, with a total value of over 18 trillion RMB (around US$3 trillion).[2]

Such a rapid expansion of the banking sector calls for a more sophisticated regulation system. On 25 April 2003, the China Banking Regulatory Commission (CBRC) was established under the direct administration of the State Council. The main role of CBRC is to regulate the banking institutions through formulating supervisory rules and regulations, authorizing the establishment of banking institutions, examining and enforcing rules, encouraging better/proper governance, collecting information and finding resolutions. As the banking sector grows, regulation issues become more complicated. Bad governance and excessive risk-taking may cause serious banking system instability and contribute to an economic crisis. The 2008 US sub-prime crisis is a good example. Conflict of interest and moral hazard in the banking industry are serious threats to the stability of the Chinese commercial banking system.

2.2. Moral hazard problems and non-performing loans

Bank managers may have incentives to take more risky lending than the optimal level. Jensen and Meckling (1976) suggest that two kinds of moral hazard problems generate such behavior. One is managerial rent-seeking, which takes place when managers pursue their private benefits by investing in 'pet projects' or through

[2] Source: China Banking Regulatory Commission (CBRC).

insufficient monitoring of loans. The other moral hazard problem arises from a conflict of interest between shareholders and creditors. Shareholders may want to make risky loans but eventually shift the risk to the depositors. Jensen and Meckling's (1976) theory implicitly suggests that both of these moral hazard problems lead to a higher loan growth rate and a larger number of NPLs.

Of course, moral hazard is not directly observable but can be inferred from observing bank behavior. As highlighted above, one of the main indicators of moral hazard problem is excessive risk-taking in lending. Foos et al. (2010) suggest that loan growth represents an important driver of the riskiness of banks. Studying the US, Canada, Japan, and European banks during 1997–2007, Foos et al. (2010) report that loan growth leads to an increase in loan losses during the next three subsequent years, causing a decline in both interest income and the capital ratio. Demirguc-Kunt (1989), Barr et al. (1994), Gorton and Rosen (1995), Berger and Udell (1994) and Shrieves and Dahl (2003) have further investigated the relationship between loan growth, non-performing loans and the risk-taking of banks. A sizable body of research also looks at moral hazard problems and the risk-taking behavior of banks in the context of shareholding structure. For example, Saunders et al. (1990) find that shareholder controlled banks are inclined to take greater risks than managerially controlled banks. Demsetz and Strahan (1997) report a positive and nonlinear relationship between market risk measures and managerial shareholdings. Jia (2009) shows that lending by joint-equity banks has been more prudent than lending by state-owned banks in China. Zhou (2014) show that the diversification of income structure of China's commercial banks has not significantly reduced banks' overall risk. Our study extends these studies by shedding further insights into the role played by shareholding structure on bank behavior and moral hazard in China's banking system.

Bernanke and Gertler (1986) point out that the impaired loans of banks may induce different bank behavior according to banks' risk preference. Prudential banks tend to be more cautious when they face increasing level of impaired loans. However, when the NPL ratio is too high, both the shareholders and bank managers have clear incentive to shift risks. Eisdorfer (2008) reports that financially distressed firms have greater risk-shifting behavior. Examining US banks, Koudstaal and Wijnbergen (2012) report that the more troubled the loan portfolio, the greater the inclination for banks to take risks. Bruche and Llobet (2011) argue that when banks face the threat of bankruptcy, they tend to roll over bad loans in order to increase their chances of recovery. The regulatory attitude is also important. Boyd and Graham (1998) and Nier and Baumann (2006) argue that when banks feel 'too big to fail' due to their big market power, or when they expect to be bailed out in case of insolvency, moral hazard problem becomes even more acute. Soedarmono and Tarazi (2015) show that greater market power in the banking industry can immediately lead to higher instability in the banking system in Asia–Pacific countries. Kim et al. (2015) also report that an increase in large banks' market power raises small banks' financial instability in Asian economies.

Evidence from above studies point out that the level of impaired loans (or NPLs) can be an important determinant of bank behavior causing them to behave differently from the norm when they face higher NPLs. We believe that the level of NPLs can be useful in identifying the presence of moral hazard in the banking sector. Hence, this paper identifies risky lending behavior and hence moral hazard conditional on a threshold level of NPLs that banks face.

2.3. NPLs, Moral Hazard and Banks in China

By the end of 2005, the CBRC announced the "Core Indicators for Risk Regulation and Supervision in Commercial Banks", which clearly state that NPLs ratio should not be higher than 5% and non-performing asset ratio should be lower than 4%.[3] Historically, Chinese banks have been considered as fragile due to the high proportions of NPLs and low capital adequacy ratios (Kauko, 2014), which is partially due to the dominance of lending to state-owned enterprises (SOEs) and strong government influence (Matthews, 2013). The level of NPLs ratio for state-owned banks (SOBs) in China has grown in the pre-reform period, reaching an average of 9.22% (CBRC, 2006).[4] Shi (2004) provides an interesting analysis of the mechanism of how commercial banks in China build up non-performing loans. He argues that the existence of dual soft budget constraints induces moral hazard in banking, causing more significant NPL problems. The argument is that, during the transition period when China switched from a centrally-planned economic system to a market-based economy, the government allowed soft budget constraints to both SOEs and SOBs. As a result, banks have had incentives to make loans to troubled firms due to the government's implicit guarantees to SOEs and hence to SOBs (Cull and Xu, 2003; Xie, 2003; Chen et al., 2013). As a result of this, Lu et al. (2005) suggest that Chinese banks have a systematic lending bias in favor of SOEs, which is more risky and has higher default risk.[5]

The Chinese government has injected substantial capital into the banking system during 2003–2008, allowing banks to write off non-performing loans and hence causing a significant fall of NPLs during that period (Dobson and Kashyap, 2006; Tan and Floros, 2013; Fu et al., 2015). Reviewing banking reforms in the late 1990s and early 2000s, Jiang et al. (2013) shows that the government has also injected significant amount of capital into SOBs. Such government support can induce moral hazard since banks become less efficient and make more risky loans due to implicit guarantees. Capital requirements alone may therefore not be sufficient to avoid banks from risk taking. For example, Haq and Heaney (2012) report evidence of a convex relationship between risk and bank capital for 15 European banks. Williams (2014) demonstrate a U-shaped relationship between bank risk and capital in the context of Asian regions.

3. Methodology

Banks may find their NPLs ratios to increase as a result of bad luck or bad management (Berger and DeYoung, 1997). In the case of the former we would expect that the bank will manage this process often by reducing lending and hence the NPLs ratio will fall. If the reason is bad management then we expect a rise in the NPLs ratio, which will be followed by additional risk-taking as managers attempt to reduce their losses through higher level of lending and hence by taking additional risk. One way of identifying such behavior and hence moral hazard is to examine whether there is a particular threshold value of NPLs ratio, such that above the threshold level risk-taking by banks rises and hence the NPLs ratio worsens.

To further motivate our using a threshold model and link NPLs with moral hazard problems, we may also need to refer back to Jensen and Meckling's (1976) theory on incentives. Managers of

[3] To support this policy we may note that the majority of the world top 100 commercial banks have maintained their NPL ratio within 5% threshold under stable macroeconomic conditions (The Banker, 2003).

[4] Matthews (2013) suggests that political influence rather than the standard market based risk management contributes to large number of non-performing loans. Luo and Ying (2014) find that Chinese firms with political connections obtain bank lines of credit, especially from state-owned banks. Yano and Shiraishi (2014) provide evidence that an increase in bank loans for non-state sector firms promote the development of financial intermediation in China.

[5] This problem is not confined to China only. For example, using data from German saving banks, Gropp et al. (2014) reported evidence of moral hazard due to policy intervention.

financial institutions have clear incentives to deviate from the interests of both investors and regulators. Moral hazard can induce excessive risk-taking, thus lowering asset quality, which eventually may cause the institution to fail. Moral hazard takes place when managers (agents) endeavor to optimize their own benefits, which are not consistent with the interests of the owners (principles). Keeley (1990) suggests that the agents can take full advantage of positive outcomes, but only bear limited responsibilities when they fail. Banks, especially Chinese commercial banks, have been insured implicitly by the central government, which leads to a higher possibility of moral hazard. Chinese bank managers are able to take excessive risks since they have nothing (or little) to lose but more to gain. Kahneman and Tversky's (1979) prospect theory also suggests that agents are risk-averse when facing sure gains, but they become risk-seeking when faced with sure losses. It is therefore reasonable to argue that bank managers have an incentive to increase risk-taking in a distressed situation.[6]

In other words, bank managers face a tradeoff between the cost and benefit for excessive risk taking.[7] Taking excessive risk may bring benefits to the banks in terms of having higher profits and improvement in reputation or to managers such as higher compensation or promotion opportunities. Managers can benefit from banks' better performance when they are in charge. Managers have clear incentive to polish their performance to gain political favor and promotion. They therefore may take high risk projects when facing financial distress. Such behavior is not unique to China. For example, Miguel and Ana's (2015) study on the core EU members' banking system also suggest the existence of moral hazard. On the other hand, excessive risk taking may be associated with further financial distress in the long-term, which can negatively affect the banks or managers. Bebchuk and Spamann (2010) and Bebchuk et al. (2010) suggest that the failure of big financial institutions in the 2008 financial crisis may be due to CEO's incentives to take excessive risks. Pierre (2013) reports that the design of CEO contract contributes to excessive risk taking than the social optimal level. Kim et al. (2014) report that banks in ASEAN countries engage more actively in risk-taking in the presence of deposit insurance (DI) causing DI-driven moral hazard. If bank managers expect that the government will rescue troubled banks, they may further increase excessive risk taking weighting the cost side considerations down. If banks anticipate that the government may intervene at a critical threshold level to save defaulting banks when the NPL reaches a certain level, then the banks may even increase the NPL ratio to such level.

Banks' day-to-day business involves a certain proportion of loans with problems. Hence we would not expect each bank to behave in a risky way. However, banks with loans above a particular threshold level would exhibit a riskier lending decision than those below that threshold level. Bank regulators may find useful to adopt a threshold approach to monitor NPLs and observe whether higher NPL levels are associated with risky lending and moral hazard.

This paper therefore uses a threshold regression model to identify moral hazard problems. The threshold regression model is designed to divide individual observations into regimes (classes) conditioned on the value of a predefined variable. The model we use here is based on Hansen (1999), which has been proved an effective tool when investigating possible asymmetric effects. It is also been used recently to study banking behavior. For example, Balboa et al. (2013) study a sample of US banks on the earnings-smoothing hypothesis allowing for nonlinear dynamics and threshold effects. In their model, the nonlinear relationship between bank earnings and loan-loss provisions is driven by managerial incentives.[8]

Given a balanced panel data (i for cross-sectional index and t for the time series part), the structural equation can be written as:

$$y_{i,t} = c_i + \beta_1 x_{i,t} I(q_{,it} \leqslant \gamma) + \beta_2 x_{i,t} I(q_{,it} > \gamma) + \varepsilon_{i,t} \quad (1)$$

where $I(\cdot)$ is the indicator function that takes value one if the statement in brackets is true, and zero otherwise, and $q_{i,t}$ is the predefined threshold variable. This model allows the threshold value to be chosen endogenously, and also allows a partial threshold effect. Based on this basic model, we can write the estimation equation according to the testable hypotheses as follows:

$$NPL_{i,t} = c_i + \sum_{j=0}^{m} \beta_{1,j} LGR_{i,t-j}(NPL_{i,t-1} \leqslant \gamma) + \sum_{j=0}^{m} \beta_{2,j} LGR_{i,t-j}(NPL_{i,t-1} > \gamma) + \theta' X_{i,t} + \varepsilon_{i,t} \quad (2)$$

The threshold variable is set to be the last period's NPLs ratio level. X is a vector that contains other explanatory variables. When banks experience significant loan losses (performing above the threshold value γ), their decision process is given by β_2 rather than β_1.

Regarding control variables, our first explanatory variable is the loan growth rate. Employing more than 16,000 individual banks data from 16 countries in the period before the 2008 global financial crisis, Foos et al. (2010) show that (abnormal) loan growth can cause significant subsequent losses with a lag of two to four years. Sinkey and Greenawalt (1991) and Clair (1992) also report evidence about the importance of loan growth on bank performance. Cottarelli et al. (2005) and Kraft and Jankov (2005) further analyze the role of loan growth in bank risk taking and resulting instability. Based on these earlier studies, we hypothesize a significant relationship between banks' loan growth rate and level of NPLs ratio in China. Normal loan growth associated with standard banking operations may reduce the NPLs ratio, but an abnormal growth rate would indicate a moral hazard problem causing subsequent further losses.

Our second explanatory variable is the bank size. The size of banks has often been considered as an important factor for NPLs. For example, Salas and Saurina (2002) argue that large banks have more diversification opportunities and thus can reduce the level of troubled loans. Rajan and Dhal (2003) report empirical evidence in support of such a relationship. Hu et al. (2004) suggest that large banks can evaluate loan quality better due to their richer resources. Wang (2014) reports that a larger bank size improves bank performance in Taiwan. As a consequence, the bank size is negatively associated with the level of NPLs. However, due to the 'too big to fail' arguments (see, for example, Louzis et al., 2012), we expect a positive relationship between the bank size and level of NPLs.

Louzis et al. (2012) use bank capital structure (leverage ratio) as another determinant of NPLs and suggest that, conditional on bank size, a higher percentage of liabilities can induce riskier behavior and thus increases NPLs. We use the equity ratio (1 minus leverage ratio) as one of the possible determinants of NPLs and its impact is expected to be negative. This may also relate to the level of capital adequacy arguments since a higher level of CAR or equity ratio both will reflect that the bank is relatively safer and will have lower NPLs (Berger and DeYoung, 1997 and Salas and Saurina, 2002).

[6] Similar arguments can be found in Keeley (1990), Allen and Gale (2001), Hellmann et al. (2000) and Repullo (2004).

[7] We thank an anonymous referee for suggesting this discussion.

[8] Other studies using threshold approach include, among others, Degeorge et al. (1999), Gasha and Morales (2004), Marcucci and Quagliariello (2009).

Deposits are also an important factor in bank balance sheets influencing the bank behavior and loan quality. Lepetit et al. (2008) suggest that the deposit to asset ratio can be considered as an indicator of bank's objective function. Soedarmono et al. (2012) report a positive relationship between the growth rate of the deposit to asset ratio and the ratio of loan loss provisions to total loans. Therefore we expect that the deposit growth rate could significantly affect NPLs as well.

Finally, many researchers find that macroeconomic conditions or business cycles can also contribute significantly to the level of NPLs. For example, Carey (1998) argues that a change in economic conditions is the most important systematic factor affecting bank losses. Using data on Italian banks, Quagliarello (2007) report evidence that business cycles affect NPLs as well. We include time dummies in the regressions to capture business cycles. Furthermore, the 2008 global financial crisis has had a strong negative impact on the financial sector. To control for the impact of the global crisis, a time trend is added into the regressions.

4. Data and descriptive statistics

Data are obtained from various sources to allow for the maximum number of observations, including Bankscope, Wind Info., and various bank annual reports. Since 2007, the China Banking Regulatory Committee has required all commercial banks to disclose their operational details and make their financial performance information available to the public. This helps us in the collection of reliable information for non-listed small- and medium-sized banks. As the threshold model of Hansen (1999) requires a balanced panel, we have had to drop some banks and observations from the sample, leaving us with data of 87 commercial banks for the period from 2006 to 2012. Our dataset includes 16 state-owned banks and joint-stock banks, 60 city commercial banks and 11 rural commercial banks, with a total number of 609 observations, which is significantly larger than most of the earlier studies on Chinese commercial banks. Policy banks are excluded from the sample due different ways of their operation. Given data availability problems, even though we have to drop a large number of city commercial banks and the majority of rural commercial banks, the sample of city commercial banks still represents an important part of our dataset in terms of asset value. The total capitalization ratio of city commercial banks relative to the country aggregate level in our sample ranges from 67 percent to 70 percent (CBRC).[9] The ratio in terms of total asset value for the full sample ranges from 72 percent to 75 percent.

In order to avoid inference problems caused by outliers, we further winsorize the data at 1% level. The key variables included are mainly balance sheet components (see Table 1 for the descriptive statistics). We observe that the size of operations of Chinese banks varies significantly from one to another. The largest bank at the end of 2012, the Industrial and Commercial Bank of China (ICBC), has more than 17 trillion RMB (or 3 trillion in US dollars) total capitalization, whereas the smallest bank in our dataset in the same year had only 8.7 billion RMB (or around 1.4 billion in US dollars) total capitalization. China's commercial banking system has grown significantly in the recent years. In terms of the loan growth rate, the average rate is 28.84%, while the largest growth rate has become 91.85% (after winsorizing). The deposit growth rate has exhibited a similar pattern in our sample period. In general, the level of capital adequacy in these commercial banks is reasonably high (12.46% on average) but with significant variations. For example, the highest level was 23.08% in 2011, while the lowest level was only 3.97% (after winsorizing). The same situation also applies to NPLs.

Table 1
Descriptive statistics of key variables.

Variables	N	Before winsorizing				
		Mean	Median	Min	Max	Std. Dev
LGR (%)	609	28.84	23.12	−48.48	1257.58	54.82
NPL (%)	609	1.92	1.19	0	29.49	2.49
DGR (%)	609	28.43	22.75	−35.19	454.52	29.86
ER (%)	609	6.3	6	−0.03	38.4	2.49
CAR (%)	609	12.46	12.02	−13.76	150.33	6.77
Size	609	18.13	17.77	14.39	23.59	1.88
Variables	N	After winsorizing				
		Mean	Median	Min	Max	Std. Dev
LGR (%)	609	26.27	23.12	−1.13	91.85	14.97
NPL (%)	609	1.83	1.19	0.17	11.07	1.88
DGR (%)	609	26.96	22.75	−1.61	92.4	16.52
ER (%)	609	6.26	6	1.6	14.4	2.11
CAR (%)	609	12.21	12.02	3.97	23.08	3.08
Size	609	18.13	17.77	14.39	23.59	1.88

Note: the variables names are in abbreviation, representatively standing for: LGR = loan growth rate, NPL = NPLs ratio (non-performing loans divided by total outstanding loans), DGR = deposit growth rate, ER = equity ratio against total assets, CAR = capital adequacy ratio, and Size = end-of-year total assets (in log term), respectively. The data, apart from the size, are winsorized at 1% level from both side to remove some extreme values.

5. Empirical results

To detect banks with high NPLs ratios that could behave differently from those with low NPLs ratios we set the threshold variable to be the last period's NPLs ratio. As discussed earlier, losses in one bank can generate incentives for bank managers to take excessive risks but only if they have a large negative impact on bank financial performance (i.e., the NPLs are relatively large). Incentives may not be directly observable, but the possibility of moral hazard could be inferred by examining bank behavior. Furthermore, by identifying a threshold value, we provide a useful indicator for regulatory authorities to monitor moral hazard problems and design policy strategies to reduce NPLs accordingly.

This study uses four threshold models, namely Models 2–5, based on Eq. (2)above. Model 1 is the benchmark linear model for comparison purposes. We first perform a Hausman test on the benchmark model and the statistic is 18.09 (p-value = 0.054), which favors the fixed effects model. Model 2 sets $m = 0$, which includes no lags of the loan growth rate but just the contemporaneous loan growth rate (LGR). Model 3, on the other hand, includes only the lagged LGR. Model 4 combines Models 2 and 3. Since the equity ratio over total asset value (ER) and capital adequacy ratio (CAR) are similar measures, Model 5 replaces ER with CAR to check the stability of Model 4. Dependent variables in all equations are expressed in current NPLs ratios.

The inclusion of lags of LGR in the models is important. Clair (1992) argues that the impact of a higher LGR is a deterioration in the quality of loans, but only with some lags, whereas the contemporaneous relation between LGR and NPLs ratio should be negative. For banks with significant previous losses (or NPLs), making additional loans (higher growth of loans) can reduce NPLs ratio temporarily, due to the dilution effect. However, while trying to achieve higher loan growth, banks may have to lower their standards or accept riskier applications, therefore potentially generating higher future losses. Hence we expect a positive relation between lagged LGR and NPLs ratio.

[9] We thank an anonymous referee for pointing out this sampling issue. The ratios of sample banks relative to country aggregate in terms of total assets are reported in Appendix B (see Fig. A1).

5.1. Threshold estimation

The first step of our empirical analysis is to identify the existence of threshold effects and to set the threshold value for each model. Table 2 reports the results for the Models 2–5. Since the LR_1 statistics are generally non-standard, we need to calculate bootstrap p-values.

The LR_1 test statistics are generally significant according to the bootstrap p-values. These results confirm the existence of the threshold effect in comparison with the linear model. The estimated threshold value γ indicates a NPLs ratio of 4.81%. To illustrate the identification of a 'non-rejection zone' when constructing confidence interval, Fig. 1 plots the LR_2 statistics against all possible threshold values. There are four panels representing each of the four models mentioned above. Given the way LR statistics are calculated, the value of LR_2 at the estimated threshold value $\hat{\gamma}$ will always equal zero. The dashed line depicts the 5% critical value (7.35).

Three of the confidence intervals reported in Table 2 are not closely bounded around the estimated threshold value (4.81%). For example, the interval for Model 2 is between 4.82% and 6.98%. Fig. 1 suggests that the reason for longer right tails of the interval is that there are a couple of small spikes. In general, the left bounds (lower bounds) of the interval are consistent, and close to the estimated threshold value. This is important for the purpose of policy design.

5.2. Regression results

After confirming the existence of a nonlinear threshold effect, we now proceed to evaluate the behavior of banks on both sides of the threshold. Before reporting regression results, we first observe the characteristics of banks that are either above or below threshold value in terms of NPLs ratio. We sort the banks above and below the threshold value according to three types: (1) state-owned and joint-stock banks, (2) city commercial banks, and (3) rural commercial banks. The bank-year number of observations and the associated shares in percentages are reported in Table 3. The majority of banks (92.8%) has their NPLs ratios lower than the threshold value (set as 4.81%). This is consistent with what we expect: banks may be affected by moral hazard problems, but only a small proportion of them with serious problems would actually behave accordingly. It is also interesting to see that banks subject to moral hazard problems are relatively more biased towards rural commercial banks and city commercial banks.

Table 4 reports the regression results for the five models. When no threshold effect is allowed, Model 1 shows that the only important factor, save the year dummies, is the bank size. The bigger the bank is, the higher the NPLs ratio will be. It is generally the case that bigger banks in China are state-owned. According to Jia (2009), these banks have been protected by the government and their lending behavior tends to have clear political motives. It is more likely that their loans go to low-efficiency industries owned by the state, which are also more likely to default, thus generating a high level of NPLs ratio. Coefficients on the year dummies are shown to have a downward trend. Obviously, the 2007–2008 financial crisis has had a negative and significant impact on the banking sector in China and its aftermath has faded slowly over time. In general, loan growth rate (LGR) and its lags are not statistically significant.

An interesting part of our estimations is when we take threshold effects into consideration and make a comparison across Models 2–4. The significant effects in the linear model remain the same for the year dummies and bank size. All the models here are considered to have partial threshold effects, in the sense that only LGR can be potentially affected by the managers' moral hazard problems. Model 2 includes only the current level of LGR and the threshold effect. It is shown in Model 2 that the loan growth ratio increases NPLs when banks have previous significant losses and reduces NPLs when banks are relatively safe. The same results are also observed in Model 3. A 15% additional loan growth (one standard deviation change) for those banks with higher NPLs ratios (relative to the threshold value) causes 0.9–1.05 percentage points increase in the NPLs ratio. Given the average annual loan growth rate of 26% for all banks and an average of 1.83% for NPLs ratio, aggressive lending of those troubled banks can bring serious trouble.

Table 2
Estimation of threshold effects.

Model	Threshold ($\hat{\gamma}$)	Conf. interval (95%)	SSE_{min}	LR_1 Stats.	P-value
2	4.93%	[4.82%,6.98%]	327.57	37.8	0.02
3	4.81%	[4.32%,7.09%]	282.75	116.53	0.00
4	4.81%	[4.03%,4.86%]	277.23	123.4	0.00
5	4.81%	[4.03%,7.09%]	269.93	112.61	0.00

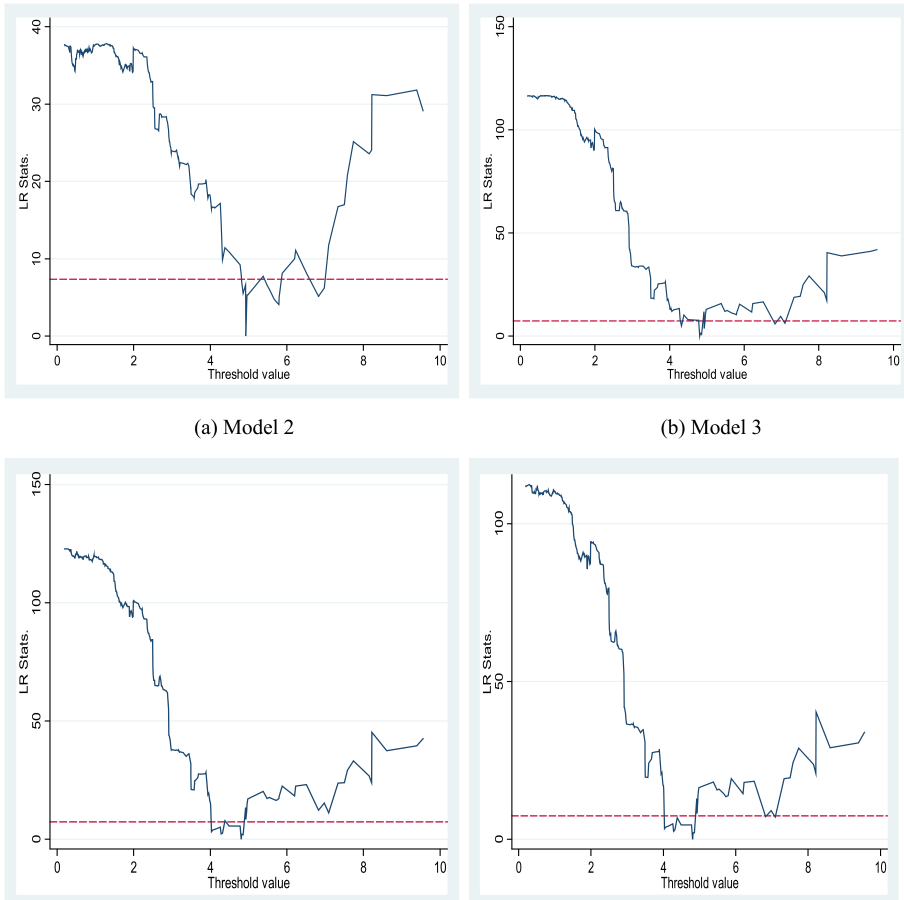
Note: p-values are constructed using 300 bootstraps, and the confidence interval is calculated using the 5% critical value for the non-rejection zone.

Above findings support our hypothesis that bank managers behave badly when they face pressure due to previous losses, and thus potentially leading to an even worse scenario. However, the benefits of taking excessive risk are not clear. When the results of Models 4 and 5 with the lagged effect and the contemporaneous impact are considered together, we observe that contemporaneous effect of LGR for those troubled banks is negative while the lagged effect remains positive and higher in value. This behavior is in accordance with Clair (1992). Banks with previous significant losses increase loans in an attempt to dilute the effect of NPLs. In other words, the NPLs ratio for the contemporaneous period is reduced due to the bigger denominator. However, this means that banks may have to take excessive risk or become less prudent when making loans, with the result that the situation would be even worse in the future. This observation is suggested by the larger negative coefficient on lagged NPLs above threshold level. Hence, our results suggest that monitoring banks with NPLs higher than the threshold value is particularly important for regulators to avoid further deterioration of already troubled banks, and to prevent them from eventual failure with the consequence of generating further instability in the system.

6. CAR or NPLs, or both?

The empirical results so far have indicated that the last period's NPLs ratio can be an important regulatory variable to monitor moral hazard problems and to avoid deterioration of asset quality in the Chinese banking system. Since the Chinese government has already decided to implement the Basel Accord, it should be interesting to estimate the same empirical model with Capital Adequacy Ratio (CAR) to test whether it can also be an effective regulatory measure. Can we, for example, identify moral hazard problems using the designated regulatory standard of CAR (8%)? To test this we replace the lagged NPLs ratio with the lagged CAR in our regressions as our new threshold variable. It is also worth noting that a higher CAR represents relatively safer banks, so we would expect an opposite sign here for CARs when it is compared to the expected sign of NPLs ratio.

Again, we test for threshold effects and estimate the threshold value first. The results are reported in Table 5. The bootstrap p-values suggest the existence of threshold effect in each model, though the estimated threshold values differ slightly. The confidence intervals are shown in Fig. 2. The lower bounds of all four models are relatively loose, but the upper bounds are consistent



(a) Model 2 (b) Model 3

(c) Model 4 (d) Model 5

Fig. 1. Constructing confidence intervals and the ‘non-rejection zone’ (NPLs Ratio).

Table 3
Bank types sorted according to threshold value (NPLs ratio).

Bank type	SOB and JS banks	City comm. banks	Rural comm. banks	Total
NPL < 4.81%	107 (95.5%)	394 (93.8%)	64 (83.1%)	565 (92.8%)
NPL ⩾ 4.81%	5 (4.5%)	26 (6.2%)	13 (16.9%)	44 (7.2%)

Note: The numbers reported in this table are bank-year observations. Shares of each type are in brackets. SOB and JS banks refer to the state-owned banks and joint-stock banks, respectively. The other two types are city commercial banks and rural commercial banks.

and close to the threshold value. The finding of a threshold of 8.18% still has a clear policy implication in that the Basel Accord requirement of 8% CAR can also signal a potential moral hazard problem. The results of sorting different types of banks according to the threshold value (CAR 8.18%) are given in Table 6. Unlike the NPLs ratio case above, the distributions of troubled banks are similar among all the three types.

Regression results are reported in Table 7. Results of Model 1 stay the same as in Table 4. The signs with respect to LGR and its lag, as expected, are opposite to those in NPLs regressions. When only LGR of the contemporaneous period is included in the threshold model, LGR has a significant impact on NPLs ratio in both regimes, with opposite signs. Safe banks reduce NPLs ratio, whereas troubled banks’ LGR increases the NPLs ratio. Very similar to the mechanism discussed in the NPLs’ threshold regression, when lagged LGR is included in estimations, we can see that the contemporaneous effect of LGR reduces troubled banks’ loan ratios. However, the higher level of the lagged NPLs coefficient would eventually dominate the short-term effect. In general, the results using CAR as the threshold variable support those of NPLs ratio. Overall, empirical evidence is robust suggesting moral hazard problem in the Chinese banking sector.

Now the question is whether CAR is sufficient to represent the health of a particular bank. In other words, how much overlapping exists when identifying troubled banks via these two measures? Table 8 gathers the information from both measures and reports the percentage of overlap across the two. From a regulatory point of view, only those banks in trouble are relevant. Thus, we only report cases where CAR is lower than the threshold value and NPLs ratio is higher than the threshold value.

In total, there are 44 bank-year observations that have higher NPLs ratios than the threshold value of 4.81%, while the bank-year number according to CAR threshold of 8.18% is only 32. When considering the overlapping cases, there are only 21 bank-year observations. In terms of percentage, only 47.73% of the total cases in the NPLs model have been correctly identified via the CAR threshold. Similarly, using NPLs ratio threshold can only identify 65.63% of the total cases found in the CAR model. There are also significant differences in each type of bank. In general, we can conclude that, although CAR can be used to monitor potential moral hazard, there is substantial benefit in also monitoring the NPLs.

Table 4
Regression results with NPLs ratio as a threshold.

	Model 1	Model 2	Model 3	Model 4	Model 5
LGR	−0.008*				
	(0.004)				
l.LGR	−0.002				
	(0.004)				
LGR*I($l.NPL < \hat{\gamma}$)		−0.010**		−0.004	−0.005
		(0.004)		(0.004)	(0.004)
LGR*I($l.NPL \geqslant \hat{\gamma}$)		0.032***		−0.029***	−0.033***
		(0.009)		(0.009)	(0.010)
l.LGR*I($l.NPL < \hat{\gamma}$)			−0.006*	−0.007**	−0.008**
			(0.003)	(0.003)	(0.003)
l.LGR*I($l.NPL \geqslant \hat{\gamma}$)			0.061***	0.075***	0.072***
			(0.007)	(0.009)	(0.009)
ER	−0.062**	−0.042	−0.058**	−0.058**	
	(0.030)	(0.029)	(0.026)	(0.027)	
CAR					−0.076***
					(0.018)
DGR	−0.005	−0.004	−0.005*	−0.003	−0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Size	0.554***	0.537***	0.578***	0.643***	0.599***
	(0.199)	(0.190)	(0.175)	(0.176)	(0.173)
Year 2007	2.243***	1.961***	1.768***	1.897***	1.746***
	(0.312)	(0.297)	(0.299)	(0.280)	(0.275)
Year 2008	1.696***	1.622***	1.606***	1.687***	1.609***
	(0.265)	(0.254)	(0.234)	(0.235)	(0.230)
Year 2009	1.037***	1.026***	0.915***	0.994***	0.955***
	(0.232)	(0.223)	(0.199)	(0.205)	(0.199)
Year 2010	0.446**	0.416**	0.517***	0.546***	0.511***
	(0.187)	(0.169)	(0.166)	(0.166)	(0.163)
Year 2011	0.092	0.086	0.097	0.107	0.084
	(0.146)	(0.141)	(0.130)	(0.130)	(0.128)
Constant	−8.766**	−8.579**	−9.344***	−10.476***	−9.003***
	(3.767)	(3.607)	(3.320)	(3.338)	(3.284)
N	522	522	522	522	522
R^2	0.373	0.412	0.502	0.511	0.526

Note: $I(\cdot)$ is the indicator function, which equals one if the statement in brackets is true, and zero otherwise. The variables with *l.* as prefix have been lagged one period backwards. LGR = loan growth rate, NPL = NPLs ratio (non-performing loans divided by total outstanding loans), DGR = deposit growth rate, ER = equity ratio against total assets, CAR = capital adequacy ratio, and Size = end-of-year total assets (in log term). Model 1 is the benchmark linear model with no threshold effect at all. Threshold variable is one period of lagged NPLs ratio, and the value of threshold is 4.81% for all models. Model 2–4 are defined in the paper, which differ from each other in regard to whether lags of LGR are included. Model 5 is to replace ER with CAR for robustness check. Standard errors are in brackets.
*** Denotes statistical significance at 1% level.
** Denotes statistical significance at 5% level.
* Denotes statistical significance at 10% level.

Table 5
Estimation of threshold effects of CAR.

Model	Threshold ($\hat{\gamma}$)	Conf. Interval (95%)	SSE_{min}	LR_1 Stats.	*P*-value
2	6.01%	[6.01%,8.27%]	344.99	13.92	0.097
3	8.18%	[4.15%,8.20%]	335.43	29.9	0.003
4	8.18%	[4.15%,8.20%]	333.14	29.68	0.030
5	5.71%	[4.15%,8.20%]	320.30	24.78	0.047

Note: *p*-values are constructed using 300 bootstraps, and the confidence interval is calculated using the 5% critical value for the non-rejection zone.

7. Robustness analysis

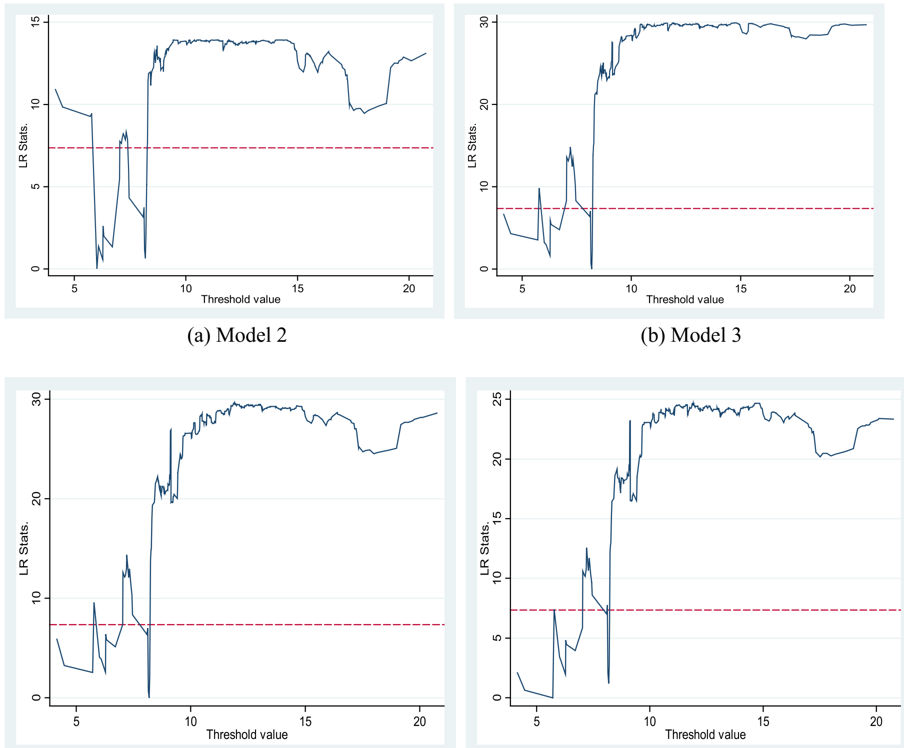
In this section we do further robustness analysis using different bank groups in estimations and employing an instrumental variable approach to deal with the potential endogeneity bias.

7.1. Estimations with different bank groups

City commercial and rural commercial banks in China operate mainly within a region but they have grown quickly over the last ten years and this calls for more attention to regulation. According to our analysis in Table 3, relative to the state-owned banks and joint-stock banks, there is a higher proportion of city and rural commercial banks in the category of high NPLs ratio. Furthermore, it is worth noting that only a small number of rural commercial banks are included in our sample due to data availability. To check the robustness of our results we therefore divide the banks into three groups as follows:

Group 1 (G1): 60 city commercial banks plus 11 rural commercial banks (excluding SOBs and Joint Stock banks); Group 2 (G2): 60 city commercial banks plus 16 SOBs and Joint Stock banks (excluding rural commercial banks); and Group 3 (G3): 60 city commercial banks (excluding all other type of banks). Given that including both contemporaneous and lagged LGR provide more informative results, the empirical analysis in this section reports estimation for models 4 and 5 only. Table 9 reports the test of threshold and estimation of the threshold value in all three subgroups.

Apart from model G1.5C (Group 1, Model 5 and using CAR as threshold), which has a bootstrap *p*-value of 0.13, all other models for all three groups in Table 9 favor the existence of the threshold effect. The estimated threshold values for Group 1 are almost the same as those of the full sample. When rural commercial banks are excluded from the sample, the threshold for NPLs ratio declines marginally; nonetheless, the confidence intervals stay similar to earlier results. When NPLs ratio is used as the threshold variable, estimating regressions with only the city commercial banks produces a slightly lower threshold value. The differences are not



(a) Model 2 (b) Model 3

(c) Model 4 (d) Model 5

Fig. 2. Constructing confidence intervals and the 'non-rejection zone' (CAR).

significant in general. If CAR is considered as the threshold variable, the empirical results are all consistently pointing to the threshold value of 8.18%.

Based on the threshold value results in Tables 9 and 10 reports the regression results for each group. For space considerations, only the coefficients for key variables (i.e., loan growth rate) and its lags interacted with thresholds are reported. Although the coefficient values differs from each other, the differences in terms of their economic significance are insignificant, and the signs of variables are generally consistent with those of the full sample analysis. Those two threshold variables (NPLs ratio and CAR) and their associated threshold values are still valid and capable of identifying moral hazard problems. Banks with significant problems either in terms of NPLs ratio or CAR tend to lend aggressively, consequently resulting in more losses in the following period.

7.2. Endogeneity issues

Loan growth rate, as a key explanatory variable, is potentially endogenous as it might affected by the current NPLs ratio. Hence we do some additional robustness analysis allowing for endogeneity.[10] Following Caner and Hansen (2004), we introduce instrumental variables and use 2SLS method to estimate the slope coefficients. Threshold values, again, are found through minimizing the sum of squared errors similar to the method used above. Thus we allow the model to have endogenous threshold as well as endogenous explanatory variables. For SOBs and joint-stock banks, the average loan growth rate of other banks in this group is used as an instrument for the loan growth rate for each bank. As for the city commercial banks and rural commercial banks, an additional concern is that their operation can potentially subject to the regional policy impacts. The instruments for these banks are therefore related to the average of same bank type located in the same city. If there is only one bank for this type in this city, the loan growth rate of the most closed (in terms of size) bank in the same province is used as the instrument.

Table 11 reports the regression results using 2SLS method. The estimated threshold values for the settings of Model 4 and Model 5 are 4.03% and 4.02%, respectively, which are close to the lower bound of confidence interval reported in Table 2. The IV regression results for model 4 and 5 using these values are reported in Model I.4A and I.5A. Furthermore, in order to check the estimated threshold value of 4.81% reported in Table 2 for model 4 and 5, Table 11 also report the 2SLS regression results using this value (as reported in Model I.4B and I.5B). In all cases, the results are qualitatively similar, which means the choice of 4.81% or 4.03% does not change the inferences qualitatively.

Table 6
Bank types sorted according to threshold value (CAR).

Bank type	SOB and JS banks	City comm. banks	Rural comm. banks	Total
CAR > 8.18%	105 (93.75%)	399 (95.00%)	64 (94.80%)	577 (94.75%)
CAR $\leqslant$ 8.18%	7 (6.25%)	21 (5.00%)	13 (5.20%)	32 (5.25%)

Note: The numbers reported in this table are bank-year observations. Shares of each type are in brackets. SOB and JS banks refer to the state-owned banks and joint-stock banks. The other two types are city commercial banks and rural commercial banks.

[10] Davidson–MacKinnon tests of exogeneity reported in Table 11 reject the null hypothesis of exogeneity at 5 and 10 percent levels, justifying the use of an instrumental variable approach to correct for endogeneity bias. The validity of our instruments are confirmed through the Anderson LM test and Cragg–Donald F test reported in Table 11. All Anderson LM tests are significant at 1% level reject the null of under identification. The Cragg–Donald F tests reject the null marginally, suggests that we do not have weak instrument problem.

Table 7
Regression results with CAR as a threshold.

	Model 1	Model 2	Model 3	Model 4	Model 5
LGR	−0.008*				
	(0.004)				
l.LGR	−0.002				
	(0.004)				
LGR*I($l.CAR < \gamma_c$)		0.022**		−0.013	−0.016
		(0.009)		(0.013)	(0.013)
LGR*I($l.CAR \geqslant \gamma_c$)		−0.010**		−0.007	−0.007*
		(0.004)		(0.004)	(0.004)
l.LGR*I($l.CAR < \gamma_c$)			0.033***	0.036***	0.033***
			(0.007)	(0.010)	(0.010)
l.LGR*I($l.CAR \geqslant \gamma_c$)			−0.004	−0.004	−0.005
			(0.004)	(0.004)	(0.003)
EA	−0.062**	−0.047	−0.061**	−0.053*	
	(0.030)	(0.030)	(0.029)	(0.030)	
CAR					−0.086***
					(0.020)
DGR	−0.005	−0.004	−0.005	−0.003	−0.003
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Size	0.554***	0.562***	0.601***	0.657***	0.585***
	(0.199)	(0.193)	(0.192)	(0.194)	(0.190)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	−8.766**	−9.035**	−9.793***	−10.798***	−8.627**
	(3.767)	(3.675)	(3.636)	(3.678)	(3.616)
N	522	522	522	522	522
R^2	0.373	0.390	0.408	0.412	0.433

Note: $I(\cdot)$ is the indicator function, which equals one if the statement in brackets is true, and zero otherwise. The variables with *l.* as prefix have been lagged one period backwards. LGR = loan growth rate, NPL = NPLs ratio (non-performing loans divided by total outstanding loans), DGR = deposit growth rate, ER = equity ratio against total assets, CAR = capital adequacy ratio, and Size = end-of-year total assets (in log term). Threshold variable is one period lagged CAR, and the value of threshold is 8.18% for all models. Model 2–4 are defined in the paper, and differ from each other in regard to whether lags of LGR are included. Model 5 is to replace ER with CAR for robustness check. Year dummies are included in all regressions. Standard errors are in brackets.
*** Denotes statistical significance at 1% level.
** Denotes statistical significance at 5% level.
* Denotes statistical significance at 10% level.

Table 8
Overlapping of two alternative measures.

	SOB & JS	City comm. banks	Rural comm. banks	Total
$CAR \leqslant 8.18\%$	7	21	4	32
$NPL \geqslant 4.81\%$	5	26	13	44
Overlapping cases	4	14	3	21
Share of corrected (over NPL)	80.00%	53.85%	23.08%	47.73%
Share of corrected (over CAR)	57.14%	66.67%	75.00%	65.63%

Note: The numbers reported in this table are bank-year observations. CAR = capital adequacy ratio; NPL = NPL ratios (non-performing loan divided by total outstanding loans); SOB and JS banks refer to the state-owned banks and joint-stock banks. The other two types are city commercial banks and rural commercial banks.

When we compare the results in Table 11 with those reported in Table 2, the contemporaneous loan growth rate loses its statistical significance; however, the lagged value of loan growth rate for those banks with higher level of NPLs ratio in the previous period are still significant and show positive effects, further confirming our hypothesis and earlier conclusion: banks facing previous significant losses have the incentive to take higher risk, which will then result in further significant losses. Overall, when endogeneity is accounted for, our core conclusion remains valid.

7.3. Discussion

We need to emphasize that such a threshold value of 4.81% may not necessarily trigger actions by the regulators in China.[11] This is an implicit value derived from our empirical analysis suggesting that bank managers may change their behavior when their banks' NPLs ratio goes above this threshold value. Our results show that the threshold effect is more relevant for the rural and city commercial banks, while the rest of banks usually have a NPL ratio lower than this threshold value. For example, there are only 5 bank-year observation for state-owned and joint-stock banks have NPLs ratio over the threshold value, whereas the number for city and rural commercial banks are 39.

Chinese banking system has normally been considered as a sector that is heavily affected by the government, both in central and local level. It is therefore natural to argue that the local governments may utilize the city and rural commercial banks to increase the local employment and boost economic growth. Hence, these banks may have high NPL ratios while continuing to take excessive risks at the mandate of local government officials. As a result, any moral hazard problems in the rural and city commercial banks may be caused more by the mandate of local government officials than a high NPL ratio. In fact, Chinese banking system has gone through a series of market reforms since 2001, which have liberalized the banking sector through disposing of NPLs, relaxing credit and interest controls, privatizing state-owned banks, and improving corporate governance. These reforms have mitigated the inefficiency of China's banking system and alleviated political control of banks (Tsai et al., 2014) and even state-owned banks' incentives have been improved due to reforms of the banking system in China (Jia, 2009). Our empirical results are based on the data from 2006 to 2012 covering the period that banks are more market-oriented. Moreover, even banks' behavior may be affected by the local government, we can still consider as some type of moral hazard problem as the managers of city and rural commercial banks can benefit from complying with the local government.

[11] We would like to thank an anonymous referee for suggesting this discussion.

Table 9
Estimation of the threshold effects for sub-bank groups.

Model	Threshold Var.	Threshold ($\hat{\gamma}$)	Conf. interval (95%)	SSE_{min}	LR_1 stats.	P-value
Panel I. Group 1 (city plus rural commercial banks)						
G1.4N	NPL	4.81%	[4.03%, 4.93%]	233.52	104.5	0.00
G1.5N	NPL	4.81%	[4.03%, 4.93%]	227.30	95.97	0.00
G1.4C	CAR	8.18%	[8.09%, 8.18%]	282.30	25.09	0.07
G1.5C	CAR	8.18%	[6.01%, 8.18%]	273.61	19.65	0.13
Panel II. Group 2 (excluding rural commercial banks)						
G2.4N	NPL	4.04%	[4.03%, 4.96%]	203.98	122.57	0.00
G2.5N	NPL	4.04%	[4.03%, 4.98%]	199.51	116.81	0.00
G2.4C	CAR	8.18%	[4.47%, 8.20%]	248.42	32.67	0.03
G2.5C	CAR	8.18%	[4.47%, 8.20%]	242.98	27.94	0.04
Panel III. Group 3 (city commercial banks only)						
G3.4N	NPL	3.57%	[3.49%, 4.96%]	156.61	106.03	0.00
G3.5N	NPL	4.03%	[3.50%, 4.98%]	154.08	101.54	0.00
G3.4C	CAR	8.18%	[8.14%, 8.18%]	195.17	25.81	0.06
G3.5C	CAR	8.18%	[8.14%, 8.18%]	192.08	22.10	0.07

Note: For model specification of each group (from G1 to G3), this table reports test results for model 4 and 5 in the full sample analysis, which include both loan growth rate and lagged loan growth rate. N means a model takes non-performing loans as threshold variable and C means a model takes CAR (capital adequacy ratio) as threshold variable. SSE_{min} is the minimum value of sum of squared residuals across regressions with all possible threshold values. *P*-values are constructed using 300 bootstraps, and the confidence intervals are calculated using the 5% critical value for the 'non-rejection zone'.

Table 10
Regression results for sub-bank groups.

Model	G1.4 N	G1.5 N	G1.4C	G1.5C
Panel I. Group 1 (city plus rural commercial banks)				
LGR*I(*l*.Tre. < $\hat{\gamma}$)	−0.002	−0.003	0.009	0.004
	(0.004)	(0.004)	(0.015)	(0.015)
LGR*I(*l*.Tre. ⩾ $\hat{\gamma}$)	−0.018*	−0.021*	−0.005	−0.006
	(0.011)	(0.011)	(0.005)	(0.005)
l.LGR*I(*l*.Tre. < $\hat{\gamma}$)	−0.005	−0.005	0.027**	0.025**
	(0.004)	(0.003)	(0.011)	(0.011)
l.LGR*I(*l*.Tre. ⩾ $\hat{\gamma}$)	0.071***	0.069***	−0.002	−0.002
	(0.009)	(0.009)	(0.004)	(0.004)
N	426	426	426	426
R^2	0.503	0.517	0.400	0.418
Panel II. Group 2 (excluding rural commercial banks)				
Model	G2.4N	G2.5N	G2.4C	G2.5C
LGR*I(*l*.Tre. < $\hat{\gamma}$)	−0.000	−0.001	−0.021*	−0.022*
	(0.004)	(0.004)	(0.012)	(0.012)
LGR*I(*l*.Tre. ⩾ $\hat{\gamma}$)	−0.044***	−0.045***	−0.002	−0.002
	(0.009)	(0.009)	(0.004)	(0.004)
l.LGR*I(*l*.Tre. < $\hat{\gamma}$)	−0.006*	−0.006**	0.044***	0.042***
	(0.003)	(0.003)	(0.010)	(0.010)
l.LGR*I(*l*.Tre. ⩾ $\hat{\gamma}$)	0.078***	0.076***	−0.003	−0.003
	(0.008)	(0.008)	(0.003)	(0.003)
N	456	456	456	456
R^2	0.512	0.523	0.406	0.419
Panel III. Group 3 (city commercial banks only)				
Model	G3.4N	G3.5N	G3.4C	G3.5C
LGR*I(*l*.Tre. < $\hat{\gamma}$)	0.002	0.001	0.001	−0.002
	(0.004)	(0.004)	(0.014)	(0.014)
LGR*I(*l*.Tre. ⩾ $\hat{\gamma}$)	−0.008	−0.010	−0.000	0.000
	(0.007)	(0.007)	(0.005)	(0.004)
l.LGR*I(*l*.Tre. < $\hat{\gamma}$)	−0.002	−0.002	0.037***	0.036***
	(0.003)	(0.003)	(0.010)	(0.010)
l.LGR*I(*l*.Tre. ⩾ $\hat{\gamma}$)	0.062***	0.061***	0.001	0.001
	(0.007)	(0.007)	(0.004)	(0.004)
N	360	360	360	360
R^2	0.513	0.505	0.393	0.402

Note: $I(\cdot)$ is the indicator function, which equals one if the statement in brackets is true, and zero otherwise. The variables with *l.* as prefix have been lagged one period backwards.
Tre. = threshold variable (NPLs ratio or CAR); LGR = loan growth rate. For all groups, Model 4N and 5N takes NPLs ratio as the threshold variable $\hat{\gamma}$, whereas model 4C and 5C use CAR (capital adequacy ratio) as the threshold variable $\hat{\gamma}$. Their values are taken from the estimated results in Table 9. The coefficients of all other variables similar to full sample analysis are not reported for space consideration (but they are all consistent). Standard errors are in brackets.
*** Denotes statistical significance at 1% level.
** Denotes statistical significance at 5% level.
* Denotes statistical significance at 10% level.

8. Conclusions and policy implications

Fast economic growth in China has expanded the commercial banking system significantly in the last couple of decades. Deeper market reforms, especially regarding the bank ownership structure, have allowed banks to operate in a modern corporate system environment and improved bank efficiency significantly. Emergence of joint-stock banks and regional commercial banks is a good example of the additional benefits of the reforms. However, the by-product is the typical problem found in the corporate finance literature: conflict of interest and agency problems can result in moral hazard in the banking system. Managers have incentives to take excessive risks when they face significant financial challenges. Consequently, an inappropriate credit expansion may result in further deterioration of asset quality and cause further financial difficulties for banks. From the regulator's point of view, it is important to identify the extent of moral hazard behavior in the commercial banking system in order to avoid potential financial instability.

Using a balanced panel data of 87 banks in China from 2006 to 2012, this paper uses one-period lagged NPLs ratio as the threshold variable to study possible moral hazard problems in the Chinese commercial banking system. The empirical results from testing and estimating Hansen's (1999) threshold model provide strong evidence that the threshold effect indeed exists. A robust threshold level of 4.81% in the NPLs ratio is found across different specifications of models, which shows that banks facing high NPLs ratio in the past behave in accordance with the prediction of moral hazard theory: banks' excessive risk-taking would temporarily relieve the problem but cause greater losses in the long run. Across all estimated models, a one standard deviation increase in loan growth (15%) for troubled banks (with NPLs above threshold level) can cause subsequently additional NPLs ratios between 0.9% and 1.05%. Given the average of 1.83% NPLs ratio for all banks in our sample, this impact is economically significant and hence should not be neglected by regulators. Further analysis using CAR as the threshold value shows that an 8% CAR requirement, per the Basel Accord, has some value of further identifying moral hazard. However, a comparison of results from NPLs ratio with those of CAR suggests that the two measures are complementary rather than substitutes. Hence, it is advisable for Chinese regulators monitor both measures closely.

Overall, our results suggest that Chinese regulators should consider NPLs ratio as a useful indicator for detecting potential bank moral hazard problem and design transparent policy goals and monitor banks closely. While the CBRC has aimed to establish a good corporate governance system in the banking system, paying attention, not only to CAR, but also to the NPLs ratio at the same time is particularly important to reduce moral hazard problems

Table 11
Regression results using instrumental variables (IV).

Model	I.4A	I.5A	I.4B	I.5B
LGR*I(*l*.Tre. $< \hat{\gamma}$)	−0.018	−0.020	−0.023	−0.023
	(0.022)	(0.020)	(0.021)	(0.019)
LGR*I(*l*.Tre. $\geqslant \hat{\gamma}$)	−0.005	−0.011	−0.003	−0.010
	(0.036)	(0.033)	(0.038)	(0.037)
l.LGR*I(*l*.Tre. $< \hat{\gamma}$)	−0.005	−0.006	−0.005	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)
l.LGR*I(*l*.Tre. $\geqslant \hat{\gamma}$)	0.044***	0.042***	0.048***	0.048***
	(0.012)	(0.012)	(0.015)	(0.015)
N	522	522	522	522
R^2	0.474	0.489	0.470	0.488
Anderson LM Stat.	10.961***	12.546***	13.894***	15.774***
Cragg–Donald F stat.	5.467	6.281	6.978	7.958*
Davidson–MacKinnon test of exogeneity	2.468*	2.249*	4.462**	4.281**

Note: $I(\cdot)$ is the indicator function, which equals one if the statement in brackets is true, and zero otherwise. The variables with *l.* as prefix have been lagged one period backwards.
Tre. = threshold variable (NPLs ratio). The estimated threshold value in the IV regressions for model 4 is 4.03% and model 5 is 4.02%. The results using these actually estimated values are labeled as I.4A and I.5A respectively. I.4B and I.5B report IV regression results using the previous estimated threshold value 4.81%. The coefficients of all other variables similar to full sample analysis are not reported (but they are all consistent with previous results). Anderson LM statistics reject the null hypothesis of under-identification in all models. For the Cragg–Donald F statistics, the associated Stock–Yogo critical values are 4.85 at 15% and 7.03 at 10% respectively. Standard errors are in brackets.
*** Denote statistical significance at 1% level.
** Denote statistical significance at 5% level.
* Denote statistical significance at 10% level.

and avoid the consequences of such incentives. Given the limited data for certain bank groups and continuously changing regulatory environment in China, our study has a limitation in that the threshold ratio reported in this paper may change over time and should therefore be interpreted with caution. We believe that moral hazard problem in the Chinese banking system will continue to exist regardless of how the regulatory framework evolves, but the threshold value triggering banks to take excessive risk may change over time. As more data become available, especially including more of the newly established rural commercial banks and city commercial banks, more reliable threshold values triggering moral hazard could be obtained and this will be a useful future research agenda. Our empirical findings and estimated threshold values may provide a good yardstick for future studies.

Appendix A.

Hansen (1999) suggests using OLS to estimate the model with a fixed effect transformation, where identifying γ is achieved by minimizing the concentrated sum of squared errors $\hat{\gamma} = argminS_1(\gamma)$. He also proposes a simplified grid search method to avoid computation-intensive problems when the cross-sectional dimension is large. The existence of the threshold can be tested through the likelihood ratio test. By denoting the sum of squared errors for the model with no threshold as S_0 and $S_1(\hat{\gamma})$ for the threshold model, the test statistic can then be calculated as:

$$LR_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \tag{A1}$$

where $\hat{\sigma}^2 = \frac{1}{n(T-1)} S_1(\hat{\gamma})$. This statistic is not standard and therefore needs a bootstrap procedure for computing empirical p-values. After confirming the threshold effect and locating the threshold value, it is worthwhile to construct the confidence interval for the threshold value. Hansen (1999) proposes the idea of a 'non-rejection zone'. Given the null hypothesis $H_0 : \gamma = \gamma_0$, another LR statistic can be constructed for all possible γ:

$$LR_2 = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \tag{A2}$$

The distribution of LR_2 is given in Hansen (1999) as:

$$P(LR_2 \leqslant x) = (1 - exp(-x/2))^2 \tag{A3}$$

Using this distribution, we can then construct the confidence interval for the threshold value. For example, given a confidence level α, the interval can be constructed with a set of γ that satisfies $LR_2(\gamma) \leqslant c(\alpha)$, whereas $c(\alpha) = -2ln(1 - \sqrt{1-\alpha})$ or 7.53 at 95% level.

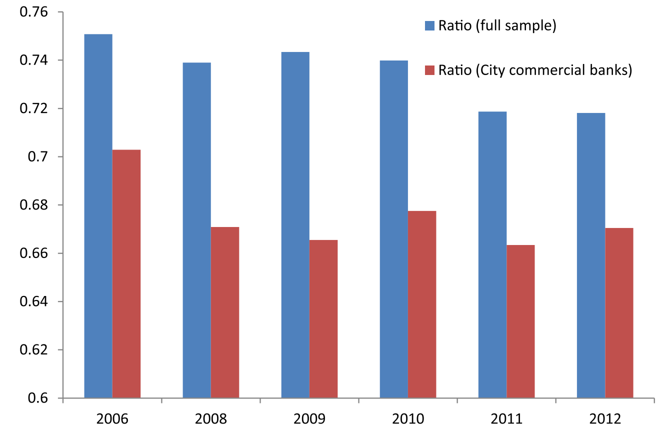


Fig. A1. The ratios of sample banks relative to country aggregate in terms of total assets (source: CBRC and authors' calculation).

Appendix B.

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