Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v16i2.5911
Vol. 16, No. 2, 109-125.

URL: www.aessweb.com

Examining the impact of liquidity risk on the operating performance of Chinese commercial banks

Hang Su[1]
You Wang[2+]

[1]*School of Economics, Fudan University, China.*
Email: 21110680038@m.fudan.edu.cn
[2]*School of International Relations, Jinan University, China.*
[2]*Brussels Centre for Competition Policy, Department of Applied Economics, Vrije Universiteit Brussel, Belgium.*
Email: you.wang@vub.be


(+ Corresponding author)

Article History
Received: 13 March 2025
Revised: 23 October 2025
Accepted: 9 January 2026
Published: 3 March 2026

Keywords
Liquidity Risk
Commercial Banks
Systemic financial risk
Relative liquidity mismatch index
Operating performance
Generalized method of moments.

JEL Classification:
G21; G32.

ABSTRACT

This study investigates the impact of liquidity risk on Chinese commercial banks' performance from 2011 to 2019, employing the Relative Liquidity Mismatch Index (RLMI) to measure liquidity risk and Return on Average Assets (ROAA) and Net Interest Margin (NIM) as performance indicators. Using panel data and a two-step Generalized Method of Moments (GMM) approach to address endogeneity, we find that liquidity risk significantly impairs bank performance, with joint-stock banks facing higher risks than state-owned banks. While overall liquidity risk remained moderate and declined by 2019 compared to 2011, the persistent negative effects highlight the need for prudent asset-liability management. These findings emphasize the importance of establishing comprehensive liquidity risk monitoring systems and implementing effective risk management strategies to safeguard bank performance and financial stability. It suggests policymakers should promote sound liquidity practices to mitigate systemic vulnerabilities in the banking sector.

Contribution/ Originality: This study constructs a tailored Relative Liquidity Mismatch Index (RLMI) based on ASF and RSF factors from the Basel Accord and empirically examines its impact on the operational performance of Chinese commercial banks using a two-step System GMM approach with expanded control variables.

1. INTRODUCTION

The global financial crisis has elevated systemic financial risk to the core of academic inquiry and policy debate. In this context, China is at a critical juncture in its efforts to prevent major financial risks. As finance constitutes a key determinant of national competitiveness, financial security is an essential dimension of national security, while financial stability serves as a necessary condition for sustaining broader economic and social stability. Commercial banks, as the most vital financial intermediaries, perform essential functions in the provision of diversified financial services. However, banking failures have the potential to generate systemic risks, whose contagion effects and destructive potential pose substantial threats to the stability of the financial system. In particular, the sharp fluctuations in the financial market are frequently induced by liquidity shocks (Zhao, Li, & Feng, 2019). The primary source of liquidity risk in commercial banks arises when they are unable to meet large withdrawal demands of depositors, forcing them to liquidate assets at discounted prices (Monfort & Renne, 2014). The initial manifestation of the financial crisis typically originates from the liquidity shortage of an individual commercial bank. As interbank linkages become increasingly interconnected, the spillover effects generated during periods of financial distress amplify the transmission of risks, ultimately leading to systemic liquidity risks within the banking sector and resulting in substantial systemic losses to the broader economy and society (Ren, Xie, Zhou, & Zhang, 2020). When the scale of contagion reaches a sufficiently large extent, “market failure" would occur (Iori, Jafarey, & Padilla, 2006). At the Fifth National Financial Work Conference held in July 2017, General Secretary Xi Jinping emphasized that: "Deepening reform is necessary to address the problems that affect and constrain the development of the financial industry." With the ongoing reform of China's financial system and the continuous advancement of financial innovation, the liquidity position of China's banking sector has exhibited a certain degree of instability. Commercial banks tend to exploit the maturity mismatch between deposits and loans to achieve higher profits. During the "money shortage" incident in June 2013, the interbank lending rate rose sharply, and the overnight SHIBOR surged to 13.440%. The liquidity shortage was primarily driven by the rapid expansion of interbank business activities and the excessive use of financial leverage (Wang & Li, 2020). The report of the 19th National Congress of the Communist Party of China pointed out that preventing systemic financial risks constitutes a fundamental and enduring priority of financial governance. It further stressed the importance of maintaining the bottom line of preventing systemic financial risks. Accurate identification and assessment of potential risks are necessary preconditions for ensuring financial security. Against this background, examining the liquidity risk of China's banking system is essential for enhancing financial resilience and safeguarding economic stability.

Based on the Basel III Accord issued by the Basel Committee, the China Banking Regulatory Commission (CBRC) released the *Guiding Opinions on the Implementation of New Regulatory Standards* in China's banking industry, which clarified the regulatory standards for capital adequacy ratio, leverage ratio, liquidity management, and loan loss provisions. These standards were developed by drawing extensively on international experience while adapting to the operational and regulatory characteristics of the domestic banking sector.

In December 2017, the Basel Committee issued the Basel IV Accord, which incorporated risks associated with insufficient market liquidity and introduced new recommendations for capital requirements in the banking industry. The China Banking Regulatory Commission (CBRC) has aligned its regulatory framework with the Basel Accord, and the new regulatory requirements are expected to exert profound and lasting effects on the business model, operating performance, and overall stability of commercial banks. Liquidity risk has consistently been one of the risks to which commercial banks attach great importance. The core of commercial bank operations lies in generating liquidity premiums by optimizing the configuration of liquidity mismatches on the balance sheet, thereby enhancing profitability. Therefore, examining the impact of liquidity risk on the operating performance of commercial banks is of particular importance.

The main contributions of this study are as follows. First, Brunnermeier and Krishnamurthy (2013) first proposed the "Liquidity Mismatch Index (*LMI*)", which measures the degree of liquidity mismatch and thus the liquidity risk of commercial banks by calculating the difference between the market liquidity of assets and the funding liquidity of liabilities. Compared with the traditional measure of deposit-loan term mismatch, the LMI provides a more comprehensive and systematic assessment, as it considers all items on the balance sheet. Bai, Krishnamurthy, and Weymuller (2018) further refined this measure by assigning empirical weights to balance sheet items. However, given the heterogeneity in balance sheet structures across commercial banks of different sizes in China, a simple difference calculation is not sufficient for cross-bank comparisons. Following the approach proposed by Gao, Xu, and Du (2018), this study adopts the Relative Liquidity Mismatch Index (*RLMI*) to measure the liquidity risk level of Chinese commercial banks. Second, building on the methodology developed by Xu (2016), we assign weights for the RLMI based on specific characteristics of commercial banks' balance sheets in China. Finally, although existing literature has rarely examined the relationship between liquidity risk and commercial bank performance, this study employs a two-step Generalized Method of Moments (GMM) estimation to empirically analyze the impact of the RLMI on the operating performance of commercial banks in China.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESIS

2.1. Literature Review

Liquidity and liquidity risk have been widely discussed in the banking and finance literature. According to Basel Committee on Banking Supervision (2000), liquidity refers to a bank's ability to fund the growth of assets and meet its obligations. A bank is considered to be liquid if it can obtain short-term funding at relatively low costs, thereby maintaining sufficient cash flows to meet its payment obligations. Given the fundamental role of banks in transforming short-term deposits into long-term loans, this maturity transformation process inherently generates liquidity risk. Drehmann and Nikolaou (2013) define liquidity risk as the possibility that a bank loses its ability to meet immediate debt repayments within a specific period of time, which occurs when a bank fails to repay its obligations on time and is thus deemed illiquid. Liquidity risk presents significant challenges for the management of financial institutions and threatens the stability of the financial system. Khan, Scheule, and Wu (2017) examine the relationship between liquidity and bank risk-taking and find that when the liquidity risk of bank funding is relatively low, the size of the bank and its capital buffer generally constrain the bank's risk-taking behavior. Vento and La Ganga (2009) first discovered the interaction between bank liquidity risk and other types of banking risks, such as credit risk and market risk. In the traditional sense, liquidity risk refers to the risk that financial institutions are unable to meet their maturing debt obligations in a timely manner and at a reasonable cost. Therefore, liquidity risk can be regarded as a cost-related issue for banks; when a bank faces liquidity risk, it not only fails to meet its liquidity needs but also incurs higher maturity funding costs.

The relationship between maturity mismatch, liquidity mismatch, and liquidity risk has been extensively examined in the banking literature. The maturity mismatch between assets and liabilities in commercial banks typically refers to the situation where loan terms exceed deposit terms. De Haan and van den End (2013) argue that maturity mismatch is a characteristic of commercial banks' operations. While the deposit-loan maturity mismatch serves as a primary source of commercial bank profitability, it is also a fundamental driver of liquidity risk (Guo & Che, 2017; Li & Geng, 2020; Xiang & Zeng, 2019). Liquidity supply is determined by the maturity of assets, whereas liquidity demand arises from the maturity of liabilities. When the average maturity of liabilities is shorter than that of assets, the resulting liquidity gap must be filled by rolling over liabilities. If this liquidity gap cannot be financed at a lower cost within a short period, liquidity risk is likely to emerge (Qiu, 2015). Most existing studies have examined liquidity risk in commercial banks within the framework of deposits-loans maturity mismatch. By analyzing both on-balance and off-balance sheet liquidity, scholars have concluded that the fundamental cause of the 2013 "money shortage" incident in China was the maturity mismatch of off-balance-sheet wealth management products. Moreover, during periods of economic downturn, tends to amplify liquidity risk in commercial banks (Peng, Wang, & Zou, 2014; Yi, 2016).

Ran (2019) and M. Zhu and Hou (2014) estimated the liquidity gap of commercial banks using the Hodrick-Prescott (HP) filter method and measured liquidity risk from the perspective of maturity mismatch. Zhu (2013) employed a vector autoregression (VAR) model to analyze the factors influencing the maturity mismatch of deposits and loans. They argue that the degree of maturity mismatch largely determines whether liquidity risk will materialize. Excessive maturity mismatch behavior in commercial banks will inevitably lead to liquidity risk (Wang & Liang, 2015). Kalkbrener and Willing (2004) used a Monte Carlo simulation to estimate the required deposit stability across different maturities, providing insights into how liquidity risk can be prevented.

However, the deposit-loan maturity mismatch framework does not account for structural mismatches in the broader business operations of commercial banks and is therefore insufficient to comprehensively measure liquidity risk. Liu, Zhao, and Tian (2019) highlight the growing prominence of liquidity mismatch in commercial banks, arguing that greater attention should be paid to the overall liquidity mismatch of the banking system, particularly the mismatch between the market liquidity of assets and the funding liquidity of liabilities. The liquidity sensitivity of different assets and liabilities is closely related to their respective maturities, and liquidity mismatch is reflected in the multi-dimensional structural differences between assets and liabilities. Therefore, maturity mismatch constitutes a form of liquidity mismatch (Qiu, 2015). Brunnermeier and Krishnamurthy (2013) were the first to introduce the "*Liquidity Mismatch Index* (*LMI*)" to measure the level of liquidity risk. Bai et al. (2018) further assessed the mismatch between the market liquidity of assets and the funding liquidity of liabilities and compared the LMI with alternative liquidity measures, including the Liquidity Coverage Ratio (LCR), the Net Stable Funding Ratio (NSFR), and the approach proposed by Berger and Bouwman (2009). Their findings suggest that *LMI* provides the most comprehensive and effective measure of liquidity risk in commercial banks.

The relationship between liquidity risk and the operating performance of commercial banks has attracted considerable attention in the literature. As the most important financial intermediaries, banks play an important role in open economies. The operating efficiency of commercial banks affects overall economic growth (Anbar & Alper, 2011). Economies with a banking sector characterized by higher performance banking are better positioned to withstand economic crises and contribute to the stability of the financial system (Athanasoglou, Brissimis, & Delis, 2008). Return on Assets (*ROA*), Return on Equity (*ROE*), Return on Average Assets (*ROAA*) and Net Interest Margin (*NIM*) are commonly used to measure the bank profitability (Anbar & Alper, 2011; Demirgüç-Kunt & Huizinga, 1999; Dietrich & Wanzenried, 2014; Lee & Kim, 2013). Khan and Syed (2013) argue that during periods of liquidity tightening, commercial banks may be forced to borrow funds from the market at extremely high interest rates, which ultimately reduces their profitability. If banks continue to increase borrowing to meet depositors' withdrawals, the debt-to-equity ratio will increase, making it difficult for them to maintain optimal asset allocation. When commercial banks are unable to meet depositors' withdrawal needs, bank failure becomes inevitable (Diamond & Rajan, 2005).

Chen, Shen, Kao, and Yeh (2018) and Diamond and Rajan (2005) emphasize that the destructive impact of liquidity risk on commercial banks, that is, arguing that liquidity risk is negatively correlated with bank profitability. Arif and Nauman Anees (2012) employed multiple linear regression to examine the impact of liquidity risk on the operating performance of the banking sector in Pakistan. They found that liquidity gaps have a significant negative impact on bank profitability and suggested that risk managers should mitigate liquidity risk through optimal cash allocation, which would also reduce banks' dependence on the repo market.

The liquidity, safety and profitability of banks collectively referred to as the "three principles" form the basis for the comprehensive evaluation of bank performance. Chi, Zhu, and Xu (1999) established a set of comprehensive evaluation indicators based on the "three principles" to assess the operating performance of commercial banks. Liquidity-related indicators include 7 indicators such as reserve ratio, medium- and long-term loan ratio and asset liquidity ratio, and others. They applied the Analytic Hierarchy Process (AHP) to assign weights to these indicators based on their impact on bank performance. Zuo (2008) also proposed the need to conduct continuous performance evaluation of commercial banks to achieve the coordination of the "three qualities" of liquidity, safety and profitability. Cao (2007) employed principal component factor analysis and used liquidity to construct an indicator system for evaluating the operating performance of commercial banks, with liquidity as one of the key indicators. The study found that the impact of liquidity on operating performance could be either positive or negative, depending on the context. Therefore, commercial banks should maintain an appropriate level of liquidity to optimize their performance.

In terms of empirical research methodology. Dietrich and Wanzenried (2014) employed the Generalized Method of Moments (GMM) to analyze the factors affecting the profitability of 10,165 commercial banks in 118 countries from 1998 to 2012. Their findings indicate that income level is a significant determinant of bank profitability. Similarly, Athanasoglou et al. (2008) also used GMM to examine bank-specific, industry-specific, and macroeconomic factors on bank profitability. In addition, the fixed effects model is also commonly applied in the literature (Anbar & Alper, 2011; Lee & Kim, 2013; Petria, Capraru, & Ihnatov, 2015).

A review of existing literature reveals that the loan-to-deposit ratio (Sun, Li, & Xie, 2018) and the liquidity gap method (Ran, 2019; Zhu, 2013; Zhu & Hou, 2014) are commonly used indicators for measuring liquidity risk.

However, Arif and Nauman Anees (2012) pointed out that most existing studies focus on analyzing liquidity risk from the liability side of the balance sheet, with relatively little attention paid to liquidity risk generated by the asset side. Therefore, this study adopts the *Liquidity Mismatch Index* (*LMI*) to measure the liquidity risk of China's commercial banks. Moreover, existing research in China has paid limited attention to the impact of liquidity risk on the operating performance of commercial banks. The majority of studies focus on the causes of liquidity risk and the factors influencing liquidity risk. In response to this gap, this study further investigates the impact of liquidity risk as measured by the LMI on the operating performance of commercial banks.

2.2. Research Hypothesis

Building upon the theoretical framework and existing literature, this study formulates the following research hypotheses:

Cash is among the most liquid assets held by banks. To meet potential withdrawal demands from depositors, banks tend to maintain higher cash reserves. However, holding excessive cash comes at a significant cost, as it limits banks' ability to allocate resources efficiently and capitalize on market profit opportunities (Arif & Nauman Anees, 2012; Khan & Syed, 2013) . Therefore, this paper makes the following hypothesis:

H_1: Cash reserves are negatively correlated with the operational performance of commercial banks.

Commercial banks primarily generate profits by engaging in maturity transformation, borrowing short-term funds and extending long-term loans. Deposits constitute a critical source for commercial banks, playing a central role in maintaining financial stability. A sufficient level of deposits enables banks to mitigate liquidity gaps resulting from depositor withdrawals, thereby reducing their reliance on central bank borrowing or high-cost interbank lending. Consequently, higher deposit levels are expected to improve the operational performance of commercial banks (Arif & Nauman Anees, 2012; Khan & Syed, 2013). Therefore, this study makes the following assumptions.

H_2: Deposit levels exhibit a positive correlation with the operational performance of commercial banks.

The Relative Liquidity Mismatch Index (*RLMI*) measures the ratio of total assets to total liabilities in a commercial bank's balance sheet, with assigned weights reflecting the liquidity sensitivity of different items. A higher RLMI indicates a greater proportion of assets relative to liabilities and reflects a lower level of liquidity risk (Gao et al., 2018). Higher liquidity is generally associated with a stronger profit-generating capacity in commercial banks (Liu & Liu, 2013). Petria et al. (2015) used the ratio of loans to consumer deposits to represent liquidity risk, arguing that a higher ratio implies greater liquidity risk. The fixed effects model analysis demonstrates that an increase in this ratio deteriorates the operating performance of commercial banks. Similarly, Chen et al. (2018) used the liquidity ratio as an exogenous variable to represent liquidity risk and concluded through empirical analysis that liquidity risk has a negative impact on the operating performance of commercial banks. Therefore, this paper makes the following assumptions.

H_3: The RLMI index is positively correlated with the operational performance of commercial banks.

The balance sheets of large commercial banks are generally more robust and diversified compared to those of smaller commercial banks. A more comprehensive regulatory framework, highly skilled professionals, and higher credit ratings and reputation can help large commercial banks attract more business opportunities (Chen et al., 2018). In addition, large banks typically exhibit a greater capacity to withstand risks, thereby enhancing their resilience in volatile market environments. Therefore, large commercial banks are believed to be more effective in improving their profitability (Anbar & Alper, 2011; Berger & Mester, 1997; Lee & Kim, 2013). Based on a fixed effects model analysis of 10 banks in Turkey from 2002 to 2010, it was found that asset size has a significant positive effect on bank profitability, indicating that large commercial banks have higher returns on total assets (*ROA*) or return on equity (*ROE*). Therefore, this study makes the following assumptions:

H_4: Bank size is positively correlated with the operational performance of commercial banks.

The cost-to-income ratio reflects the efficiency and profitability of commercial banks. A higher cost-to-income ratio indicates a lower profit-generating capacity, as operating costs account for a greater proportion of operating income (Arif & Nauman Anees, 2012; Chen et al., 2018; Khan & Syed, 2013).

H_5: The cost-to-income ratio is negatively correlated with the operational performance of commercial banks.

The total asset-equity ratio (*REA*) reflects the loss-absorbing capacity of commercial banks. Banks maintaining a higher *REA* may forgo investment opportunities due to excessive risk aversion, thereby reducing their competitiveness in the market; conversely, a lower *REA* indicates insufficient capitalization, increasing the bank's exposure to financial risks. Therefore, the relationship between *REA* and the operating performance of commercial banks may be positive or negative.

H_6: The relationship between the total assets-to-equity ratio and the operational performance of commercial banks may be either positive or negative.

3. MODEL AND VARIABLE SELECTION

The Relative Liquidity Mismatch Index (*RLMI*) is the primary explanatory variable influencing the operating performance of commercial banks. Additionally, other bank-specific variables such as bank size, total deposits, and cash reserves also affect the operating performance of Chinese commercial banks. This study employs the two-step system GMM estimation to empirically test the six hypotheses proposed above.

3.1. Model and Estimation Method

This study constructs a dynamic panel regression model to examine the relationship between liquidity risk and the operating performance of commercial banks. According to existing literature, bank panel data are typically analyzed using fixed effects models, random effects models, or vector autoregression (VAR) models. However, when lagged variables are important or when endogeneity exists, the regression coefficients estimated from these models may suffer from severe bias.

Arellano and Bond (1991) proposed the Generalized Method of Moments (Difference GMM) to address this issue. Nevertheless, this method is susceptible to weak instruments and finite sample bias. To improve estimation accuracy, Arellano and Bover (1995) and Blundell and Bond (2002) developed the GMM estimator, which combines the difference equation and the level equation. Specifically, a set of lagged difference variables are used as instrumental variables for the level equation under the assumption that the first-difference instruments are uncorrelated with the fixed effects. This approach allows for the inclusion of additional instruments, thereby improving the estimation efficiency.

Blundell and Bond (2002), using a Monte Carlo simulation, demonstrated that the System GMM estimator exhibits smaller bias compared to the Difference GMM estimator. The System GMM approach includes one-step system GMM and two-step system GMM. Although the two-step system GMM suffers from downward bias in standard errors, the standard covariance matrix in the two-step effectively alleviates the problems of serial autocorrelation and heteroskedasticity in the model (Hu & Qiao, 2013; Jiang, 2010; Zhang & Zhang, 2016; Zhou, Xie, & Wang, 2019). Therefore, this study adopts the two-step system GMM method to estimate the model. The *Collapse* option is employed to reduce the number of instruments to mitigate the problem of degrees of freedom loss. In addition, robust standard errors corrected by Windmeijer (2005) for finite samples are used to address the downward bias of standard errors. Since the current operating performance of commercial banks may be influenced by their past performance, the lagged dependent variable is also included in the model as an independent variable. Based on this, the dynamic panel regression model constructed in this paper is:

$$Y_{i,t} = \alpha Y_{i,t-1} + \beta RLMI_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}$$

where $Y_{i,t}$ represents the operating performance of bank i in year t, $Y_{i,t-1}$ represents the operating performance of bank i in year $t-1$, including two types of variables: return on average assets (*ROAA*) and net interest margin (*NIM*)

; $RLMI_{i,t}$ represents the Relative Liquidity Mismatch Index (*RLMI*) of bank *i* in year *t*, which is the core explanatory variable in our regression model; $X_{i,t}$ is the control variable: bank size (*SIZE*), cost-to-income ratio (*RCI*), total asset-to-equity ratio (*REA*), total deposits (*DE*), cash (*CA*) , total deposits (*DE*) and cash (*CA*) have all been logarithmically transformed. recorded as *LDE* and *LCA* ;α is a constant term; $\varepsilon_{i,t}$ is an independent disturbance term.

It is necessary to conduct relevant tests to verify whether the estimation results are valid when using the two-step System GMM estimation method. First, the Arellano-Bond test is employed to examine whether the residuals of the level equation exhibit serial correlation. The null hypothesis assumes there is no residual serial correlation. If the test results indicate that AR(1) detects first-order autocorrelation but AR(2) fails to detect second-order autocorrelation, the null hypothesis cannot be rejected, suggesting that the model specification is valid.

Secondly, the Hansen test is conducted to examine validity of the selected of instruments, where the null hypothesis is that the instruments variables are valid.

Finally, the Difference-in-Hansen test is used to assess the validity of additional GMM-type instruments, reflecting whether the System GMM estimator outperforms the Difference GMM. The null hypothesis is that the additional instruments are valid.

In addition, this study also presents the regression results of the Ordinary Least Squares (OLS) and Fixed Effects (FE) models. Despite their limitations, they can still be used as comparison results to verify the high efficiency of the two-step system GMM.

3.2. Variables and Data Sources

This study selects return on average assets (*ROAA*) and net interest margin (*NIM*) (Chen et al., 2018; Heffernan & Fu, 2010) to represent the operating performance of commercial banks as explained variables; Relative Liquidity Mismatch Index (*RLMI*), bank size (natural logarithm of total assets, *SIZE*), natural logarithm of total deposits (*LDE*), cost-to-income ratio (*RCI*), total assets-to-equity ratio (*REA*), and natural logarithm of cash (*LCA*) (Arif & Nauman Anees, 2012; Chen et al., 2018; Heffernan & Fu, 2010; Khan & Syed, 2013) as explanatory variables.

Table 1. Variable definitions, measurements, and data sources.

Variable Category	Notation	Variable	Measure	Data source
Explained variable	*ROAA*	Return on average assets (ROAA)	Net profit / Average total assets	Annual reports of banks
	NIM	Net interest margin (NIM)	Interest earning rate - Interest paying rate	Annual reports of banks
Core explanatory variables	*RLMI*	Relative liquidity mismatch index (RLMI)	Asset-side liquidity / Liability-side liquidity	Standardized balance sheet, compiled and calculated by the authors
Control variables	$ROAA_{i,t-1}$	Lagged return on average assets	Net profit of the previous period / Average total asset in previous period	Annual reports of banks
	$NIM_{i,t-1}$	Lagged net interest margin	Interest earning rate in previous period - Interest paying rate in previous period	Annual reports of banks
	SIZE	Bank size	Natural logarithm of total assets	Annual reports of banks
	LDE	Log of total deposits	Natural logarithm of total deposits, including savings deposits and corporate demand & time deposits	Annual reports of banks
	LCA	Log of cash holdings	Natural logarithm of cash balance held by the bank	Annual reports of banks
	REA	Total asset-to-equity ratio	Owners' equity / Total assets	Annual reports of banks

This paper selects 14 major joint-stock listed banks as samples. They are Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, Bank of China, Bank of Communications, Everbright Bank, China Guangfa Bank, Hua Xia Bank, Minsheng Bank, Ping An Bank, Shanghai Pudong Development Bank, Industrial Bank, China Merchants Bank, and China CITIC Bank. These include China's five large state-owned commercial banks: Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China, China Construction Bank, and Bank of Communications. The sample banks represent the major commercial banks in China. The financial indicator data of listed banks are relatively complete. The data required to calculate the Relative Liquidity Mismatch Index (RLMI) comes from the balance sheet of the Global Detailed Format standard of the Bankscope database, and the rest of the data comes from the annual reports of various commercial banks.

4. EMPIRICAL PROCESS AND REGRESSION ANALYSIS

The primary explanatory variable in the regression model constructed in this study is the Relative Liquidity Mismatch Index (*RLMI*), which represents the liquidity risk of China's commercial banks. Therefore, *RLMI* is calculated first.

4.1. Calculation of RLMI Index

LMI reflects the mismatch between the market liquidity of the asset side and the financing liquidity of the liability side and is used to estimate the liquidity risk of commercial banks (Brunnermeier & Krishnamurthy, 2013). *LMI* of commercial bank *i* in year *t* is.

$$LMI_t^i = \sum_k \lambda_{t,a_k} a_{t,k}^i - \sum_{k'} \lambda_{t,l_{k'}} l_{t,k'}^i$$

Where, $\sum_k \lambda_{t,a_k} a_{t,k}^i$ represents the market liquidity of assets, $\sum_{k'} \lambda_{t,l_{k'}} l_{t,k'}^i$ represents the financing liquidity of liabilities, $a_{t,k}^i$ and $l_{t,k'}^i$ represents the value of assets *k on the asset side and* the value of liabilities k' on the liability side of a commercial bank *i* in year *t*, respectively. The values of $a_{t,k}^i$ and $l_{t,k'}^i$ will change with the changes in period and type of assets and liabilities. λ_{t,a_k} represents the market liquidity weight of asset *k* in year *t*. The higher the market liquidity risk, the higher the liquidity of assets. $\lambda_{t,l_{k'}}$ represents the financing liquidity weight of liabilities k' in year *t*. The higher the financing liquidity risk, the lower the liquidity of liabilities. Usually, the values of λ_{t,a_k} and $\lambda_{t,l_{k'}}$ are between 0 and 1 and change with changes in market conditions. Although Brunnermeier and Krishnamurthy (2013) comprehensively considered the mismatch between the market liquidity of assets and the financing liquidity of liabilities, they ignored that the balance sheet composition of large banks and small banks may be different. Since *LMI* cannot accurately and directly compare the liquidity risk levels of commercial banks of different sizes, following on Gao et al. (2018), we use the Relative Liquidity Mismatch Index (*RLMI*) to estimate the liquidity risk level based on the balance sheet of China's commercial banks:

$$RLMI = \frac{\sum_k \lambda_{t,a_k} a_{t,k}^i}{\sum_{k'} \lambda_{t,l_{k'}} l_{t,k'}^i}$$

RLMI refers to the value obtained by summing the selected items on the asset and liability sides of the balance sheet after assigning reasonable weights, then comparing them. When the ratio is greater than 1, it indicates that the liquidity risk of the commercial bank is low; when the ratio equals 1, it signifies that the market liquidity of assets and the financing liquidity of liabilities are in equilibrium; when the ratio is less than 1, it suggests that the commercial bank faces a higher liquidity risk level. The key to calculating the *RLMI* lies in determining the weights of asset-side and liability-side items. There are two main methods for determining weights: the static weight method and the empirical method designed by Bai et al. (2018). Considering that the asset and liability structure of China's commercial banks is relatively simple, this paper employs the static weight method.

Asset side weight.

$$\lambda_{t,a_k} = 1 - RSF$$

Liability side weight.

$$\lambda_{t,l_{k'}} = 1 - ASF$$

The Net Stable Funding Ratio (NSFR), established by the Basel Committee, is an international regulatory indicator designed to measure the level of liquidity risk. The NSFR is defined as the ratio of Available Stable Funding (ASF) to Required Stable Funding (RSF).

The ASF refers to the portion of capital and liabilities expected to remain with a financial institution for more than one year. The ASF coefficients are set at 0%, 50%, 90%, 95%, and 100%, where a coefficient of 100% indicates that the corresponding liability item is fully available beyond one year.

The RSF represents the total amount of stable funding that a bank is required to hold, considering the liquidity characteristics and remaining maturities of assets, as well as liquidity risks arising from off-balance sheet exposures. The RSF coefficients include 0 %, 5 %, 10 %, 15 %, 50 %, 65%, 85 % and 100%, where a coefficient of 0% indicates the highest-level liquidity.

Based on this framework, and drawing on the asset and liability items selected by Xu (2016) according to the characteristics of Chinese commercial banks, this study refines the indicators and constructs the corresponding weighting scheme. The specific weight assignment is presented in the following Table 2.

Table 2. Weight distribution of assets and liabilities of Chinese commercial banks.

Assets	**RLMI weight**
Other securities	15%
Other loans	15%
Mortgage	35%
Consumer loans	35%
Corporate loans	35%
Derivative financial instruments	50%
Held-to-maturity financial assets	50%
Financial assets at fair value through trading	85%
Financial assets at fair value through profit or loss	85%
Available-for-sale financial assets	85%
Reverse repurchase agreements, securities borrowing, and cash collateral	90%
Cash and deposits with central banks	100%
Liabilities	**RLMI weight**
Fixed deposits	5%
Other customer deposits	5%
Customer deposits	5%
Short-term borrowings and debt securities with a historical cost of less than 1 year	5%
Current deposit	10%
Other liabilities	50%
Taxes payable liabilities	50%
Deferred tax liabilities	50%
Repurchase agreements, loan securities, cash collateral	90%
Derivative financial instruments	100%
Bank deposits	100%

Based on the determined weights, Table 3 shows the calculation results of the Relative Liquidity Mismatch Index (*RLMI*) of Chinese commercial banks.

Table 3. Relative liquidity mismatch index (RLMI) of Chinese commercial banks.

Bank	2011	2012	2013	2014	2015	2016	2017	2018	2019
Large state-owned commercial banks									
Bank of China	1.88	1.79	1.86	1.82	1.74	1.89	1.84	1.73	1.66
Industrial and Commercial Bank of China	2.46	2.47	2.63	2.53	2.23	2.32	2.39	2.30	2.26
China Construction Bank	2.62	2.63	2.85	2.60	2.23	2.13	2.31	2.09	1.99
Agricultural Bank of China	2.90	2.90	2.92	2.69	2.44	2.33	2.45	2.19	2.13
Bank of Communications	1.73	1.74	1.70	1.47	1.37	1.27	1.25	1.24	1.39
Joint-stock commercial banks									
China Everbright Bank	1.65	1.28	1.40	1.51	1.43	1.15	1.40	1.34	1.26
China Guangfa Bank			1.62	1.53	1.31	1.31	1.24	1.22	1.13
Huaxia Bank	1.82	1.69	1.60	1.61	1.67	1.47	1.56	1.46	0.93
China Minsheng Bank	1.87	1.51	1.85	1.51	1.41	1.03	1.10	1.25	1.09
Ping An Bank		1.26	1.24	1.45	1.26	1.07	1.30	1.49	1.66
Shanghai Pudong Development Bank	1.56	1.53	1.39	1.39	1.18	1.18	1.18	1.12	1.20
Industrial Bank	1.29	1.29	1.44	1.24	0.92	0.96	1.04	1.16	0.89
China Merchants Bank	2.21	1.84	1.69	1.72	1.50	1.43	1.51	1.54	1.41
China CITIC Bank	1.48	1.92	1.79	1.54	1.28	1.32	1.44	1.44	1.42

Figure 1 shows, the liquidity risk of joint-stock commercial banks is generally higher than that of large state-owned commercial banks. With the deepening of financial reform and gradual liberalization of interest rates, joint-stock commercial banks have increasingly focused on improving their profitability while relaxing their internal control over liquidity risk. For example, the RLMI of Huaxia Bank in 2019 (0.93) and Industrial Bank in 2015 (0.92), 2016 (0.96), and 2019 (0.89) were all below 1, indicating a relatively high potential liquidity risk that warrants close attention. However, the overall liquidity risk level of Chinese commercial banks is within a reasonable range, and their liquidity positions are generally sufficient to meet normal liquidity demands (Table 3).

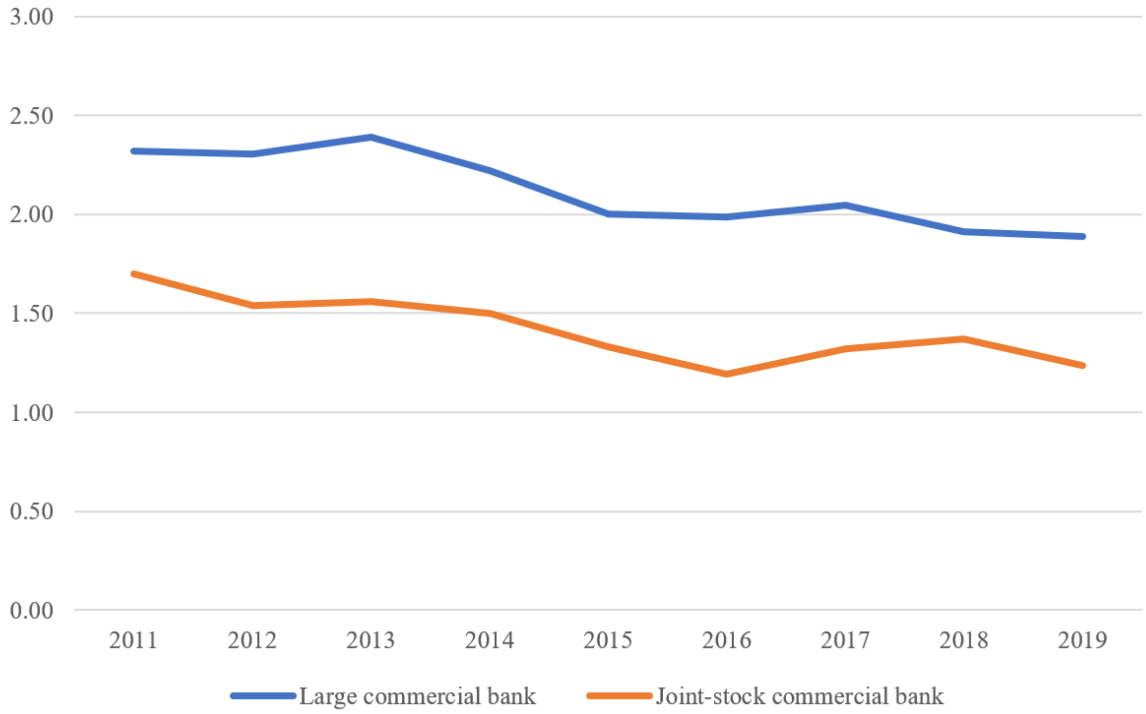

Figure 1. Trends in liquidity risk of Chinese commercial banks.

4.2. Descriptive Statistics

According to the results of the Relative Liquidity Mismatch Index (*RLMI*) calculation and the variables selected in this paper, *Stata 14.1* statistical software is used to perform descriptive statistics on the original data. The results are shown in Table 4.

Table 4. Descriptive statistics of variables.

Variables	Mean	SD	Min.	Max.	Obs.
Panel A: Dependent variables					
ROAA	1.045	0.225	0.480	1.470	125
NIM	2.240	0.393	1.060	3.140	126
Panel B: Independent variables					
$ROAA_{i,t-1}$	1.063	0.222	0.480	1.470	112
$NIM_{i,t-1}$	2.263	0.398	1.060	3.140	112
SIZE	22.519	0.847	20.942	24.128	123
LDE	16.012	0.875	14.486	17.691	123
RCI	30.642	4.453	21.59	41.920	125
REA	0.069	0.010	0.048	0.091	123
LCA	13.651	0.987	12.058	15.370	123
RLMI	1.665	0.491	0.890	2.920	123

The Return on Average Assets (*ROAA*) and Net Interest Margin(*NIM*) are commonly used to measure the profitability of commercial banks (Chen et al., 2018; Heffernan & Fu, 2010). Higher values of these indicators indicate stronger profitability. In terms of *NIM*, China Minsheng Bank (3.14) recorded the highest operating performance in 2011, with an NIM of 3.14.

The cost-to-income ratio exhibits a considerable disparity between the maximum and minimum values, with a difference of 20.33 percentage points. The highest cost-to-income ratio was observed for China Guangfa Bank, reaching 41.92. Overall, from the data reflected in Table 1, the profitability of Chinese commercial banks is relatively high. However, there are significant differences in profit-generating capacity among banks, and their operational efficiency varies considerably.

4.3. Regression Analysis

4.3.1. Stationarity Test

First, we need to test the stability of panel data to ensure the validity of regression results. This paper adopts the Fisher-ADF test method to perform a unit root test on selected variables. The results are shown in Table 5.

Table 5. Unit root test.

Variables	Fisher-ADF test	Conclusion
ROAA	67.670 (0.000)	Stationary
NIM	52.319 (0.004)	Stationary
RLMI	46.880 (0.014)	Stationary
SIZE	71.598 (0.000)	Stationary
LDE	8.825 (1.000)	Unstationary
LCA	69.957 (0.000)	Stationary
REA	23.001 (0.733)	Unstationary
RCI	158.093 (0.000)	Stationary

The above table shows that *LDE* and *REA* are non-stationary variables, while *ROAA*, *NIM*, *RLMI*, *SIZE*, *LCA*, and *RCI* are stationary variables.

4.3.2. Cointegration Test

After conducting the stationarity test, *LDE* and *REA* are identified as non-stationary variables and are classified as first-order integrated variables. A cointegration test is then performed to examine whether a long-term equilibrium relationship exists between the two variables. Since both variables are integrated of the same order, they meet the necessary conditions for conducting the cointegration test. The results of the cointegration test are presented in Table 6.

Table 6. Cointegration test results of LDE and REA.

Statistics	P-value
Gt	0.046
Ga	0.928
Pt	0.000
Pa	0.021

It can be seen from the above table that, at the 5% significance level, the P values of three statistics pass the test and reject the null hypothesis, indicating that there is a long-term stable relationship between the two variables.

4.3.3. Regression Model Test

This study employs the Ordinary Least Squares (OLS) model, the Fixed Effects (FE) model, and the two-step System GMM model to compare the regression results. Before deciding whether to use the FE model, a Hausman test is conducted. The test results indicate that the p-value is statistically significant at the 0.01 level, leading to the rejection of the null hypothesis and supporting the use of the FE model. Second, a Davidson and MacKinnon (1993) test is conducted to examine whether the model suffers from endogeneity issues. The test results are presented in Table 7.

Table 7. DM test.

Davidson-MacKinnon test	
DM value	26.996
P-value	0.000

The DM test results show that the P value is 0.000. At a significance level of 5%, the null hypothesis is rejected, suggesting the presence of endogenous variables in the model. Based on this result, this study employs the two-step System GMM estimation method using the *xtabond2* command in Stata 14.1. Specifically, *L. ROAA* and *L.NIM* represent the first-order lagged variables of Return on Average Assets (*ROAA*) and Net Interest Margin (*NIM*), respectively. According to the requirements of the *xtabond2* command, GMM instruments are used for endogenous variables, while IV instruments are used for exogenous variables (Roodman, 2006).

Therefore, this study selected the first-order lagged dependent variable, Bank Size (*SIZE*), and the Relative Liquidity Mismatch Index (*RLMI*) as GMM instruments in the level equation. The natural logarithm of Cash Holdings (*LCA*), the natural logarithm of Total Deposits (*LDE*), the Cost-to-Income Ratio (*RCI*), and the Total Asset-to-Equity Ratio (*REA*) were used as IV-type instruments. Additionally, the collapse option is applied to restrict the lag structure of GMM-type instruments to avoid the loss of degrees of freedom.

4.4. Results of Empirical Analysis

The AR (1) and AR (2) tests of the two-step system GMM indicate that the residual sequence of the difference equation exhibits first-order autocorrelation but no second-order autocorrelation at the 5% significance level, confirming the appropriateness of the model specification. The Hansen and Difference-in-Hansen tests validate the selection of both the overall instrumental variables and each instrumental variable within the GMM subset.

As proposed by Bond (2002), if the GMM estimator of the first-order lagged dependent variable falls between the OLS and FE estimators, the system GMM estimation is considered reliable. As shown in Table 8, the first-order coefficient of the dependent variable NIM, estimated using the two-step system GMM, is 0.658, which lies between the FE estimator (0.304, underestimated) and the OLS estimator (0.732, overestimated). Similarly, the first-order GMM coefficient of the lagged *ROAA* is 0.647, falling between the FE estimator (0.486, underestimated) and the OLS estimator (0.914, overestimated). These results confirm the robustness of the two-step system GMM estimation.

When *NIM* is used as the dependent variable, only the coefficient of *LDE* is not statistically significant, whereas when *ROAA* is used as the dependent variable, both *RCI* and *REA* are not significant. This suggests that the model including *NIM* provides a better fit. Consequently, the model with *NIM* as the dependent variable is primarily selected for analysis. The estimation results from the two-step system GMM indicate that the impact of the one-period lagged net interest margin (*L.NIM*) on the current *NIM* is significant at the 0.1% level, confirming the presence of a typical inertia effect. The natural logarithm of cash volume (*LCA*) is negatively correlated with the profitability of commercial banks at the 1% significance level, supporting Hypothesis 1. Although the estimated coefficient of the natural logarithm of total deposits (*LDE*) is not significant, the results indicate that total deposits have a positive impact on the operational performance of commercial banks. The Relative Liquidity Mismatch Index (*RLMI*) exhibits a positive effect on bank profitability at the 5% significance level, confirming Hypothesis 3. This finding suggests that lower liquidity risk is associated with better operational performance in commercial banks. At the 5% significance level, bank size (*SIZE*) is negatively correlated with bank profitability, contradicting the initial hypothesis but aligning with the findings of previous studies (Athanasoglou et al., 2008; Berger & Humphrey, 1997; Chen et al., 2018). This result may be attributed to diminishing scale effects, where increased size does not necessarily translate into higher profitability. The cost-to-income ratio (*RCI*) is negatively associated with commercial bank performance at the 0.1% significance level, supporting Hypothesis 5 and indicating that banks with lower operational efficiency tend to have lower profitability.

Table 8. Empirical results.

Estimation method	Two-step system GMM		FE		OLS	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Panel A: Dependent variable NIM						
L.NIM	0.658***	9.74	0.304***	3.79	0.732***	13.16
LCA	-0.0670**	-3.51	-0.114	-0.84	-0.0451	-1.50
LDE	0.931	1.39	1.836***	4.14	1.129**	3.28
RLMI	0.474*	2.47	0.290**	3.39	0.107	1.45
SIZE	-1.428*	-2.6	-2.091***	-5.91	-1.223***	-3.59
RCI	-0.0543**	-3.34	-0.0346***	-4.34	-0.0188**	-3.27
REA	11.73*	2.79	-0.869	-0.32	3.407	1.46
_cons	18.95***	5.02	21.39***	6.84	10.77***	4.15
AR(1)	0.041					
AR(2)	0.719					
Hansen	1.000					
Difference-in-Hansen	1.000					
Panel B: Dependent variable ROAA						
L.NIM	0.647***	4.27	0.486***	8.19	0.914***	23.10
LCA	-0.0231*	-2.47	-0.0545	-1.18	-0.00196	-0.17
LDE	0.752*	2.44	0.472**	3.05	0.142	1.07
RLMI	0.214**	3.09	0.107***	3.6	0.0356	1.24
SIZE	-0.822*	-2.67	-0.606***	-4.94	-0.158	-1.20
RCI	-0.0084	-1.21	0.00318	1.15	-0.000106	-0.04
REA	1.703	1.32	0.929	1.00	1.033	1.13
_cons	6.918*	2.86	7.005***	5.91	1.224	1.27
AR(1)	0.041					
AR(2)	0.666					
Hansen	1.000					
Difference-in-Hansen	1.000					

Note: t statistic : * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Furthermore, the coefficients of the total asset-equity ratio (*REA*) and *NIM* are positive at the 5% significance level. Since the total asset-equity ratio reflects a bank's capacity to absorb losses, excessive asset holdings may reduce profit opportunities and negatively impact operational performance. However, the positive coefficient in this study suggests that the total asset-equity ratio of the sampled banks remains within a reasonable range, thereby contributing positively to their operational performance. A potential negative impact may only emerge if the ratio continues to increase beyond an optimal threshold.

5. CONCLUSION

Based on the balance sheets of Chinese commercial banks, this study constructs the Relative Liquidity Mismatch Index (*RLMI*) by incorporating the ASF and RSF factors from the Basel Accord to assess the liquidity risk level of Chinese commercial banks. The empirical results, supported by rigorous hypothesis testing in Table 9, demonstrate that the overall liquidity level of the Chinese banking system remains moderate, with a relatively low probability of liquidity risk. This reflects the effectiveness of China's stringent financial risk prevention measures, regulatory oversight, and policy interventions in maintaining financial stability.

Furthermore, this study empirically examines the impact of liquidity risk on the operational performance of 14 commercial banks in China from 2011 to 2019, incorporating additional control variables such as cash reserves and total deposits to analyze the determinants of bank profitability. The results demonstrate that the two-step System GMM model provides a better estimation of the relationship between explanatory and dependent variables compared to the FE model. In terms of coefficient significance, Net Interest Margin (*NIM*) serves as a more effective measure of commercial bank profitability than return on average assets (*ROAA*). Moreover, a higher level of liquidity significantly contributes to improving the operational performance of commercial banks. However, against the backdrop of global economic uncertainty and the deepening reform of China's financial system, the mismatch between market liquidity and financing liquidity in Chinese commercial banks has become increasingly complex. A continued decline in the Relative Liquidity Mismatch Index (*RLMI*) could significantly heighten liquidity risks for individual commercial banks, which may further lead to systemic financial instability within the banking sector.

Table 9. Hypothesis test conclusion.

Assumptions	Conclusion
H1: Cash reserves are negatively correlated with the operating performance of commercial banks.	Accept
H2: There is a positive correlation between deposit levels and the operating performance of commercial banks.	Accept
H3: The RLMI index is positively correlated with the operating performance of commercial banks.	Accept
H4: Bank size is positively correlated with the operating performance of commercial banks.	Reject
H5: There is a negative correlation between the cost-to-income ratio and the operating performance of commercial banks.	Accept
H6: The correlation between the total assets-to-equity ratio and the operating performance of commercial banks can be positive or negative.	Accept

6. POLICY IMPLICATION

The conclusions of this study emphasize the importance of maintaining rigorous supervision over liquidity risk in China's commercial banks. Although holding cash reserves increases management costs and reduces profitability, cash remains one of the most liquid assets, and maintaining an adequate level of reserves can mitigate potential liquidity risks. Since liquidity risk arises from the mismatch between the market liquidity of assets and the financing liquidity of liabilities, commercial banks should avoid excessive profit-driven strategies that overlook liquidity mismatches. Instead, they must establish a balanced asset-liability structure to effectively mitigate and manage liquidity risk. Additionally, commercial banks should closely monitor international liquidity risk regulatory indicators, changes in domestic financial policies, and macroeconomic fluctuations to prevent liquidity shocks. From a regulatory perspective, reforms to the existing supervision framework and management mechanisms are necessary to establish a comprehensive liquidity risk management system. The principles of safety, liquidity, and profitability should be integrated to develop a regulatory framework aligned with international best practices, with consideration given to incorporating the liquidity mismatch index as a regulatory indicator. Strengthening cooperation between the central bank and commercial banks is crucial to ensuring both risk prevention and operational efficiency, thereby safeguarding the stability of the banking system.

Funding: This research is supported by China Scholarship Council (CSC).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by the corresponding author.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

Anbar, A., & Alper, D. (2011). Bank specific and macroeconomic determinants of commercial bank profitability: Empirical evidence from Turkey. *Business and Economics Research Journal*, *2*(2), 139-152.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277-297. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29-51. https://doi.org/10.1016/0304-4076(94)01642-d

Arif, A., & Nauman Anees, A. (2012). Liquidity risk and performance of banking system. *Journal of Financial Regulation and Compliance*, *20*(2), 182-195. https://doi.org/10.1108/13581981211218342

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, *18*(2), 121-136. https://doi.org/10.1016/j.intfin.2006.07.001

Bai, J., Krishnamurthy, A., & Weymuller, C. H. (2018). Measuring liquidity mismatch in the banking sector. *The Journal of Finance*, *73*(1), 51-93. https://doi.org/10.1111/jofi.12591

Basel Committee on Banking Supervision. (2000). *Sound practices for managing liquidity in banking organisations*. Basel: Bank for International Settlements.

Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *The review of Financial Studies*, *22*(9), 3779-3837. https://doi.org/10.1093/rfs/hhn104

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175-212. https://doi.org/10.1016/s0377-2217(96)00342-6

Berger, A. N., & Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking & Finance*, *21*(7), 895-947. https://doi.org/10.1016/s0378-4266(97)00010-1

Blundell, R., & Bond, S. (2002). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Bond, S. R. (2002). Dynamic panel data models: A guide to micro data methods and practice. *Portuguese Economic Journal*, *1*, 141-162.

Brunnermeier, M., & Krishnamurthy, A. (2013). Introduction to "Risk topography: Systemic risk and macro modeling". In Risk Topography: Systemic Risk and Macro Modeling. In (pp. 1-12). Chicago: University of Chicago Press.

Cao, Y. (2007). Research on evaluation of operating performance in Chinese shareholding commercial banks. *Journal of Beijing Technology and Business University (Social Science)*, *6*, 80–84.

Chen, Y.-K., Shen, C.-H., Kao, L., & Yeh, C.-Y. (2018). Bank liquidity risk and performance. *Review of Pacific Basin Financial Markets and Policies, 21*(01), 1850007.

Chi, G., Zhu, Z., & Xu, C. (1999). Three-element-based comprehensive evaluation model on commercial bank's operating performance. *Chinese Journal of Management Science, 4*, 58–67.

Davidson, R., & MacKinnon, J. G. (1993). *Estimation and inference in econometrics*. New York: Oxford University Press.

De Haan, L., & van den End, J. W. (2013). Bank liquidity, the maturity ladder, and regulation. *Journal of Banking & Finance, 37*(10), 3930-3950. https://doi.org/10.1016/j.jbankfin.2013.07.008

Demirgüç-Kunt, A., & Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *The World Bank Economic Review, 13*(2), 379-408.

Diamond, D. W., & Rajan, R. G. (2005). Liquidity shortages and banking crises. *The journal of Finance, 60*(2), 615-647. https://doi.org/10.1111/j.1540-6261.2005.00741.x

Dietrich, A., & Wanzenried, G. (2014). The determinants of commercial banking profitability in low-, middle-, and high-income countries. *The Quarterly Review of Economics and Finance, 54*(3), 337-354.

Drehmann, M., & Nikolaou, K. (2013). Funding liquidity risk: definition and measurement. *Journal of Banking & Finance, 37*(7), 2173-2182.

Gao, L., Xu, Z., & Du, S. (2018). System liquidity risk measurement on China's commercial banks: Based on the perspective of liquidity mismatch. *East China Economic Management, 32*(4), 110–116.

Guo, L., & Che, S. (2017). Maturity mismatch between assets and liabilities of commercial banks and its countermeasures. *Modern Management Science, 10*, 45–47.

Heffernan, S. A., & Fu, X. (2010). Determinants of financial performance in Chinese banking. *Applied Financial Economics, 20*(20), 1585-1600. https://doi.org/10.1080/09603107.2010.505553

Hu, B., & Qiao, J. (2013). How does China's OFDI affect its exports? An empirical analysis using dynamic panel data models and system GMM estimators. *Economic Management, 35*, 11–19.

Iori, G., Jafarey, S., & Padilla, F. G. (2006). Systemic risk on the interbank market. *Journal of Economic Behavior & Organization, 61*(4), 525-542. https://doi.org/10.1016/j.jebo.2004.07.018

Jiang, Y. (2010). On the convergence and its nonlinearity of China's provincial urban-rural income inequality: Evidence from dynamic panel and threshold panel models. *Contemporary Finance & Economics, 6*, 19–25.

Kalkbrener, M., & Willing, J. (2004). Risk management of non-maturing liabilities. *Journal of Banking & Finance, 28*(7), 1547-1568.

Khan, M. K. R., & Syed, N. A. (2013). Liquidity risk and performance of the banking system (RETRACTED). *JISR Management and Social Sciences & Economics, 11*(2), 55-70.

Khan, M. S., Scheule, H., & Wu, E. (2017). Funding liquidity and bank risk taking. *Journal of Banking & Finance, 82*, 203-216. https://doi.org/10.1016/j.jbankfin.2016.09.005

Lee, J. Y., & Kim, D. (2013). Bank performance and its determinants in Korea. *Japan and the World Economy, 27*, 83-94.

Li, B., & Geng, S. (2020). Measurement of term mismatch risk of commercial banks. *Statistics & Decision, 36*, 125–129.

Liu, J., Zhao, P., & Tian, J. (2019). Study on measurement of liquidity risk of commercial banks based on time-varying model. *The Theory and Practice of Finance and Economics, 40*, 1–10.

Liu, X., & Liu, J. (2013). Leverage, liquidity, and operating performance: A panel data analysis of China's listed commercial banks from 2004 to 2011. *Studies of International Finance, 3*, 88–95.

Monfort, A., & Renne, J.-P. (2014). Decomposing euro-area sovereign spreads: credit and liquidity risks. *Review of Finance, 18*(6), 2103-2151.

Peng, J., Wang, J., & Zou, K. (2014). The recognition and control on liquidity risk of deposit and loan maturity mismatch from the macro-prudential perspective. *The Theory and Practice of Finance and Economics, 4*, 2–8.

Petria, N., Capraru, B., & Ihnatov, I. (2015). Determinants of banks' profitability: Evidence from EU 27 banking systems. *Procedia Economics and Finance, 20*, 518-524. https://doi.org/10.1016/s2212-5671(15)00104-5

Qiu, X. (2015). Maturity mismatch and bank interest margin. *Journal of Financial Research, 5*, 83–100.

Ran, R. (2019). Analysis of liquidity risks measurement and influencing factors in light of the maturity mismatch of commercial banks. *Journal of Contemporary Financial Research*, *1*, 1–10.

Ren, Y., Xie, J., Zhou, J., & Zhang, J. (2020). Study on the characteristics and effects of local government's liquidity credit risk network. *Journal of Hunan University (Social Sciences)*, *34*(4), 65–73.

Roodman, D. (2006). *How to do xtabond2*. Paper presented at the North American Stata Users' Group Meetings 2006. No. 8. Stata Users Group.

Sun, L., Li, J., & Xie, T. (2018). An empirical study on the determinants of liquidity levels of listed commercial banks in China. *Financial Theory & Practice*, *8*, 12–16.

Vento, G. A., & La Ganga, P. (2009). Bank liquidity risk management and supervision: Which lessons from recent market turmoil? *Journal of Money, Investment and Banking*, *10*(10), 78-125.

Wang, H., & Li, S. (2020). Multiplex networks infection and control of financial systemic risk. *Journal of Dalian University of Technology (Social Sciences)*, *41*(5), 29–41.

Wang, Y., & Liang, Z. (2015). Maturity mismatch, liquidity crisis, and asset prices: A theoretical model and numerical simulation. *South China Finance*, *3*, 21–26.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25-51.

Xiang, H., & Zeng, Q. (2019). Maturity mismatch, liquidity Creation and Bank Fragility. *Finance and Trade Economics*, *40*(008), 50-66.

Xu, Z. (2016). *The research on the liquidity risk of Chinese commercial banks on macro-prudential framework*. Doctoral Dissertation. University of International Business and Economics.

Yi, H. (2016). Examining the liquidity risk of commercial banks through maturity mismatch. *Finance & Economy*, *6*, 46–49.

Zhang, S., & Zhang, J. (2016). Environmental regulation and the extensive and intensive margins of export: Evidence from intra-product specialization and dynamic estimation using the two-step system GMM method. *World Economy Study*, *1*, 76–86.

Zhao, J., Li, Q., & Feng, S. (2019). Competitive neutrality, financing constraint unequivaleece and economic effect evaluation. *Chinese Review of Financial Studies*, *11*, 15–35.

Zhou, P., Xie, L., & Wang, Y. (2019). Dynamic evolution and driving factors of agricultural total factor productivity in China: Evidence from the DEA-Malmquist index and two-step system GMM approach. *Lanzhou Academic Journal*, *12*, 170–186.

Zhu, D. (2013). An analysis of deposit-loan maturity mismatch and liquidity risk in commercial banks. *South China Finance*, *10*, 89–92.

Zhu, M., & Hou, Z. (2014). Investigating the funding mismatch of Chinese commercial banks: Evidence and reflections from the "cash crunch" in China. *Studies of International Finance*, *4*, 62–69.

Zuo, X. (2008). Theoretical research on the operating performance evaluation of commercial banks. *On Economic Problems*, *10*, 107–111.