CRISPUS

General and Social Science: Current Trends

*CAO Yiran and WANG Dong.. Gen Soc. Sci. Cur. Tr. 2019:1:1:3* **2019: Vol 1: Iss 1: 3**

Original Research Article

# The Effects of Shadow Banking on Stability and Profitability of China's Commercial Banks Evidence from Panel VAR

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**Received:** 07 January 2019

**Accepted:** 20 March 2019

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## ABSTRACT

We apply vector auto regression (VAR) to bank-level panel data from 16 commercial banks to study the dynamic relationship between the size of shadow banking, stability and profitability of commercial banking system. By adopting orthogonalized impulse-response and variance decomposition functions we are able to separate the `shadow banking factors' that influence the level of the soundness and profitability of China's commercial banks. We find that the size of shadow banking positively/negatively relates to the profitability/stability of China's commercial banks in the short term. But in the long run, the effects tend to be weakened before which a short inverse also presents.

**Keywords:** Shadow Banking, Commercial Bank, Stability, Profitability, Panel VAR

**JEL Codes:** B23, B27, G21

## INTRODUCTION

The shadow banking system is a web of specialized financial institutions that channel funding from savers to investors through a range of securitization and secured funding techniques [1]. Although shadow banks conduct credit and maturity transformation similar to that of traditional banks, they do so without a strong safety net, such as publicly guaranteed deposit insurance or lender of last resort facilities from central banks [2].

In China, shadow banks are financial firms that perform similar functions and assume similar risks to banks. Because of a series of constraints imposed by central bank, as well as the advantages of shadow banks that they have lower capital and liquidity requirements, a number of businesses pushed away from traditional banks towards shadow banking since 2010. According to the report of the Chinese Academy of Social Sciences [3], the scale of the shadow banking system in China reached 14.6 trillion yuan (based on official data) or 20.5 trillion yuan (based on market data) at the end of 2012, the former accounted for 29% of GDP and 11% of the total assets of the banking industry, while the latter accounted for 40% of GDP and 16% of the total assets of the banking industry.

The rapid development of shadow banking in China has been a two-edged sword. It is known that shadow banks can help spur economic growth by making financial services cheaper and more widely available, but there is obviously a trade-off in terms of lowered financial stability. Haunted by the severe crisis in the US financial system in 2008, shadow banking has also been a great concern and especially acute given China's very rapid rate of credit creation and the lack of transparency in much off balance sheet or non-bank activity [4]. Although there is less use than that in the West of practices or instruments such as securitization, derivatives, CDOs or CDS, instruments in China such as Trust Beneficiary Rights and repurchase agreements using loans as collateral can bring some of the similar risk [5].

Having the dominated status in China's traditional banking system, commercial banks has a stake in the health of the shadow banking system in multiple ways. However, the magnitude, direction as well as duration of such an effect are still obscure. Thus, researchers pay more attention to how the shadow banking relates to traditional banking business in recent year. Based on previous research, we propose to adopt the stability and profitability as explained variables in this paper, to comprehensively explore the impact of shadow banking on the performance of China's commercial banks. To specify, stability is an opposite indicator to the crisis of banking system, which is adopted to measure the robustness of commercial banks. Profitability is also an important indicator in reflecting financial status of commercial banks. Therefore, research on the impacts of shadow banking growth on commercial banking system has important theoretical and practical significance.

## LITERATURE REVIEW

### Shadow banking

Studies on shadow banking can be traced back to the 1960s. Gurley and Shaw [6] studied the money creation of almost all non-bank financial institutions within the framework of the internal currency-external currency. Adrian et al. [7] provided a more refined description of shadow banks, defining them as financial intermediaries that conduct maturity, credit, and liquidity transformation without explicit access to central bank liquidity or public sector credit guarantees. Market participants in China usually refer to nonbank financial institutions, such as trust companies, brokerage firms, small lenders and financial guarantors, as shadow banks. Certain off balance sheet and informal bank lending is also often viewed as shadow banking. The rationale behind this classification is that these activities generally involve regulatory arbitrage and have the potential to increase systemic risks [8].

Schwarcz [9] argued that shadow banking, as a form of financial innovation, was able to improve the return of financial institute via reducing transaction costs. Iwaisako [10] put that due to information asymmetry, the fact is that shadow banking causes information asymmetry by amplifying complexity or making products and financial transactions more difficult to disclose and understand, by which way it gained more profits than traditional banks and fuelled its further expansion. Similarly, Chinese scholar Ba S [11] shared the view that shadow banking is essentially financial innovation, which essentially gain more return through information asymmetry and bypassing regulation. In addition, according to risk diversification theory and investment portfolio theory raised by Markowitz [12], the correlation of shadow banking and traditional loan business effective to diversify risk while improving return.

However, extensive literature held that it was not free to enjoy the benefits brought about by the shadow banking, since it decreased banks capabilities of letting loans and monitoring risks, so as to negatively impact banks important functions as liquidity providers [13]. Scholars also focused on the operating mechanism of shadow banking, the way of risk transmission and the process of triggering financial crisis. The BIS [14] pointed out that the risk of shadow banking naturally shifts along with credit risk to commercial banking system due to financial innovation, leverage manipulation, and excessive trading. In other word, the risk introduced by capital market will spread to the whole financial sector. Baily et al. [15] believed that shadow banks were highly leveraged under non-transparent information, which results in more liquidity risk and systematic risk. Adrian and Shin [16] believed that in a market-lead financial system, shadow banking could promote the integration of banks and capital markets and exacerbated financial vulnerabilities through off balance sheet services. Elliott et al. [3] stated that the main risk of the China's shadow sector is that the trust company lending is intrinsically risky, and suffers from a maturity mismatch. In addition, Sheng et al. [17] proved that the China's shadow banking could increase the complexity of monetary policy and also exacerbated systematic risks. Moreover, Ying and Enyuan [18] illustrated that shadow banking may enlarge instability of China's financial market by using sell-off mechanism, vicious circle mechanism, spread mechanism, anticipation mechanism and refinancing mechanism.

## The stability of commercial banks

In terms of the measurement method for the stability of commercial banks, Tang and Wang [19] applied the Sharp ratio to represent the robustness level of China's commercial banks, regarding Sharp ratio as an indicator for the risk-adjusted return. Brauers et al. [20] developed a methodology that comparing different MCDA methods to evaluate commercial banks with features of decreasing information asymmetry. Fanger et al. [21] adopted CAMEL[1] based categorization to evaluate the financially stability of commercial banks.

## The profitability of commercial banks

Regarding the literature relates to the evaluation for banks profitability, following the early studies of Short [22] and Bourke [23], the literature argued that financial market structure and entry barriers constitute the main external force driving bank profits. However, more recent studies distinguishing managerial (internal) from environmental (external) factors treat financial market structure as just one of a number of external influences that affect bank profitability, and thus include trade interdependence, economic growth, inflation, market interest rates and ownership. Among the internal factors, management controllable factors are bank specific financial ratios representing cost efficiency, liquidity, asset quality, and capital adequacy. Moreover, although

[1]Capital adequacy, Asset quality, Management quality, Earnings and Liquidity

accounting and financial ratios provide important and useful information for assessing banking performance, Seiford & Zhu [24] indicated that many factors relative to bank performance, e.g. assets, revenue, profit, market value, number of employees, investments, and customer satisfaction are better factors for reflecting banking profitability and productivity.

Based on above literature review, we propose two hypotheses to be tested in the following sections:

Hypothesis 1: There will be a negative association between the size of shadow banking and the financial stability of commercial banks.

Hypothesis 2: There will be a positive association between the size of shadow banking and the profitability of commercial banks.

## DATA

The database for commercial banks in this paper is the fiscal data of 16 listed China's commercial banks from 2005 to 2017. Accordingly, we also select the data for shadow banking in the period of 2015-2017.

### Shadow banking (Increment)

There is a range of estimation methodology for the size of shadow banking in China, depending on the definition of shadow banking and estimates of some important statistics. In this paper, we adapt the broad definition of shadow banking, i.e., the financial institutions and credit intermediary services that outside the traditional banking system, to evaluate the size of China's shadow banking. More specifically, around two-third of China's shadow banking consist of loans that are originated by commercial banks and would have been made directly by them and retained on their books; The other one-third of shadow banking appears to arise from a reluctance or inability of banks to effectively lend money to certain segments, plus a natural tendency for some business to be won by non-bank competitors even when competing on a level playing field.

In recognition that banks ceased to be the only finance sources that mattered and it became necessary to examine a fuller range of financial activity. Thus, in this paper, the estimation for the size of China's shadow banking start with figures provided from year 2002 by the Total Social Financing (TSF) released by the central bank and the National Bureau of Statistics of China. In practical, after subtracting the balance of RMB loans, foreign currency loans, corporate bonds, and domestic non- financial companies stock financing from TSF, the sum of Entrusted Loans (EL), Trust Loans (TL), and Undiscounted Bankers Acceptances (UBA) is adopted as a proxy variable for the size of China's shadow banking.

### Stability of Commercial Banks

Referring to The Guidelines for the Compilation for financial Stability indicators compiled by IMF, we select non-performing loan ratio, provision coverage ratio, capital adequacy ratio, core capital adequacy ratio and loan-deposit ratio as proxy banking stability indicators (Bank Stability Index, BSI) to measure the level of the soundness of China's commercial banks.

Based on the international general standard, regulatory requirements of Chinese Banking Regulatory Commission, annual reports of the commercial banks and scholars research, we determinate the critical value of indicators shown in Table 1. A mapping method is adopted to transfer raw data to corresponding interval for better comparison.

*Calculation Methodology:*

Non-performing loan/loan-deposit: the smaller, the better.

Mapped value = [(Original value - Lower bound) / Original interval length] * Mapping interval length + Lower bound of mapping interval

Provision coverage / Capital adequacy / Core capital adequacy: the larger, the better.

Mapped value = [(Upper bound - Original value) / Original interval length] * Mapping interval length + Lower bound of mapping interval

BSI (Bank Stability Index) = Arithmetic average of {NPL; PC; CAR; CCAR; LDR}, a smaller BSI indicates the more stable commercial banking.

| Stability Degree | Safe | Normal | Concerned | Dangerous |
|---|---|---|---|---|
| **Indicator mapping value interval** | [0; 20] | (20; 50] | (50; 80] | (80; 100] |
| **Non-performing loan rate (NPL)** | [0; 1] | (1; 5] | (5; 10] | (10; 100] |
| **Provision Coverage (PC)** | [150;1) | [100; 150) | [80; 100) | [0; 80] |
| **Capital Adequacy Ratio (CAR)** | [12; 100] | [8; 12) | [4; 8) | [0; 4) |
| **Core Capital Adequacy Ratio (CCAR)** | [6; 100] | [4; 6) | [2; 4) | [0; 2) |
| **Loan-Deposit Ratio (LDR)** | [0; 50] | (50; 75] | (75; 85] | (85; 100] |

**Table 1:** Core Indicators Intervals of Banking System.

## Profitability of Commercial Banks

In order to assess the profitability of commercial banks, we apply Return on Average As-sets (ROAA) as the proxy variable of Banks Profitability Index (BPI). ROAA is an effective indicator for presenting how successfully the banks maintain their profitability. In addition, taking into account the characteristic of the high leverage in banking sectors, it is more feasible to measure banks profitability by adopting ROAA rather than ROAE. Scholars also believe that ROAA measures the profitability of the total asset, so it can be regarded as a long-term index [25]. So in our study, consistent with previous literatures, we choose ROAA reported by Wind terminal and banks annual reports as the proxy for BPI. So far, all variables have been well defined and quantified, a summary shown in Table 2.

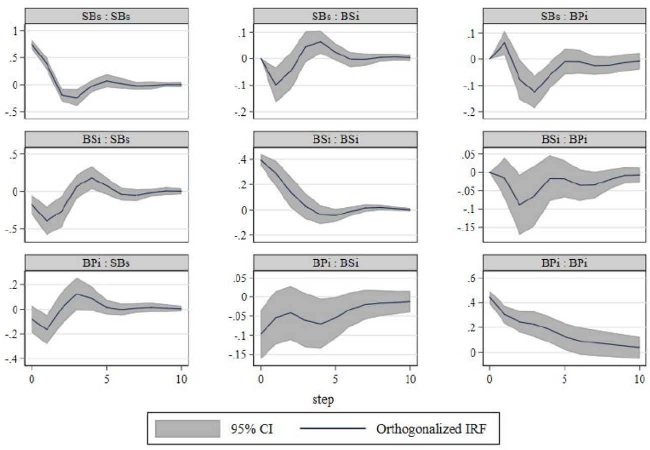


**Figure 1:** Impulse response among {SBS, BPI, BSI}

**Table 2:** Variables Summary.

| Variables | Proxy indicators | Data Sources |
|---|---|---|
| **The size of Shadow Banking (SBS)**[1] | Entrusted Loans, Trust Loans, Undiscounted Bankers' Acceptances | The Peoples Bank of China, National Bureau of Statistics |
| **Bank Stability Index (BSI)** | Non-Performing Loan ratio, Provision Coverage ratio, Capital Adequacy ratio, Core Capital Adequacy ratio, Loan-Deposit ratio | Wind Terminal, Bank scope, Banks Annual report |
| **Bank Profitability Index (BPI)** | Return on average asset (ROAA) | [1]Unit: 100 billion Yuan |

# EMPIRICAL ANALYSIS

## Model Selection

As the purpose of this research is exploring the impact of the size of China's shadow banking on profitability and stability of commercial banks, and further finding out the causality among these three variables, it is suitable to adopt VAR model to achieve this expectation. However, the official data of Total social Financing (TSF) was released since 2002 by the central bank and the National Bureau of Statistics, even worse, the complete data of listed Chinese commercial banks was announced from 2005. Therefore, the data length cannot meet the VAR requirement.

In this case, the prior methodology is the Panel Data Vector Auto-regression (PVAR) model proposed by Holtz-Eakin et al. [26]. Panel VAR model combines the advantages of panel analysis and VAR model, which can overcome the weakness of the sample size and can also check individual fixed effects and time effects by introducing individual effect variables and time-effect variables. Meanwhile, panel VAR model also allows us to analyse the dynamic response of variables in the face of particular impulses. In PVAR model, we assume that t is the length of the time series, m is the order of the lag term, then when $T \geq m + 3$, the parameters of the model can be estimated; when $T \geq 2m + 2$, a stable lag parameter can be estimated. The model in this paper meet the latter requirement, where $m = 2^2$, $t = 13$, thus, a stable lag parameter can be estimated.

[2]The order of lag term is selected by AIC, BIC, and QIC criteria

## Model Setting

A general PVAR Model could be described as follows:

$$z_{i,t} = a_0 + \sum a_j z_{i,t-j} + \alpha_i + v_{i,t} + e_t$$

where $z_{i,t}$ is a three-variable vector that contains all endogenous variables {SBS, BSI, BPI}. SBS, the sum of Entrusted Loans, Trust Loans and Undiscounted Bankers Acceptances derived from TSF, is our proxy for the size of shadow banking; BSI is the combination of a series of financial ratios, which is the proxy variable of the stability of commercial banks, BPI is ROAA (Return on average return), measured as banks profitability.

$SBS_{i,t}$ measures the size of shadow banking of bank *i* at time *t*; $BPI_{i,t}$ represents the profitability of bank i at time t, similarly, $BSI_{i,t}$ measures the stability of commercial bank i at time t. We also introduce fixed effects, donated by i in the model, in order to allow for individual heterogeneity in the levels of variables. The model also allows for bank-specific time dummies, $v_{i,t}$, which are added to model to capture aggregate, bank-specific micro shocks that caused by the size of shadow banking. $e_{i,t}$ is assumed to be a random disturbance that follows normal distribution.

Before setting the Panel-VAR model, we first check the stationary of the panel data to be estimated. In order to enhance the effectiveness of the traditional unit root test, we conduct IIC, IPS and ADF fisher test respectively. We only accept the panel data are stationary when they passed all of three approaches of unit root test. The results are shown as Table 3.

According to the P value shown above, the panel data for SBS, BPI, and BSI all pass the stationary tests: LLC, IPS and ADF Fisher, so we believe the panel data are stationary in this case. (All data has been standard normalized before conducting the stationary test). Therefore, we use the original panel data of SBS, BPI and BSI to set PVAR model for the following discussion.

Considering the PVAR model requires stricter stability condition that all elements within the model are presumed to be stationary [27], we also carry out stability condition test with the result shown that all the eigenvalues lie inside the unit circle, thus, the PVAR satisfies stability condition, which is a fundamental requirement for conducting impulse response and variance decomposition in the following discussion.

In Table 4, based on the three model selection criteria by Andrew and Lu and the overall coefficient of determination, panel VAR with 2 lags is the preferred model in this case, since this has the smallest MBIC, MAIC, and MQIC. Thus, we introduce 2 lags for our panel VAR model.

| lag | J | J p-value | MBIC | MAIC | MQIC |
|---|---|---|---|---|---|
| 1 | 82.36424 | 0.0000002 | -48.64058 | 28.36424 | -2.923215 |
| 2* | 31.58923 | 0.0245796 | -55.74731 | -4.410768 | -25.26907 |
| 3 | 23.56224 | 0.0050498 | -20.10603 | 5.562242 | -4.866908 |

**Table 4:** Results of Lag orders selection with MBIC, MAIC, MQIC

| | LLC | | IPS | | ADF Fisher | |
|---|---|---|---|---|---|---|
| | **Adjusted t*** | **P value** | **W-t-bar** | **P value** | **Chi-square** | **P value** |
| **SBS** | -7.5106 | 0.000 | -3.1742 | 0.0008 | 58.3066 | 0.003 |
| **BPI** | -5.9861 | 0.000 | -3.7005 | 0.0001 | 149.4901 | 0.000 |
| **BSI** | -6.3229 | 0.000 | -3.189 | 0.0007 | 86.3423 | 0.000 |

**Table 3:** Results of Stationary test.

## RESULTS

Based on the above discussion, we apply GMM to estimate the coefficients of the PVAR model after the fixed effects and the bank time dummy variables have been removed. In Table 5 we report the results of the model with three variables {SBS,BSI,BPI}. Reported numbers show the coefficients of regressing the column variables on lags of the row variables.

**Table 5:** GMM Estimation Results

| | *BPIt* | | *BSIt* | | *SBSt* | |
|---|---|---|---|---|---|---|
| | **Coef.** | **P value** | **Coef.** | **P value** | **Coef.** | **P value** |
| **BPIt-1** | 0.701 | 0.000** | 0.003 | 0.967 | -0.461 | 0.000** |
| **BSIt-1** | -0.002 | 0.976 | 0.676 | 0.000** | -0.787 | 0.000** |
| **SBSt-1** | 0.082 | 0.016* | -0.13 | 0.003** | 0.514 | 0.000** |
| **BPIt-2** | 0.026 | 0.743 - | 0.097 | 0.066 | 0.366 | 0.000** |
| **BSIt-2** | -0.203 | 0.005** | -0.229 | 0.001** | 0.152 | 0.071 |
| **SBSt-2** | -0.202 | 0.000** | 0.092 | 0.022* | -0.584 | 0.000** |
| ***5% significance level** | | | | ****1% significance level** | | |

From the results of GMM estimation, we find that different lags may induce different impacts among variables form both magnitude and direction aspects. In particular, $SBS_{t-1}$ has the positive effect on $BPI_t$ while has the negative impact on $BSI_t$, and the coefficients are statistically significant with the p-value of 0.016 and 0.003 respectively. However, the results are just opposite when it comes to lag 2, namely, $SBS_{t-2}$ has the negative effect on $BPI_t$ while has the positive impact on $BSI_t$, and the effects of them are significant at 1% and 5% level respectively. Apart from that, the p-value also show that the lag 1 of the stability and profitability of commercial banks all present an obvious influence in the size of China shadow banking, which indicates a bidirectional relationship between explain variables and explained variables.

### Impulse response

In order to further examine the dynamic relationship between variables, we simulate the impulse response function of BSI, SBG and BPI. The impulse response function is used to measure the impact of a standard deviation of the random disturbance term on the current and future values of other variables. It can intuitively depict dynamic interactions and effects between variables, and can also judge hysteresis effect from dynamic responses.

The Figure 1 report the impulse-response among the three variables {SBS, BPI, BSI}, we observe from the first row that there is a reversed response for BSI when a standard deviation shock of SBS is given. In the first one to two lags, the impulse of SBS induce a negative response to BSI while this response changes its direction afterwards and the trend convergent after period 5. However, the BPI shares the inverse pattern with the BSI, specifically, given a standard deviation impulse of SBS, the BPI has a positive reaction in the first two periods, after which the response turns to be deeply negative. Similarly, the effect of size of shadow banking gradually dies away after step 5. Considering the response of BPI and BSI are all originate from 0, the SBS is prior to {BPI, BSI}. Namely, the shock of SBS is not appearing in the current period, instead, it will make a difference to {BPI, BSI} in the next few periods.

## Variance decomposition

In order to accurately examine the level of influence among {SBS, BPI, BSI}, and compare the contribution of various shocks to endogenous variables, we further adopt the variance de-composition to evaluate the specific variance contribution for each variable response. Table 6 shows the variance decomposition results for the given 5th and 10th prediction periods.

| Impulse/Response | S | BPI | BSI | SBS |
|---|---|---|---|---|
| BPI | 5 | 0.911 | 0.026 | 0.062 |
| BSI | 5 | 0.076 | 0.865 | 0.059 |
| SBS | 5 | 0.048 | 0.254 | 0.698 |
| BPI | 10 | 0.909 | 0.03 | 0.06 |
| BSI | 10 | 0.089 | 0.851 | 0.059 |
| SBS | 10 | 0.048 | 0.259 | 0.693 |

**Table 6:** Variance decomposition

We discuss general results first before proceeding to the ones of our particular interest. We observe that the results at 5th periods and 10th period are quite similar, indicating that the whole system tends to be stable and effects do not have significant changes after 5th periods. Moreover, the fluctuation of {SBS, BPI, BSI} are mainly come from their own effects, which account for 69.8%, 91.1% and 86.5% respectively at 5th period.

In particular, apart from its own effect, the fluctuation of BSI is significantly introduced by the size of shadow banking, with a proportion of 25.4% and 25.9% in period 5 and 10 respectively. Compare to BSI, the effect of shadow banking are relatively less significant on the profitability of commercial banks.

## The Granger Causality Test

The Granger causality test is a statistical hypothesis test for determining whether one series is useful in forecasting another. Ordinarily, regressions reflect "mere" correlations, but Clive Granger argued that causality in economics could be tested for by measuring the ability to predict the future values of a series using prior values of another series. Thus, to verify the results that found out from above discussion and further focus on the predictability of one variable to another, we adopt the Granger-causality analysis to examine the causality among 3 variables {SBS, BPI, BSI}.

From the results in Table 7, we observe that the SBS has bidirectional Granger causalities with {BPI, BSI} under the 1% significance level. We emphasize that the causality from shadow banking to the profitability of banks is notable with a P-value of 0.0000, in the meanwhile, SBS also has remarkable predictability towards the robustness of China's commercial banks. Moreover, there are also Granger causalities between BSI and BPI with a P-value of 0.013, although they are negatively related according to previous discussion.

## CONCLUSION

The size of shadow banking is negatively related to the soundness of commercial banks in short term but this effect gradually inverse until die way in the long run.

In the short term, the incremental size of shadow banking will deteriorate the stability of commercial banking system, the reasons mainly come from its non-transparent nature and risky financial instruments involved. On one hand, banks may involve into default risks by entering into repurchase agreements using loans or WMPs as collateral, so that the trust company can transfer the ultimate economic risk to banks. Typically trust loans extend to high risk borrowers such as real estate developers, local government financing vehicle and manufacturing firms. On the other hand, banks themselves may explore shadow banking services by the issuance of wealth management products as off balance sheet business, WMPs has been a major source of funding that has fuelled the rise in shadow banking credit.

In the long run, more specially, after the stage that shadow banking exacerbated the stability of commercial banking, regulations will be reinforced by the government or relevant departments to ease the adverse impacts on one hand. Moreover, the indirect effect of stress caused by the instability of financial system in the trust sector would most likely to improve the liquidity position of the banks. This is because a crisis of confidence in trust-issued WMPs would lead individual investors to the safety of state-guaranteed bank deposits.

In general, China's shadow banking sector presents relatively low risk of triggering a panic in commercial banking system, the fundamental reason for this is that liquidity is abundant, due to the high levels of deposits from households and businesses, reliance on fragile wholesale funding sources is minimal.

The size of shadow banking is positively related to the profitability of commercial banks in short term but this effect gradually inverse until die way in the long run.

In the short run, the reason for positive relationship between shadow banking and profitability of commercial banks is obvious that the fund absorbing from WMPs are usually used to invest in more profitable projects, which allows commercial banks as well as bank depositors to earn more interest profit. In addition, because of the competition brought by other types of shadow banks, commercial banks have to expand their shadow banking businesses. Thus, the profitability of commercial banks will be enhanced by the increased size of China's shadow banking.

The negative impact in the long term could be explained from two paths. First, the profitability of commercial banks will be directly affected by the size of shadow banking. From the results of our empirical analysis, the increment (positive/negative) in the size of shadow banking two phrases earlier will have a negative effect on the current size. Thus, the cut down on the profit of commercial banks happen simultaneously with the shrink in the shadow banking scale. Second, the profitability of commercial banks has an indirect association with the size of shadow banks connected by the stability of banking system. As discussed earlier, the size of shadow banking two phases ago is positively related with the soundness of commercial banks, it is make sense for a negative relationship between the two variables due to the risk return trade-off.

| Excluded/Equation | BPI | | BSI | | SBS | |
|---|---|---|---|---|---|---|
| | Chi square | P value | Chi square | P value | Chi square | P value |
| BPI | N/A | N/A | 4.308 | 0.1160 | 28.9490 | 0.0000** |
| BSI | 8.7030 | 0.0130* | N/A | N/A | 14.4950 | 0.0010** |
| SBS | 45.7400 | 0.0000** | 10.5660 | 0.0050** | N/A | N/A |
| *5% signi cance level | | | | **1% signi cance level | | |

**Table 7:** Result of the Granger Causality Test.

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**Cite this article as:** CAO Yiran and WANG Dong. The Effects of Shadow Banking on Stability and Profitability of China's Commercial Banks Evidence from Panel VAR. Gen Soc. Sci. Cur. Tr. 2019: 1: 3.