Optimal Credit Guarantee Ratio: Evidence from Asia

Naoyuki Yoshino and Farhad Taghizadeh-Hesary[1]

Abstract

Difficulty in accessing finance is one of the critical factors constraining the development of small and medium-sized enterprises (SMEs) in Asia. Owing to their significance to national economies, it is important to find ways to provide SMEs with stable finance. One efficient way to promote SME financing is through credit guarantee schemes, where the government guarantees a portion (ratio) of a loan provided by a bank to an SME. This research provides a theoretical model and an empirical analysis on factors that determine optimal credit guarantee ratio. The ratio should be able to fulfill the government's goal of minimizing the bank's nonperforming loans to SMEs, and at the same time fulfill the government policies for supporting SMEs. Our results show that three categories of factors can determine the optimal credit guarantee ratio: (i) government policy, (ii) macroeconomic conditions, and (iii) banking behavior. It is crucial for governments to set the optimal credit guarantee ratio based on macroeconomic conditions and vary it for each bank or each group of banks based on their soundness, in order to avoid moral hazard and ensure the stability of lending to SMEs.

Keyword: SME credit, credit guarantee ratio, non-performing loans

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[1] Naoyuki Yoshino, PhD, Dean, Asian Development Bank Institute (ADBI), Tokyo, Japan, Professor Emeritus, Keio University, Tokyo, Japan (e-mail: nyoshino@adbi.org); and Farhad Taghizadeh-Hesary, PhD, Assistant Professor of Economics, Keio University, Tokyo, Japan, Visiting Professor, Graduate School of Economics, The University of Tokyo and Research Assistant to the Dean, Asian Development Bank Institute (ADBI), Japan (e-mail: farhadth@gmail.com, farhadth@z3.keio.jp).

Contents

ABBREVIATIONS

AIC	–	Akaike information criterion
CGS	–	credit guarantee schemes
CPI	–	consumer price index
GDP	–	gross domestic product
NPL	–	nonperforming loan
PCA	–	principal component analysis
SME	–	small and medium-sized enterprise
VECM	–	vector error correction model

1. INTRODUCTION

Small and medium-sized enterprises (SMEs) in Asia are frequently hailed as the backbone of the economies. There is widespread consensus on their significant role in economic growth, employment creation, boosting foreign trade, and poverty alleviation. Over the period 2007–2012, they accounted for 98% of all enterprises and 38% of the gross domestic product (GDP) on average and employed 66% of the national labor force (statistics in this paragraph from ADB 2015). They also play a significant role in trade. Thirty percent of total export value was accounted for by SMEs in Asia on average during the above-cited period. In the People's Republic of China, SMEs accounted for 41.5% of total export value in 2012, up 6.8% year-on-year, while in Thailand, they accounted for 28.8% of total export value, growing 3.7% year-on-year. SMEs that are part of global supply chains have the potential to promote international trade and mobilize domestic demand.

Because of the economic significance of SMEs, it is important to find ways to provide them with stable finance. However, SMEs usually have severe difficulties with raising money. The undersupply of credit to SMEs is caused by asymmetric information, high default risk, and lack of collateral. These factors make it far more difficult for SMEs to access finance compared with large enterprises. Lenders prefer to increase the flow of funds to larger firms, which aren't as limited by these factors and are considered lower risk. In order to address this problem, various government and donor initiatives have emerged, in developed as well as developing and emerging economies, to establish credit guarantee schemes (CGSs) to reduce the supply–demand gap in SME finance.

CGSs have been used over the decades in many countries and in various forms to increase the flow of funds to targeted sectors and segments of the economy, including SMEs. A CGS makes lending more attractive by absorbing or sharing the risks associated with lending. A CGS can also increase the amount of funds lent to enterprises beyond its own collateral limits, because the guarantee is a form of collateral. A CGS can assume the additional role of loan assessor and monitor and thereby improve the quality of lending (Zander et al. 2013). However, guarantee funds have a cost, which is paid by fees charged and/or subsidized by the government or a third-party institution.

Many countries, such as Japan, previously had full guarantee schemes which covered 100% of the default cost incurred by borrowers (Uesugi et al. 2006). However, recently the Japanese government revised its policy and now implements a partial credit guarantee, as the full guarantee created moral hazard: when government covers the full default costs and absorbs the full risk, then the lending institution has little incentive to assess and monitor the healthiness of the borrower. This can raise the number of nonperforming loans in the banking system and reduce the productivity of public reserves. Hence, partial credit guarantee schemes can be an optimal model. The guarantee can provide a substitute for collateral-based lending.

However, the literature on loan guarantees leaves three important questions unanswered. First, what is the optimal credit guarantee ratio (i.e., share of the loan covered by the guarantee) which can fulfill the government's goal of minimizing banks' nonperforming loans to SMEs and at the same time fulfill the government objective of supporting SMEs? Second, will the ratio be constant regardless of macroeconomic conditions? Third, should the rate should be constant for all banks or should it vary based on a bank's financial soundness?

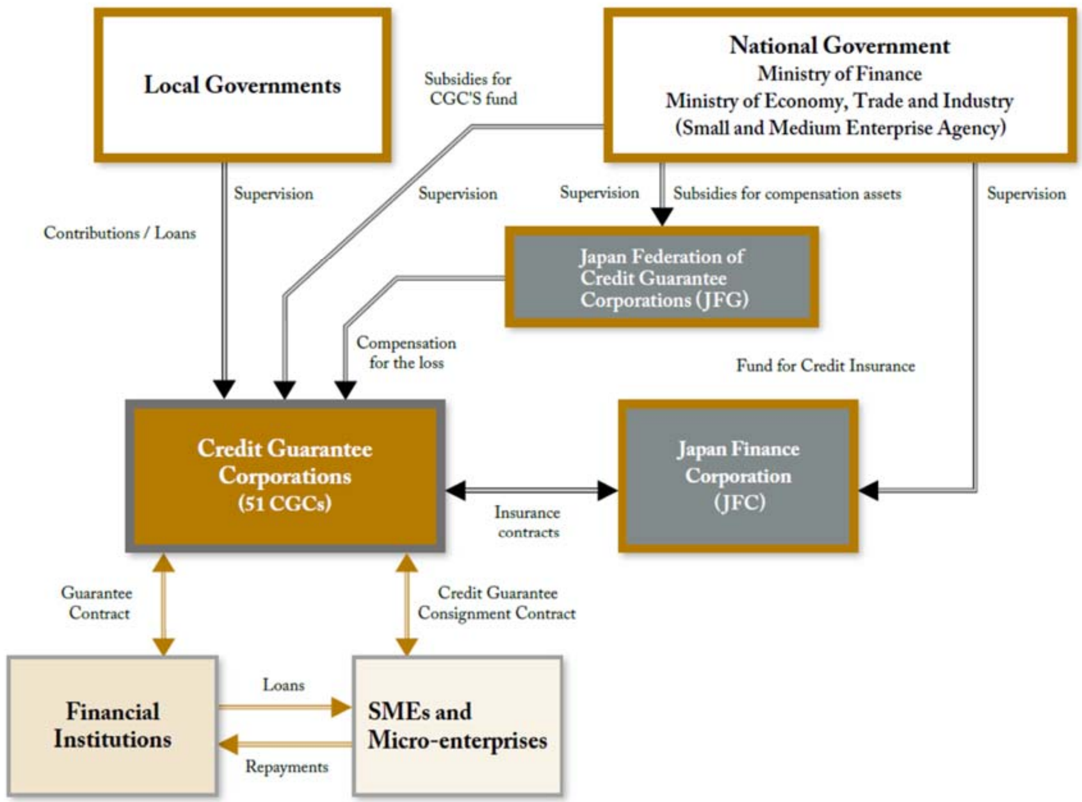
This chapter addresses these three questions.

2. AN OVERVIEW OF CREDIT GUARANTEE SCHEMES WITH EXAMPLES FROM ASIA

CGSs were used in several countries at least since the early 20th century (Beck et al. 2008). Japan was an early innovator. CGSs spread first throughout Europe and the Americas in the 1950s and then to Africa, Asia, and Oceania in the 1960s and 1970s (Zander et al. 2013). In 2011, there were 8,402 credit guarantee institutions around the world (ADB 2014).

A CGS normally consists of three parties: a borrower, a lender, and a guarantor. The borrower is often an SME seeking finance. The borrower typically approaches a bank or other financial institution for a loan. Because of information asymmetry, the loan request is frequently turned down. This is where the guarantor comes in. The guarantor is a credit guarantee corporation (CGC) or agency, usually run by a government or trade association, that seeks to facilitate access to debt capital by providing lenders with the comfort of a guarantee for a substantial portion of the debt (Riding and Haines 2001).

Figure 1: Credit Guarantee Scheme (Japan)



JFG (2014)."Credit Guarantee System in Japan". Japan Federation of Credit Guarantee Corporations (JFG): Tokyo

In Japan, the CGCs are funded by the Ministry of Finance through the Ministry of Economy, Trade and Industry and also by local governments. The national government thereby provides direct subsidies to CGCs and subsidies for compensation assets to Japan Federation of Credit Guarantee Corporations, which provides compensation in case of losses to CGCs. The national government also provides funds for credit insurance to Japan Finance Corporation, which insures the contracts.[2] Local governments also support CGCs by providing contributions and loans to them. In 2013, 1.46 million SMEs in Japan, out of a total of 3.8 million SMEs, were guaranteed by the CGSs, a coverage share of 37.9%. There are 51 CGCs in Japan, one for each prefecture and one in each

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[2] Japan Finance Corporation, under the SME Credit Insurance Act (Act No. 264 of 1950), insures guaranteed liabilities (i.e., credit guarantees) provided by CGCs to SMEs and micro businesses that fall short in terms of collateral or creditworthiness when raising funds from financial institutions or issuing corporate bonds. The reason behind the establishment of the Credit Insurance System is to promote the development of the MSME sector by insuring guarantees for SME loans and similar liabilities. It is designed so that the Credit Insurance System and the Credit Guarantee System together facilitate the smooth supply of business funds for MSMEs. This mechanism is known as the Credit Supplementation System and plays an important role in the Japanese government's SME finance policy.

of the cities of Kawasaki, Gifu, Nagoya and Yokohama. At the end of 2013, their total liabilities stood at approximately 30 trillion yen.

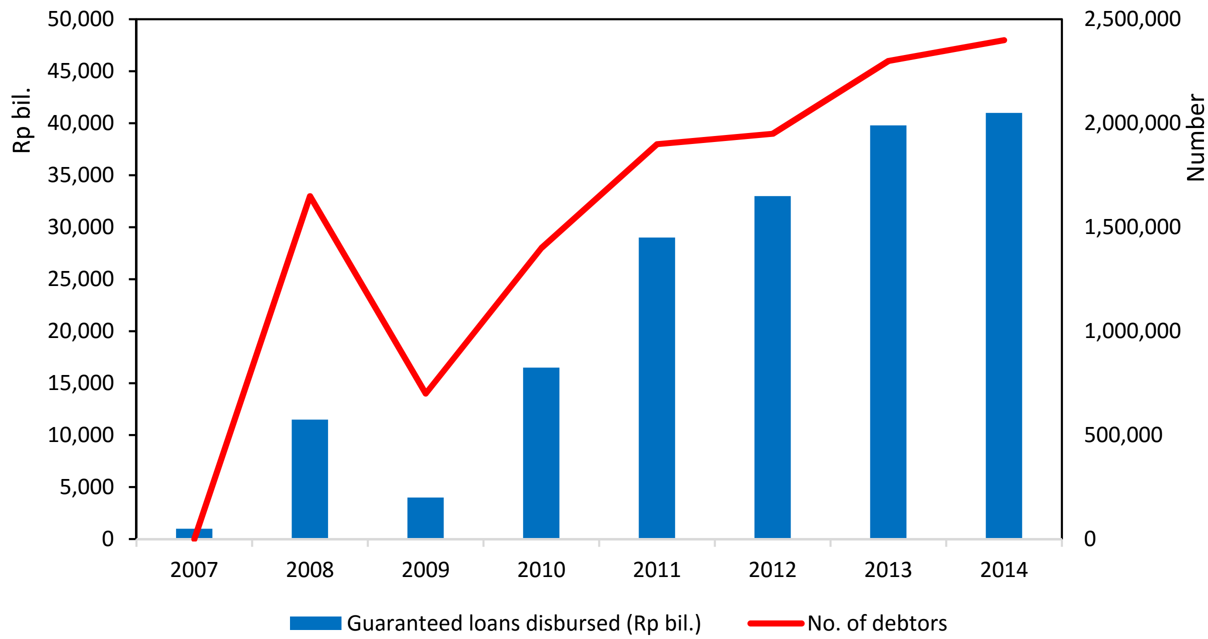
A CGS makes it easier for banks to lend to SMEs because if an SME defaults, the CGC will cover a large share of the lender's losses. For example, if the guarantee ratio is 80%, it means when a SME defaults the bank can recover 80%. If there was no guarantee, the bank might not be able to recover any portion of the loan. In Japan, after the tsunami and earthquake disaster of Fukushima in March 2011, the government raised the guarantee ratio to 100% (full guarantee) because many SMEs found it much more difficult to borrow from banks. However, a full guarantee creates a moral hazard regarding banks. In case of a full guarantee, when a SME defaults, the entire loan will be recovered for the bank. As result, banks do not carefully monitor the business of the SMEs and determine whether they are sound before continuing to lend money. More recently, since the majority of the losses of SMEs after the Fukushima disaster were recovered, the ratio was reset to 80% Credit guarantee schemes have been established in several countries throughout Asia, including India, Indonesia, Malaysia, the Republic of Korea, Solomon Islands, and Viet Nam. The guarantee coverage rates vary among countries: in Kazakhstan it is up to 70%, in India 75%, and in Indonesia 70%–80%. The question is, what is the optimal credit guarantee ratio for each country? In the following sections, we provide an overview of CGSs in three countries—Indonesia, the Philippines, and Thailand—and an answer to this question.

2.1. Indonesia

The number of MSMEs has been growing annually by more than 2%, and the sector was not seriously damaged by the change in the external environment caused by the global financial crisis of 2008/2009. As of the end of 2013, 57.9 million MSMEs operated in Indonesia, accounting for 99.9% of total enterprises. According to the 2011 data, primary industry (agriculture, forestry, and fisheries) accounted for 48.8% of MSMEs, followed by trade (28.8%) as a combined figure of the wholesale and retail trade and the hotel and restaurant sector.

The credit guarantee industry in Indonesia has two layers: central guarantee institutions and regional guarantee institutions. Credit guarantee institutions provide various types of products for MSMEs and cooperatives through banks and nonbanking financial institutions, including Islamic guarantees. People's Business Credit (KUR) is a public credit guarantee scheme designed for MSMEs that guarantees 70%–80% of the credit applied, while the remaining 20%–30% credit risk is taken by participating banks. KUR is delivered by 7 commercial banks and 26 regional development banks, with concessional lending rates. Figure 2 shows guaranteed loans disbursed by KUR and number of debtors.

Figure 2: Credit Guarantees—KUR (Indonesia)



KUR = Kredit Usaha Rakyat (People's Business Credit).

Source: ADB. 2015. *Asia SME Finance Monitor 2014*. Manila.

2.2. Philippines

In the Philippines in 2012, the number of registered MSMEs reached 940,886, a 15.2% increase from the previous year, representing 99.6% of total enterprises. By business sector, MSMEs in trade and repair (wholesale and retail trade and repair of motor vehicles and motorcycles) accounted for 46.4% of total MSMEs in 2012, followed by services with 39.4% and manufacturing with 12.5%. MSMEs employed 64.9% of total workforce employment in the Philippines in 2012.

There are two major credit guarantee programs for MSMEs in the Philippines. One is provided by the Small Business Corporation, which is a government financial institution, and another is the Credit Surety Fund Program of the Bangko Sentral ng Pilipinas[3] (BSP). The SBC, with a guarantee ratio of 70%, provided 80 million Philippine pesos (P) in guarantees during 2013, and P112 million from January to June 2014. The total lending guaranteed by the SBC between 2002 and mid-2014 was P1.6 billion. (Table 1).

The BSP Credit Surety Fund Program, from the time of its inception in 2008 to 31 October 2014, guaranteed cumulative loans for 10,515 beneficiaries. As of 18 December 2014, 37 CSFs were operating in 27 provinces and 10 cities nationwide.

In cooperation with the BSP, the Development Bank of the Philippines also offers a CSF credit facility, through which qualified cooperatives and nongovernment organizations (NGOs) may

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[3] The central bank of the Republic of the Philippines.

apply for loans, either for relending to their members who need funding for their business (wholesale) or directly to a cooperative or NGO for its own entrepreneurial business activities (retail). Based on the its 2013 annual report, the Development Bank of the Philippines has supported a total of 29 CSFs, with 428 participating cooperatives and NGOs.

Table 1: Small Business Corporation's Credit Guarantee Program (Philippines)

Item	2004	2005	2006	2007	2008	2009
Loan origination (pesos)	287,970,000	228,740,870	316,061,318	212,555,000	166,500,000	82,500,000
Guaranteed amount[a] (pesos)	221,964,500	168,696,109	214,955,744	131,346,500	107,810,172	58,300,000
Guarantee payments (pesos)	2,420,793	664,869	6,216,703	11,607,602	10,448,183	…
Item	2010	2011	2012	2013	2014[b]	Total[c]
Loan origination (pesos)	136,600,000	40,200,000	182,550,000	134,018,000	194,980,207	2,374,523,395
Guaranteed amount[a] (pesos)	66,890,000	26,390,000	125,635,000	80,312,600	112,286,145	1,604,081,970
Guarantee payments (pesos)	1,122,163	2,106,533	…	…	973,924	35,560,771

P = Philippine peso, SME = small and medium-sized enterprise.

[a] Guaranteed amount is computed as approved credit line or loan amount x guarantee cover (%). Based on historical data, average guarantee cover is 70%, but there were special cases where the guarantee cover is below 70%, such as in 2010.

[b] January to June 2014.

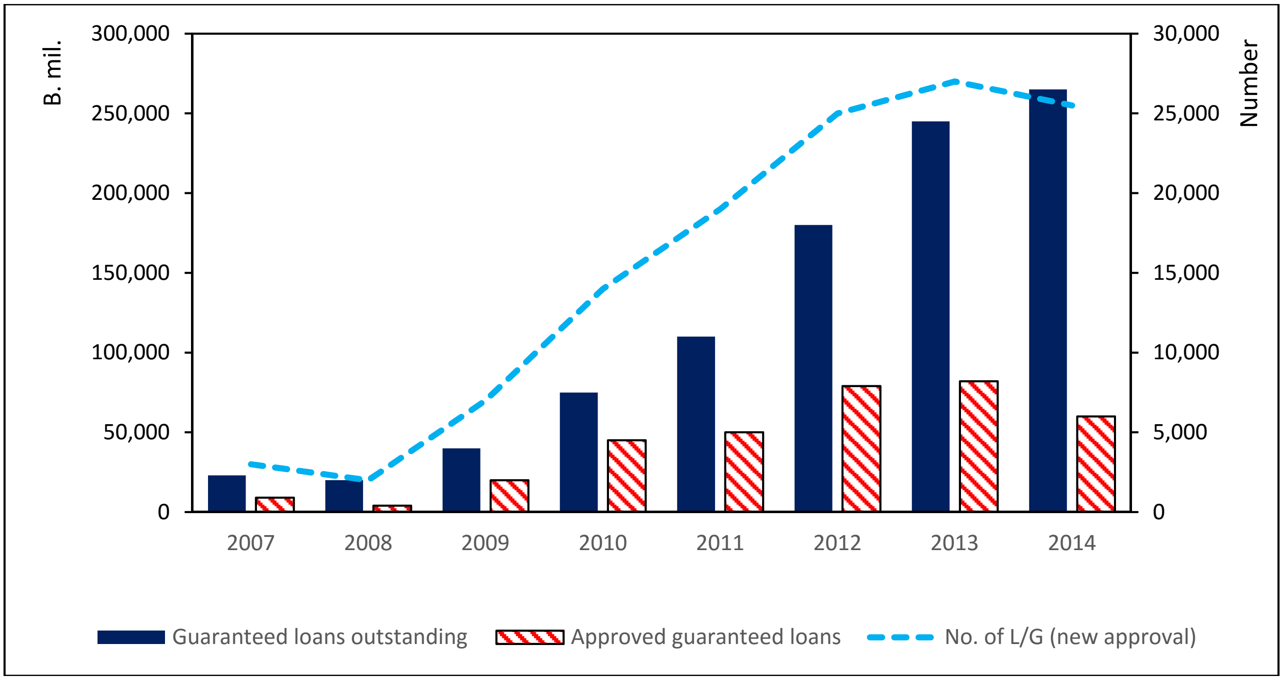
[c] Total amount from 2002 to June 2014.

Source: ADB. 2015. *Asia SME Finance Monitor 2014*. Manila.

2.3. Thailand

SMEs play a critical role in driving the Thai economy, accounting for 97.2% of total enterprises and numbering 2.76 million. In 2013 The SME sector was seriously damaged by the 2008/2009 global financial crisis and the devastating flooding of 2011, with a 9.2% decrease in the number of SMEs in 2011, but the sector has recovered since this. In 2013, 43.5% of SMEs operated in the wholesale and retail trade, and automotive repair), followed by the service sector (including hotels and restaurants) with 39.1%. SMEs employed 11.4 million workers, or 81% of the country's total workforce, in 2013. The service sector was a dominant group in SME employment, accounting for 44.7% of total SME employees, followed by the trade sector at 31.7%.

Figure 3: Credit Guarantees—Thai Credit Guarantee Corporation



L/G = letter of guarantee.
Source: ADB. 2015. *Asia SME Finance Monitor 2014*. Manila.

The Thai Credit Guarantee Corporation is a state-funded guarantee institution started in 2009 as part of economic stimulus measures following the global financial crisis. Its aim is to support SME access to bank loans. The Thai Credit Guarantee Corporation guarantees 100% of the payment stated in each letter of guarantee issued to participating banks, when prosecuted. However, it is done under the condition that the nonperforming guarantee does not exceed 16% of the average guarantee outstanding in each portfolio that pools all guaranteed SME loans from the participating bank every year.

Besides the aforementioned program, there are specialized portfolio guarantee schemes for (i) start-up SMEs operating for not more than 3 years, which was launched in 2013 with a limit of B10 billion; and (ii) the One Tambon (village) One Product and Community Businesses Scheme, launched in the second half of 2014 with a limit of 10 billion baht (B).

The share of guaranteed loans to total SME loans by commercial banks reached 6.1% in 2014, which was almost eight times higher than 2008 (0.8%). Newly approved guarantees amounted to B61,051 million with 25,250 letters of guarantee in 2014 (Figure 3).

3. THE MODEL

We develop a model to calculate the optimal credit guarantee ratio for SME loans. The model differentiates the guarantee ratio based on three factors: (i) the financial soundness of the lending institution, (ii) macroeconomic conditions, and (iii) government policy objectives. With this model, sound institutions can access a higher guarantee ratio than those that are less sound. Furthermore, the ratio would be lower in a better macroeconomic situation because the risk of SME default will decrease. The part of the model used to categorize banks based on soundness draws on the work of Yoshino and Hirano (2011, 2013) and Yoshino, Taghizadeh-Hesary, and Nili (2015).

3.1. Policy Objective Function

The equation below shows the policy objective function of the government:

$$U = w_1\left(L - L^*\right)^2 + w_2\left(\rho - \rho^*\right)^2 \quad (1)$$

where U is the government objective function. Eq. 1 shows that there are two objectives for the government in determining the optimal credit guarantee ratio for bank loans to SME. The first objective is to stabilize the quantity of loans to SMEs $\left(L - L^*\right)$, where L is actual SME loans and L^* is desired SME loans. The second objective of the government is to set the nonperforming loans ratio to a desired ratio $\left(\rho - \rho^*\right)$, where ρ is the current default risk ratio of loans, and ρ^* is the desired default risk ratio of loans. w_1 and w_2 in Eq. 1 are the policy weights for the two objectives. w_1 is the weight for stabilizing SME loans, and w_2 is the weight for reducing the nonperforming loan ratio. If the two objectives have equal weight, then $w_1 = w_2 = 0.5$.

In Eq. 1, $L^* = (1+a)L_{t-1}$, where a is the desired growth rate of SME loans and is set by the government. For example, if the government wants to increase bank lending to SMEs by 2% from the previous year, a is equal to 0.02. Also in Eq. 1, $\rho^* = (1-b)\rho_{t-1}$, where b is the change in the desired nonperforming loan ratio compared with the previous year. If the government wants to reduce the nonperforming loan ratio by 10% compared with a year earlier, then b is set equal to 0.1.

The loan demand function for Eq. 1 is:

$$L = l_o - l_1 r_L + l_2 Y^e \quad (2)$$

where l_o is the fixed demand for loans, r_L is the loan interest rate, and Y^e is expected GDP. l_1 is the coefficient of the interest rate on loans and is theoretically negative. When the interest rate increases, the demand for loans will decrease, which means the slope of the function is negative. In good economic conditions the demand for loans will increase, hence l_2 is expected to be positive.

3.2. Optimal Credit Guarantee Ratio

Eq. 3 and Eq. 4 present the profit maximization behavior of banks:

$$\text{Max. } \Pi = r_L(L)L - \rho(g, Y, P_L, P_S, M, Z)L - r_D D - C(L, D) \quad (3)$$

$$\text{Subject to: Banks's balance sheet} \quad (1-\rho)L + \rho L = D + A \quad (4)$$

where, r_L is the interest rate on loans, which is the function of loans (L), Y is GDP, g is credit guarantee ratio (for example, 0.80 means 80% of the bank's losses are covered by the credit guarantee corporation and 0.20% are not covered), P_L is price of land, P_S is stock price, M is money supply, Z represents financial profile of the bank r_D is interest rate on deposits, D is deposits, and C is the bank's operational costs such as employee wages and computer and equipment costs which depends on lending and deposits.

When the credit guarantee ratio (g) is raised by the supporting organization, which is most often a government entity, it means in case of SME default, the government share of the loan default burden is increased, hence it will have less pressure on the lending institutions which is a bank, which means share of banks from the loans default risk will decrease (ρ). There is significant empirical evidence regarding the countercyclical behavior of NPL The general explanation is that higher real GDP growth usually translates into more income, which improves the debt servicing capacity of borrowers. Conversely, when there is a slowdown in the economy the ρ is likely to increase as unemployment rises and borrowers have difficulty repaying their debts (Salas and Suarina 2002; Rajan and Dhal 2003; Fofack 2005; Yoshino and Hirano 2011, 2013; Klein 2013; Yoshino, Taghizadeh-Hesary, and Nili 2015). In Yoshino, Taghizadeh-Hesary, and Nili's paper (2015), the loan default risk ratio depends on the various macroeconomic factors mentioned above (Y, P_L, P_S, M). When land prices increase, collateral value increases as well, so default risk ratio ρ will decline. When business conditions improve, increases in GDP growth and stock prices cause a reduction in default risk ρ . Several studies found that NPLs are affected by stock prices, arguing that a drop in share prices might lead to more default via wealth effects and decline in the value of collaterals (Klein 2013). Fofack (2005) found that broad money supply (M2) has positive covariance structure with nonperforming loans in a group of sub-Saharan African countries. An increase in the aggregate stock of money has contributed to a deterioration of bank portfolios in these countries and resulted in the accumulation of NPLs. In a more recent study on the Iranian banking sector, Yoshino, Taghizadeh-Hesary, and Nili (2015) also found significant association between M1 and Iranian Banks' NPLs

Eq. 4 shows the bank's balance sheet. The first component $(1-\rho)L$ shows good loans, and the second component ρL shows nonperforming loans or bad loans. On the right-hand side of this equation, A is the bank's capital.

From Eq. 2, we can write the interest rate on the loan as below:

$$r_L = \frac{1}{l_1}\left(l_o + l_2 Y^e - L\right) \tag{5}$$

In the next step, in order to get the amount of loan in equilibrium, we get first-order condition of the bank's profit function with respect to loan (L) as below:

$$\frac{\partial \Pi}{\partial L} = -\frac{1}{l_1} \times L + \left[\frac{1}{l_1}\left(l_o + l_2 Y^e - L\right)\right] - \rho(g, Y, P_L, P_S, M, Z) - r_D - \rho'_L = 0 \tag{6}$$

Then we write Eq. 6 for L. The result is Eq. 7, which shows the amount of loan in equilibrium:

$$L = \frac{l_1}{2}\left[\frac{l_0}{l_1} + \frac{l_2}{l_1} Y^e - \rho(g, Y, P_L, P_S, M, Z) - r_D - \rho'_L\right] \tag{7}$$

In the last part, we get the first-order condition of the government policy objective function with respect to the optimal credit guarantee ratio (g):

$$\frac{\partial U}{\partial g} = 2w_1\left(L - L^*\right).\frac{\partial L}{\partial g} + 2w_2\left(\rho - \rho^*\right).\frac{\partial \rho}{\partial g} \tag{8}$$

which is equal to:

$$= 2w_1\left(L - L^*\right).\left(\frac{-l_1}{2}.\frac{\partial \rho}{\partial g}\right) + 2w_2\left(\rho - \rho^*\right).\frac{\partial \rho}{\partial g} \tag{9}$$

In Eq. 2 we showed that the profit of the bank is a function of various factors including default risk ratio ρ. The higher the default risk, the lower the profit for the bank (Yoshino and Hirano 2011, 2013). Hence, we need to develop a model to capture those factors that affect this ratio:

$$\rho = f\left(g, Y, P_L, P_S, M, Z\right) \tag{10}$$

In the development of Model 10 we were inspired by Yoshino and Hirano (2011) and Yoshino, Taghizadeh-Hesary, and Nili (2015). However, Model 10 is the modified and updated version of the model presented in these two aforementioned papers. There are many other scholars who have assessed the impact of macroeconomic variables on bank loan defaults. For instance, Louizis et al. (2002) found that nonperforming loans in the Greek banking system can be explained mainly by macroeconomic variables (GDP, unemployment, interest rates, public debt). In a more recent study, Baselga-Pascual et al. (2015) found that bank loan defaults are directly affected by higher inflation and economic crisis and reversely by liquidity. Although the four macro variables stated in Eq. 10 (GDP, stock price, land price, and money supply) can capture macro shocks, some banks can fail even if the macro financial system is sound. So additional variables are needed that can capture idiosyncratic uncertainty in the economy. This why we inserted Z in the model— to capture micro shocks to each bank or to each group of banks. Z denotes the banks' financial profile, which we will further explain below. If the banking behavior improves it will have an impact on the banks' soundness and on the level of NPLs. Hence, our model has the ability to capture macro and micro shocks. Considering the aforementioned papers' findings, we can write Eq. 10 as follows:

$$\rho = f\left(g, Y, P_L, P_S, M, Z\right) = -\alpha_1 g - \alpha_2 Y - \alpha_3 P_L - \alpha_4 P_S + \alpha_5 M - \alpha_6 Z \tag{11}$$

In the next step, we insert the loan demand function from Eq. 2 in Eq. 9, and write the expanded version of ρ as in Eq. 11, in Eq. 9 and then write it for g, yielding the result below:

$$g = -\frac{1}{\alpha_1\left(\frac{w_1 l_1^{\,2}}{4} + w_2\right)} . w_1 \frac{l_1^{\,2}}{4}\left(\frac{l_0}{l_1} + \frac{l_2}{l_1} y^e - r_D - \rho_L'\right) + \frac{l_1}{2\alpha_1} L^* - \frac{w_2}{\alpha_1}\rho^* - \frac{\alpha_2}{\alpha_1} Y - \frac{\alpha_3}{\alpha_1} P_L - \frac{\alpha_4}{\alpha_1} P_S + \frac{\alpha_5}{\alpha_1} M + \frac{\alpha_6}{\alpha_1} Z \tag{12}$$

As is clear from Eq. 12, the optimal credit guarantee ratio is a function of various factors including the actual current amount of loans to SMEs, the desired level of SMEs' loans, the desired default risk ratio of loans, fixed demand for loans, deposit interest rate, expected GDP, the weight for stabilizing the SME loans (policy rate), the weight for reducing the nonperforming loan ratio (policy rate), marginal increase of nonperforming loans by increase of additional loans, price of land, price of stock, GDP, money supply, and the financial profile of banks. It means based on the macroeconomic situation and government policies for supporting SMEs and for reducing NPLs, g should vary. On the other hand, each bank has a different g, because they have different banking behavior.

4. EMPIRICAL SURVEY

As mentioned in the introduction, the third question of this research is whether a credit guarantee corporation should provide the same guarantee ratio for all lending institutions? Or should it differ the ratios based on the healthiness of the lending institution? As Model 12 shows, the optimal credit guarantee ratio depends on banking behavior and should vary based on their soundness. Lenders that are more sound and are managing their nonperforming loans should receive a higher guarantee ratio.

Therefore, we need to categorize banks according to their soundness and adjust the guarantee ratio for each group based on the result. In the following section we provide an empirical survey for a group of banks from an Asian country, and categorize them based on their soundness. Then, in the last part of section 4.1, we will calculate the optimal credit guarantee ratio for each group of banks based on this model.

Section 4.2. is for the robustness check of our model, in order to show how the NPL/L (default risk ratio) of nonperforming loans, which is the main factor for calculation of the optimal credit guarantee ration, changes in different macroeconomic conditions and in different bank-level conditions..

4.1. Grouping Banks Based on Their Soundness

In our model, healthier banks should receive a higher credit guarantee rate from the government. To enable us to identify the healthier group of banks, classification or *credit rating* is needed.

Extensive empirical research devoted to analyzing the stability and soundness of financial institutions dates back to the 1960s. Ravi Kumar and Ravi (2007) provided a comprehensive survey of the application of statistical and intelligent techniques for predicting the default of banks and firms. Despite its obvious relevance, however, the development of reliable quantitative methods for the prediction of banks' credit rating has only recently begun to attract strong interest. These studies are mainly conducted within two broad research strands focusing on statistical and machine learning techniques, and may address both feature selection and classification. Poon et al. (1999) developed logistic regression models for predicting financial strength ratings assigned by Moody's, using bank-specific accounting variables and financial data. Factor analysis was applied to reduce the number of independent variables and retain the most relevant explanatory factors. The authors showed that loan provision information, and risk and profitability indicators, added the greatest predictive value in explaining Moody's ratings. Huang et al. (2004) compared support vector machines and backpropagation neural networks to forecast the rating of financial institutions operating in markets in the United States and Taipei,China, respectively. In both cases five rating categories were considered, based on information released by Standard & Poor's and TRC. The analysis of variance was used to discard noninformative features. In this study, support vector machines and neural networks achieved comparable classification results. However, the authors found that the relative importance of the financial variables used as inputs by the optimal models were quite different between the two markets. A study by Orsenigo and Vercellis (2013) presented an empirical evaluation of two linear and nonlinear techniques—principal component analysis (PCA) and double-bounded tree-connected Isomap (dbt–Isomap)—to assess their effectiveness for dimensionality reduction in bank credit rating prediction, and to identify the key financial variables endowed with the greatest explanatory power. Extensive computational tests concerning the classification of six banks' ratings datasets showed that the use of dimensionality reduction accomplished by nonlinear projections often induced an improvement in the classification accuracy, and that dbt-Isomap outperformed PCA by consistently providing more accurate predictions.

In our present research on credit rating of banks we employ the statistical techniques used by Yoshino and Taghizadeh-Hesary (2014a, 2015) for credit rating and classification of small and medium-sized enterprises (SMEs). They used PCA and cluster analysis and applied various financial variables of 1,363 SMEs in Asia. In our present paper, we assign credit ratings to and classify a group of Asian banks into two groups, so that the healthier group receives a higher credit guarantee than the less-sound group.

To be able to do so and to ensure our results are credible, we need to select variables that capture all relevant characteristics of the banks that are the subject of our examination.

4.1.1. Selection of Variables

It is widely known that ratings are directly affected by the financial performance of banks. Based on this assumption, we focus on banks' financial profiles and employ eight financial variables that describe all general characteristics of banks (Table 2).

Table 2: Variables Examined

No.	Symbol	Definition
1	L–D	Total loans/total deposits
2	PR–L	Properties/total loans
3	(SD+LD)–D	(Saving deposits + long-term deposits)/total deposits
4	A–L	Total assets/total loans
5	SC–L	Securities/total loans
6	CA–D	Cash/total deposits
7	CBR–D	Accounts receivable from central bank/total deposits
8	OBR–D	Accounts receivable from other banks/total deposits

Note: Properties are land, buildings, and other hard assets owned by banks. Securities include shares of corporate stock or mutual funds, bonds issued by corporations or governmental agencies, limited partnership units, and various other formal investment instruments that are negotiable and fungible. Accounts receivable from the central banks includes reserve requirement (or cash reserve ratio) and other sums that are normally in the form of cash stored physically in a bank vault (vault cash) or deposits made with a central bank. Accounts receivable from other banks are sums loaned to other banks.

Source: N. Yoshino, F. Taghizadeh-Hesary, and F. Nili. 2015. *Estimating Dual Deposit Insurance Premium Rates and Forecasting Non-performing Loans: Two New Models.* ADBI Working Paper 510. Tokyo: Asian Development Bank Institute.

Loans, properties, securities, cash, accounts receivable from the central bank, and accounts receivable from other banks are components of a financial institution's assets. The higher these variables, the more stable and sound a particular financial institution tends to be. At the next stage, two statistical techniques are used: PCA and cluster analysis. The underlying logic of both techniques is dimension reduction (i.e., summarizing information on numerous variables in just a few variables), but they achieve this in different ways. PCA reduces the number of variables into components (or factors), whereas cluster analysis reduces the number of banks by placing them in small clusters. In this survey, we use components (factors), which are the result of PCA, and subsequently carry out a cluster analysis to classify the banks.

4.1.2. Principal Component Analysis

PCA is a standard data reduction technique that extracts data, removes redundant information, highlights hidden features, and visualizes the main relationships that exist between observations.[4] PCA is a technique for simplifying a dataset by reducing multidimensional datasets to lower dimensions for analysis. Unlike other linear transformation methods, PCA does not have a fixed set of basis vectors. Its basis vectors depend on the dataset, and PCA has the additional advantage of indicating what is similar and different about the various models created (Ho and Wu 2009). Through this method we reduce the eight variables listed in Table 2 to determine the minimum number of components that can account for the correlated variance among the banks.

To examine the suitability of these data for factor analysis, we perform the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity. KMO is a measure of sampling adequacy to indicate the proportion of common variance that might be caused by underlying factors. High KMO values (higher than 0.6) generally indicate that factor analysis may be useful, which is the case in this

[4] PCA can also be called the Karhunen–Loève Transform, named after Kari Karhunen and Michel Loève.

study: KMO = 0.61. If the KMO value is lower than 0.5, factor analysis will not be useful. Bartlett's test of sphericity reveals whether the correlation matrix is an identity matrix, indicating that variables are unrelated. A level lower than 0.05 indicates that there are significant relationships among the variables, which is the case in this study: significance of Bartlett's test <0.00.

Next, we determine how many factors to use in our analysis. Results should that 3 factors are significant. (Z1, Z2 and Z3). Taken together, Z1 through Z3 explain 82.421% of the total variance of the financial ratios.

In running the PCA, we use direct oblimin rotation. Direct oblimin is the standard method to obtain a non-orthogonal (oblique) solution, i.e., one in which the factors are allowed to be correlated. To interpret the revealed PCA information, the pattern matrix must subsequently be studied. Table 3 presents the pattern matrix of factor loadings using the direct oblimin rotation method, where variables with large loadings—absolute value (>0.5) for a given factor—are highlighted in bold.

Table 3: Factor Loadings of Financial Variables after Direct Oblimin Rotation

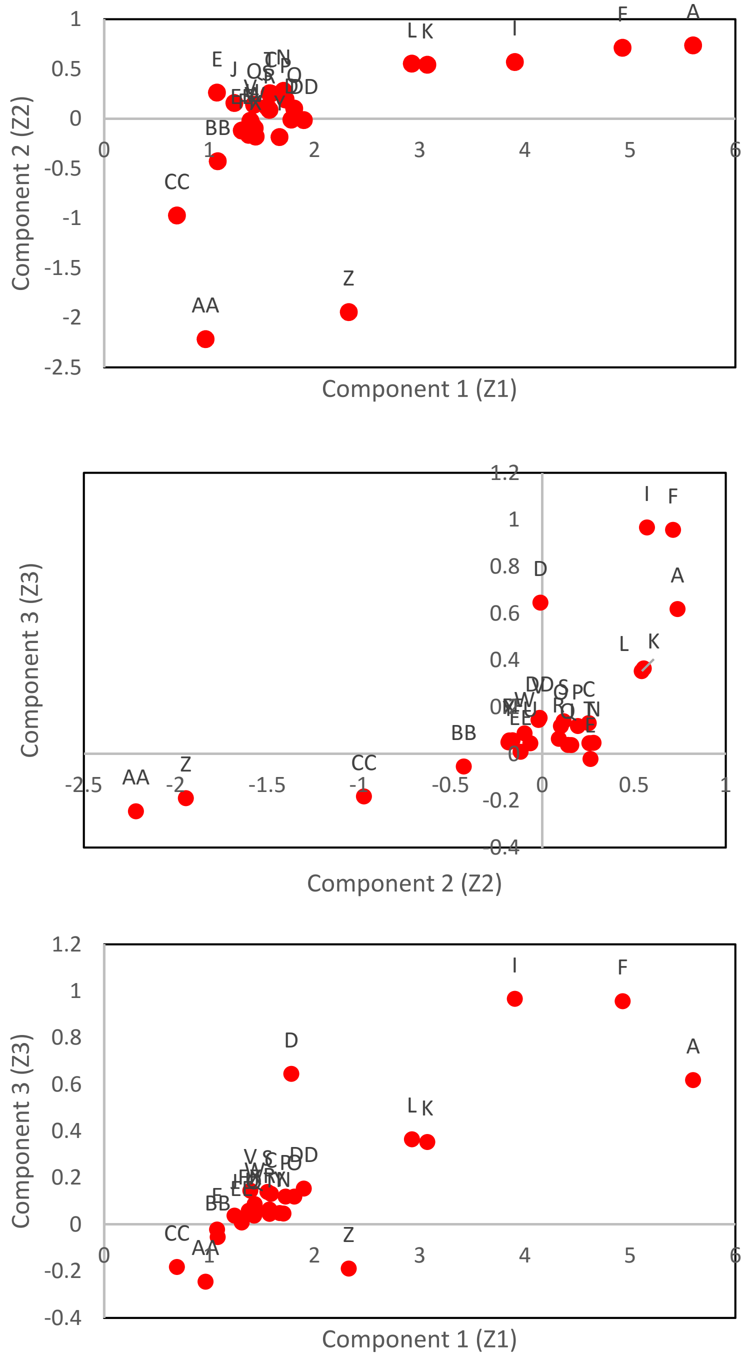
Variables (Financial Ratios of Banks)	Component		
	Z1	Z2	Z3
L–D	(0.238)	**(0.912)**	(0.143)
PR–L	0.042	0.190	**0.780**
(SD+LD)–D	(0.287)	**0.819**	(0.123)
A–L	**0.987**	0.083	0.130
SC–L	(0.096)	(0.140)	**0.875**
CA–D	0.379	**(0.536)**	0.039
CBR–D	**0.954**	(0.104)	(0.102)
OBR–D	**0.981**	(0.011)	(0.117)

( ) = negative.
Note: The extraction method is principal component analysis. The rotation method is direct oblimin with Kaiser normalization. For definitions of the variables, please refer to Table 1.

As can be seen in Table 3, the first component, Z1, has three variables with an absolute value (>0.5), which are all positive—(i) total assets/total loans, (ii) accounts receivable from central bank/total deposits, and (iii) accounts receivable from other banks/total deposits. For Z1, the variables with large loadings are mainly assets, hence Z1 generally reflects the assets of the examined banks. As this factor explains the greatest variance in the data, it is the most informative indicator of a bank's overall financial health. Z2 represents deposits and this component has three major loading variables: (i) total loans/total deposits, which is negative; (ii) (saving deposits + long-term deposits)/total deposits, which is positive; and (iii) cash/total deposits. If the amount of deposits increases, Z2 increases. Z3 has two major loadings, which are (i) properties/total loans, (ii) securities/total loans, so it reflects 1/total loans. The larger the amount of loans, the smaller Z3.

Figure 4 shows the distribution of the three components (Z1, Z2, and Z3) for 28 out of a total of 32 Iranian banks.

Figure 4: Distribution of Factors for 28 Banks

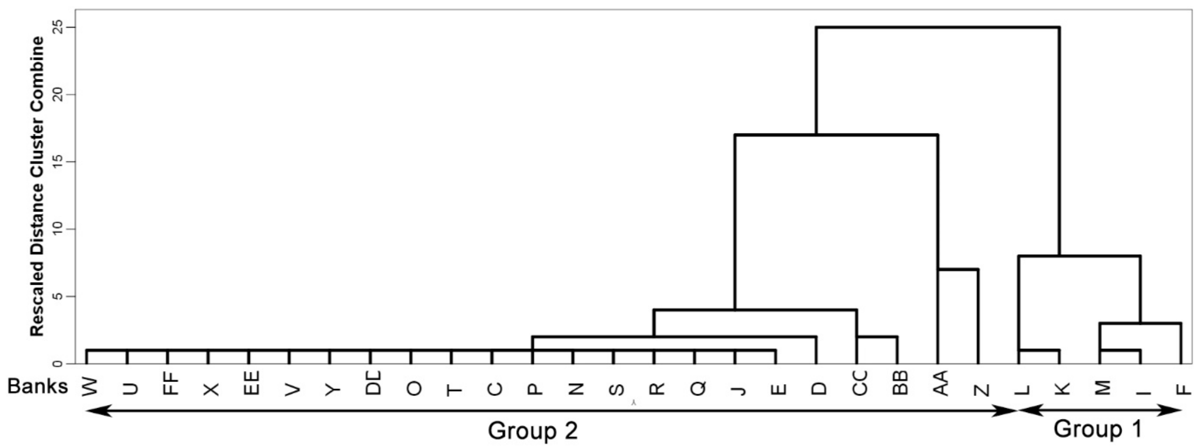


Note: Each star represents one bank, which has been named alphabetically, A, B, C, … , Z, AA, BB, CC, DD, EE and FF for 32 banks. Four banks (banks B, G, H, and M) were outliers in positive parts of the graphs and are not visible in the above graphs.

4.1.3. Cluster Analysis

In this section, we take the three components that were obtained in the previous section and identify those banks that have similar traits. We then generate clusters and place the banks in distinct groups. To do this, we employ cluster analysis, which organizes a set of data into groups so that observations from a group with similar characteristics can be compared with those from a different group (Martinez and Martinez 2005). In this case, banks are organized into distinct groups according to the three components derived from the PCA obtained in the previous section. The series can be described by a tree display called the dendrogram (Figure 5). Figure 5 shows the dendrogram that results from this hierarchical clustering.

Figure 5: Dendrogram



The resulting dendrogram (hierarchical average linkage cluster tree) provides a basis for determining the number of clusters by sight. In the dendrogram shown in Figure 5 the horizontal axis shows 28 banks, which have been named alphabetically. As mentioned above, 32 banks have been the subject of our examination. However, four banks have outlying positive data that are far removed from the data for the other 28 banks. We do not include these four banks in our cluster analysis as our result would not be a rational clustering. This is the reason Figure 5 shows only 28 banks on the horizontal axis.

The dendrogram classifies the banks into two main clusters (Group 1 and Group 2), but it does not show which of these two clusters contain the financially healthier banks, so we have to take one further step. By comparing the classification resulting from cluster analysis (Figure 5) and the distributions of factors in Figure 4 we can conclude that the sequence of banks on the horizontal axis of our dendrogram is based on their soundness. Among these 28 banks, bank F has the highest stability and soundness, whereas bank W has the lowest.

4.1.4. Robustness Check of Banks' Credit Rating

For robustness, we check the rankings of 3 of the 28 banks for all eight examined financial variables. We randomly pick one bank from Group 1 and one from Group 2, and the bank that is in the middle of the credit ranking selected. The results are summarized in Table 4.

Table 4: Robustness Check for Three Sample Banks

Bank	Credit rank	Rank of L–D	Rank of PR–L	Rank of (SD+LD)–D	Rank of A–L	Rank of SC–L	Rank of CA–D	Rank of CBR–D	Rank of OBR–D
I	2	24	1	16	3	5	8	21	2
R	14	14	17	12	15	9	11	9	7
W	28	11	20	22	20	6	10	3	18

Note: Credit rank is the ranking shown by our dendrogram—the lower this number, the healthier the bank. For definitions of the variables, please refer to Table 2

The first randomly picked bank from Group 1 is bank I. Bank I is the second most sound and is a stable bank according to our credit rating result, and the robustness check supports this result (Table 4). This bank shows fairly stable and healthy status in most of our eight financial variables. It is the top bank for PR–L (properties/loans), meaning this bank has a relatively large amount of properties compared with the amount of loans, which means it is stable. It ranks second for OBR–D (accounts receivable from other banks/total deposits), fifth for SC–L (securities/loans), and third for A–L (assets/loans)—these results indicate that this bank has sufficient assets, which favors its stability and soundness. Although it has one of the lowest ranks for L–D (loans/deposits), this suggests this bank is trusted by depositors, and therefore the amount of deposits is large compared with loans. The second bank in our robustness check is bank R, which can be found in the middle of the horizontal axis of our dendrogram with a credit rank of 14, which is close to the middle of these 28 banks. When considering bank R's ranking in terms of the eight variables, for most of these variables it appears in the middle of the ranking. If we take a simple average of the rank of this bank in our eight variables, the result is almost 12, which is close to the credit rank of 14 suggested by our method. The third bank in our robustness check is bank W, a bank we picked randomly from Group 2. Bank W has the lowest soundness and stability in this group and among all 28 banks. When considering the ranking of this bank in our eight variables in Table 2, it is apparent that this bank is not sound. It has very low rankings for PR–L (properties/loans), (SD+LD)/D ([saving deposits + long-term deposits]/total deposits), A–L (assets/loans), and OBR–D (accounts receivable from other banks/total deposits), which suggests this bank is unsound and unstable—it has the lowest credit rank of the banks examined.

4.1.5. Calculation of the Optimal Credit Guarantee Ratio

As mentioned earlier, the optimal credit guarantee ratio in our model depends on three groups of factors: macroeconomic variables, government policies, and banking profile. These three groups consist of various variables including price of land, price of stock, gross domestic product (GDP), money supply, actual SME loans, fixed demand for loans, deposit interest rate, expected GDP, marginal increase of nonperforming loans by increase of additional loans, desired SME loans, desired default risk ratio of loan, weight for stabilizing the SME loans, weight for reducing the nonperforming loan ratio, and financial profile of banks. For calculation of the optimal credit guarantee ratio for the two categories of banks in our survey (section 4.1.3) based on their soundness, for those variables that were existing (such as macroeconomic variables) we used their actual variables. For those variables that were not accessible for us such as the government policies, we set assumptions. Results shows that for Group 1 the optimal credit guarantee ratio is 0.775% and for Group 2 (banks that are less healthy), the calculated optimal credit guarantee ratio is 0.683%. There is clearly a significant difference between the two rates. It means governments, in order to avoid moral hazard and incentivize Group 2 banks to raise their level of healthiness and manage their nonperforming loans, should give different rates to each groups.

4.2. Robustness Check of the Optimal Credit Guarantee Model

One of the key elements of Model 15 is loan default risk ratio ρ. Based on Model 10, it depends on credit guarantee ratio, macroeconomic factors, and the bank's profile. To show how each group of banks' ρ response to macroeconomic shocks as well as idiosyncratic shocks we develop an econometrics model.

As mentioned above, for our empirical analysis in this paper we use macroeconomic data and financial profiles of 32 banks in an Asian economy to forecast the default risk ratio for each group of banks (Group 1 and Group 2). As per Eq. 10, we need to use macroeconomic variables (real GDP, price of land, price of stock, money) and Zi, which represents the financial profile of banks and captures idiosyncratic shocks, to see the response of different groups of banks' ρ. In our empirical analysis, for the macroeconomic variables we employed real GDP, and instead of the price of stock and the price of land, due to lack of data, we used the consumer price index (CPI), which is the best representative for the price level in an economy and can be used as a substitute for these two price levels. For the monetary variable we used M1.

Eq. 10 has three categories of variables that determine ρ—the first category consists of g or optimal credit guarantee ratio, the second category consists of the macroeconomic variables described above; the third category is Zi, reflecting the financial profile of banks. The latter category is made up of three significant components—Z1, Z2, and Z3—obtained using principal component analysis in section 4.1.2. with their factor loadings presented in Table 3 Using the loadings of each of the eight financial ratios, we obtained Z1, Z2, Z3 for each group (Group 1 and Group 2), and since those eight financial ratios of banks are time-series variables, Z1, Z2, Z3 will be also time-series variables. For our empirical analysis, we use monthly data from 2011M1 to 2013M12.

Since we have two groups of banks, we should run two regressions—one for each group. The left-hand side of Eq. 10 for each group's regression will be the sum of NPLs of that group/total loans of that group of banks; the right-hand side of Eq. 10 will be the macroeconomic variables and three components (Z1, Z2, Z3) for that group of banks. Here we are assuming that that ρ is only determined by macro variables and banking behavior.

4.2.1. Data Analysis

To evaluate the stationarity of all series, we used an Augmented Dickey–Fuller (ADF) test. The results we obtained imply that all variables are nonstationary. These variables include GDP growth rate; CPI inflation rate (inflation rate of each month compared with the same month of the previous year); M1 growth rate (growth rate of M1 in each month compared with the same month of the previous year—the original quarterly data were converted to monthly data); sum of NPLs/sum of total loans for Group 1 and Group 2 of the banks; and Z1, Z2, Z3 for each group of banks. However, when we applied the unit root test to their first differences, we were able to reject the null hypothesis of unit roots for each of the variables. These results suggest that all variables each contain a unit root. When we performed the unit root test and discovered that the variables are nonstationary in level and stationary at first difference, they were integrated of order one. The next step was to conduct a cointegration analysis to examine whether a long-run relationship exists among these variables.

4.2.2. Cointegration Analysis

We conduct a cointegration analysis using Johansen's technique by assuming a linear deterministic trend and for two cases—with intercept, and with intercept and trend. Given the short period of our data, the Akaike information criterion (AIC) suggests using variables with one lag. The results of the cointegration rank test using trace are presented in Table 5.

Table 5: Cointegration Rank Test (Trace)

Group 1 of Banks

	Intercept			Intercept and trend		
Hypothesized no. of CEs	Eigenvalue	Trace statistic	Prob.	Eigenvalue	Trace statistic	Prob.
None	0.80	192.62*	0.00	0.80	217.14*	0.00
At most 1	0.75	136.33*	0.00	0.75	160.38*	0.00
At most 2	0.61	87.91*	0.00	0.62	111.82*	0.00
At most 3	0.53	55.01*	0.01	0.55	77.80*	0.00
At most 4	0.39	28.35	0.07	0.51	49.89*	0.01
At most 5	0.25	11.06	0.21	0.35	24.98	0.06
At most 6	0.02	0.86	0.35	0.25	10.10	0.12

Group 2 of Banks

	Intercept			Intercept and trend		
Hypothesized no. of CEs	Eigenvalue	Trace statistic	Prob.	Eigenvalue	Trace statistic	Prob.
None	0.80	167.96*	0.00	0.81	200.61*	0.00
At most 1	0.75	112.06*	0.00	0.80	141.91*	0.00
At most 2	0.48	64.19	0.13	0.58	86.33	0.07
At most 3	0.46	41.23	0.18	0.47	55.63	0.20
At most 4	0.24	19.41	0.46	0.38	33.63	0.31
At most 5	0.21	9.58	0.31	0.24	16.82	0.43
At most 6	0.03	1.17	0.28	0.19	7.34	0.31

CE = cointegrating equation, prob. = probability.
Note: * denotes rejection of the non-cointegrating hypothesis at the 5% level.
Prob. shows MacKinnon–Haug–Michelis p-values.

As is clear from Table 5, the above test rejects the null hypothesis of non-cointegrating variables for Group 1 and Group 2. This means that all variables are cointegrated and there is a long-run association among variables, or, in other words, in the long run, these seven variables (NPL/L, GDP growth rate, CPI inflation rate, M1 growth rate, Z1, Z2, and Z3) for each group of banks move together. Hence, we should run a vector error correction model (VECM). The AIC results of our linear deterministic VECM indicate that it's slightly better to estimate the model by including trend and intercept than to include just intercept for both bank groups, so we have also retained this finding.

4.2.3. Vector Error Correction Model

We estimate Model 10 in a VECM setting including the seven variables —ρ (or NPL/L), GDP growth rate, CPI inflation rate, M1 growth rate, Z1, Z2, and Z3—for each group. The VECM can be defined as follows (see Yoshino, Taghizadeh-Hesary, and Nili 2013 and Yoshino et al. 2014):

$$dV_t = A(O)dV_t + \Pi V_{t-1} + \varepsilon_t \tag{14}$$

for

$$V = \left(\rho, gdp, cpi, m1, Z_1, Z_2, Z_3\right) \tag{15}$$

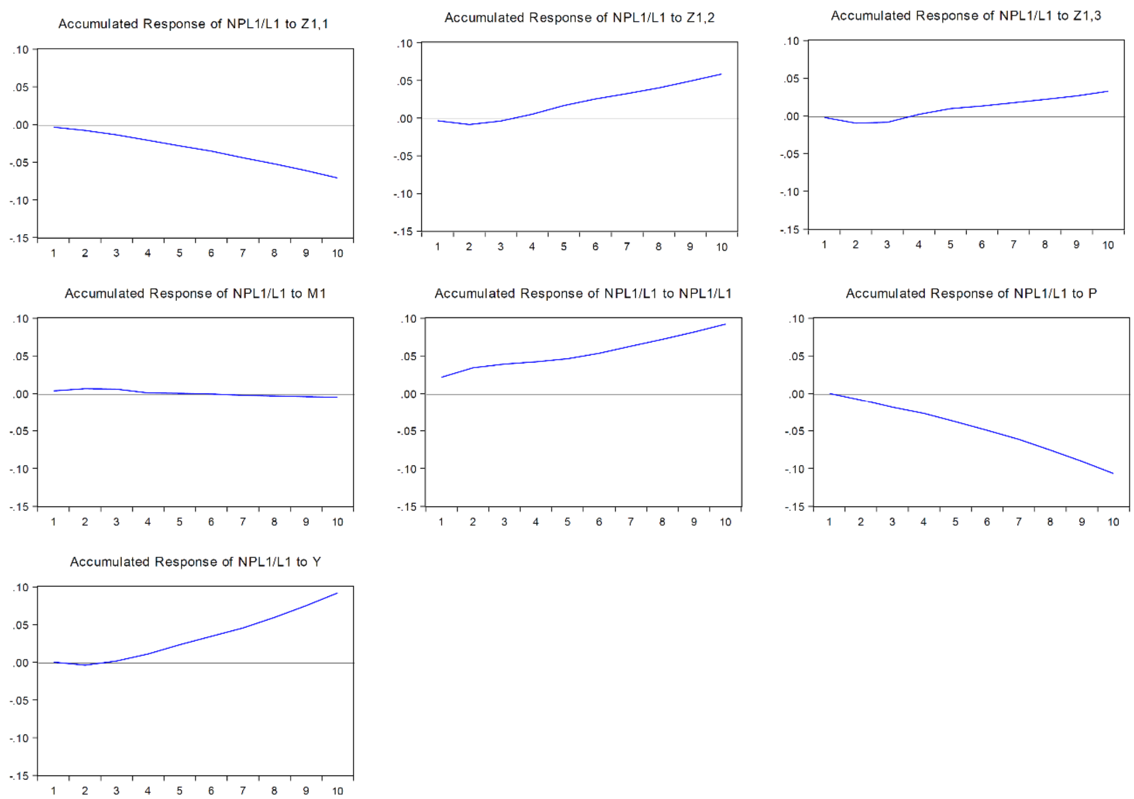
where d denotes the first differences, O is the lag operator, and ε is an error term. Π can be written as $\Pi = \alpha\beta'$, where α and β are $p \times r$ matrixes, and p is the number of variables in V. gdp is GDP growth rate, cpi is CPI inflation rate, and m1 is M1 growth rate. β is a vector of the cointegrating relationship and α is a loading matrix defining the adjustment speed of the variables in V to the long-run equilibrium defined by the cointegrating relationship. The rank of Π is denoted by *r.* As mentioned above, the AIC standard suggests one lag.

4.2.4. Impulse Response Analysis

In this section, we conduct impulse response analysis on the resultant VECM from the previous subsection, in order to provide further evidence of the dynamic response of ρ **or** NPL/L to macro and idiosyncratic innovations. (For more information on impulse response analysis, see Yoshino and Taghizadeh-Hesary 2014b and Taghizadeh-Hesary et al. 2015)

The accumulated response of NPL/L to macro and idiosyncratic innovations for Group 1 of the banks is shown in Figure 6.

Figure 6: Response of NPL/L to Innovations (Group 1 of Banks)



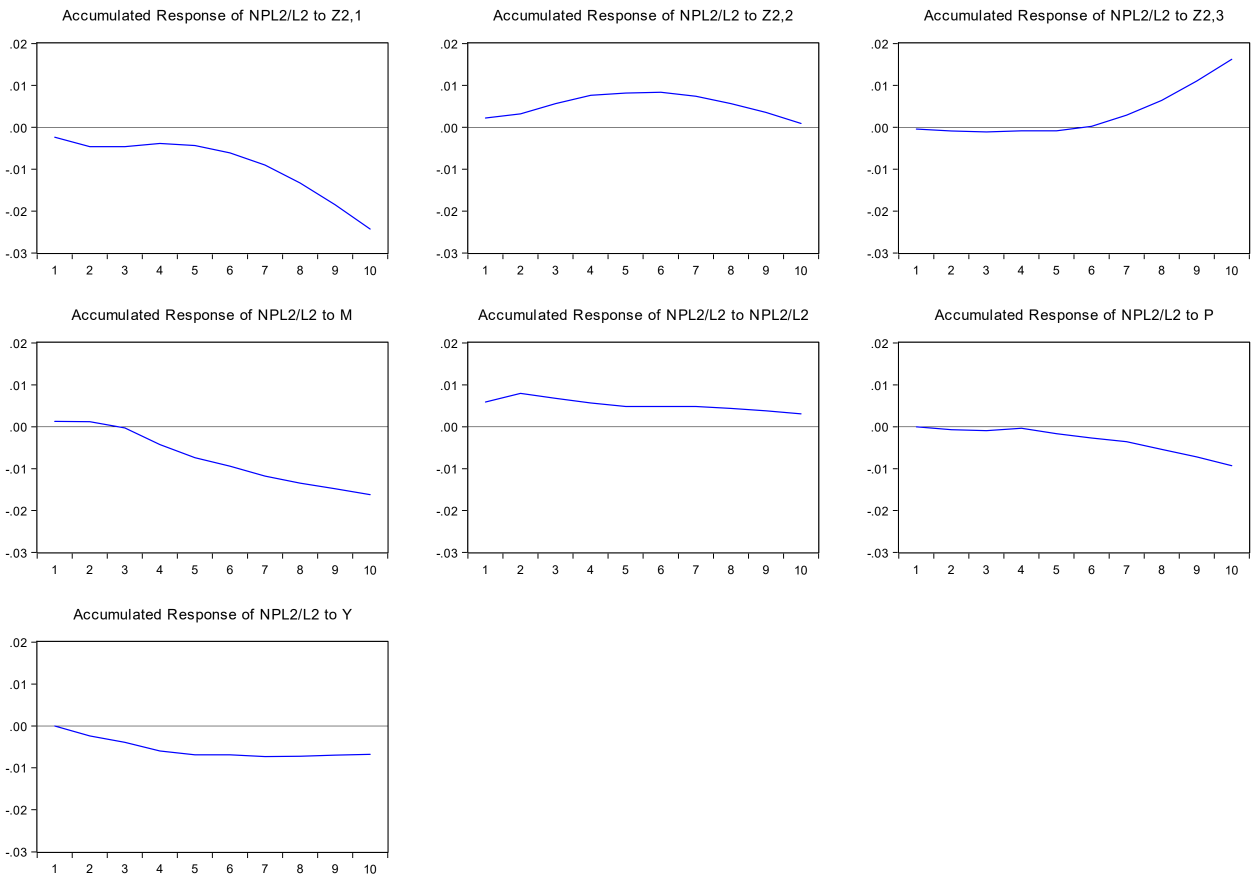
Note: Accumulated response to Cholesky one-standard deviation innovations. NPL_1/L_1 is the ratio of nonperforming loans over total loans for Group 1 of the banks; $Z_{1,1}$ denotes the first component, $Z_{1,2}$ the second component, and $Z_{1,3}$ the third component, all three for Group 1; M1 denotes M1 growth rate, P denotes consumer price index inflation rate, and Y denotes gross domestic product growth rate.

The three graphs in the first row of Figure 6 show accumulated responses of ρ **or** NPL/L to an unanticipated positive shock to Z1, Z2, Z3 for Group 1 of the banks. The response of NPL/L to Z1 is statistically negative and very persistent. This means a positive shock to Z1, which mainly represents assets, will decrease NPL/L of Group 1. An unanticipated positive shock to Z2, which represents deposits, has a statistically negative effect on NPL/L of Group 1 and builds up over the first 3 months, after which it becomes insignificant, meaning an unanticipated increase in deposits will reduce the NPL/L for Group 1. An unanticipated positive shock to Z3, has a statistically negative effect on NPL/L of Group 1 and builds up over the first 3 months, after which it becomes insignificant.

The four other graphs in Figure 6 show accumulated responses of NPL/L of Group 1 of the banks to positive shocks to macro variables and to lagged NPL/L. The response of NPL/L to M1 growth rate shocks is statistically positive and builds up over the first 5 months, after which it becomes insignificant. An unanticipated positive shock to P (CPI inflation) has a statistically negative and persistent effect on NPL/L of Group 1, which is consistent with Yoshino and Hirano (2011, 2013). When prices increase, collateral value increases, which means default risk or NPL/L will decrease. An unanticipated positive shock to Y (GDP growth rate) has a statistically negative effect on NPL/L of Group 1 and builds up over the first 2 months, after which time it becomes insignificant. This result is also consistent with Yoshino and Hirano's (2011) findings. When business conditions improve, increases in GDP growth cause a reduction in default risk (NPL/L). Moreover, Figure 6 shows that for Group 1, current NPL/L affects by lagged NPL/L.

Figure 7 depicts the accumulated responses of NPL/L to macro and idiosyncratic innovations for Group 2 of the banks.

Figure 7: Response of NPL/L to Innovations (Group 2 of Banks)



Note: Accumulated response to Cholesky one-standard deviation innovations. NPL_2/L_2 is the ratio of nonperforming loans over total loans for Group 2 of the banks; $Z_{2,1}$ denotes the first component, $Z_{2,2}$ the second component, and $Z_{2,3}$ the third component, all three for Group 2; M1 denotes the M1 growth rate, P the consumer price index inflation rate, and Y the gross domestic product growth rate.

Group 2 shows similar responses to innovations to macro variables. This indicates that focusing only on a model based on macro variables for calculating the optimal credit guarantee ratio is a misleading as it is possible that under good economic conditions some banks show negative financial performance and have high default risk. It also means that not only macro variables but also bank-level variables are important in determining the optimal credit guarantee ratio.

The responses of Group 2's NPL/L to an unanticipated positive shock to Z1 and Z3 is similar to Group 1's responses, but for shocks to Z2 the responses differ. The response of Group 2's NPL/L to positive shocks to Z2 is statistically positive and persistent, which goes against our finding for Group 1. This means that increasing deposits, which is good news for banks, tends to result in an increase in NPL/L for Group 2. This shows that Group 2 does not manage their NPL/L well—by expanding their business and accepting more deposits the NPL/L ratio increases, which indicates that Group 2 is not as sound as Group 1.

These results confirm our findings in the previous sections of this paper. Moreover, it backs up our suggestion that macro variables and policy variables are not sufficient to calculate the credit guarantee ratio. The ratio should be determined for each bank or for each group of banks based on their soundness, because banking behavior is one of the most important factors in determination of credit guarantee ratio.

5. CONCLUSION

Small and medium-sized enterprises (SMEs) in Asia are frequently hailed as the backbone of the economies. However, SMEs usually have severe difficulties with raising money. The undersupply of credit to SMEs is mainly due to asymmetric information, high default risk, and lack of collateral. These factors make it more difficult for SMEs to access finance compared with large enterprises. Lending institutions prefer to increase the flow of funds to larger firms, which aren't as limited by these factors and are considered lower risk. In order to address this problem, various government and donor initiatives have emerged, in developed as well as developing and emerging economies, to establish credit guarantee schemes. The public credit guarantee scheme is a tool to reduce the supply–demand gap in SME finance.

A credit guarantee scheme involves at least three parties: a borrower, a lender, and a guarantor. The borrower is often an SME or microenterprise seeking debt capital. This borrower typically approaches a private financial institution (bank) for a business loan. Because of asymmetry of information, the private lender frequently turns down the loan request. This is where the guarantor comes into the picture. The guarantor (credit guarantee corporation), usually a government or trade association, seeks to facilitate access to debt capital by providing lenders with the comfort of a guarantee for a substantial portion of the debt.

However, the literature on loan guarantees has left three important questions unanswered: (i) What is the optimal credit guarantee ratio to fulfill government's goal for minimizing banks' nonperforming loans to SMEs while at the same time fulfilling the government policies for supporting SMEs? (ii) Should this rate be constant regardless of the macroeconomic status? (iii) Should this rate be same for all banks, or should it vary based on a bank's soundness?

In order to answer these questions, we have developed a theoretical model as well as an empirical survey. The model developed in this survey shows that the optimal credit guarantee ratio is determined by three groups of variables: (i) government policies for NPL reduction and SME support, (ii) macroeconomic variables, and (iii) bank-level variables or banking behavior. Our model shows that the optimal credit guarantee ratio is a function of various factors including the current amount of SME loans, the desired level of SME loans, the desired default risk ratio of loans, fixed demand for loans, deposit interest rate, expected GDP, weight for stabilizing the SME loans (policy rate), weight for reducing the nonperforming loan ratio (policy rate), marginal increase of nonperforming loans by increase of additional loans, price of land, price of stock, GDP, money supply, and the financial profile of banks.

One of the key elements in the theoretical model that we developed for calculations of optimal credit guarantee ratio is loan default risk ratio. In order to provide sufficient proof for our theoretical model, we developed a VECM model for capturing the impact of macro variables and bank-level variables on two different groups of banks that were categorized based on their soundness. The results of the empirical analysis demonstrate that loan default ratio is affected by macro variables; however, macro variables were not enough to explain this ratio, and banking behavior must also be considered, because it is possible that some banks will behave well in a bad economic situation or in an economic downturn.

In other words, the optimal credit guarantee ratio should vary for each bank, or for each group of banks, based on their financial soundness. Sound banks should receive a higher guarantee ratio from the government, and less healthy banks should receive a lower guarantee to avoid a moral hazard problem. Moreover, this rate should vary based on economic conditions. Governments should lower the guarantee ratio in good economic conditions where the default risk of SME loans is reduced, and raise it in bad economic conditions to protect the SME financing and economic growth.

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