

Taghizadeh-Hesary, Farhad; Yoshino, Naoyuki; Fukuda, Lisa

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A model for calculating the optimal credit guarantee fee for small and medium-sized enterprises

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ADB Working Paper Series

**A MODEL FOR CALCULATING THE OPTIMAL
CREDIT GUARANTEE FEE FOR SMALL AND
MEDIUM-SIZED ENTERPRISES**

Farhad Taghizadeh-Hesary, Naoyuki Yoshino,
and Lisa Fukuda

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Farhad Taghizadeh-Hesary is an associate professor of economics at Tokai University and a visiting professor at the Faculty of Economics of Keio University. Naoyuki Yoshino is dean and chief executive officer of the Asian Development Bank Institute and Professor Emeritus of Keio University in Tokyo, Japan. Lisa Fukuda is a graduate student at the University of Queensland in Brisbane, Australia.

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Please contact the authors for information about this paper.

Email: farhad@aoni.waseda.jp

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Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

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Abstract

Small and medium-sized enterprises (SMEs) have difficulties in accessing finance because of information asymmetry and a lack of collateral. A credit guarantee scheme is a suitable method to unlock lending to SMEs; however, it involves SMEs paying a fee, which needs to account for their risk. The question is how to calculate the optimal fee. The paper provides a theoretical model for calculating the optimal credit guarantee fee. In the empirical part, this study investigates whether selected macroeconomic variables and the financial health of SMEs have a statistically significant impact on the default risk ratio of SMEs, which is the main determinant of the fee. We use selected macroeconomic variables and the financial profiles of 1,363 SMEs that are customers of an Iranian bank. We use principle component analysis and two vector error correction models, and we provide a robustness test using the generalized method of moments. The empirical results support our hypothesis that the credit guarantee fee should be different for sound (lower) and unsound (higher) SMEs to avoid moral hazard but also according to the macroeconomic state (a decrease in a recession and an increase in a boom).

Keywords: SME finance, credit guarantee scheme, credit guarantee fee, credit constraints

JEL Classification: H81, G21

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1. INTRODUCTION

The high default risk ratio and low credit ratings of small and medium-sized enterprises (SMEs), especially relative to larger corporations, are a common theme across both developed and developing economies. Difficulty in accessing finance, which is mainly due to their higher risk, is one of the critical factors constraining the development of SMEs. Both internal and external factors shape the default risk ratio of an SME, causing severe credit constraints to be one of the most significant challenges that SMEs face.

Given their importance for national economies, it is imperative to find ways to provide SMEs with stable finance. This is a topical issue, especially in those regions in which SMEs dominate the economies, like Asia. In Asia, SMEs form the foundation of economies, constituting a large share of the GDP, employment, and trade. According to the Asian Development Bank, in its assessment of SMEs across 20 countries in Asia and the Pacific from 2011 to 2014, SMEs accounted for 42% of the GDP, 62% of the national employment, and 96% of the total enterprises on average (Yoshino and Taghizadeh-Hesary 2018a). In a least-developed economy, Cambodia, SMEs accounted for 99.8% of the total enterprises and 71.8% of the national labor force in 2014. In an emerging economy, Thailand, the same economic indicators were 97.2% and 81%, respectively, in 2013 (ADB 2015).

The internal factors that heighten SMEs' default risk and hence pose challenges when approaching financial institutions for external finance include the lack of a complex business structure, little organizational hierarchy, and informal business operations. Weak or unstructured accounting systems typically produce financial statements, which raises difficulties in reducing the opacity of SMEs' financial health in a way that communicates sound creditworthiness to banks (Yoshino and Taghizadeh-Hesary 2018b). Consequently, it leads banks to perceive them as posing high default risk and thus high lending risk, which prevents them from extending loans. These internal factors, which are intrinsic to SMEs, are the most pressing concern for government economic development strategies, as external finance represents SMEs' primary source of funding for working capital, investment, performance, and growth (Kersten et al. 2017).

Credit guarantee schemes (CGSs) are widespread across emerging and developed economies, increasing and smoothing the flow of accessible credit from financial institutions to enterprises and minimizing the supply–demand gap in the credit market. While they exist in various forms, they all act to alleviate banks' direct lending risk by fulfilling collateral requirements and conducting reliable credit risk assessments of SMEs' business ventures to improve SMEs' creditworthiness (ADB 2016). As the asymmetric problem is between two entities, a bank (as the lender) and an SME (as the borrower), CGSs introduce a credit guarantee corporation (CGC) that provides a (full or partial) credit guarantee for a certain portion of a loan that the bank extends, thus sharing or absorbing the risks associated with SMEs' business venture, as the guarantee is essentially a form of collateral. This reduces the risk of non-performing loans, and a higher level of lending to SMEs becomes more attractive and feasible (Yoshino and Taghizadeh-Hesary 2018b).

We propose that guarantee fee rates should be more flexible and vary depending not only on creditworthiness but also on the macroeconomic state of the economy (recession or boom). This is because it poses a widespread external shock to various sectors of the economy, which are interdependent and include the banking sector. SMEs are particularly vulnerable to such economic changes—especially credit

shortages during a crisis—as they tend to be younger and riskier and have lower adaptive speed and capacity in their capital structure than larger firms (Daskalakis, Balios, and Dalla 2017; Farinha, Spaliara, and Tsoukas 2019). As such, uncontrollable external factors can exert an adverse impact on SMEs' default risk, and the calculation of the optimal guarantee fee for each unique SME should account for this. In addition, high fees will create another burden for SMEs and low fees cannot secure sufficient financial resources for CGSs, hence the motivation behind this study.

The main objective of this paper is to develop a theoretical model for the calculation of the optimal credit guarantee fee. In the empirical parts, the objective is to explore the impact of selected macroeconomic variables and SMEs' financial health (creditworthiness) on their default risk ratio and to determine whether the relationship is economically and statistically significant. The aim is to determine the optimal guarantee fee given that the default risk largely dictates it.

To our knowledge, no literature has provided a theoretical model based on SMEs' creditworthiness and macroeconomic factors for calculating the optimal credit guarantee fee in the context of CGSs. The closest and most relevant study to our research is Yoshino and Taghizadeh-Hesary's (2019a) study, which investigated the factors that influence the optimal guarantee ratio (the percentage of loans to SMEs that a CGC guarantees) and concluded that it should be unique to each individual SME and vary depending on the same factors as our research (macroeconomic conditions and the financial health of SMEs). This paper motivated and provided the basis for our research. We take an innovative approach by focusing on the optimal guarantee fee. Previous studies have encouraged the amendment of CGSs in way that accounts for changes in the macroeconomic state in which SMEs operate (Yamori 2015). As Li and Lin (2017) and Ndiaye et al. (2018) concluded, macroeconomic factors and the business cycle have twice as much influence as microeconomic factors in shaping SMEs' performance and the effectiveness of CGCs in mitigating lending risk. The global financial crisis (GFC) of 2008–09 and the way in which it affected the supply of external credit and the logistic framework and effectiveness of CGSs in supporting SMEs sparked rigorous study. Lawrenz and Oberndorfer (2018) and Wang et al. (2019) agreed that the decline in the credit supply from the GFC particularly adversely affected SMEs and that they struggled to compensate by using alternative financial channels, such as trade credit. Consistent with Daskalakis, Balios, and Dalla (2017), the financial system needs broadening in a way that supports SMEs in lowering their transaction costs and improves the adaptive capacity in the capital structure, as long-term debt ratios (i.e. bank loans) show a lagged adjustment speed relative to their short-term counterparts during a crisis, especially since these firms, in the early stages of development, show a positive relationship between formal finance and innovation (Wellalage and Fernandez 2019). Our robustness results confirm that macro variables, policy variables, and SMEs' creditworthiness need joint consideration to calculate the optimal credit guarantee fee with the aim of avoiding moral hazard, reducing the non-performing assets of CGCs, and improving the soundness and stability of the financial system as a whole.

Our theoretical framework provides that the credit guarantee fee should vary depending on macroeconomic fluctuations; it should increase in the midst of an economic boom and decrease in a recession. A boom generates greater economic activity that is above the expected level of output, which means higher production levels that increase the capital demand and lower the default risk ratio of bank loans. To ease economic activity and prevent the formation of an economic bubble, the credit guarantee should increase to slow down economic activity, complementary to contractionary monetary policy. Vice versa, in the case of a recession, in which the economic activity is lower than the expected levels and there is a lower capital demand, the credit guarantee fee should

decrease to accommodate SMEs' lower output levels and higher default risk ratio and ease the burden on private marginal costs as support in alleviating the challenges in accessing external finance. The guarantee fee should also depend on SMEs' creditworthiness; it should be lower for SMEs with lower default risk and higher for those with higher default risk to incentivize them to improve their financial health.

To test our hypothesis and observe the impact of SMEs' financial status and selected macroeconomic variables on the default risk ratio, the main component of the credit guarantee fee, we employ a statistical analysis technique (principle component analysis) with a sample of 1,363 SMEs that are customers of an Iranian bank (section 4.1). The four financial categories (components) that we use to reflect SMEs' financial health are: (i) net income (Z1); (ii) short-term assets (Z2); (iii) liquidity (Z3); and (iv) capital (Z4). The selected macroeconomic variables include the real GDP (Y_t), consumer price index (CPI P_t), and money supply (M1).

Then, in section 4.2, we employ two vector error correction models (VECMs) to assess the impact of bank financial variables (components) and macroeconomic variables on the default risk ratio of two groups of SMEs—Group A consists of sound SMEs and Group B contains unsound SMEs. We define the firms that we consider to be unsound in this study as those with risk-weighted assets that are greater than their shareholders' equity. For the robustness test, we use the generalized method of moments (GMM), as section 4.2 provides.

The empirical findings from the VECM, which are consistent with those of the GMM, show that not all the relationships between the categories of financial variables (Z1, Z2, Z3, and Z4) and the default risk ratio are statistically significant and that they differ by group. For Group A (sound SMEs), an unexpected positive shock to short-term assets (Z2) and liquidity (Z3), leading to a reduction in default risk, is statistically significant. However, the same positive shock to net income (Z1) and capital (Z4) and its effect on the default risk ratio are not significant. This indicates that net income and capital are not a concern for sound SMEs. For Group B, the reduction in default risk from unexpected positive shocks to net income (Z1), short-term assets (Z2), and capital (Z4) is statistically significant and persistent over several periods. The same applies to liquidity (Z3) but only up to four periods, after which it becomes insignificant. This means that Group B has more financial issues across all four components and can improve its default risk by improving these four financial categories.

The default risk ratio of both groups of SMEs (sound and unsound) shows similar responses to unexpected macroeconomic shocks; a positive shock to the real GDP and price level (CPI) leads to a reduction in the default risk ratio for each group due to improved economic activity and lower credit constraints, such as a higher collateral value from a higher price level. The relationship between default risk and M1 is not statistically significant for both groups. Due to the similarity in the response of the default risk ratio to positive macroeconomic shocks, despite the clear distinction between the riskiness of the two groups of SMEs (sound and unsound), it is evident that macroeconomic variables alone are insufficient to determine default risks (and hence credit guarantee fees). The calculation of an optimal guarantee fee for an SME needs to include the financial health of SMEs (creditworthiness), as it is also a major determinant.

Our paper contributes knowledge on practical measures for improving the effectiveness of CGSs in reducing the supply–demand credit gap and the risk of non-performing loans. Varying the credit guarantee fee according to macroeconomic conditions can be a mechanism for smoothing the behavior of banks and the business cycle. Furthermore, varying the credit guarantee fee based on the creditworthiness of SMEs will prevent moral hazard and act as an incentive for unsound SMEs to improve their soundness for paying lower fees.

2. LITERATURE REVIEW

Scholars have agreed that constraints in access to finance deriving from asymmetric information between banks (as lenders) and SMEs (as borrowers) and underdeveloped venture capital markets are among the most significant challenges that SMEs face (Altman, Esentato, and Sabato 2018; Ullah 2019; Wellalage and Fernandez 2019). The most common and greatest credit constraints for smaller firms include high interest rates, high collateral requirements, and complex procedures for obtaining bank loans (Yoshino and Taghizadeh-Hesary 2018a).

Given the significant contribution of SMEs across a wide spectrum of economic indicators (e.g., GDP, employment, and capital investment) in most Asian economies, it is imperative to conduct and obtain true and reliable credit risk assessment of SMEs to maximize their potential for attaining external finance (Kersten et al. 2017). Amid the lack of availability of public data on SMEs' bank loan defaults, as well as difficulties in evaluating SMEs' financial history and prospects, scholars have sought to develop credit rating frameworks that indicate SMEs' creditworthiness. For example, Altman, Esentato, and Sabato (2018) utilized a multivariate model that compares the financial profiles of SMEs based on whether they have historically defaulted to predict the probability of default. As a more innovative approach, Yoshino and Taghizadeh-Hesary (2018b) proposed to derive the credit rating of SMEs from two statistical analysis techniques (principal component analysis and cluster analysis) using financial and non-financial data that contain underlying default risk information. Tanoue, Kawada, and Yamashita (2017) investigated the determinants of SMEs' probability of default as a proxy for banks' lending risk and found that the amount of required collateral, the loan size, and credit guarantees are key factors.

Studies have widely explored the effectiveness of CGSs as a tool for reducing SMEs' default risk from banks' perspective and hence minimizing the credit demand–supply gap, in particular the credit guarantee and the amount of lending risk (guarantee ratio) that the CGC should absorb. The literature has consistently asserted that credit guarantees increase the loan supply to SMEs. Wilcox and Yasuda (2018) found that the Japanese government's guarantees act as complements, rather than substitutes, to non-guaranteed loans, as they alleviate banks' risk adversity and hence make them willing to extend loans to risky SMEs. This is a common theme of CGSs across ASEAN countries, as Tambunan (2018) found, and Malaysia ranks the highest in the total number of loans granted to micro, small, and medium-sized enterprises. Liang et al. (2017) implied increasing the credit guarantee ratio, as it can lead to greater bank efficiency, since the scheme secures the lending risk. Leonello (2018) supported this, arguing that a higher guarantee ratio can help in stabilizing an economy's fiscal balance and the solvency of the banking sector by strengthening the interrelationship between the two entities.

As Blasio et al. (2018) found, although the scheme improves credit flows toward SMEs at high risk of loan denial, credit guarantees increase the likelihood of loan default. SMEs within the guarantee scheme are 1.17% more likely to default relative to those without

guarantees, meaning the enhancement of adverse selection due to lowered liability. Likewise, Yoshino and Taghizadeh-Hesary (2019a) argued that there is a need to adjust guarantee ratios according to each SME to account for heterogeneity across SMEs. Their theoretical model and empirical analysis show that they should vary depending on three factors: (i) public policy; (ii) banks' profit-maximizing strategy; and (iii) the current state of the macroeconomy. Overall, the ratio should be such that it minimizes banks' non-performing loans (NPLs) as well as meeting the government policy objective of reducing asymmetric information while accounting for varying degrees of creditworthiness. This paper provided our primary motivation and is the most relevant to our study on finding an optimal guarantee fee.

To our knowledge, no existing literature has provided a theoretical model for the calculation of the optimal credit guarantee fee. In addition, we could not find any earlier study that sought to determine whether there is an economic and statistically significant relationship between default risk as a proxy for a credit guarantee fee, the macroeconomic state, and the creditworthiness of SMEs. Our paper fills this gap in a way that positions CGSs as a safety valve for smoothing banking behavior, in which the rate varies depending on the stage of the business cycle and the subsequent financial health of SMEs in controlling for the risk of adverse selection and moral hazard. Generally, the rate should be lower in an economic recession and higher in an economic boom. This is important for borrowers (SMEs), which tend to be discouraged from demanding bank loans, especially as they are more susceptible to recessive macroeconomic effects via the financial sector (Lawrenz and Oberndorfer 2018).

3. THEORETICAL MODEL FOR THE OPTIMAL GUARANTEE FEE

The model consists of three main sectors, the bank, the credit guarantee corporation, and the SME. The design in calculating the optimal credit guarantee fee considers the behavior and function of each of these agents.

3.1 Behavior of a Bank

Eq. 1 is a bank's profit equation:

$$\Pi_t^{BANK} = r_t^L L_t - \rho_{1t}(1 - \theta_{1t})L_{1t} - \rho_{2t}(1 - \theta_{2t})L_{2t} - r_D D_t - C_t(L_{1t}, L_{2t}, D_t) \quad (1)$$

where Π_t^{BANK} denotes the bank's profit, r_t^L is the lending interest rate, L_t is the total amount of bank loans, and ρ_{1t} and ρ_{2t} are the default risk ratio of Groups 1 and 2 of SMEs (borrowers). L_{1t} and L_{2t} are the loan amounts of each group, r_D denotes the deposit interest rate, and D_t is the total amount of deposits at the bank. C_t is the operational costs of a bank, which are a function of the amount of loans to both groups of borrowers, and the amount of deposits, θ_{it} , is the optimal credit guarantee ratio for each group of borrowers. That is, if, for group a of borrowers, θ_a is 0.8, it means that the credit guarantee corporation guarantees 80% of the loan to borrower a .

We assume that the operation cost function of the bank is quadratic, as in Eq. 2:

$$C_t = a_1(L_{1t})^2 + a_2(L_{2t})^2 + a_3(D_t)^2 \quad (2)$$

We also assume that the total bank loan comprises lending to Groups 1 and 2 of borrowers, as in Eq.3:

$$L_t = L_{1t} + L_{2t} \quad (3)$$

Eq. 4 shows that the bank balance sheet is Asset (Loans) = Debt (Deposits) + Capital:

$$L_t = D_t + K_t \quad (4)$$

Substituting Eq. 3 in Eq. 4 results in:

$$L_{1t} + L_{2t} = D_t + K_t \quad (5)$$

To solve the bank's profit maximization, we set first-order conditions for the bank's profit equation (Eq. 1) with respect to L_{1t} and L_{2t} . The results are Eq. 6 and Eq. 7:

$$\frac{\delta \Pi_t^{BANK}}{\delta L_{1t}} = r_{1t}^L - \rho_{1t}(1 - \theta_{1t}) - r_D - 2a_1L_{1t} \quad (6)$$

$$\frac{\delta \Pi_t^{BANK}}{\delta L_{2t}} = r_{2t}^L - \rho_{2t}(1 - \theta_{2t}) - r_D - 2a_2L_{2t}L_{1t} \quad (7)$$

We assume perfect competition in deriving the solution:

$$L_{1t} = \frac{1}{2a_1} \{r_{1t}^L - \rho_{1t}(1 - \theta_{1t}) - r_D\} \quad (8)$$

$$L_{2t} = \frac{1}{2a_2} \{r_{2t}^L - \rho_{2t}(1 - \theta_{2t}) - r_D\} \quad (9)$$

3.2 Credit Guarantee Corporation's Behavior

Table 1 shows the revenue and costs of the CGC:

Table 1: CGC's Revenue and Costs

Costs (Guarantee Payment)	Revenue (Fee)
$\theta_{1t}\rho_{1t}L_{1t}$	$\alpha_{1t}L_{1t}$
$\theta_{2t}\rho_{2t}L_{2t}$	$\alpha_{2t}L_{2t}$

Note: α_{1t} and α_{2t} are the optimal credit guarantee fee that Group 1 and Group 2 of borrowers have to pay to the credit guarantee corporation, respectively, to be eligible for the guarantee coverage; CGC = credit guarantee corporation.

Source: Authors' compilation.

The CGC will allocate the fee revenue from each group of borrowers as guarantee repayment costs for the same group, as it is not profit seeking. This is because credit guarantee corporations in the majority of cases are public entities and non-profit organizations. Therefore, α_{1t} is the credit guarantee fee that the CGC receives from each group of borrowers:

$$\alpha_{1t} = \theta_{1t}\rho_{1t} \text{ and } \alpha_{2t} = \theta_{2t}\rho_{2t} \quad (10)$$

3.3 Behavior of SMEs

We assume that borrowers consist of two groups of SMEs. Eq. 11 and Eq. 13 show the profit function of each group:

$$\text{Profit function for Group 1 of SMEs: } \Pi_{1t}^{SME} = P_{1t}Y_{1t} - r_{1t}^L k_{1t} - w_{1t}N_{1t} - \alpha_{1t}k_{1t} \quad (11)$$

$$\text{Cobb–Douglas production function: } Y_{1t} = A_{1t}(k_{1t})^{q_1}(n_{1t})^{s_1} \quad (12)$$

$$\text{Profit function for Group 2 of SMEs: } \Pi_{2t}^{SME} = P_{2t}Y_{2t} - r_{2t}^L k_{2t} - w_{2t}n_{2t} - \alpha_{2t}k_{2t} \quad (13)$$

$$\text{Cobb–Douglas production function: } Y_{2t} = A_{2t}(k_{2t})^{q_2}(n_{2t})^{s_2} \quad (14)$$

For the profit function of each group of SMEs in Eq. 12 and Eq. 14, we use a Cobb–Douglas function, as we assume that SMEs satisfy all their capital demand (k) using bank loans (L). For each group, Π_{it}^{SME} denotes the profit, P_{it} is the price, Y_{it} is the total number of products, and r_{it}^L is the borrowing interest rate from the bank. k_{it} is the capital demand, which is equal to L_{it} , N_{it} is the labor input, w_{it} is the wage rate that each group of SMEs pays to the laborers, and α_{it} is the credit guarantee fee of each group of SMEs. q_1 and s_2 are the output elasticities of capital and labor, which we assume to be equal to 1 and the same for both groups of SMEs.

Next, we derive the profit maximization equation for each group of SMEs. The first-order condition of Group 1 of SMEs w.r.t. k_1 results in Eq. 15:

$$\frac{\delta \Pi_{1t}^{SME}}{\delta k_{1t}} = P_{1t}q_1 \frac{Y_{1t}}{k_{1t}} - r_{1t}^L - \alpha_{1t} \quad (15)$$

Setting it equal to zero results in Eq. 16:

$$P_{1t}q_1 \frac{Y_{1t}}{k_{1t}} = r_{1t}^L + \alpha_{1t} \quad (16)$$

Writing Eq. 16 for k_{1t} gives us the loan demand function for Group 1 of SMEs (Eq. 17):

$$k_{1t} = \frac{P_{1t}q_1 Y_{1t}}{(r_{1t}^L + \alpha_{1t})} = L_{1t} \quad (17)$$

Similarly, we derive the loan demand function for Group 2 of SMEs (Eq. 18):

$$k_{2t} = \frac{P_{2t}q_2 Y_{2t}}{(r_{2t}^L + \alpha_{2t})} = L_{2t} \quad (18)$$

3.4 Credit Guarantee in Two Cases (Boom and Recession)

In designing an SME financing policy for calculating the optimal credit guarantee fee, it is important to separate the SMEs' behavior in two periods of boom (bubble) and recession and adjust the fee accordingly. A boom is when the expected output (Y_t^e) increases, and it decreases in a recession.

$$\text{Case 1: Boom} \quad \rho \downarrow \text{ and } Y^e \uparrow \Rightarrow k \uparrow \Rightarrow L \uparrow \quad (19)$$

Eq. 19 states that, in a boom or bubble period, the economic activities improve, so the sales and output increase and the default risk ratio of bank loans reduces. Additionally, enterprises, including SMEs, have a higher capital demand, hence their loan demand increases.

$$\text{Case 2: Recession} \quad \rho \uparrow \text{ and } Y^e \downarrow \Rightarrow K \downarrow \Rightarrow L \downarrow \quad (20)$$

Eq. 20 states that, in a recession, economic activities slow down so that the sales and output decrease and the default risk of loans increases. Subsequently, the demand for capital and borrowing of loans from enterprises, including SMEs, shrinks, in contrast to a boom period.

3.4.1 Loan Demand of SMEs in a Boom and a Recession

Eq. 21 shows the loan demand of both groups of SMEs in a boom:

$$\text{Boom} \rightarrow \begin{pmatrix} r_B^1 = -l_1^B L_1^B + l_2^B Y_B^e - \alpha_B^1 \\ r_B^2 = -l_1^B l_2^B + l_2^B Y_B^e - \alpha_B^2 \end{pmatrix} \rightarrow \text{Loan Demand by SME} \quad (21)$$

Eq. 22 shows the loan demand of both groups of SMEs in a recession:

$$\text{Recession} \rightarrow \begin{pmatrix} r_R^1 = -l_1^R L_1^R + l_2^R Y_R^e - \alpha_R^1 \\ r_R^2 = -l_1^R l_2^R + l_2^R Y_R^e - \alpha_R^2 \end{pmatrix} \rightarrow \text{Loan Demand by SME} \quad (22)$$

3.4.2 Banks' Profit-Maximizing Behavior in a Boom and a Recession

In this sub-section, we consider a dynamic case for bank profit maximization:

$$V_B = \pi_t^B + \beta \pi_{t+1}^R \Rightarrow \text{Dynamic Profit Maximization} \quad (23)$$

Eqs 24 and 25 are a bank's profit-maximizing solutions in the case of a boom with monopolistic competition. In other words, the loan supply equations for Group 1 and Group 2 of SMEs are as follows:

$$\frac{\partial \pi_t^B}{\partial L_1^B} = -l_1^B L_1^B + r_1^B - \rho_1^B (1 - \theta_1^B) - r_D - 2a_1 L_1^B = 0 \quad (24)$$

$$\Rightarrow L_1^B = \left(\frac{1}{l_1^B + 2a_1} \right) \{r_1^B - \rho_1^B (1 - \theta_1^B) - r_D\}$$

$$\frac{\partial \pi_t^B}{\partial L_2^B} = -l_2^B L_2^B + r_2^B - \rho_2^B (1 - \theta_2^B) - r_D - 2a_1 L_2^B = 0 \quad (25)$$

$$\Rightarrow L_2^B = \left(\frac{1}{l_2^B + 2a_1} \right) \{r_2^B - \rho_2^B (1 - \theta_2^B) - r_D\}$$

Eqs 26 and 27 are the bank's profit-maximizing solutions in the case of a recession with monopolistic competition. In other words, the loan supply equations for Group 1 and Group 2 of SMEs are the following:

$$\frac{\partial \pi_{t+1}^R}{\partial L_1^R} = -l_1^R L_1^R + r_1^R - \rho_1^R (1 - \theta_1^R) - r_D - 2a_1 L_1^R = 0 \quad (26)$$

$$\Rightarrow L_1^R = \left(\frac{1}{l_1^R + 2a_1} \right) \{r_1^R - \rho_1^R (1 - \theta_1^R) - r_D\}$$

$$\frac{\partial \pi_{t+1}^R}{\partial L_2^B} = -l_2^R L_2^R + r_2^R - \rho_2^R (1 - \theta_2^R) - r_D - 2a_1 L_2^R = 0 \quad (27)$$

$$\Rightarrow L_2^R = \left(\frac{1}{l_2^R + 2a_1} \right) \{r_2^R - \rho_2^R (1 - \theta_2^R) - r_D\}$$

3.4.3 Behavior of the CGC in a Boom and a Recession

Table 2 shows the CGC's revenue and costs in the case of a recession and a boom. The left- (right-)hand-side column shows the case of a recession (boom), and the first (second) row shows the CGC's revenue from Group 1 (Group 2) of SMEs, that is, the guarantee costs for each group of SMEs.

Table 2: CGC's Revenue and Costs in a Recession and a Boom

Recession	Boom
$\rho_1^R \theta_1^R L_R^1 = \alpha_1^R L_R^1$	$\rho_1^B \theta_1^B L_B^1 = \alpha_1^B L_B^1$
$\rho_2^R \theta_2^R L_R^2 = \alpha_2^R L_R^2$	$\rho_2^B \theta_2^B L_B^2 = \alpha_2^B L_B^2$

Source: Authors' compilation.

Table 3 shows the credit guarantee fee adjustment for business cycles, where β is the adjustment coefficient.

Table 3: Adjustment for the Business Cycle

Adjustment for the Business Cycle	
$(\rho_1^B \theta_1^B L_B^1) + \beta(\rho_1^R \theta_1^R L_R^1)$	$\alpha_1^B L_B^1 + \beta(\alpha_1^R L_R^1)$
$(\rho_2^B \theta_2^B L_B^2) + \beta(\rho_2^R \theta_2^R L_R^2)$	$\alpha_2^B L_B^2 + \beta(\alpha_2^R L_R^2)$

Source: Authors' compilation.

3.5 Optimal Credit Guarantee Fee

To calculate the optimal credit guarantee fee, we require the welfare function of the government (Eq. 28).

W = welfare function of the government:

$$W = W_1^B (L_1^B - \bar{L}_1)^2 + W_2^B (L_2^B - \bar{L}_2)^2 + \beta W_1^R (L_1^R - \bar{L}_1) + \beta W_2^R (L_2^R - \bar{L}_2) \quad (28)$$

$$\frac{\partial W}{\partial \alpha_1^B} = 2W_1^B (L_1^B - \bar{L}_1) \frac{\partial L_1^B}{\partial \alpha_1^B} = 2W_1 (L_1^B - \bar{L}_1) \left(\frac{-1}{l_1^B + 2a_1} \right)$$

$$\bar{L}_1 = L_1^B = \left(\frac{1}{l_1^B + 2a_1} \right) \{(-l_1^B L_1^B + l_2^B Y_B^e - \alpha_1^B) - \rho_1^B (1 - \theta_1^B) - r_D\}$$

$$(l_1^B + 2a_1) \bar{L}_1 = \{(-l_1^B \bar{L}_1 + l_2^B Y_B^e - \alpha_1^B) - \rho_1^B (1 - \theta_1^B) - r_D\}$$

Then, we obtain the optimal credit guarantee fee for Group 1 of SMEs in a boom (α_1^B) from Eq. 29:

$$\alpha_1^B = (2l_1^B + 2a_1) \bar{L}_1 + l_2^B Y_B^e - \rho_1^B (1 - \theta_1^B) - r_D \quad (29)$$

From Eq. 20, we can derive the other equations accordingly: i) the optimal credit guarantee fee for Group 1 of SMEs in a recession; ii) the optimal credit guarantee fee for Group 2 of SMEs in a boom; and iii) the optimal premium fee for Group 2 of SMEs in a recession.

4. EMPIRICAL STUDY

The key element of the optimal credit guarantee fee is the default risk ratio (ρ) of SMEs (as in model 29). This means that, for those SMEs that have a higher default risk, the credit guarantee fee needs to be higher. Conversely, for SMEs with a lower default risk, CGCs need to charge a lower fee to avoid moral hazard and incentivize riskier SMEs to improve their soundness. This policy will also help the CGC in reducing the non-performing assets.

The objective of this section is to determine the impact of SMEs' creditworthiness and selected macroeconomic variables on the default risk ratio—the main component of the credit guarantee fee. Therefore, in section 4.1, we employ a statistical analysis technique (principle component analysis) with a sample of 1,363 SMEs that are customers of an Iranian bank. Then, in section 4.2, we use two vector error correction models (VECMs) to assess the impact of bank-level variables (components) and macroeconomic variables on the default risk ratio of two groups of SMEs. We classify Group A as sound SMEs and Group B as unsound SMEs. For this paper, we define an “unsound” financial profile as one with risk-weighted assets that are greater than the shareholders' equity. Section 4.2 provides a robustness test using the generalized method of moments (GMM).

4.1 Statistical Analysis

4.1.1 Selection of the Variables

To find the default risk and distinguish the sampled SMEs by their creditworthiness, we use five financial categories that are indicative of a firm's financial health: (i) liquidity, (ii) profitability, (iii) leverage, (iv) coverage, and (v) activity. Following Yoshino and Taghizadeh-Hesary (2014, 2015) and Altman and Sabato (2007), we select various financial ratios for each of these categories, as Table 4 shows. Our model has some inconsistencies with other literature, as some studies have argued that quantitative variables are insufficient for determining SMEs' default risk and that it is necessary to include qualitative variables to increase the predictive power (Lehmann 2003; Grunert, Norden, and Weber 2004). However, Chen and Shimerda (1981) showed that nearly 50% of 100 possible financial ratios are indicative of a firm's default risk.

For the statistical analysis, we employ PCA and cluster analysis. They are similar in that they condense multiple variables into just a few by essentially summarizing information. Each is unique in the way in which it achieves this. PCA reduces the eleven financial variables selected (Table 4) into the five financial categories (factors) specified above by keeping only relevant information, highlighting hidden features, and distinguishing primary relationships between the financial variables. The variable for cluster analysis is the number of SMEs, so we can reduce them by grouping them into small clusters. In our study, we run cluster analysis on the components (or factors) that are resultant of PCA so that we can group SMEs according to their default risk (sound or unsound).

Table 4: Examined Variables

No.	Symbol	Definition	Category
1	Equity_TL	Equity (book value)/total liabilities	Leverage
2	TL_Tassets	Total liabilities/total assets	
3	Cash_Tassets	Cash/total assets	Liquidity
4	WoC_Tassets	Working capital/total assets	
5	Cash_Sales	Cash/net sales	
6	EBIT_Sales	Ebit/sales	Profitability
7	Rinc_Tassets	Retained earnings/total assets	
8	Ninc_Sales	Net income/sales	
9	EBIT_IE	Ebit/interest expenses	Coverage
10	AP_Sales	Accounts payable/sales	Activity
11	AR_TL	Accounts receivable/total liabilities	

Notes: Retained earnings refer to the percentage of net earnings that the company does not pay out as dividends but retains for reinvestment in its core business or for paying debt; the balance sheet records it under shareholders' equity. Ebit refers to earnings before interest and taxes. Accounts payable refers to an accounting entry that represents an entity's obligation to pay off a short-term debt to its creditors; the accounts payable entry appears on a balance sheet under current liabilities. Accounts receivable refers to money that customers (individuals or corporations) owe to another entity in exchange for goods or services that have been delivered or used but not yet paid for; receivables usually come in the form of operating lines of credit and are usually due within a relatively short time period, ranging from a few days to 1 year.

Source: Authors' description.

4.1.2 Principal Component Analysis

PCA is a standard statistical technique that reduces multidimensional datasets to a lower number of dimensions to simplify and minimize the observations for effective analysis. In the context of our study, it allows us to explain the correlated variance among SMEs using the minimum number of components. Furthermore, PCA is a linear transformation method in which, unlike others, the set of basis vectors is not fixed. Rather, it varies according to the dataset. An additional advantage of PCA is that it indicates similarities and differences between the various models produced (Bruce-Ho and Dash-Wu 2009).

To ensure that the data collected are sufficient for factor analysis and hence the testing of our research question, we conduct the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity. The KMO test measures sampling adequacy, giving the proportion of common variance that underlying factors may cause. We derive the KMO value as 0.71, which confirms that factor analysis is useful in our study, as it is above the threshold of 0.60 (we deem KMO values below 0.5 as not useful). Secondly, Bartlett's test of sphericity determines whether there is a statistically significant relationship among the variables by indicating whether the correlation matrix is an identity matrix. The significance level reflects this: lower than 0.05 indicates that there is a statistically significant relationship among the variables. This is the case for the financial variables in our study, as we find the significance of Bartlett's test to be lower than 0.001.

Next, we determine the minimum number of components to use for our analysis by using Table 5, which reports the estimated factors and their eigenvalues. To keep factors for analysis, their eigenvalues must be greater than 1, which means that they explain more than 10% of the variance. Thus, we only use the first four factors (Z1 to Z4), which cumulatively explain 70% of the total variance of the financial ratios.

Table 5: Total Variance Explained

Component	Eigenvalues	% of Variance	Cumulative Variance %
Z1	3.30	30.00	30.00
Z2	2.19	19.90	49.90
Z3	1.25	11.38	61.28
Z4	1.08	9.78	71.06
Z5	0.94	8.56	79.62
Z6	0.75	6.79	86.41
Z7	0.56	5.09	91.50
Z8	0.48	4.36	95.86
Z9	0.32	2.87	98.73
Z10	0.13	1.14	99.87
Z11	0.09	0.13	100.00

Source: Authors' calculations.

In running PCA, we use direct oblimin rotation to allow factors to correlate based on the non-orthogonal (oblique) solution. Finally, using this method produces a pattern matrix of factor loadings (Table 6) for the analysis and interpretation of the PCA results. For each factor, the figures highlighted in bold in Table 6 indicate variables that have large loadings (>0.5) in absolute values. For the first factor, Z1, there are four variables: cash/net sales, ebit/sales, net income/sales, and accounts payable/sales. These indicate that Z1 reflects an SME's net income. It is the most indicative of an SME's creditworthiness among the four factors, as it has the greatest explanatory power for the variance in the data.

Table 6: Factor Loadings of Financial Variables after Direct Oblimin Rotation

Variables (Financial Ratios)	Component			
	Z1	Z2	Z3	Z4
Equity_TL	0.009	0.068	0.113	0.705
TL_Tassets	-0.032	-0.878	0.069	-0.034
Cash_Tassets	-0.034	-0.061	0.811	0.098
WoC_Tassets	-0.05	0.762	0.044	0.179
Cash_Sales	-0.937	0.021	0.083	0.009
EBIT_Sales	0.962	0.008	0.024	-0.004
Rinc_Tassets	0.014	0.877	0.015	-0.178
Ninc_Sales	0.971	-0.012	0.015	0.014
EBIT_IE	0.035	0.045	0.766	-0.098
AP_Sales	-0.731	-0.017	-0.037	-0.016
AR_TL	0.009	-0.041	-0.104	0.725

Notes: The extraction method is principal component analysis. The rotation method is direct oblimin with Kaiser normalization.

Source: Authors' calculations.

Z2 has three variables with significant loadings, which indicate that the factor reflects short-term assets. Liabilities/total assets is negative, which means that an SME operates on its internal assets rather than on its liabilities. Working capital/total assets is positive, meaning that the SME holds short-term assets. Thirdly, retained earnings/total assets is positive, indicating that the SME has positive profit that it stores within the firm or in the

bank. These significant financial variables show that an SME's short-term assets are healthy, as it is self-sufficient in operating on its working capital and using little external credit.

Z3 has two variables with significant loadings, which are positive and indicate that the factor reflects SMEs' liquidity. Cash/total assets, being positive, shows that an SME has high earnings and is abundant in cash—the most liquid asset.

Lastly, Z4 also has two variables with significant loadings, which are positive: equity (book value)/total liabilities and accounts receivable/total liabilities. They show that an SME's equity base outweighs its liabilities. Hence, Z4 reflects capital.

Table 7: Component Correlation Matrix

Component	Z1	Z2	Z3	Z4
Z1	1	0.037	-0.031	-0.005
Z2	0.037	1	0.106	0.102
Z3	-0.031	0.106	1	0.033
Z4	-0.005	0.102	0.033	1

Note: The extraction method is principal component analysis. The rotation method is direct oblimin with Kaiser normalization.

Source: Authors' calculations.

Table 7 presents a correlation matrix of the components. It confirms that there is no significant correlation between the four factors, so the results are meaningful and useful for interpretation. Figure 1 presents the distribution of the four components, clearly separating Group A (sound SMEs) and Group B (unsound SMEs). Sound SMEs appear in the positive area, whereas unsound SMEs are in the negatives, and this is consistent in all six graphs in the figure. These results show that the four factors (Z1, Z2, Z3, and Z4), derived from the selected financial variables, are adequate measures of SMEs' creditworthiness, as SMEs are distinct according to their financial health.

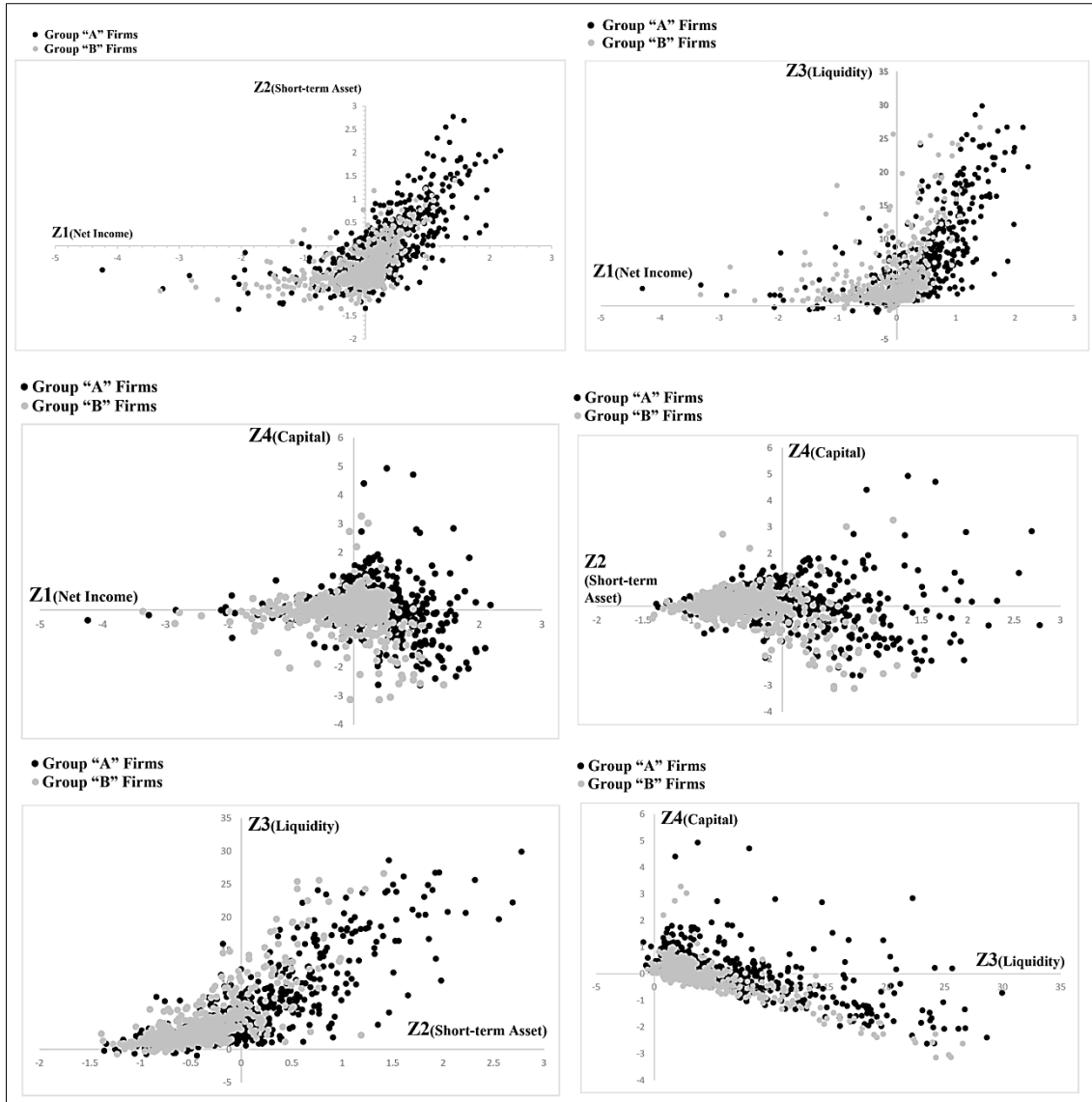
4.2 Empirical Model

As mentioned above, for our empirical analysis, we use macroeconomic data and the financial profiles of 1,363 SMEs, which are customers of an Iranian bank, to assess the impact of the financial components that we obtained from section 4.1 and the macroeconomic variables on the default risk ratio of the two groups of SMEs.

In the development of the empirical model (model 30), we use a theoretical framework (section 4) that Yoshino and Hirano (2011) and Yoshino, Taghizadeh-Hesary, and Nili (2019b) inspired. However, we modify and update the model that the two aforementioned papers present. There are numerous scholars who have assessed the impact of macroeconomic variables on bank loan defaults and/or SMEs' loan defaults. For instance, Baselga-Pascual, Trujillo-Ponce, and Cardone-Riportella (2015) found that higher inflation and economic crises directly affect bank loan defaults and that liquidity affects them reversely. Ghosh (2015) measured annual NPLs in all 51 US states for the period 1984–2013 and employed both static fixed effects and dynamic-GMM estimation techniques. He found that the state GDP and household income growth, HPI, unemployment, and inflation rates affect NPLs. In addition, he showed that most state-level banking industry variables significantly affect NPLs. Anastasiou, Louri, and Tsionas (2016) looked at the determinants of NPLs in the euro-area banking system for the period

1990Q1–2015Q2 using GMM estimations. They found that the roles of income tax and the output gap are significant.

Figure 1: Distribution of Factors for SME Groups A and B



Group A = sound SMEs; Group B = unsound SMEs. The firms that this study considers to be unsound have risk-weighted assets that are greater than their shareholders' equity.

Source: Authors' calculations.

Table 8: Correlation Matrix of Four Components (Group A of SMEs)

Component	Z1A	Z2A	Z3A	Z4A
Z1A	1	0.021	-0.028	-0.003
Z2A	0.021	1	0.113	0.181
Z3A	-0.028	0.113	1	0.021
Z4A	-0.003	0.181	0.021	1

Source: Authors' calculations.

Table 9: Correlation Matrix of Four Components (Group B of SMEs)

Component	Z1B	Z2B	Z3B	Z4B
Z1B	1	0.017	-0.161	-0.003
Z2B	0.017	1	0.008	0.096
Z3B	-0.161	0.008	1	0.157
Z4B	-0.003	0.096	0.157	1

Source: Authors' calculations.

Tables 9 and 10 are the correlation matrix of the factors for Group A and Group B, respectively. They confirm that there is no significant correlation between the four factors for each group.

Although the four macro variables that Yoshino and Hirano (2011) and Yoshino, Taghizadeh-Hesary, and Nili (2019b) used (GDP, stock price, land price, and money supply) can capture macro shocks, SMEs can fail even when the macro-financial system is sound. Hence, additional variables that can capture firm-level performance are necessary:

$$\rho_{jt} = \vartheta_0 + \vartheta_1 Z_{ijt} + \vartheta_2 Y_t + \vartheta_3 M_t + \vartheta_4 P_t \quad (30)$$

Following Eq. 30 that we developed, we need to use macroeconomic variables (GDP, stock price, land price, and money supply) and Z_{ijt} , which represents the financial profile of SMEs and captures firm-level shocks and the four components for each SME ($Z_{1j}, Z_{2j}, Z_{3j}, Z_{4j}$ where j is: Group A or B) obtained from section 4.1 to determine the response of the default risk ratio (ρ) of each group of SMEs (Group A and Group B).

In our empirical analysis, for the macroeconomic variables, we use the real GDP (Y_t), and, instead of the price of stock and the price of land, due to a lack of data, we use the consumer price index (P_t), which is the best representative of the price level in an economy and can act as a substitute for these two price levels. For the monetary variable, we use M1. We use the monthly data of Iran for the period from January 2007 to December 2016.

Since we have two groups of SMEs (Group A, sound, and Group B, unsound), we run two regressions—one for each group. The left-hand side of the regression (Eq. 30) for Group j will be the sum of their NPLs over the total loans. The right-hand side of Eq. 30 will be the macroeconomic variables and the four components of Group j . We assume that an SME's default risk ratio is only a result of macroeconomic variables and their financial profile.

4.2.1 Stationarity Test

To evaluate the stationarity of all the series, we use an augmented Dickey–Fuller (ADF) with break test. The results that we obtain imply that all the variables are non-stationary without a break. We set the lag length selection automatically based on the Schwarz information criterion. These variables include the real 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—we convert the original quarterly data into monthly data); sum of NPLs/sum of total loans for Group A and Group B of SMEs; and $Z_{1j}, Z_{2j}, Z_{3j},$ and Z_{4j} (where $j = A$ or B). However, when we apply the unit root test to their first differences, we are able to reject the null hypothesis of unit roots for each of the variables. These results

suggest that all the variables contain a unit root. When we perform the unit root test and discover that the variables are non-stationary in level and stationary at first difference, they are integrated of order one. The next step is to conduct a cointegration analysis to investigate 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 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. Table 10 presents the results of the cointegration rank test using trace.

Table 10: Cointegration Rank Test (Trace)

Group A of SMEs						
Hypothesized No. of CEs	Intercept			Intercept and Trend		
	Trace Statistic	Eigen Value	Prob.	Trace Statistic	Eigen Value	Prob.
None	223.94	0.87	0.00*	281.57	0.93	0.00*
At most 1	151.07	0.72	0.00*	188.08	0.80	0.00*
At most 2	105.24	0.61	0.01*	130.27	0.66	0.00*
At most 3	71.54	0.51	0.03*	91.68	0.57	0.03*
At most 4	46.24	0.46	0.07	61.45	0.47	0.07
At most 5	24.62	0.34	0.17	38.99	0.38	0.11
At most 6	10.05	0.20	0.27	22.23	0.34	0.13
At most 7	1.80	0.05	0.17	7.68	0.19	0.27
Group B of SMEs						
Hypothesized No. of CEs	Intercept			Intercept and Trend		
	Trace Statistic	Eigen Value	Prob.	Trace Statistic	Eigen Value	Prob.
None	218.01	0.87	0.00*	267.01	0.90	0.00*
At most 1	144.26	0.67	0.00*	186.35	0.77	0.00*
At most 2	105.20	0.65	0.01*	134.16	0.66	0.00*
At most 3	67.83	0.49	0.07	95.76	0.62	0.01*
At most 4	43.73	0.40	0.11	61.71	0.48	0.07
At most 5	25.51	0.32	0.14	38.44	0.35	0.13
At most 6	11.86	0.26	0.16	23.13	0.32	0.10
At most 7	1.29	0.03	0.25	9.48	0.23	0.15

SME = small and medium-sized enterprises, CE = cointegrating equation, prob. = probability.

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

Source: Authors' compilation.

The above test rejects the null hypothesis of non-cointegrating variables for Group A and Group B of SMEs. For Group A, the trace test in both cases—i) intercept with no trend and ii) intercept with trend—indicates four cointegrating equations at the 0.05 level. For Group B, the trace test in the case of intercept with no trend shows three co-integrating equations, and for the case of intercept with trend it indicates

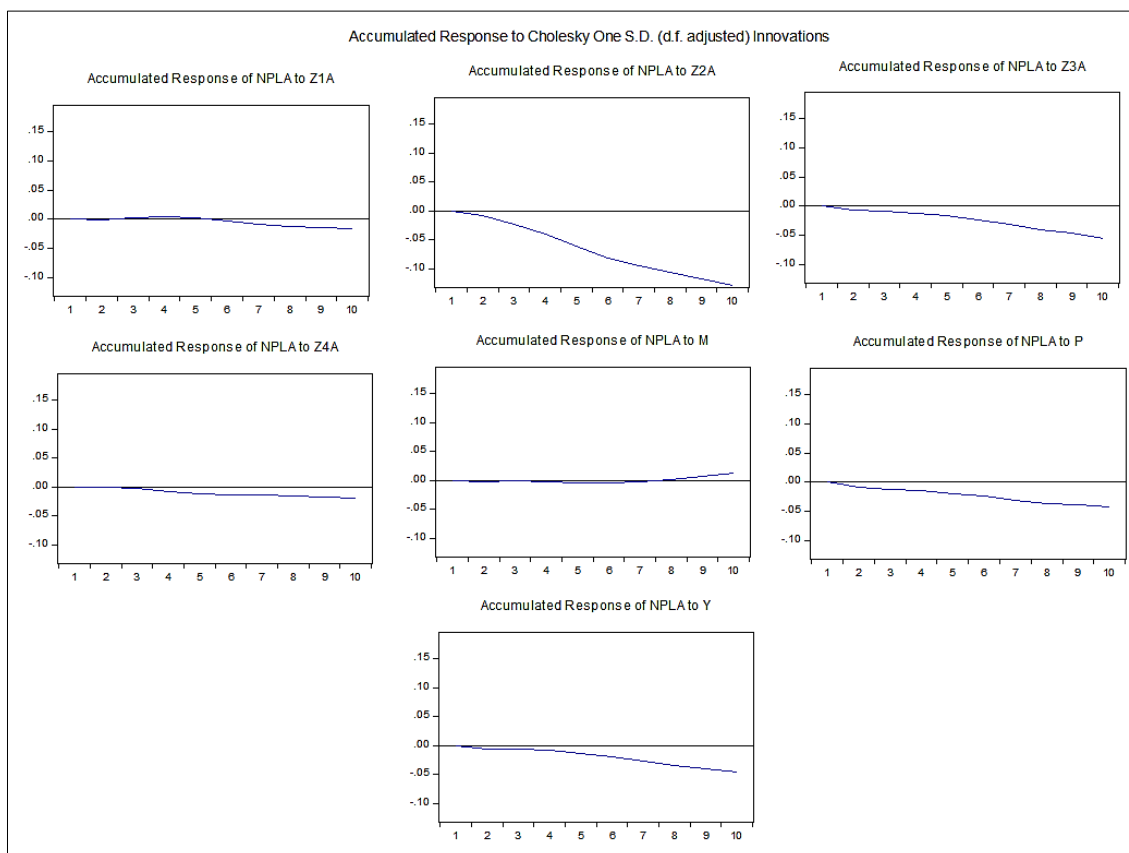
four cointegrating equations at the 0.05 level. This means that all the variables are cointegrated and there is a long-run association among the variables. In other words, in the long run, these eight variables (NPL/L, GDP growth rate, CPI inflation rate, M1 growth rate, Z1, Z2, Z3, and Z4) for each group of SMEs move together.

Hence, we should run a vector error correction model (VECM). The AIC results of our linear deterministic VECM indicate that it is slightly better to estimate the model by including the trend and intercept than to include just the intercept for both SME groups, so we also retain this finding. We estimate model 30 in a VECM setting including the eight variables— ρ (or NPL/L), GDP growth rate, CPI inflation rate, M1 growth rate, Z1, Z2, Z3, and Z4—for each group of SMEs (Groups A and B). To provide evidence of the dynamic response of ρ or NPL/L of each group of SMEs to macro- and firm-level innovations, we perform impulse response analysis, as section 4.2.3 shows.

4.2.3 Impulse Response Analysis

In this section, we conduct impulse response analysis on the resultant VECM from the previous subsection. Figure 2 shows the accumulated response of NPL/L to macro- and firm-level innovations for Group A of the SMEs.

Figure 2: Response of NPL/L to Innovations (Group A SMEs)



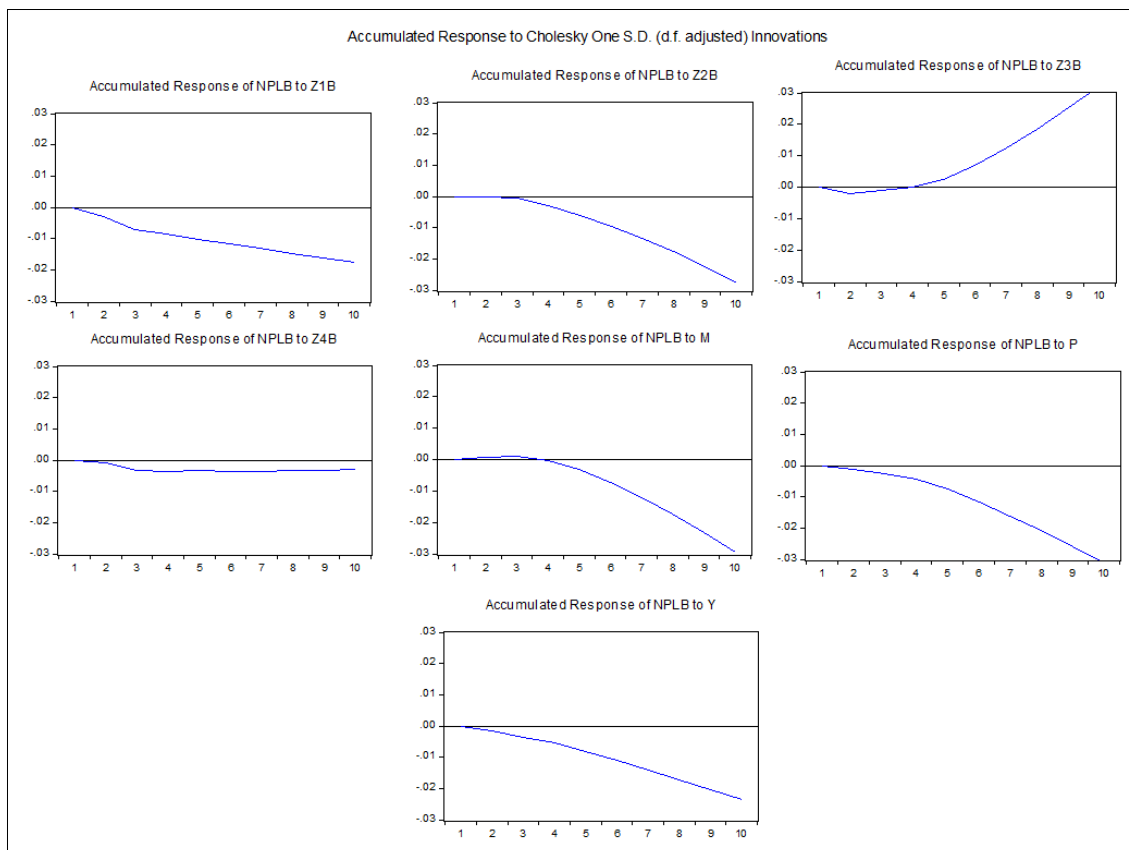
Note: Accumulated response to Cholesky one-standard deviation innovations. NPL/L is the ratio of nonperforming loans to total loans for Group A of SMEs; Z_{1A} denotes the first component (net income), Z_{2A} the second component (short-term asset), Z_{3A} the third component (liquidity), and Z_{4A} the fourth component (capital) for Group A of SMEs (sound SMEs); M denotes the M1 growth rate; P denotes the consumer price index inflation rate; and Y denotes the gross domestic product growth rate.

Source: authors' compilation.

Figure 2 show the accumulated responses of ρ or NPL/L of Group A of SMEs to an unanticipated positive shock to Z1, Z2, Z3, and Z4 for Group A of SMEs. As it is a positive shock to Z2 (short-term assets) and Z4 (liquidity), it reduces the NPL/L in Group A of SMEs persistently. For the two other components, Z1 (net income) and Z4 (capital), the dynamic responses are not significant, which means that this group of SMEs does not have a net income and capital problem. However, holding more short-term assets and liquidity can improve the SMEs' business activity and reduce their default risk, which would positively affect the soundness of the CGS.

As for the macro shocks, the response of the NPL/L of Group A of SMEs to M1 growth rate shocks is not significant. An unanticipated positive shock to the price level (CPI inflation) has a statistically negative and persistent effect on the NPL/L of Group A, which is consistent with Yoshino and Hirano (2011, 2013) and Yoshino, Taghizadeh-Hesary, and Nili (2019b). When prices increase, the collateral value increases, which means that the default risk or NPL/L will decrease. An unanticipated positive shock to Y (the real GDP growth rate) consistently has a statistically negative effect on the NPL/L of Group A. This result is also in line with Yoshino and Hirano's (2011) and Yoshino and Taghizadeh-Hesary's (2019a) findings. When the business conditions improve, increases in the GDP growth cause a reduction in the default risk (NPL/L). Moreover, Figure 6 shows that, for Group A, the lagged NPL/L affects the current NPL/L.

Figure 3: Response of the NPL/L to Innovations (Group B of SMEs)



Note: Accumulated response to Cholesky one-standard deviation innovations. $NPLB$ is the ratio of nonperforming loans to total loans for Group B of SMEs; Z_{1B} denotes the first component (net income), Z_{2B} the second component (short-term assets), Z_{3B} the third component (liquidity), and Z_{4B} the fourth component (capital) for Group B of SMEs (sound SMEs); M1 denotes the M1 growth rate; P denotes the consumer price index inflation rate; and Y denotes the gross domestic product growth rate.

Source: authors' compilation.

Figure 3 depicts the accumulated responses of the NPL/L to macro- and firm-level innovations for Group B of SMEs.

Group B shows similar responses to innovations to macro variables. This indicates that using only macro variables in a model for calculating the optimal credit guarantee fee is misleading, as it is possible that, under good economic conditions, some SMEs will show negative financial performance and have high default risk. It also means that not only macro variables but also firm-level variables are important in determining the optimal credit guarantee fee.

The responses of Group B's NPL/L to an unanticipated positive shock to Z1 (net income), Z2 (short-term assets), Z3 (liquidity), and Z4 (capital) is negative. Except for Z3, which is significant for four periods and after that becomes insignificant, the response of all the other components is persistently significant. This means that Group B of SMEs has more financial problems in terms of short-term assets, liquidity, capital, and net income. They can improve their default risk by improving these financial statuses.

The results support our suggestion that macro variables and policy variables are not sufficient to calculate the credit guarantee fee. It is necessary to determine the ratio for each group of SMEs based on their soundness, because the creditworthiness of SMEs and the default risk ratio of SME loans are major determinants of the optimal credit guarantee fee.

4.3 Robustness Test

For the robustness check, we employ two separate generalized method of moments (GMM) tests for the default risk ratio of both groups of SMEs. Numerous scholars have proved the reliability of the GMM method, such as Arellano and Bond (1991), Kahouli and Maktouf (2015), Lin (2015), and Martinez-Zarzoso, Felicitas, and Horsewood (2009). Arellano and Bond (1991) argued that the GMM estimator, including the lagged endogenous variable as an explanatory variable, is more convenient and gives more consistent and robust results in the presence of arbitrary heteroskedasticity. We can write a general regression model in the form of GMM as follows:

$$\Phi_{it} = \varphi_0 + \varphi_1 Y_{it-1} + \varphi_2 X_{it} + \varepsilon_{it} \quad (31)$$

where Φ indicates the dependent variable (the default risk ratio or NPL/L of each group of SMEs), and X represents all the explanatory variables (four components for each group of SMEs, the GDP growth rate, the CPI inflation rate, and the M1 growth rate), and ε_{it} is the error term.

To derive reliable empirical estimations, we must conduct some preliminary tests. We run the GMM estimation to ascertain the coefficients. Tables 11 and 12 report the results of the GMM estimation for Group A and Group B of SMEs, respectively.

Table 11: Generalized Method of Moments (Group A SMEs)

Explanatory Variables	Coefficients	Significant at the 1% Level
Constant	1.73	Yes
NPLA(-1)	0.98	Yes
Z_{1A}	-0.024	No
Z_{2A}	-0.149	Yes
Z_{3A}	-0.004	Yes
Z_{4A}	-0.082	No
Y	-0.092	Yes
M	0.004	No
P	-0.120	Yes
Hansen Test for over-identified restrictions		No

Note: The dependent variable is the ratio of nonperforming loans to total loans for Group A of SMEs; $NPIA(-1)$ is the ratio of nonperforming loans to total loans for Group A of SMEs with one lag; Z_{1A} denotes the first component (net income), Z_{2A} the second component (short-term assets), Z_{3A} the third component (liquidity), and Z_{4A} the fourth component (capital) for the Group A SMEs (sound SMEs); Y denotes the gross domestic product growth rate; M denotes the M1 growth rate; and P denotes the consumer price index inflation rate. Estimation weighting matrix: HAC (Bartlett kernel, Newey–West fixed bandwidth = 4.0000).

Source: Authors' compilation.

Table 12: Generalized Method of Moments (Group B SMEs)

Explanatory Variables	Coefficients	Significant at the 1% Level
Constant	2.34	Yes
NPLB(-1)	0.83	Yes
Z_{1B}	-0.43	Yes
Z_{2B}	-0.38	Yes
Z_{3B}	-0.09	Yes
Z_{4B}	-0.28	Yes
Y	-0.12	Yes
M	0.007	No
P	-0.14	Yes
Hansen Test for overidentified restrictions		No

Note: The dependent variable is the ratio of nonperforming loans to total loans for Group B of SMEs; $NPIA(-1)$ is the ratio of nonperforming loans to total loans for Group A of SMEs with one lag; Z_{1A} denotes the first component (net income), Z_{2A} the second component (short-term assets), Z_{3A} the third component (liquidity), and Z_{4A} the fourth component (capital) for Group A of SMEs (sound SMEs); Y denotes the gross domestic product growth rate; M denotes the M1 growth rate; and P denotes the consumer price index inflation rate. Estimation weighting matrix: HAC (Bartlett kernel, Newey–West fixed bandwidth = 4.0000).

Source: Authors' compilation.

There are several assumptions behind the use of the GMM, and we need to test each of them. First, we assume that there is no serial correlation in the error terms, that the regressors are not correlated with the error term, and that the error term is weakly exogenous with the regressors. We use lagged explanatory variables as instrumental variables. As with the other instrumental variable estimators, we need to test the validity of the instruments. For this purpose, we conduct the Hansen test for over-identified restrictions, with the null hypotheses being that the instruments are valid during the estimation. As shown in Tables 11 and 12, we fail to reject the null hypothesis, meaning that our instruments are valid.

The results of the GMM are consistent with the VECM results, confirming that the macroeconomic variables affect both groups of SMEs' default risk ratio. However, the macro variables are not enough, and we need to consider the firm-level variables for the calculation of the credit guarantee fee. Our results show that each group of SMEs has different responses to the four components derived from their financial statements. The dependent variable, which is the default risk ratio of SME loans and the main determinant of the credit guarantee fee, shows a significant association with Z2 (short-term assets) and Z3 (liquidity). On the other hand, Group B of SMEs' default risk ratio shows a significant association with all four components. This confirms that Group B has more financial difficulty. Our robustness results also confirm that it is necessary to consider macro variables and SMEs' credit status together to calculate the optimal credit fee to avoid moral hazard, reduce the non-performing assets of CGCs, and improve the soundness and stability of the overall financial system.

5. CONCLUSION AND POLICY IMPLICATIONS

Numerous studies have highlighted the importance of SMEs in developing as well as developed economies and have shown severe credit constraints to be one of the most significant challenges. To alleviate this issue, scholars have scrutinized the effectiveness of CGSs, especially after the negative impacts of the GFC on financial systems. There is consistency in the literature indicating the need to re-evaluate CGSs to integrate them more closely with the working of the macro economy and improve its flexibility in adjusting to the unexpected (Yamori 2015; Daskalakis, Balios, and Dalla 2017; Li and Lin 2017; Ndiaye et al. 2018). One important issue in the context of CGSs concerns the level of the optimal credit guarantee fee. High fees will create another burden for SMEs and low fees cannot secure sufficient financial resources for the CGS.

Our theoretical framework and empirical results provide important policy implications for CGCs. Our theoretical model proves that it is necessary to consider both macro variables and SMEs' creditworthiness together, along with policy variables, to calculate the optimal credit guarantee fee. It should be higher (lower) for SMEs with high (low) default risk but concurrently account for the present macroeconomic state.

In a boom, in which the actual economic output increases toward the expected levels, the fee should be higher to prevent aggressive lending and avoid the formation of an economic bubble. In a recession, in which the actual economic output decreases away from the expected levels, then the fee should be lower to accommodate greater credit constraints from formal financial institutions and encourage the loan demand from SMEs.

Our empirical analysis shows that the default risk ratio of SME loans, which is the main determinant of the credit guarantee fee, responds differently to the financial performance of each group of SMEs based on their financial soundness. This means that macroeconomic factors are not enough for the calculation of the credit guarantee fee and that the fee needs to vary for each group of SMEs depending on their creditworthiness.

Thus, this mechanism for the optimal guarantee fee—as derived from our theoretical and empirical model—acts to smooth the behavior of both banks and SMEs and, aggregately, the business cycle. Additionally, it improves the effectiveness of CGSs through the prevention of moral hazard and the reduction of NPLs of CGCs and the overall health and stability of the financial system. Therefore, our findings give meaningful insight for the future amendment of current CGSs.

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