CREDIT RISK ANALYSIS OF SMALL AND MEDIUM-SIZED ENTERPRISES BASED ON THAI DATA

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Abstract

SMEs often have severe difficulties raising money. Considering the bank-dominated characteristic of economies in Asia, banks are the main source of financing. In order to prevent the accumulation of non-performing loans in the small and medium-sized enterprise (SME) sector, it is crucial for banks to distinguish healthy SMEs from risky ones. This chapter examines how a credit rating scheme for SMEs can be developed when access to other financial and non-financial ratios is not possible by using data on lending by banks to SMEs. We employ statistical techniques on five variables from a sample of 3,272 Thai SMEs and classify them into subgroups based on their financial health. The source of data used for the credit risk analysis in this research is the National Credit Bureau of Thailand. By employing these techniques, banks could reduce information asymmetry and consequently set interest rates and lending ceilings for SMEs. This would ease financing to healthy SMEs and reduce the number of non-performing loans to this important sector.

Contents

1. INTRODUCTION

According to calculations by Thailand's Office of Small and Medium Enterprises Promotion (OSMEP), the country is home to more than 2.7 million enterprises, 99.7% of which are small and medium-sized enterprises (SMEs) and 0.3% large enterprises (at the end of 2014) (OSPEM 2015). SMEs in Thailand make a structural contribution to the economy. They account for a significant share of employment (78.5% of total employment in 2016) and almost 42.2% of contribution to the GDP (OECD/ERIA 2018).

Since SMEs are an important sector of the Thai economy, it is important to increase their resilience. One way to do this is to provide them with stable finance. SME credit, which amounted to 33.51% of total commercial bank loans in 2018 Q1, is still small in scale, whereas the ratio of non-performing loans (NPLs) remains high in SME lending, at 4.5% compared with the gross NPL rate of 2.9% in 2018 Q1 (Bank of Thailand 2018a). The lack of collateral is a critical barrier to raising business funds for Thai SMEs.

Moreover, new start-up enterprises face increased difficulty in obtaining credit due to a lack of credit history, leading to them being perceived as high risk for finance by banks.

Asymmetry of information makes the recognition of healthy SMEs among risky borrowers difficult. If the credit history of SMEs is assessed thoroughly, then it is possible for banks to ask for lower collateral from SMEs that will make the lending of banks to SMEs easier. A main requirement for achieving this goal could be establishing a comprehensive nationwide SME database. One existing SME database is Japan's Credit Risk Database (CRD), which contains data from 14.4 million SMEs, including default data from 3.3 million corporations and sole proprietorships. The data are collected from credit guarantee corporations and financial institutions (Yoshino and Taghizadeh-Hesary 2015a). Another existing example is Thailand's National Credit Bureau (NCB) database.

In the absence of a nationwide comprehensive SME credit risk database, however, it is important for banks to start to accumulate SME data and carry out credit risk assessments on them by applying credit rating techniques. For the credit rating of SMEs, Yoshino and Taghizadeh-Hesary (2014a) proposed a statistical analysis of the quality of SMEs that can be helpful in facilitating bank financing.

The motivation for this paper comes from the fact that, unlike for large firms, an extensive credit rating scheme/index for small and medium-sized firms is lacking. Developing a credit-rating index would not only shield banks from risky lending by reducing information asymmetry, but also lower borrowing costs for SMEs that have good financial health and prospects to grow. In this research, we seek to show that even if comprehensive data on SMEs is not available or is difficult to collect, it is possible to carry out the credit risk assessment and credit scoring of SMEs by relying on their borrowing history from banks. We believe that following a specific criterion like the one we are developing in this chapter for assessment of the creditworthiness of SMEs is more rational and fair than is the case if lending institutions do not consider any index but rely on the personal judgement of the bank clerk who might be subject to moral hazard, biased output and possible corruption.

In the following Section 2, we illustrate the importance of SMEs in the context of Thailand. In Section 3, we highlight the SMEs' financial support program in Thailand. Section 4 introduces the NCB. Section 5 explains the credit risk analysis using Thai SME data, followed by the methodologies we use. We show that credit ratings for SMEs can be based on variables that are easily obtained—such as total loans, the

amount of outstanding loans, initial loan amounts, and past due amounts—which is particularly useful when access to SMEs' financial statements is not available. Section 6 provides the concluding remarks.

2. IMPORTANCE OF SMALL AND MEDIUM-SIZED ENTERPRISES FOR THE THAI ECONOMY

SMEs are the key drivers of the Thai economy. In Table 1 and Figures 1, 2, and 3, we present the number of SMEs, employment, GDP growth rate and credit allocated to SMEs in Thailand. These figures show that the contributions of SMEs to the Thai economy in terms of number, employment, and GDP are all very large. However, bank loans to this sector, considering its contribution to the economy, are still small.

The total number of enterprises in Thailand at the end of 2014 was 2,744,198, of which 2,736,744 were SMEs, or 99.73% of the total number of enterprises. The SMEs in Thailand experienced 0.76% growth compared to 2013 as a whole. The number of small enterprises totaled 2,723,932, accounting for 99.26% of the country's total number of enterprises and 99.53% of the country's total number of SMEs. SMEs are predominantly found in the wholesale and retail trade sectors and automobile repair (42.37%). The next largest share is for the service sector (37.87%). The third share is for the manufacturing sector (18%), while SMEs in agriculture account for about 1.1% of the total number of SMEs in Thailand (OSMEP 2015). There is a particularly high concentration around the capital: Bangkok and its environs account for 27.6% of SMEs, with Bangkok alone accounting for around 18.1%. The next highest concentrations can be found in Chonburi (3.4%) and Chiang Mai (3.2%) (OECD/ERIA 2018).

Table 1: Number of Enterprises in Thailand Classified by Size

Size of Enterprises	2013			2014		
	Number of Enterprises	Ratio to Total Number of Enterprises	Ratio to SMEs	Number of Enterprises	Ratio to Total Number of Enterprises	Ratio to SMEs
Small and Medium Enterprises (SMEs)	2,716,038	99.73	100	2,736,744	99.73	100
Small Enterprises (SEs)	2,716,038	99.27	99.53	2,723,932	99.26	99.53
Medium Enterprises (MEs)	12,645	0.46	0.47	12,812	0.47	0.47
Large Enterprises (LEs)	6,966	0.26	–	7,062	0.26	–
Unknown	392	0.01	–	392	0.01	–
Total	2,723,396	100.00	–	2,744,198	100.00	–

Source: Office of Small and Medium Enterprises Promotion (OSMEP 2015).

In common with much of Southeast Asia, there appears to be a "missing middle"[1] in Thailand's production structure (OECD/ERIA 2018). As is clear in Table 1, only 0.47% of enterprises, or fewer than 13,000, are observed to be medium-sized. Conversely, there are slightly more large firms than in other ASEAN countries. Micro-enterprises are not disaggregated in official SME statistics but are included in the small enterprise count.

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[1] A lack of medium size companies occurring in less developed countries is called a "missing middle".

Figure 1: Employment by Small and Medium-Sized Enterprises in Thailand
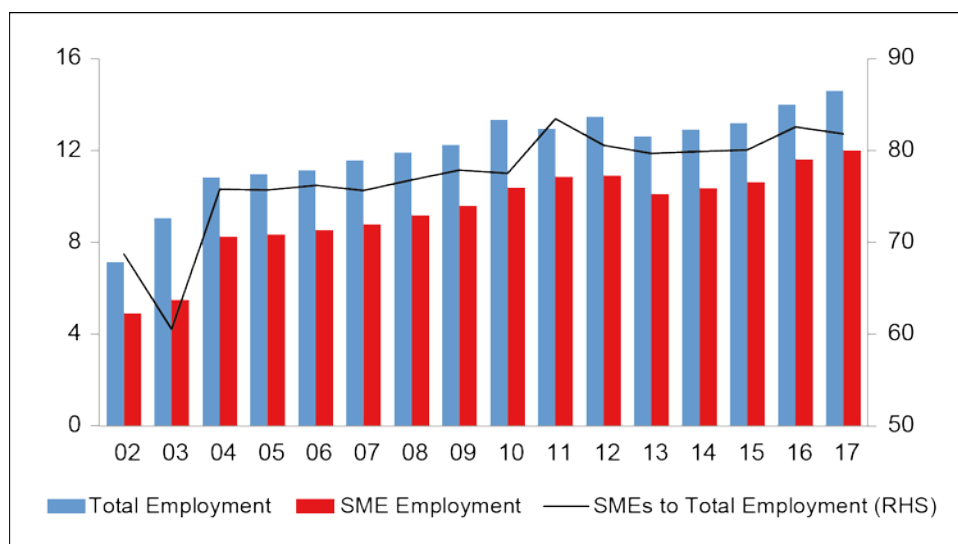
Note: Left axis unit is millions of employees. Right axis is the share of SMEs in total employment (percentage).
Source: Office of Small and Medium Enterprises Promotion (OSMEP 2015).

Figure 1 shows contributions of SMEs to employment in Thailand. SMEs in Thailand account for a significant share of employment. More than 12 million employees are working in SMEs in Thailand, and the contribution of SMEs to employment in Thailand has risen from less than 70% in 2002 to more than 80% in 2017.

Figure 2: Growth Rate of Total GDP and GDP of SMEs
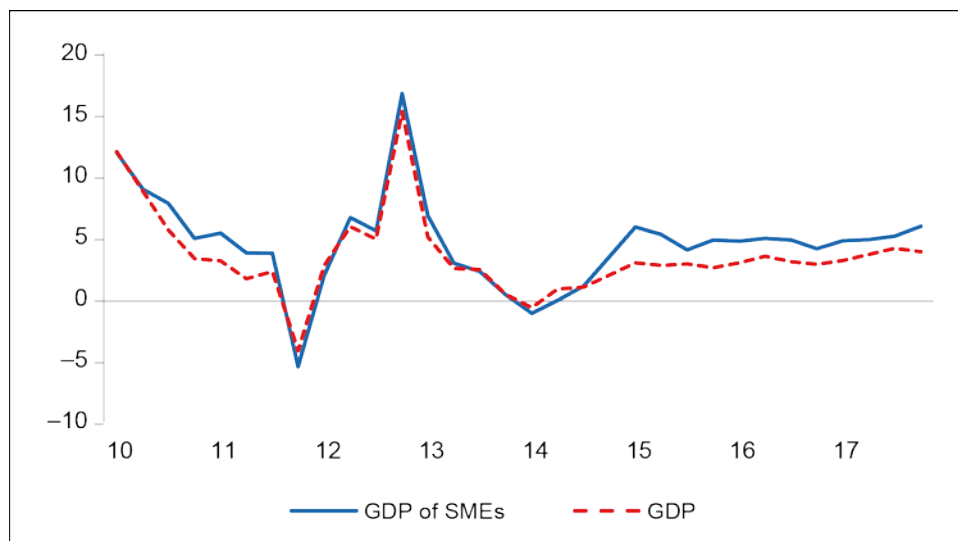
Note: The horizontal axis shows the year; the vertical axis is the GDP growth rate (percentage).
Source: Bank of Thailand (2018b).

While the contribution of SMEs to employment in Thailand is significant, SMEs account for a relatively low share of GDP (42.2%). Figure 3 compares the total GDP growth rate of Thailand with the GDP growth rate of the SME sector. The dashed line is the GDP growth rate of the whole economy and the constant line is for the SME sector. As is clear, since 2014 the SME sector GDP growth has overtaken the whole economy GDP

growth rate. This means that the supportive government plans were effective[2] (Oxford Business Group, 2018) and the share of SMEs in Thailand's GDP is gradually rising.

Figure 3: Total Loans Outstanding and SME Loans in Thailand, 2010 Q1–2018 Q1
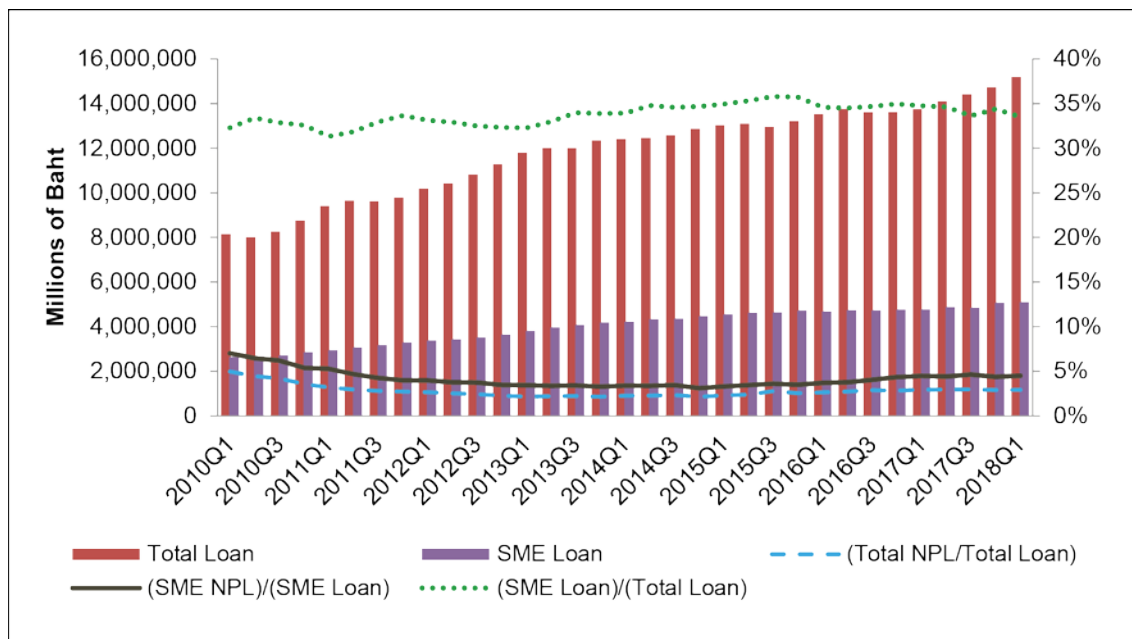
Note: Total NPL is total non-performing loans outstanding of all commercial banks registered in Thailand. Total Loan is total loans outstanding of all commercial banks registered in Thailand. SME NPL is non-performing loans outstanding for all commercial banks registered in Thailand to SMEs, and SME Loan is loans outstanding for all commercial banks registered in Thailand to SMEs.

Source: Created by the authors using data from the Bank of Thailand (2018a).

Figure 3 shows the commercial banks' total loans outstanding and loans outstanding to SMEs and their non-performing loan ratios from 2010 Q1 until 2018 Q1. The share of SME loans in total commercial banks loans is almost constant. This share in 2010 Q1 was 32.28% and in 2018 Q1 slightly rose to 33.51%. On the other hand, as it is clear that SMEs' non-performing loan ratio of SME loans is much higher compared to the ratio of total NPLs in total loans. In 2010 Q1, 6.45% of total SME loans were NPL; however, at the same time, only 4.97% of total commercial loans in Thailand were NPL. In 2014, SMEs' NPL ratio reduced to less than 3.2%; however, in recent years it has been rising. As Figure 3 shows, this ratio is currently increasing again and the NPLs of SMEs is slightly diverging from total NPLs. In 2018 Q1, SME NPLs divided by total SME loans was almost 4.5%, while total NPLs divided by total loans was 2.91%. This shows the necessity of credit risk assessment for SMEs in order to direct the bank loans only to healthy SMEs and avoid lending to risky SMEs, thus reducing the NPL ratio of SME loans.

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[2] The Thai Government launched a series of support mechanisms aimed at boosting SME exports, supporting digital business development and e-commerce activities, and increasing access to finance at commercial banks and the Thai bourse. These efforts helped SMEs strengthen domestic operations and expand their presence regionally, boosting macroeconomic development and stability, and further supporting ongoing efforts to develop a digital economy.

3. SME FINANCIAL SUPPORT PROGRAM IN THAILAND

During recent years, the Thai government has implemented several support programs to promote the SME sector and to ease SMEs' access to finance in the country. Thailand's SME policy has its roots in the Asian financial crisis and a push by policymakers to diversify and establish a broader base for growth. It broadly adopts the service delivery approach to SME policy, providing services (such as training programs for SME entrepreneurs) to help SMEs increase their competitiveness. Its main policy priorities in this area are internationalization and productivity enhancement. In line with its diversification objectives, the country has identified priority sectors for targeted support (OECD/ERIA 2018). Turner et al. (2016) examined the role of the Thai government in economic development through the promotion of SMEs, exploring the interaction between the government and the private sector, the challenges facing SMEs and the effectiveness of the SME promotion policy being considered in terms of implications for future policy. The authors showed that the Thai government has played an important role in supporting the development of SMEs as a means of achieving sustained and healthy economic growth. They added that a committed SME promotion policy from the government and closer cooperation between the state and the private sector are needed for the further development of SMEs. Integration of the government agencies related to SME promotion should be enhanced to facilitate a whole-of-government approach.

Thailand has a moderately high level of financial sector development according to global indices. It performs well on indicators of financial soundness and product availability, but may need to undertake additional steps to enhance the legal and institutional environment for getting credit, particularly in the area of creditor rights. Some measures have been put in place to provide SMEs with additional collateral, such as a guarantee scheme (OECD/ERIA 2018).

In this section, we shed light on policy and regulations in relation to SME promotion and both bank-based lending and non-bank-based lending to SMEs.

3.1 Policy and Regulation

The National Board of SME Promotion is the government body responsible for national SME promotion policies and plans, and is chaired by the country's Prime Minister. OSMEP is a government agency for planning and coordinating national SME policies across government organizations in Thailand. OSMEP commenced operations in 2001 under the supervision of the National Board of SME Promotion, and is responsible for formulating the midterm SME Promotion Master Plan. To date, three master plans have been formulated by the office. The third SME Promotion Master Plan, covering 2012–2016, developed four strategies that addressed a conducive business environment, competitiveness, balanced growth across the country, and the business capability of Thai SMEs for international economic integration. Promoting SME access to finance is one of the strategic actions under the pillar of developing a conducive business environment for Thai SMEs. To support a smooth transition of SME business to the new economic environment brought by the Association of Southeast Asian Nations (ASEAN) Economic Community to be launched in late 2015, the national SME policy has attached importance to strengthening the country's knowledge base and international networks so that Thai SMEs can operate easily in the integrated regional economy. To this end, OSMEP conducted several studies (e.g., consumer behavior in ASEAN countries, promotion guidelines for Thai SME high growth sectors, financial structure analysis of SMEs, and construction business analysis in 22 Thai provinces)

which contributed to policy directions on the promotion of SMEs in the country. [3] In 2013, OSMEP formulated the SME Promotion Strategic Plan and Action Plan by Sector, addressing three target industrial sectors: (i) spa and health services; (ii) wholesale and retail trade; and (iii) information/digital content. There were five basic strategic criteria: (i) strengthening capacity; (ii) creating long-term stability for business; (iii) highlighting speed networks and having alliances both inside and outside the country; and (iv) creating popularity, fame, and story. The regulatory structure in the Thai financial sector is two-pronged. The Bank of Thailand regulates and supervises commercial banks and licensed non-banking-financial institutions, while the Fiscal Policy Office under the Ministry of Finance regulates specialized financial institutions (state-owned banks), including the Small and Medium Enterprise Development Bank. However, the Bank of Thailand inspects specialized financial institutions as appointed by the Ministry of Finance. The Thailand country strategy, initiated by the Office of National Economic and Social Development Board in 2012, mapped out an inclusive growth strategy as part of four strategic pillars. These addressed the target of increasing SME contribution to GDP by 40% or more. The Bank of Thailand's Five-Year Strategic Plan 2012–2016 also addressed the need to extend more loans and financial services to SMEs under the strategic pillar of creating a high value-added economy. The Securities and Exchange Commission has continuously struggled to develop SME capital markets in Thailand, implementing three programs: (i) educating and incentivizing SMEs to issue corporate bonds through free seminars, concessional rating fees, bond application fee exemption, and registration fee exemption in the Thai Bond Market Association; (ii) a program named IPO, Pride of the Province, to assist local firms to tap into capital markets through free training courses, consultations, and listing fee exemptions; and (iii) a program to allow accredited investors, including institutional investors and high net worth individuals, to invest in riskier products, such as unrated bonds (ADB 2015).

3.2 Bank-based Lending

Finance is an unavoidable problem for SME promotion. In this section, we look at the modes of bank-based financing of SMEs in Thailand. Bank-based lending is practiced most in Thailand. There are two kinds of bank-based finance: direct lending and letter of guarantee. In the former, banks directly lend to SMEs, whereas the Thai Credit Guarantee Corporation approves loans to SMEs and issues letters of guarantee.

3.2.1 Banking Sector

Thailand's financial intermediation level is high, with domestic credit to the private sector amounting to 147.3% of GDP in 2016 and SME loans accounting for 34% of total bank loans extended by private banks, or USD 153 billion, in 2017 (World Bank 2016a). However, surveys suggest that a relatively high share of small enterprises (44.8%) have had loan applications rejected, in contrast to their larger peers (World Bank 2016b). This may indicate a persistent financing gap or low creditworthiness, particularly for small and micro firms.

One big challenge in relation to Thailand's SME loans is the high NPL ratio of SMEs compared to the total NPL ratio, as shown in Figure 3. This means that the role of credit assessment of SMEs is very important in order to recognize healthy SMEs among the risky SMEs. Lending to risky SMEs will further increase the NPL ratio of SME loans. Another important policy is promotion of the government's credit guarantee

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[3] Executive summaries of OSMEP studies are available at http://www.sme.go.th/eng/index.php/data-alert/alert/report-smes-year/report-year (OSMEP 2015).

scheme to cover a part of the bank's risk of lending to SMEs which will reduce the NPL ratio of SME loans.

3.2.2 Credit Guarantee Scheme

To reduce the supply–demand gap in SME finance, various government and donor initiatives have emerged in both developed and developing and emerging economies to establish credit guarantee schemes (CGSs). CGSs have been used in many countries and in various forms over the decades 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 it (Yoshino and Taghizadeh-Hesary 2018a).

Since its inception in 1991, the Thai Credit Guarantee Corporation (TCG) has acted as a single guarantor of loans to SMEs. The state-owned corporation, funded by the Ministry of Finance, has evolved through three stages of development: (i) full-cover guarantee (1992–2004); (ii) 50% partial guarantee (2004–2009); and (iii) portfolio guarantee (2009–). The portfolio guarantee scheme (PGS) started as part of the Thai economic stimulus measures following the 2008–2009 global financial crisis. Provided that the SME is a major client, the TCG guarantees 100% of the payment stated in each letter of guarantee issued for participating banks when prosecuted, but up to 15.5% of the average guarantee outstanding in each portfolio that pools all guaranteed SME loans from the participating bank every year. The PGS is a special measure with a limited period of 5–7 years (ADB and OECD 2014).

Figure 4: Credit Guarantees: Thai Credit Guarantee Corporation
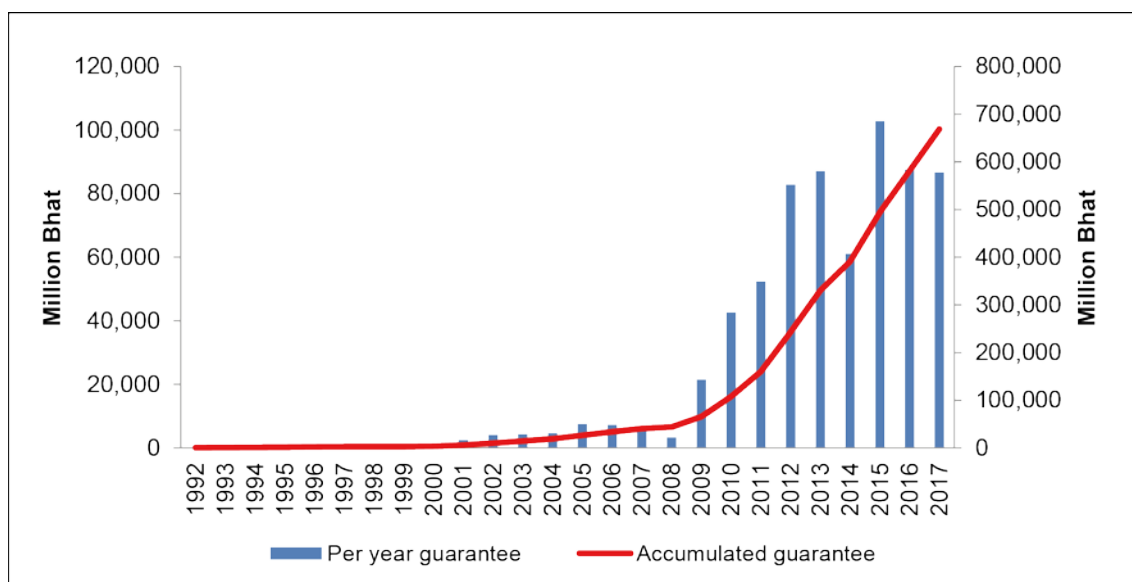
Source: Thai Credit Guarantee Corporation (2018).

Figure 4 shows that the credit guarantee scheme in Thailand in the past ten years has experienced significant growth. Accumulated guarantee approval continued to increase from Bhat 735 million to Bhat 668,420 during 1992–2017. Likewise, per year guarantee approval increased from Bhat 151 million to Bhat 86,634 million in the same period.

3.3 Non-Bank-based Lending

In this section, we discuss SME financing through capital markets, which is already being practiced in Thailand.

3.3.1 Capital Markets

The Market for Alternative Investment (MAI) has been growing rapidly in recent years. The MAI was established under the Stock Exchange of Thailand in 1998, aiming to provide opportunities for entrepreneurs and SMEs to tap into long-term growth capital. As of 2 December 2014, the MAI held 109 listed companies, with total market capitalization of THB 392 billion and total turnover value of THB 859 billion. So far, 18 companies have successfully moved from the MAI to the main board of the Stock Exchange. During 2014 alone, 18 companies were newly listed on the MAI and four companies moved to the main board. This indicates that the MAI has become a preparatory venue for SMEs to tap into the regular market of the Stock Exchange and to lead them to a business growth cycle. The service sector (excluding financial services) and the manufacturing sector are the most active issuers in the MAI, accounting for 28.4% and 26.6%, respectively, of total listed companies, as of 2 December 2014. Domestic individuals and institutions are the main investors in MAI stocks, accounting for 98% of trading in 2014. Foreign investor participation in the MAI accounted for 2% of trading in 2014.

The MAI offers concessional listing requirements for issuers compared to the main board, such as two years' business operations (three years for the main board); minimum paid-up capital of B20 million after public offering (B300 million for the main board); and no fewer than 300 minority shareholders (1,000 for the main board). Only common stocks and warrants are traded on the MAI. The Securities and Exchange Commission has continuously considered new capital market instruments that SMEs are able to tap into, one of which is a bond instrument. The Commission and the TCG are together exploring the potential of guaranteed SME bond products in Thailand.

However, as the TCG is not legally allowed to provide guarantees for NBFIs, the Small Industry Credit Guarantee Corporation Act B.E. 2534 (1991) needs to be amended so that the Corporation can enter the guaranteed bond business.

4. INTRODUCTION OF THE NATIONAL CREDIT BUREAU

Data used in this chapter's empirical analysis are from the National Credit Bureau of Thailand. This section introduces Thailand's national SME database.

4.1 Thailand's National Credit Bureau

The NCB is well known among debtors, businessmen, and SMEs as the organization that collects and processes the credit information of clients of financial institutions. However, the exact responsibilities and duties of the NCB are little known, as people believe that the credit bureau can place people on a blacklist, sells credit information to telesales businesses, and is responsible for credit rejections. Today, with the help of an awareness campaign by the NCB, people have a proper understanding of the NCB's roles and how the credit report is important to their living.

4.1.1 Why the Credit Bureau?

The NCB was established in 1998 under a Thai government policy. The government realized that a significant cause of the economic crisis in Thailand was that the country's financial sector did not have an organization to collect credit information thoroughly and systematically. Financial institutions then performed an inaccurate analysis of credit because they did not know the overall obligations or payment histories of borrowers: they were relying on their own information, which caused asymmetric information in making credit decisions.

The government supported the establishment of two credit bureaus for collecting and assembling credit information and payment history of financial institutions' clients, as well as serving credit inquiries to financial institutions under clients' consent. Later, in 2005, the two credit bureaus merged to become the National Credit Bureau, running under the Credit Information Business Act B.E. 2545.

The NCB is a private company that does not seek profit maximization. Its shareholders are customers or members, and the board of directors consists of experts and executives from the Ministry of Finance, financial institutions, and insurance companies. Credit information meets the international standards of credit bureaus in other countries.

Besides the credit information security that the NCB provides in the credit report as a standard product, the NCB has implemented systems of continuous improvement for its members, especially its risk management tools. Credit scoring is one risk management tool, using statistical methods to evaluate the possibility of delinquency in the future. The service was launched in 2016. There are two credit scoring models, the individual model and the SME model. Credit scoring has a score range from 300 to 900 and is graded as AA–HH. This is a risk assessment tool that will assess borrowers' possibility of delinquency. The score will indicate the possibility of delinquency in the next 12 months of 10,000 people who have a score in the same range. Financial institutions will consider this score with their credit policy and other factors to decide whether they will approve the granting of credit or which interest rate should be given to the borrower.

Moreover, the NCB has prepared an early warning system that is calculated from the existing database. This system notifies members to prevent increasing default and be careful in their credit analysis process, such as notification of total accounts which have more than a 90-day default. This could alert the financial institution before the debt hits the industry.

5. ANALYSIS OF CREDIT RISK

5.1 Theoretical Background

In this section, we present the theoretical model and then the empirical analysis run by Yoshino et al. (2016). In this subsection, we show through a simple mathematical model how the development of a credit risk analysis for SMEs could reduce banks' lending rates toward this important sector.

Eq. 1 and Eq. 2 present the profit maximization behavior of banks on credit and deposit operations:

$$\text{Max } \Pi = r_L(L)L - \rho(CRA, z_i)L - r_D D - C(L, D) \tag{1}$$

Subject to bank's balance sheet $(1-\rho)L + \rho L = D + A$ (2)

where r_L is the interest rate on loans, which is a function of loans (L); ρ is the default risk ratio of loans (SME loan and large enterprises loans), which is a function of various issues including the credit risk analysis (CRA) and Z_i representing other factors including macro-variables and the financial profile of the banks (see, inter alia, Yoshino and Hirano 2011, 2013; Klein 2013; Yoshino, Taghizadeh-Hesary and Nili, 2015); r_D is interest rate on deposits; D is deposits; and C is the operational costs of the bank, such as wage payment for employees, and computer and equipment costs, which depend on lending and deposits.

Eq. 2 shows the bank's balance sheet: the first component $(1-\rho)L$ shows good loans; the second component ρL shows non-performing loans or bad loans. On the right hand side of this equation, A is the bank's capital.

Substituting Eq. 2 in Eq. 1 and getting the first order condition with respect to Loan (L) for the profit maximization behavior of banks, and setting it equal to 0, will result in Eq. 3:

$$\frac{\partial \Pi}{\partial L} = r_L - \rho(CRA, z_i) - r_D - \frac{\partial C}{\partial L} = 0$$ (3)

Writing Eq. 3 for r_L results in Eq. 4, which shows banks' optimal interest rate on loans:

$$r_L = \rho(CRA, z_i) + r_D + C'_L$$ (4)

where C'_L is equal to $\frac{\partial C}{\partial L}$ which denotes the marginal operational costs of banks by increasing additional loans, which is a function of CRA and Z_i. Eq. 4 show that the credit risk analysis on SMEs will help banks to recognize healthy SMEs from non-healthy ones and expand their lending to sound SMEs. On the other hand, they will reduce their lending to risky enterprises. This will reduce the default risk ratio of bank loans on SMEs, raise banks' profit and reduce the lending rate to SMEs.

From here, we run our credit risk analysis on Thai SMEs. An efficient and comprehensive method for credit rating has been proposed in a study by Yoshino and Taghizadeh-Hesary (2014a). The study uses five categories of financial ratio—liquidity, profitability, leverage, coverage, and activity—and each category is explained by several financial ratios. Two statistical techniques, principal component analysis and cluster analysis, are employed to reduce the dimensions of the data—i.e., summarizing the information on multiple variables to a few variables becomes simpler when judging the health of SMEs based on them. The method classifies and ranks SMEs into different groups depending on their financial soundness[4] (Yoshino et al. 2016).

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[4] This method can also be used for credit rating in non-SME sectors. In a recent study, Yoshino, Taghizadeh-Hesary, and Nili (2015) used this method for credit rating and classifying 32 Iranian banks. Based on the results, the banks were classified into two groups and rated based on their soundness.

5.2 Data and Variables

We used 2015 Commercial Credit Scoring Data from the NCB of Thailand. The dataset contains 1 million SMEs with their credit history: loan amounts, default status, past due amount, past due days, etc. For simplicity, we selected 3,272 observations for the principal component analysis.[5] For the cluster analysis, we took 1,197 observations that were used in the principal component analysis.[6] Table 2 describes the variables we used in the empirical part of this chapter.

Table 2: Description of Examined Variables

Series No.	Variable	Description	Mean	Minimum	Maximum
1	Initial amount	Principal amount	11,393,080	10,192	8,790,000,000
2	Past due days	Overdue days code	6.924817	1	11.00
3	Past due amount	Past due incurred	12,929,693	2	3,748,031,686
4	Total loans	Total loans lent	39,638,340	4	49,995,000,000
5	Outstanding amount	Outstanding amount	19,636,365	0	8,852,398,916

Note: Definitions of overdue days are as follows:

004: Overdue 91–120 days

005: Overdue 121–150 days

006: Overdue 151–180 days

007: Overdue 181–210 days

008: Overdue 211–240 days

009: Overdue 241–270 days

010: Overdue 271–300 days

011: Overdue more than 301 days

Source: Yoshino et al. (2016).

In the next stage, two statistical techniques are used: principal component analysis and cluster analysis. The underlying logic of both techniques is dimension reduction—summarizing information on multiple variables into just a few variables—but they achieve this in different ways. Principal component analysis reduces the number of variables into components (or factors). Cluster analysis reduces the number of SMEs by placing them in small clusters. In this survey, we use components (factors) that are the result of principal component analysis and then run the cluster analysis in order to group the SMEs.

5.3 Principal Component Analysis

Principal component analysis is a standard data-reduction technique that extracts data, removes redundant information, highlights hidden features, and visualizes the main relationships that exist between observations.[7] Principal component analysis is a technique for simplifying a dataset by reducing multi-dimensional datasets to lower dimensions for analysis. Unlike other linear transformation methods, principal component analysis does not have a fixed set of basis vectors: its basis vectors

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[5] As there were too many zeros in the observations, we selected only SMEs with non-zero variables and randomly selected 3,272 observations from them.

[6] Outlier observations were excluded.

[7] Principal component analysis can also be called the Karhunen–Loève theorem (KLT), named after Kari Karhunen and Michel Loève.

depend on the dataset. Principal component analysis has the additional advantage of indicating what is similar and different about the various models created (Bruce-Ho and Dash-Wu 2009; Jolliffe 2002). Through this method, we reduce the five variables listed in Table 2 to determine the minimum number of components that can account for the correlated variance among SMEs.

We performed the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity to examine the suitability of our data for factor analysis. KMO measures the sample adequacy, which indicates the proportion of common variance that might be caused by underlying factors. High KMO means that factor analysis may be useful, while a value of less than 0.5 indicates lower suitability for factor analysis. KMO in this study was 0.50; thus we proceeded with factor analysis.

We then determined how many factors to use in our analysis. Table 3 reports the factors and their estimated eigenvalues. We used factors that explained more than 20% of the variance—i.e., an eigenvalue greater than or equal to 1. Thus, only three factors were retained, which together explain 69.33% of the variance. Accordingly, five variables in the dataset can be explained by the three main components.

Table 3: Total Variance Explained

Component	Eigenvalue	% of Variance	Cumulative %
Z1	**1.39**	**27.85**	**27.85**
Z2	**1.07**	**21.42**	**49.27**
Z3	**1.00**	**20.06**	**69.33**
Z4	0.92	18.50	87.83
Z5	0.61	12.17	100.00

Note: Extraction method: principal component analysis. When components are correlated, the sums of squared loadings cannot be added to obtain the total variance.

Source: Yoshino et al. (2016).

In running the principal component analysis, we used direct oblimin rotation. This is the standard method to obtain a non-orthogonal (oblique) solution—that is, one in which the factors are allowed to be correlated. In order to interpret the information revealed in the principal component analysis, the pattern matrix must then be studied. Table 4 presents the pattern matrix of factor loadings by use of the direct oblimin rotation method, where variables with large loadings—absolute value (>0.6) for a given factor—are highlighted in bold.

In Table 4, we present three significant components. The first component, Z1, received main loadings from two variables, total loans and initial amount. This implies that the higher the total loans and initial amount, the larger Z1 will be. Z1 is called 'flow amount of loan'. The second component that was significant in our credit analysis was Z2. It received the highest loadings from one variable, past due amount, with positive loading; it is called 'expected NPL'. We can infer that the higher the past due amount, the higher Z2 will be. The third component was Z3, which received the highest loading from outstanding amount. This means that if the outstanding amount of loans of SMEs increases, Z3 will increase. Z3 is called 'stock amount of loans'. Thus we have these three components based on the significant loadings they received.

Table 4: Factor Loadings of Loan Variables after Direct Oblimin Rotation

| | Component | | |
Variable	Z1	Z2	Z3
Total loans	**0.834**	−0.009	0.004
Initial amount	**0.833**	0.018	0.017
Past due amount	0.029	**0.834**	−0.242
Outstanding amount	0.023	−0.083	**0.896**
Past due days	0.034	−0.590	−0.407

Notes: Extracted from principal component analysis using direct oblimin rotation with Kaiser normalization. Values greater than 0.5 in absolute terms are in bold. Components receive their main loadings from the bold variables.

Source: Yoshino et al. (2016).

Table 5 shows the correlation matrix for components Z1, Z2, and Z3. As can be seen, none of the correlations is significant, suggesting that a regular orthogonal rotation method to force an orthogonal rotation would have been applicable. Nevertheless, our application of the oblique rotation method provided an orthogonal rotation since there is no significant correlation between the components.

Table 5: Component Correlation Matrix

	Z1 Flow Amount of Loan	Z2 Expected NPL	Z3 Stock Amount of Loans
Z1 Flow amount of loan	1.000	−0.008	−0.025
Z2 Expected NPL	−0.008	1.000	0.065
Z3 Stock amount of loans	0.025	0.065	1.000

Note: Extracted from principal component analysis with direct oblimin rotation with Kaiser normalization.

Source: Yoshino et al. (2016).

5.4 Cluster Analysis

In this section, we group SMEs with similar characteristics using the cluster analysis method. Clustering divides observations into groups with certain similar traits. In this survey, we use the three significant components that we obtained from the principal component analysis to group SMEs into different clusters. Clustering is useful to compare a group that has similar characteristics within the group to another group of observations with different characteristics from the former but similar within-group features.

In this case, SMEs were organized into distinct groups according to the three significant components derived from the principal component analysis used in the previous section. Cluster analysis techniques can themselves be broadly grouped into three classes: hierarchical clustering, optimization clustering, and model-based clustering. [8] We used the method most prevalent in the literature, hierarchical

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[8] The main difference between the hierarchical and optimization techniques is that in hierarchical clustering the number of clusters is not known beforehand. The process consists of a sequence of steps where two groups are either merged (agglomerative) or divided (divisive) according to the level of

clustering. This produced a nested sequence of partitions by merging (or dividing) clusters. At each stage of the sequence, a new partition is optimally merged with (or divided from) the previous partition according to some adequacy criteria. The sequence of partitions ranges from a single cluster containing all the individuals to a number of clusters (*n*) containing a single individual. The series can be described by a tree display, or dendrogram (Figure 5). Agglomerative hierarchical clustering proceeds by a series of successive fusions of the *n* objects into groups. In contrast, divisive hierarchical methods divide the *n* individuals into progressively finer groups. Divisive methods are not commonly used because of the computational problems they pose (Everitt, Landau, and Leese 2001; Landau and Chis Ster 2010; Rousseeuw 2005). Below, we use the average linkage method, which is a hierarchical clustering technique.

5.5 Average Linkage Method

The core idea of the average linkage method is that the distance between each cluster is regarded as the average distance from all observations in one cluster to all points in another cluster. Average linkage averages all distance values between pairs of cases from different clusters. At different distances, different clusters are formed, which can be represented by a dendrogram. The average linkage method is robust and takes cluster structure into account (Martinez and Martinez 2005). The basic algorithm for the average linkage method can be summarized as:

1. N observations start out as N separate groups. The distance matrix D=(dij) is searched to find the closest observations—for example, Y and Z.

2. The two closest observations are merged into one group to form a cluster (YZ), producing N–1 total groups. The process continues until all the observations are merged into one large group (Rousseeuw 2005).

Figure 5 shows a dendrogram, where the y-axis marks the distance at which the clusters merge, while the objects (SMEs) are placed along the x-axis such that the clusters do not mix. The dendrogram shows the formation of three main groups. The resultant dendrogram does not tell us in which cluster SMEs of a particular financial category lie. This can be achieved by plotting the distributions for factors for each member of the major categories.

The scatter plot in Figure 6 shows that there are three different groups of SMEs in three different dimensions.[9] This is proof of our dendrogram, because our dendrogram also categorized the SMEs into three groups. Moreover, we picked random samples from each group the dendrogram gave us and found that Group A is the healthiest group. As we move on the horizontal line to the right, soundness declines, meaning that Group C has the lowest soundness, and Group B is in between.

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similarity. Eventually, each cluster can be subsumed as a member of a larger cluster at a higher level of similarity. The hierarchical merging process is repeated until all subgroups are fused into a single cluster (Martinez and Martinez 2005). Optimization methods, on the other hand, do not necessarily form hierarchical classifications of the data, as they produce a partition of the data into a specified or predetermined number of groups by either minimizing or maximizing some numerical criteria (Feger and Asafu-Adjaye 2014).

[9] Scatter plots of other sets of components (Z1–Z2) and (Z1–Z3) show almost similar classifications. Here we keep the one that was the clearest.
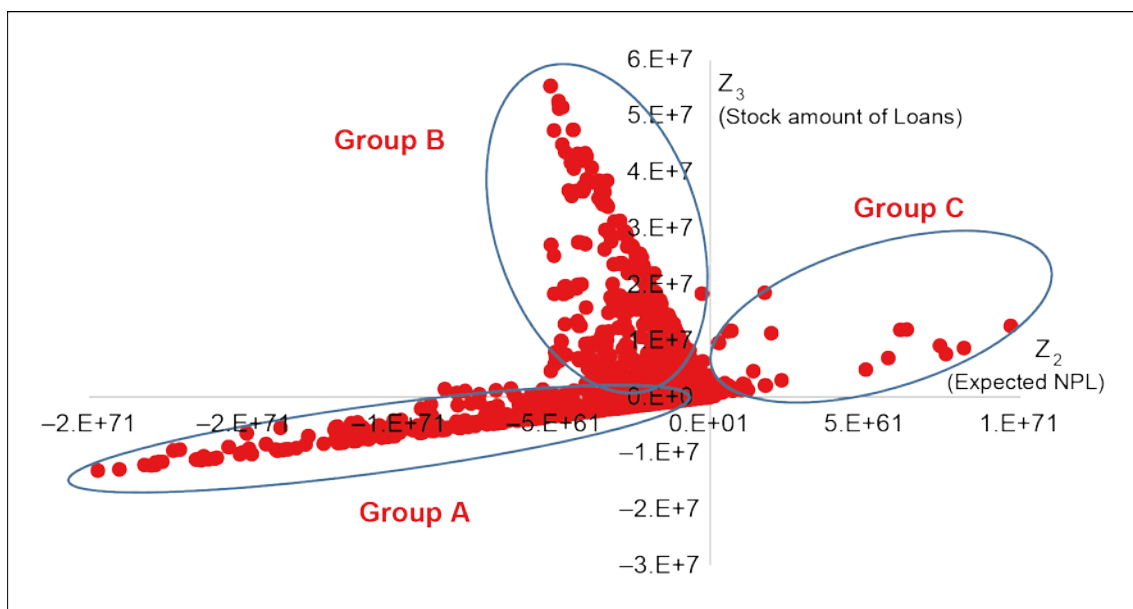
Figure 5: Dendrogram
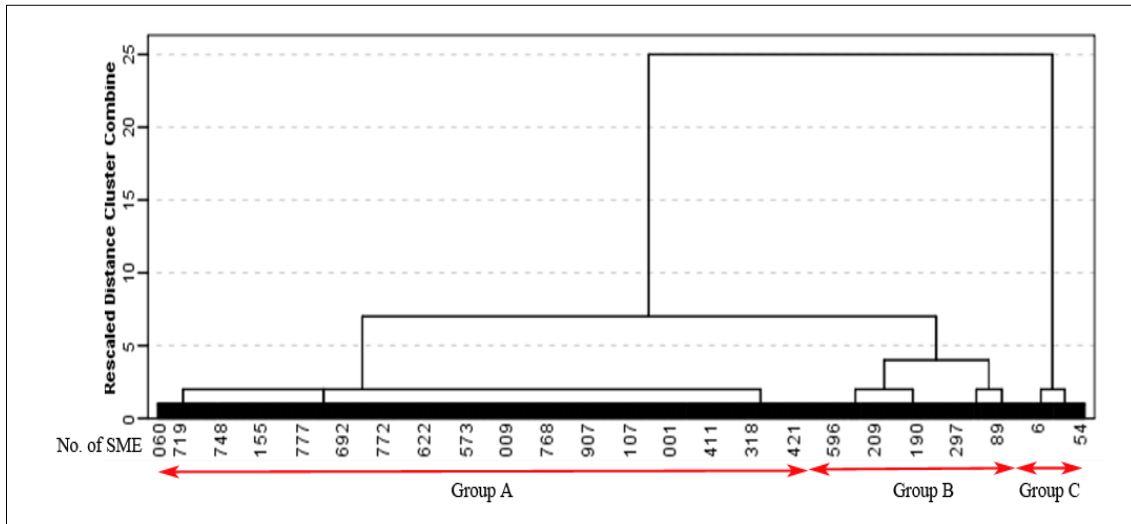
Note: Group A is the most creditworthy group of SMEs. Group C has the least credit healthiness. Group B is between the two.

Source: Yoshino et al. (2016).

Figure 6: Distribution of Factors

Note: The x-axis is the Z2 component (expected NPL) and the y-axis is the Z3 component (stock amount of loans). Each dot shows one SME. Group A is the most creditworthy group of SMEs. Group C has the least credit healthiness. Group B is between the two.

Source: Yoshino et al. (2016).

Our dendrogram results are contrary to the dendrogram of Yoshino and Taghizadeh-Hesary (2014a). For the credit risk analysis, Yoshino and Taghizadeh-Hesary introduced 11 financial ratios of SMEs (equity [book value]/total liabilities, cash/total assets, working capital/total assets, cash/net sales, retained earnings/total assets, etc.), which represent the positive characteristics of the examined SMEs. This means that the larger these variables are, the healthier a certain SME is. Their cluster analysis shows the healthier SMEs on the right side of the dendrogram, and the SMEs with

reduced financial health toward the left of the x-axis. However, the variables in our analysis are the other way around. Our variables are lending variables (past due amount, past due days, outstanding amount, etc.) and mainly represent the negative characteristics of SMEs. Therefore the resultant components (Z1, Z2, and Z3) also show the negative features of SMEs. This means that the lower these variables/components are, the better the health of a certain SME is. This is the reason why in our results, Group A (the left group on x-axis of the dendrogram) is the healthiest group, and as we move on the horizontal line toward the right, soundness declines, meaning that Group C has the lowest financial healthiness.

5.6 Robustness Check of the Method

To highlight the validity of the method we employed for predicting risk outcomes, there is one more step to go, because it might be questioned that the framework developed in this chapter derives risk factors based on factor analysis and clustering without demonstration of the usefulness of the factors for predicting actual risks or alternative outcomes. To show the validity of this model, additional work has been done on a sample consisting of 999 SMEs from an Asian country. The reason that we used another sample database for the robustness check is that, due to limitations of the current research's sample database, the default data of SMEs were not available; however, we could obtain the default data of SMEs for this second sample. The definition of a default enterprise in this new sample is 90 days' delay in interest payment.

$$Y = c + \alpha_1 A_1 + \alpha_2 A_2 + \alpha_3 A_3 + u \tag{5}$$

From the financial ratios[10] of the sample, and by applying principal component analysis, technique, three significant components were released (A_1, A_2, A_3). Using these three components, we ran a regression for an equation (Eq. 5) wherein the dependent variable is the default, being a binary variable (0 or 1) and the right hand side of the equation is a constant (c), three components (A_1, A_2, A_3) and u the error term.

Eq. 5 is a maximum likelihood-binary probit (quadratic hill climbing) model. We ran the regression using the ordinary least squares method. Using probit models to assess the impact of macro-level variables and micro-level variables on the default has long been popular among scholars (Amaral, Abreu, and Mendes 2014; Mizen and Tsoukas 2012; Moulton, Haurin, and Shi 2015). However, the advantage of our method compared to a normal probit employing just financial ratios as the explanatory variable is that our prediction is based on factor analysis. Each factor contains information on several variables (financial ratios), and in preparing these factors, unnecessary information is eliminated by statistical techniques. Hence we believe this is a more complete method and the robustness check stated in this sub-section affirms it. The pseudo R-squared[11]

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[10] To see the financial variables used, see Yoshino and Taghizadeh-Hesary (2015b).

[11] When analyzing data with a probit regression, an equivalent statistic to R-squared does not exist. The model estimates from a probit regression are maximum likelihood estimates arrived at through an iterative process. They are not calculated to minimize variance, so the ordinary least squares approach to goodness-of-fit does not apply. However, to evaluate the goodness-of-fit of logistic models, several pseudo R-squareds have been developed. These are pseudo R-squared because they look like R-squared in the sense that they are on a similar scale, ranging from 0 to 1 (though some pseudo R-squareds never achieve 0 or 1), with higher values indicating better model fit, but they cannot be interpreted as one would interpret an ordinary least squares R-squared, and different pseudo R-squareds can arrive at very different values.

represents the percentage of variation in the dependent variable (Y=default) explained by variation in the independent variables (components).

The results of probit model regression are demonstrated in Table 6.

Table 6: Probit Regression Results

Variable	Definition	Coefficient	Std. Error	Z-Statistic	Prob.
C	Constant	1.14	0.09	13.06**	0
A_1	Liabilities	1.00	0.16	6.31**	0
A_2	Short-term assets	−2.17	0.14	−15.40**	0
A_3	Liquidity	−1.02	0.21	−4.75**	0

McFadden R-squared:[12] 0.76.

Note: The dependent variable in this regression is default. The regression method is ordinary least squares. ** shows a significant result in 0.01.

Source: Yoshino et al. (2016).

The first component in Table 6, which represents the liability[13] of the SMEs, has a positive impact on default. It means default SMEs had higher liabilities, and it is statistically significant. The second component, representing short-term assets, had negative alteration of the default variable which was statistically significant. This indicates that the default SMEs in this survey primarily had lower short-term asset reserves. The last component (component 3), which represents liquidity, had a significant negative role in alteration of the default variable. This means the higher the liquidity of the SME, the lower the default risk will be. As Table 6 shows, the McFadden R-squared—which is a pseudo R-squared—is 0.76. This means that in 76% of cases the default variable (Y) is explained by independent components, which is quite large and acceptable. However, when instead of the component we used financial ratios as themselves, the R-squared was 0.65. This means that components, because they include information about different financial ratios, are able to forecast the default better.

6. CONCLUDING REMARKS

SMEs play a significant role in the Thai economy. The country counts more than 2.7 million enterprises, of which 99.7% are SMEs and 0.3% large enterprises (as at the end of 2014) (OSPEM 2015). SMEs in Thailand demonstrate a structural contribution

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[12] $\hat{Y} = c + \alpha_1 A_1 + \alpha_2 A_2 + \alpha_3 A_3$ where $\hat{Y}$ is the estimated default by use of the components, and Y is the actual default (Y), where u is the error term. The R-squared can be calculated as below:

$$R - squared = \frac{\sum\left(\hat{Y} - \bar{Y}\right)^2}{\sum\left(Y - \bar{Y}\right)^2} = \frac{\sum\left(c + \alpha_1 A_1 + \alpha_2 A_2 + \alpha_3 A_3 - \bar{Y}\right)^2}{\sum\left(Y - \bar{Y}\right)^2}$$ where the $\bar{Y}$ is the average of Y.

[13] The first component, A1, receives significant loading from two variables, one of which is positive (total debt/total asset) and one negative (equity/total debt). For A1, the ratios with large loadings include total debt: hence A1 generally reflects the liabilities of an SME. As this factor explains the most variance in the data, it is the most informative indicator of the overall financial health of an SME. Z2 reflects short-term assets. This component has two major loading variables: (a) retained income/total assets and (b) accounts receivable/total debt, both of which are positive. Z3 reflects the liquidity of SMEs. This factor has two variables with large loadings (liquidity/sales and cash/total assets), both with positive values, which shows an SME that is cash-rich. Hence, it mainly reflects the liquidity conditions of an SME.

to the economy. They account for a significant share of employment (78.5% of total employment in 2016) and almost 42.2% of contribution to the GDP.

However, SMEs often have severe difficulties raising money. The under-supply of credit to SMEs is mainly because of asymmetrical information, high default risk and lack of collateral. SMEs have more difficulties accessing finance compared to large enterprises. Lending institutions mainly prefer to increase the flow of funds to the latter sector, since the aforementioned factors are lower in this group.

The high cost of monitoring SMEs in the absence of credible credit rating companies results in many financial institutions being less interested in lending to SMEs. The setting up of a credit rating scheme for SMEs is possible by employing statistical techniques on various financial and non-financial variables of SMEs. These techniques could be applied by financial institutions, lending agencies, and credit risk analyzing bureaus.

This chapter examined how a credit rating scheme for SMEs can be developed when we do not have access to all financial ratios and only have data on lending from banks to SMEs. By using a sample of 3,272 Thai SMEs and applying statistical analysis techniques, our results show that by using lending data available from lending institutions—i.e., data on total loans, initial amounts of loans, and past due days—we can describe the soundness of SMEs. The variables in this analysis are used to cluster SMEs into different subgroups and sort them based on their financial health.

The robustness check stated in this chapter shows that risk factors achieved using statistical techniques can explain 76% of the default cases in a sample consisting of 999 SMEs. This means that that credit risk analysis can clarify the risk factors that have an impact on increasing the default risk ratio of loans, which is in accordance with the theoretical part of this paper.

The main policy implication of this chapter is that banks and financial institutions can use credit risk analysis techniques like the one demonstrated in this chapter. Credit risk analysis will help banks to recognize healthy SMEs among non-healthy ones and expand their lending to sound SMEs. On the other hand, it will help to avoid the risk of default for firms with poor financial health. Use of this method will help banks to set borrowing ceilings and interest rates for different SMEs based on their creditworthiness. This will reduce borrowing costs—i.e., lower interest rates for financially healthy SMEs. Banks will also benefit, as the number of non-performing loans for SMEs would diminish.

In addition, with the adoption of the Basel Capital Adequacy Requirements, banks are reluctant to fund riskier borrowers such as small enterprises and start-up businesses. The second policy recommendation is introducing hometown investment trust (HIT) funds in Thailand as a suitable financing schemes for risky business sectors (Yoshino 2013).

HIT funds are a new form of financial intermediation that have become popular in Japan in a relatively short span of time. They are spreading in Japan and have already entered many other Asian countries, including Cambodia and Viet Nam, as well as outside the Asian region—for example, in Peru. HIT funds can be sold by regional banks and post offices. Such trust funds would not be guaranteed by credit associations or banks. The terms of a trust fund would have to be fully explained to investors—e.g., where their funds would be invested and what would be the risks associated with the investment—in order to strengthen trust fund investors' confidence and help the trust fund market gro. (Yoshino and Taghizadeh-Hesary, 2014b).

I. HIT funds reduce information asymmetry. Often the lenders and borrowers know each other.

II. HIT funds supply risk capital stably. As bank lending for risky capital has been tightened, SMEs and start-up ventures find it difficult to gather funds. HIT funds can be very helpful for these businesses.

III. HIT funds are project-driven. Unlike mutual funds, where investors actually do not know the projects they are investing in, they can choose to invest in projects in their locality.

IV. HIT funds are a form of crowdfunding, where the investors are mainly local people. The investors can receive the product and output of the project that they are investing in (for example, investing in a HIT fund for a farm and using the product of that farm instead of a cash return). There is a 'warm' feeling behind HIT funds, as investors are sympathetic to the company/project owners.

V. HIT funds are now advertising through several internet companies in Japan so that even non-local investors can select the funds that they are interested in it and invest. The backbone of these funds is transparency, that allows trust for the investors. Investors monitor exactly where their money is invested, who the owner of the project is, what the products are, etc.

VI. The internet companies that act as project intermediaries assess the projects and select those that are expected to have success; they do not accept and do not advertise very risky projects. These intermediaries need to receive a license from the government. In Japan, they need to receive a Type II Financial Instruments Business license from the Financial Services Agency (FSA), which is the regulator and supervisor of the financial system.

VII. The intermediary companies are not asset management companies; they only introduce HIT projects for the development of various products. They simply act as intermediaries and therefore do not provide any guarantee (Yoshino and Taghizadeh-Hesary 2018b).

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