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Working Paper

SME credit risk analysis using bank lending data: An analysis of Thai SMEs

ADB Working Paper, No. 536

Provided in Cooperation with:

Asian Development Bank Institute (ADBI), Tokyo

Suggested Citation: Yoshino, Naoyuki; Taghizadeh-Hesary, Farhad; Charoensivakorn, Phadet; Niraula, Baburam (2015) : SME credit risk analysis using bank lending data: An analysis of Thai SMEs, ADB Working Paper, No. 536, Asian Development Bank Institute (ADBI), Tokyo

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ADB Working Paper Series

**SME Credit Risk Analysis Using Bank Lending Data:
An Analysis of Thai SMEs**

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No. 536
July 2015

Asian Development Bank Institute

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The authors are grateful to the National Credit Bureau (NCB) of Thailand for providing the necessary data for this research.

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Suggested citation:

Yoshino, N., F. Taghizadeh-Hesary, P. Charoensivakorn, and B. Niraula. 2015. SME Credit Risk Analysis Using Bank Lending Data: An Analysis of Thai SMEs. ADBI Working Paper 536. Tokyo: Asian Development Bank Institute. Available: <http://www.adb.org/publications/sme-credit-risk-analysis-using-bank-lending-data-analysis-thai-smes/>

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Abstract

Small and medium-sized enterprises (SMEs) are the backbone of most Asian economies. The main obstacle to the development of the SME sector is the lack of stable finance. Considering the bank-dominated characteristic of economies in Asia, banks are the main source of financing, and the lack of a comprehensive credit rating database has been a bottleneck for SMEs. This paper 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 Thai SMEs and classify them into subgroups based on their financial health. 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 amount of non-performing loans to this important sector.

JEL Classification: G21, G23, G24, G32

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1. INTRODUCTION

Small and medium-sized enterprises (SMEs) play a significant role in the Thai economy. In 2012 there were 2.7 million SMEs in Thailand, comprising 98.5% of total enterprises. In the same year, SMEs accounted for 37.0% of gross domestic product (GDP) and 80.4% of the workforce. Likewise, Thai SMEs also contributed 28.8% of total exports and 31.9% of total imports by value in 2012 (ADB 2014).

Since SMEs are an important sector of the Thai economy it is important to increase their resilience. One of the ways to increase their resilience is to provide them with stable finance. SME credit, which amounted to 32.8% of total commercial bank loans in 2012, is still small in scale, whereas the ratio of non-performing loans (NPLs) remains high in SME lending, at 3.4% compared with the gross NPL rate of 2.2% in Q2 2013. The lack of collateral is a critical barrier for Thai SMEs in raising business funds (ADB 2014).

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 by banks for finance. Financing through regional funds, i.e., hometown investment trust funds (HIT funds), is another stable way of financing risky capital (Yoshino 2013).

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. A main requirement for the development of SMEs could be establishing a comprehensive 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)'s database.

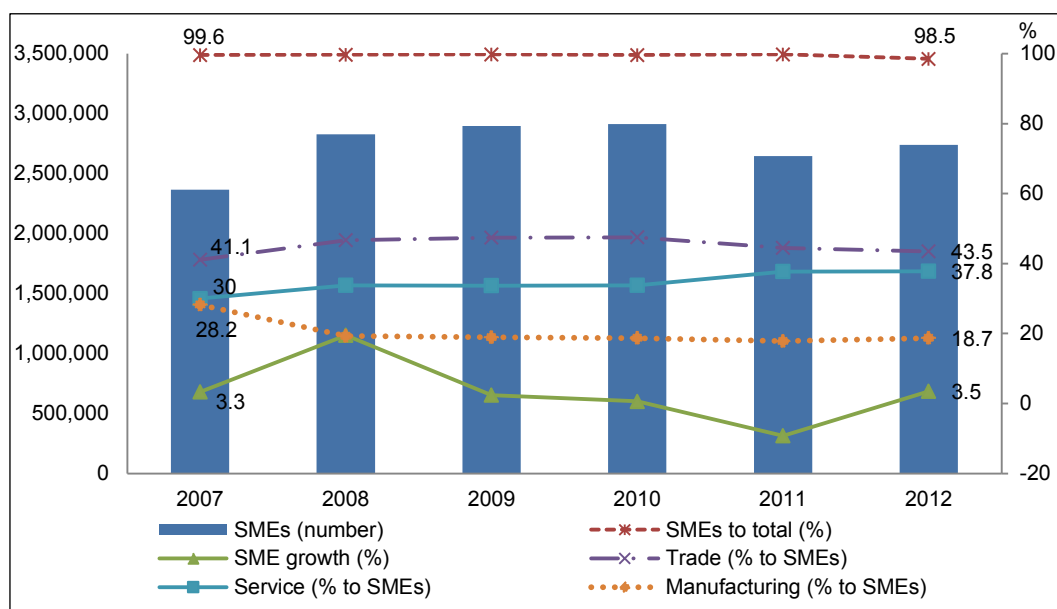
The motivation for this paper comes from the fact that, unlike for large firms, there lacks an extensive credit rating scheme/index for small and medium-sized firms. Developing a credit-rating index would not only shield banks from risky lending by reducing information asymmetry but also lower borrowing costs for SMEs that have good financial health and prospects to grow.

In the following Section 2, we illustrate the importance of SMEs in the context of Thailand. In Section 3, we highlight the importance of credit rating. Section 4 introduces the National Credit Bureau (NCB). Section 5 explains the credit risk analysis in the context of Thailand, followed by the methodologies we use. We show that credit ratings for SMEs can be based on variables that can be 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 the financial statements of SMEs 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 Figures 1, 2, 3, and 4, we present the number of SMEs, employment, contribution to GDP, and share of trade of SMEs from 2007 to 2012. These figures show that the contributions of SMEs to the Thai economy in terms of number, employment, and GDP are all very large.

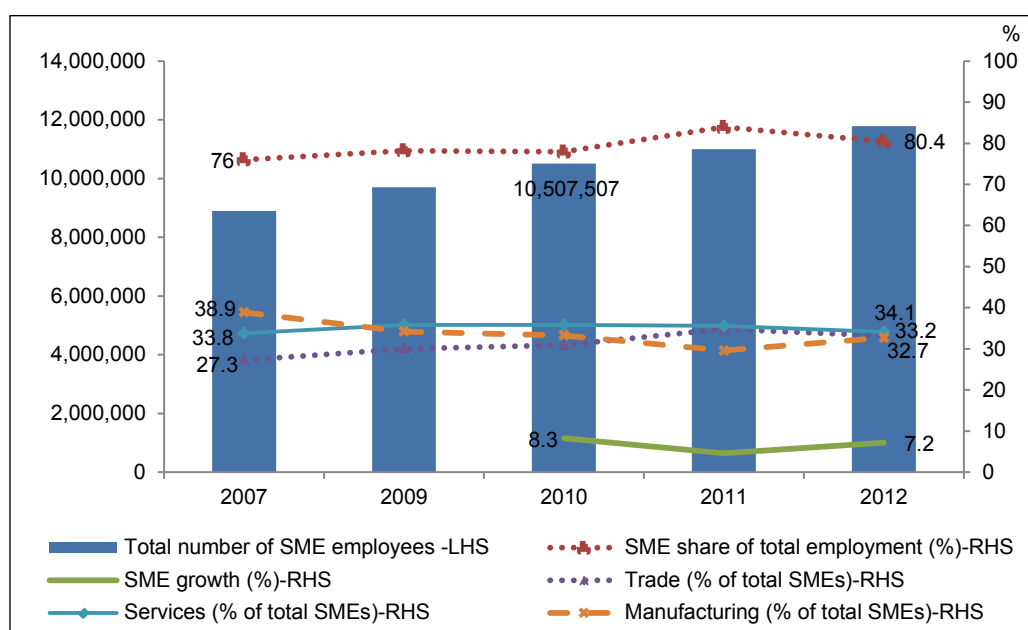
Figure 1: Number of Small and Medium-sized Enterprises in Thailand



SME = small and medium-sized enterprise. Numbers refer to the left-hand scale and percentages refer to the right-hand scale.
 Source: ADB (2014).

Figure 1 represents the total number of SMEs in Thailand from 2007 to 2012. As of 2012 there are approximately 2.7 million SMEs that occupy 98.5% of all enterprises in Thailand. With the global financial crisis of 2008, the growth rates of SMEs declined in the subsequent years. Flooding in 2011 triggered a negative growth rate (-9%) in the number of SMEs, but recovered to 3.5% growth in 2012. Sector wise, in the 2007–2012 period, SMEs in the service sector experienced the largest percentage growth, from 30% to 37.5%, followed by those in the trading sector, from 41.1% to 43.5%. In the same period, the percentage of SMEs in the manufacturing sector sharply declined from 28.2% to 18.7%, a decrease of around 10%, suggesting that the sector was hit the worst by the global financial crisis of 2008 and the floods in 2011.

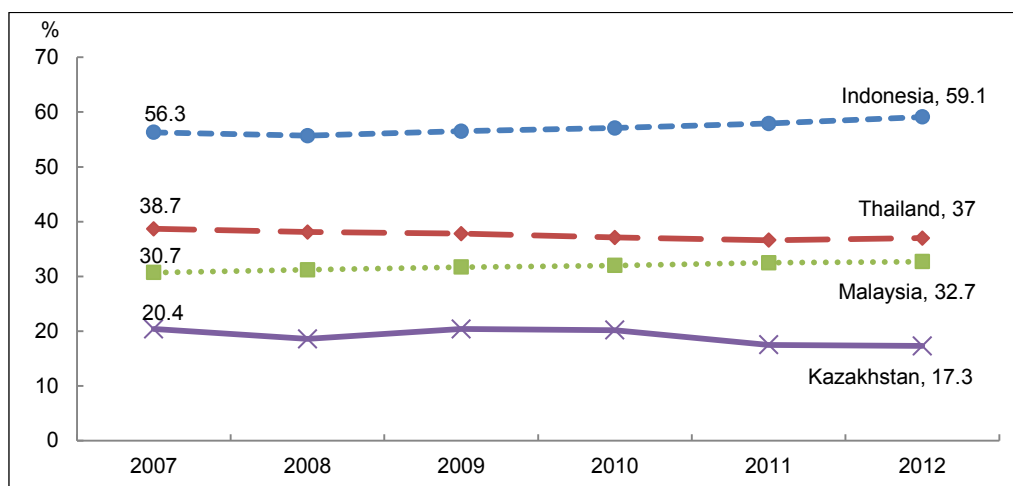
Figure 2: Employment by Small and Medium-sized Enterprises in Thailand



LHS = left-hand scale, RHS = right-hand scale, SME= small and medium-sized enterprise.
 Source: ADB (2014).

Figure 2 represents the employment dynamics of Thai SMEs from 2007 to 2012. The percentage of SME employment to total employment steadily grew from 76.0% in 2007 to 83.9% in 2011, but fell back to 80.4% in 2012. Each of the sectors—services, trade, and manufacturing—contributed to more than 30% of employment by SMEs. Sector wise, employment by trading SMEs increased by about 5%, but that of manufacturing declined by 6.2%, which can be attributed to the decline in the growth rate of SMEs in this sector as can be seen in Figure 1. The growth rate of employment by SMEs has dropped from 8.3% in 2010 to 7.3% in 2012.

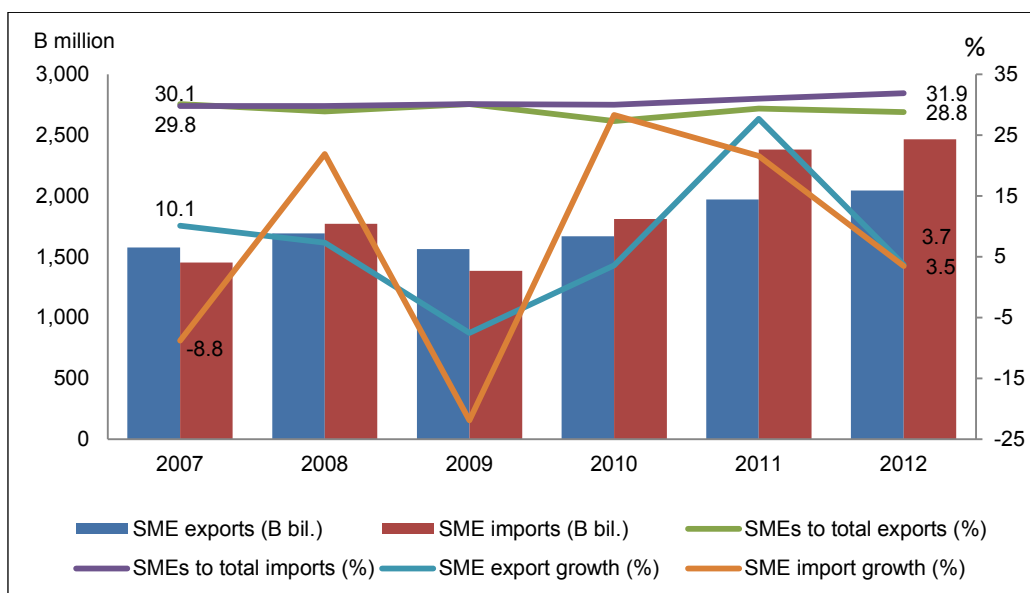
Figure 3: Contribution of Small and Medium-sized Enterprises to Gross Domestic Product



Source: ADB (2014).

Figure 3, compares the percentage contribution to GDP by SMEs in Thailand to some selected Asian countries. While the contribution of SMEs in Thailand at 37% of total GDP is higher than Malaysia at 32.7%, it lags far behind Indonesia, whose SMEs contributed to 59.1% of GDP in 2012. The contribution of SMEs to GDP in Thailand declined by 1.7% in the period 2007–2012, while Malaysia and Indonesia saw a rise in the contribution of SMEs to their GDPs in the same period.

Figure 4: Exports and Imports of Thai Small and Medium-sized Enterprises



Bil. = billion, SME= small and medium-sized enterprise.

Source: ADB (2014).

Figure 4, illustrates total exports and imports by Thai SMEs. Since 2010, imports by Thai SMEs have been greater than exports, compared to total exports and imports. Import growth, which was negative (-8.8%) in 2007, further plummeted to -21% in 2009, but increased to 3.5% in 2007. The fact that the proportion of manufacturing SMEs has been declining has resulted in greater imports. The growth rates of imports and exports have remained about 3.5% in 2012.

3. SMALL AND MEDIUM-SIZED ENTERPRISE CREDIT PRACTICES IN THAILAND

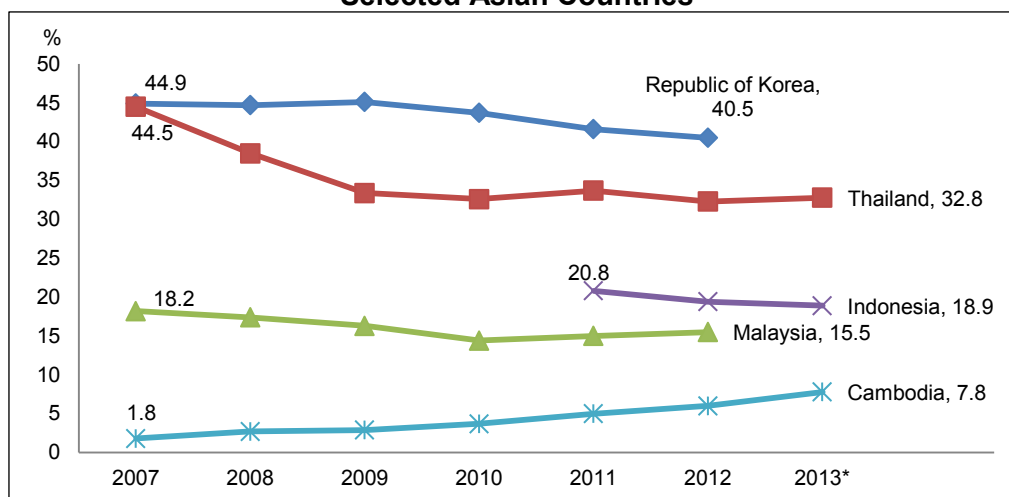
3.1 Bank-based Lending

Finance is an unavoidable problem for SME promotion. In this section, we look at the modes of financing of SMEs in Thailand. Bank-based lending is mostly practiced 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 letter of guarantees.

3.1.1 Banking Sector

Bank lending to SMEs in Thailand recovered from the global financial crisis of 2008–2009 and has continued on an increasing trend, even during the flooding of 2011. In 2013, SME credit accounted for 32.8% of total commercial bank lending. This lending ratio was almost the same as that to GDP (33.7%) (ADB 2014).

Figure 5: Ratio of Small and Medium-sized Enterprise Loans to Total Loans in Selected Asian Countries



* Data for Cambodia, Indonesia, and Thailand are as of the third quarter, end-August, and second quarter, respectively.

Source: ADB (2014).

Figure 5 compares the percentage of SME loans to total loans for Thailand and selected Asian countries. Thailand fares better than its Association of Southeast Asian Nations counterparts, namely Malaysia, Indonesia, and Cambodia. But the percentage of SME loans to total loans has declined by about 12%, i.e., from 45% in 2007 to 32.8% in Q2 2013. The Republic of Korea holds the highest ratio of SME loans to total loans, 40.5% in 2012. Sector-wise, SMEs in the trade (29.8%), services (26.0%), and manufacturing (22.8%) sectors are the primary receiver of bank loans. Since 2009, the Thai Credit Guarantee Corporation has

overseen a portfolio guarantee scheme and increased the volume of outstanding loans to SMEs.

Table 1: Banking Sector–Small and Medium-sized Enterprise Loans in Thailand

Item	2007	2008	2009	2010	2011	2012	Q2 2013
Loans Outstanding							
SME loans to GDP* (%)	32.6	32	28.9	28.2	31.2	32.1	33.7
SME loans to total loans* (%)	44.5	38.5	33.4	32.6	33.7	32.3	32.8
SME loans, total (B billion)	3,640	4,391	4,826	5,048
SME loans, PFIs** (B billion)	786	1,099	1,180	1,102
SME loans, commercial banks (B billion)	2,775	2,907	2,609	2,854	3,292	3,646	3,946
Total loans, total (B billion)	7,394	8,856	9,473	10,955	12,493	14,222	15,020
Total loans, PFIs** (B billion)	1,165	1,307	1,666	2,192	2,711	2,944	3,006
Total loans, commercial banks (B billion)	6,229	7,549	7,807	8,763	9,782	11,278	12,014
SME Loans by Sector* (B billion)							
Primary industry	83	77	69	70	69	76	80
Mining	10	15	16	15	18	13	15
Manufacturing	749	739	681	723	801	843	901
Electricity, gas, and water supply	82	82	72	71	93	129	145
Construction	113	113	100	108	116	127	134
Wholesale and retail trade	705	714	697	783	930	1,093	1,176
Transportation	66	75	72	72	88	107	114
Service	720	827	674	786	914	948	1,025
Real estate	245	264	227	224	264	311	356
Others	0.2	0	0	0.2	0.1	0.3	0.4
Nonperforming Loans*							
SME NPLs (B billion)	186	154	131	126	133
Gross NPLs (B billion)	376	313	266	254	264
SME NPLs to SME loans (%)	7.1	5.4	4	3.5	3.4
SME NPLs to total loans (%)	2.4	1.8	1.3	1.1	1.1
Gross NPLs to total loans (%)	4.8	3.6	2.7	2.3	2.2
Credit Guarantees, TCG							
Guaranteed loans outstanding (B billion)	22	22	40	73	113	180	...
Approved guaranteed loans (B billion)	6	3	22	43	52	83	...
No. of letters of guarantee (accumulated)	8,999	8,631	13,084	24,593	39,045	59,469	...
No. of letters of guarantee (new approval)	2,298	1,366	5,763	13,346	17,641	24,357	...

... = not available, GDP = gross domestic product, NPL = nonperforming loan, PFI = public financial institution, SME = small and medium-sized enterprise, TCG = Thai Credit Guarantee Corporation.

* Based on commercial bank loans.

** Five PFIs combined: Small and Medium Enterprise Development Bank, Government Savings Bank, Islamic Bank of Thailand, Bank for Agriculture and Agricultural Cooperatives, and Export-Import Bank of Thailand.

Sources: Bank of Thailand and Thai Credit Guarantee Corporation; ADB (2014).

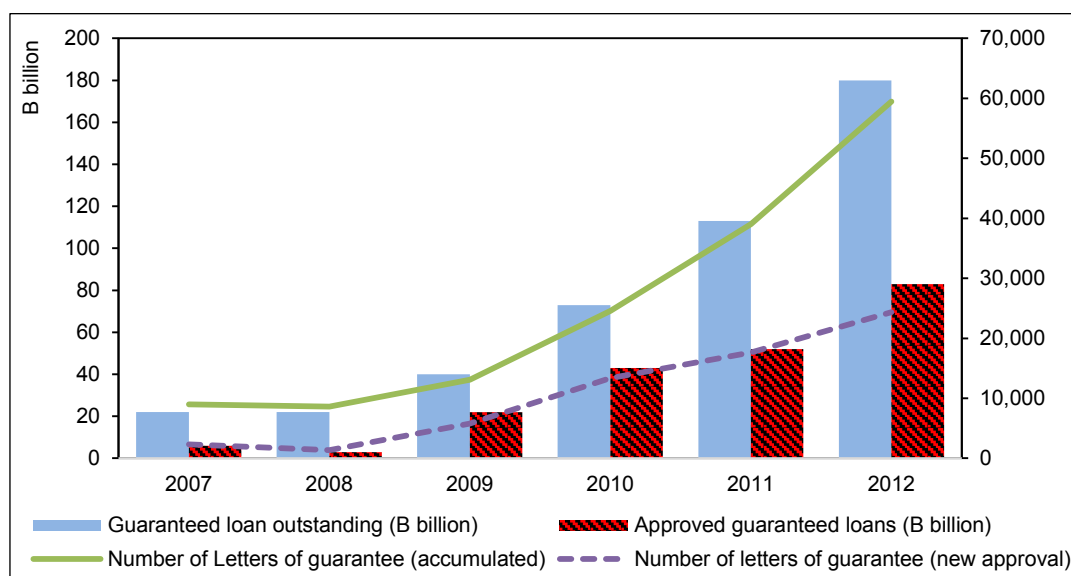
Table 1 shows the banking sector's SME loans in Thailand. The ratio of non-performing loans to total SME loans remained quite high at 3.4% in Q2 2013, although it follows a gradually declining trend. The number and amount of credit guarantees and letters of guarantee to SMEs have also been increasing.

3.1.2 Credit Guarantee System

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 6: Credit Guarantees—Thai Credit Guarantee Corporation



Source: ADB (2014).

Figure 6, shows that the credit guarantee scheme has been quite successful in financing SMEs in Thailand. Guaranteed loans outstanding continued to increase from B22 billion to B180 billion during 2007–2012. Likewise, the number of accumulated letters of guarantee totaled 59,469 in 2012, from 8,999 in 2007.

3.2 Non-bank based Lending

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

Besides capital markets, a new promising method of finance, the hometown investment trust fund, could also be adopted in Thailand to help finance risky enterprises, such as small enterprises and venture and local businesses (Yoshino 2013).

3.2.1 Capital Markets

The Market for Alternative Investment (MAI) was established in 1998 with the purpose to create new fundraising opportunities for innovative business with high potential growth as well as provide a greater range of investment alternatives. Since its inception in 1998, the Thailand-initiated Market for Alternative Investment (MAI) has been attractive to entrepreneurs. As of 8 March 2015, 113 companies have been listed in the MAI (Market for

Alternative Investment 2015). MAI deals with equity products but not bonds and trading. Its mission is to provide opportunities for entrepreneurs and small and medium-sized firms to:

1. Access funds
2. Achieve sustainable growth through transparency, good, governance
3. Strengthen competitiveness through powerful networking

3.2.2 Hometown Investment Trust Funds

Hometown investment trusts Fund (HIT funds) are a new form of financial intermediation that has become popular in Japan in a relatively short span of time. With the adoption of the Basel Capital Adequacy Requirements, banks are reluctant to fund riskier borrowers such as small enterprises, venture businesses, and local small businesses. HIT funds are still sold by regional banks, credit rating agencies 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 the risks associated with the investment would be in order to strengthen trust fund investors' confidence and help trust fund market grow. (Yoshino and Taghizadeh-Hesary, 2014b)

1. Hometown investment trust funds reduce information asymmetry. Often the lenders and borrowers know each other.
2. The table supply of Risk Capital: As the 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.
3. HIT funds are project-driven. Unlike mutual funds where investor actually do not know the projects they are investing on, they can choose to invest on projects in their locality.

4. INTRODUCTION OF THE NATIONAL CREDIT BUREAU

Data used in this survey are from the National Credit Bureau. 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 the clients of financial institutions. However, not many people know the exact responsibilities and duties of the NCB. Some people believe that the credit bureau can place people on a blacklist, or that it sells credit information to telesales businesses, and most people believe that the credit bureau is responsible for credit rejections.

4.2 Why the Credit Bureau?

The NCB was established in 1998 under a policy by the Thai government. 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.

Firstly, 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 together and became the National Credit Bureau running under the Credit Information Business Act B.E. 2545.

The NCB is a private company that operates under a good governance policy and does not seek profit maximization. The 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 is treated impeccably to meet the international standards of credit bureaus in other countries.

5. ANALYSIS OF CREDIT RISK

An efficient and comprehensive method for credit rating has been proposed by 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 for judging the health of SMEs based on them. The method classifies and ranks SMEs into different groups depending on their financial soundness.¹

5.1 Data and Variables

We used Commercial Credit Scoring Data 2015 from the National Credit Bureau (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 (PCA).² For the cluster analysis, we took 1,197 observations that were used in the PCA.³ Table 2 describes the variables we used in this paper.

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 over 301 days

Source: Authors' compilation.

In the next stage we used PCA and cluster analysis. The main objective of the analyses is to reduce the dimension of the data, but they each do so in slightly different ways. PCA

¹ This method can also be used for credit rating even in non-SME sectors. For 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.

² As there were too many zeros in the observations, we selected only SMEs with non-zero variables and randomly selected 3272 observations from them.

³ Outlier observations were excluded.

reduces the number of variables into components or factors, whereas cluster analysis groups observations, i.e., SMEs in this case, into clusters. SMEs that have similar characteristics are placed into the same groups.

5.2 Principal Component Analysis

PCA is a standard data reduction technique which identifies patterns in data, expressing it in such a way that it highlights the similarities and differences between observations. When the data is multivariate, it is often difficult to visualize by graphical representation. Thus, PCA serves as an alternative powerful tool for analyzing data in this situation. Another advantage of using PCA is that once a pattern in the data is found, it can be compressed by reducing the number of dimensions/variables but without losing much of the information (Jolliffe 2002)

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 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: Authors' compilation.

We used direct oblimin rotation. This method helps to obtain a non-orthogonal (oblique) solution in which factors are allowed to correlate. In order to interpret the revealed PCA information, we need to analyze the pattern matrix.

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

Variable	Component		
	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 with 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: Authors' compilation.

In Table 4, we present three significant components. The first component, i.e., Z1, received main loadings from two variables, *total loans* and *initial amount*. This implies that the higher *total loans* and *initial amount*, the larger Z1 will be. The second component that was significant in our credit analysis was Z2. It received the highest loadings from two variables, firstly, from *past due amount* with positive loading, and secondly *past due days*, which has negative loading. We can infer that the higher *past due amount*, the higher Z2 will be. Accordingly, the higher *past due days*, the lower Z2 is as they have a negative relationship. 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. Thus we have these three components based on the significant loadings they received.

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

Table 5: Component Correlation Matrix

	Z1	Z2	Z3
Z1	1.000	-0.008	-0.025
Z2	-0.008	1.000	0.065
Z3	-0.025	0.065	1.000

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

5.3 Source: Authors' compilation. Cluster Analysis

In this section, we group SMEs with similar characteristics by 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 that has different characteristics from the former but similar within-group features.

In this survey we use a hierarchical cluster as this is a widely used method.⁴ It produces a sequence of partitions by dividing or merging the observations that form a cluster. The sequence is further divided or merged from previous partitions depending upon certain adequacy criterion (Rousseeuw 2005) to form a tree-like structure called a dendrogram (Figure 7). The hierarchical clustering is divided into agglomerative or divisive clustering, depending upon the algorithm. In the former, observations are combined into groups in successive stages whereas in the latter they divide into finer groups.

5.4 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

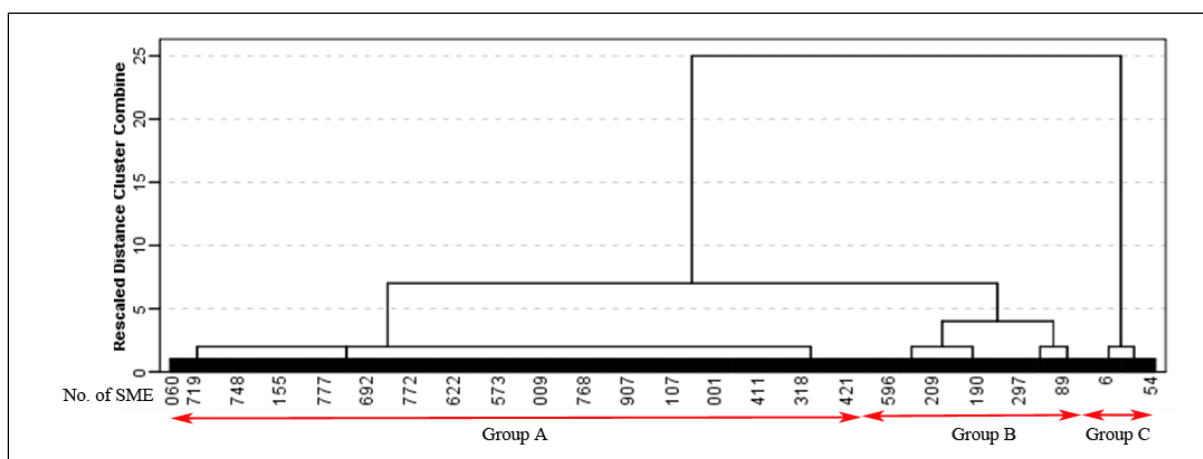
⁴ The main difference between the hierarchical and optimization techniques is that in hierarchical clustering the number of clusters is not known beforehand. The process consists of a sequence of steps where two groups are either merged (agglomerative) or divided (divisive) according to their level of 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 specified or predetermined number of groups by either minimizing or maximizing some numerical criterion (Feger and Asafu-Adjaye 2014).

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 $D=(d_{ij})$ 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).

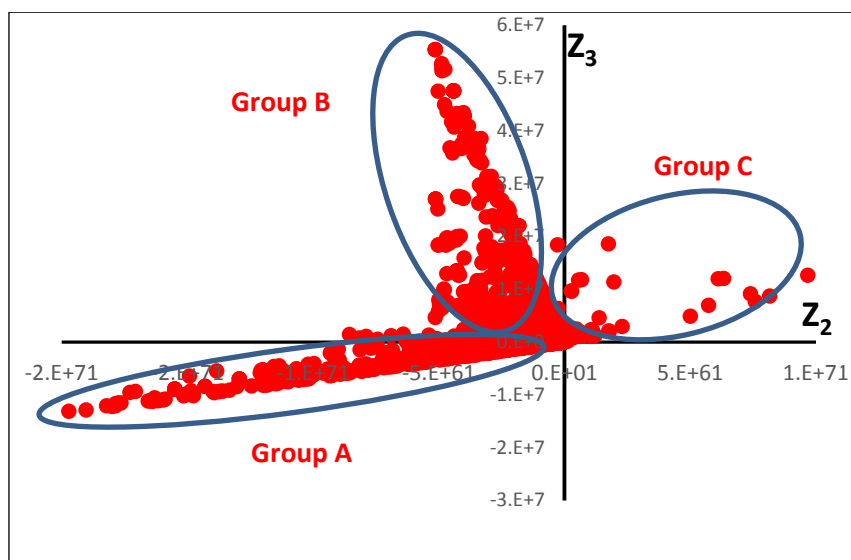
Figure 7 shows a dendrogram, where the y-axis marks the distance at which the clusters merge, while the objects (SMEs) are placed along the x-axis such that the clusters do not mix. The dendrogram (Figure 7) shows the formation of three main groups. The resultant dendrogram does not tell us in which 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.

Figure 7: Dendrogram



Source: Authors' compilation.

Figure 8: Distribution of Factors



Note: the x-axis is the Z2 component and the y-axis is the Z3 component. Each dot shows one SME.
Source: Authors' compilation.

The scatter plot in Figure 8 shows that there are three different groups of SMEs in three different dimensions.⁵ 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.

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.

6. CONCLUDING REMARKS

Since the contribution of SMEs to Asian economies is crucial there arises a need to provide them with easier access to finance. The high cost of monitoring SMEs in the absence of a credible credit rating index results in many financial institutions being less interested to lend 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 done by financial institution, lending agencies and credit risk analyzing bureaus.

This paper examines 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 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 policy implication is that banks and financial institutions can make use of this method to set borrowing ceilings and interest rates for different SMEs. This would reduce borrowing costs, i.e., lower interest rates for financially healthy SMEs, and would also help to avoid the risk of default for firms with poor financial health. Banks would also benefit as the amount of non-performing loans for SMEs would diminish.

⁵ 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.

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