

# Analysis of Credit Ratings for Small and Medium-Sized Enterprises: Evidence from Asia

NAOYUKI YOSHINO AND FARHAD TAGHIZADEH-HESARY\*

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In Asia, small and medium-sized enterprises (SMEs) account for the major share of employment and dominate domestic economies, yet providing these companies with access to finance is a challenge across the region. Asian economies are often characterized as having bank-dominated financial systems and underdeveloped capital markets, in particular with regard to venture capital. As a result, banks are the main source of financing for SMEs. It is crucial for banks to be able to distinguish healthy from risky companies. If they can do this, lending and financing SMEs through banks will be easier. In this paper, we explain the importance of SMEs in Asia. Then, we provide a scheme for assigning credit ratings to SMEs by employing two statistical analysis techniques—principal component analysis and cluster analysis—applying 11 financial ratios of 1,363 SMEs in Asia. If used by the financial institutions, this comprehensive and efficient method could enable banks and other lending agencies around the world, and especially in Asia, to group SME customers based on financial health and adjust interest rates on loans and set lending ceilings for each group.

*Keywords:* Asian economies, SME credit rating, SME financing

*JEL codes:* G21, G24, G32

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## I. Introduction

Small and medium-sized enterprises (SMEs) are the backbone of Asian economies, accounting on average for 98% of all enterprises, 66% of the national labor force, and 38% of gross domestic product (GDP) during 2007–2012 (ADB 2014). Over the same period, SMEs accounted for an average of more than 30% of total export value. In the People's Republic of China (PRC) in 2012, SMEs accounted for 41.5% of total export value, up 6.8% year-on-year (y-o-y), while in Thailand

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they made up 28.8% of total export value, with 3.7% y-o-y growth. SMEs that are part of global supply chains have the potential to promote international trade and mobilize domestic demand.

Because of the significance of SMEs to Asian national economies, it is important that ways be found to provide them with stable access to finance. Asian economies are often characterized as having bank-dominated financial systems and capital markets, in particular venture capital markets, that are not well-developed. This means banks are the main source of financing. Although the soundness of banking systems has improved significantly since the 1997/98 Asian financial crisis, banks have been cautious about lending to SMEs, even though such enterprises account for a large share of economic activity. Start-up companies, in particular, are finding it increasingly difficult to borrow money from banks because of strict Basel III capital requirements (Yoshino and Hirano 2011, 2013). Riskier SMEs also face difficulty in borrowing money from banks (Yoshino 2012).<sup>1</sup> Hence, an efficient credit rating scheme that rates SMEs based on their financial health would help banks to lend money to SMEs in a more rational way while at that same time reducing the risk to banks.

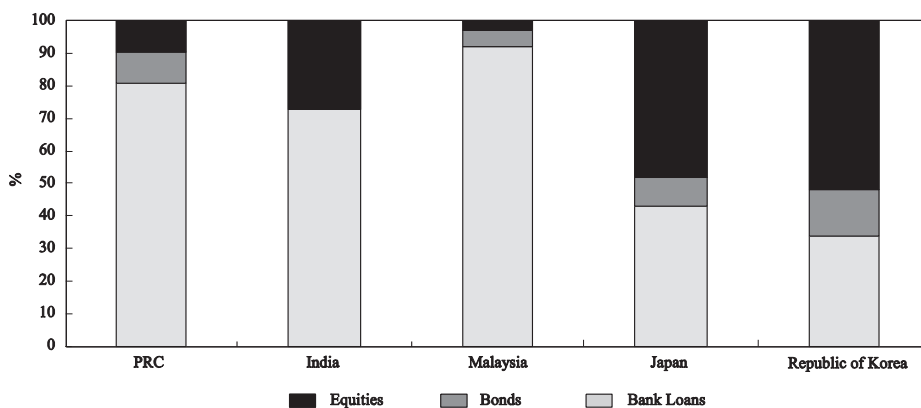
Various credit rating indexes such as Standard and Poor's (S&P) rate large enterprises. By looking at a large enterprise's credit rating, banks can decide to lend them up to a certain amount. For SMEs, the issue is more complicated as there are no comparable ratings. Nevertheless, there is a useful model in Japan. In a government-supported project, 52 credit guarantee corporations collected data from Japanese SMEs. These data are now stored at a private corporation called Credit Risk Database (CRD). If similar systems could be established in other parts of Asia to accumulate and analyze credit risk data, and to measure each SME's credit risk accurately, banks and other financial institutions could use it to categorize their SME customers based on their financial health. SMEs would also benefit as they could both raise funds from the banks more easily and gain access to the debt market by securitizing their claims.

In Section II, we describe the characteristics of Asian economies, in particular the important role played by SMEs. In Section III, we explain the advantages of preparing a complete SME database in each country. In Section IV, we propose a way of establishing SME credit ratings using statistical techniques and financial ratios. This captures all the characteristics of SMEs, including leverage, liquidity, profitability, coverage, and activity. This method can be used by banks all around the world, especially in Asia, to group SMEs based on their financial health, and adjust loan interest rates and set lending ceilings accordingly for each group. Section V contains concluding remarks.

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<sup>1</sup>For more information on SME financing constraints, see Vermoesen, Deloof, and Laveren (2013).

Figure 1. **Financial Markets in Asia**  
(Equity markets, bond markets, and bank loans as % of total)



PRC = People's Republic of China.

Source: Kashiwagi, S. 2011. Presentation at FSA Financial Research Center International Conference. Tokyo. 3 February.

## II. Characteristics of Asian Economies

### A. High Potential Growth

Asian economies have had relatively high economic growth rates over the past 2 decades and further strong growth is expected over the next few years, driven by the region's expanding middle class. Populations are young in most of Asia. If Asian economies continue to expand, the rates of return on investments in the region will be higher than those in other regions. Thus, there is huge potential for growth and financial investment in Asia (Yoshino 2012).

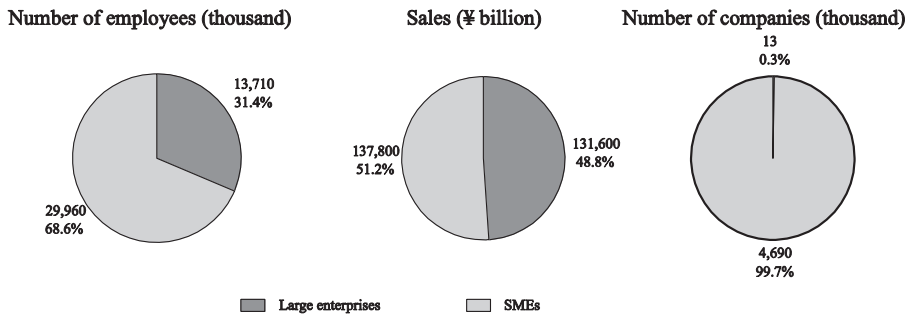
### B. Bank-Dominated Financial Systems and the Economic Importance of Small and Medium-Sized Enterprises

Figure 1 shows the size of the equity and bond markets in comparison to bank loans in Asia.

Figure 2, Table 1, and Figure 3 show the shares of SMEs in the economies of Japan, the PRC, and Indonesia. SMEs dominate the domestic economy, in terms of the number of firms and the share of employment, in all three countries.

As shown in Figure 2, more than 99% of all businesses in Japan are SMEs; they also employ most of the working population and account for a large proportion of economic output.

Figure 2. Small and Medium-Sized Enterprises in Japan



SME = small and medium-sized enterprise.

Source: Government of Japan, Ministry of Economy, Trade and Industry. 2011. *White Paper on Small and Medium Enterprises in Japan*. Tokyo.

Table 1. Small and Medium-Sized Enterprises in the People's Republic of China

Item	2007	2008	2009	2010	2011	2012
<b>Number of SMEs</b>						
SMEs (number)	333,858	422,925	431,110	449,130	316,498	334,321
SMEs to total (%)	99.1	99.3	99.3	99.2	97.2	97.3
<b>Employment by SMEs</b>						
SME employees ('000)	60,521	68,671	67,877	72,369	59,357	...
SMEs to total (%)	76.8	77.7	76.9	75.8	64.7	...
<b>SME Exports</b>						
SME exports (CNY billion)	4,303	4,773	4,152	4,919	4,142	4,423
SMEs to total exports (%)	58.6	57.9	57.6	54.7	41.6	41.5

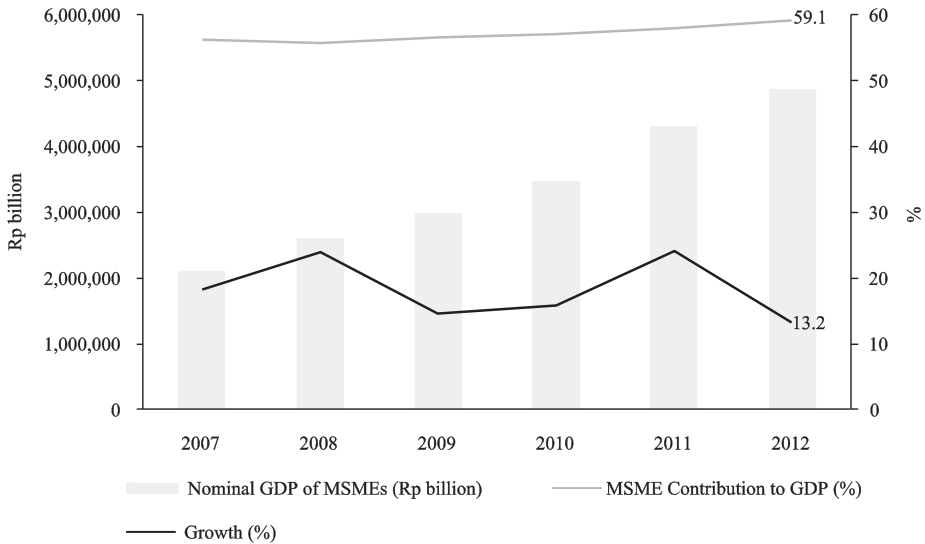
... = data not available, SME = small and medium-sized enterprise.

Notes: The data cover industrial enterprises above a certain operational scale. For 2007–2010, “above operational scale” refers to all industrial enterprises that generated a minimum annual income of CNY5 million from their core business. For 2011–2012, it refers to all industrial enterprises that generated a minimum annual income of CNY20 million from their core business. The industry sector includes mining; manufacturing; and electricity, gas, and water production and supply industries. Data for 2007–2010 are based on the following criteria: number of employees fewer than 2,000, sales of CNY300 million or less, or total assets of CNY400 million or less. Medium-sized enterprises must have more than 300 employees, sales of more than CNY30 million, and total assets of CNY40 million or more; the rest are small businesses. Data for 2011–2012 are based on 2011 SME classification criteria. Industrial micro, small, and medium-sized enterprises are defined as enterprises that employ fewer than 1,000 persons or whose annual turnover does not exceed CNY400 million. A medium-sized enterprise is defined as an enterprise that employs more than 300 persons and whose annual turnover exceeds CNY20 million. A small enterprise is defined as one that employs more than 20 persons and whose annual turnover exceeds CNY3 million. A micro enterprise is defined as an enterprise that employs fewer than 20 persons or whose annual turnover does not exceed CNY3 million. Data on micro enterprises in 2011–2012 are not available.

Source: ADB. 2014. *Asia SME Finance Monitor 2013*. Manila.

In the PRC, the number of SMEs has expanded steadily since the government introduced the Reform and Opening-up Policy in 1978. As can be seen from Table 1, SMEs have played a crucial role in boosting the economy, increasing employment opportunities, and creating industries. According to the Ministry of Commerce, there were 12.5 million enterprises (most of which were SMEs) registered with the State Administration for Industry and Commerce, and 37.6 million privately or individually owned businesses at the end of 2011. SMEs contributed 50% of tax

Figure 3. **Micro, Small, and Medium-Sized Enterprise Contribution to Gross Domestic Product in Indonesia**



GDP = gross domestic product, MSME = micro, small, and medium-sized enterprise.

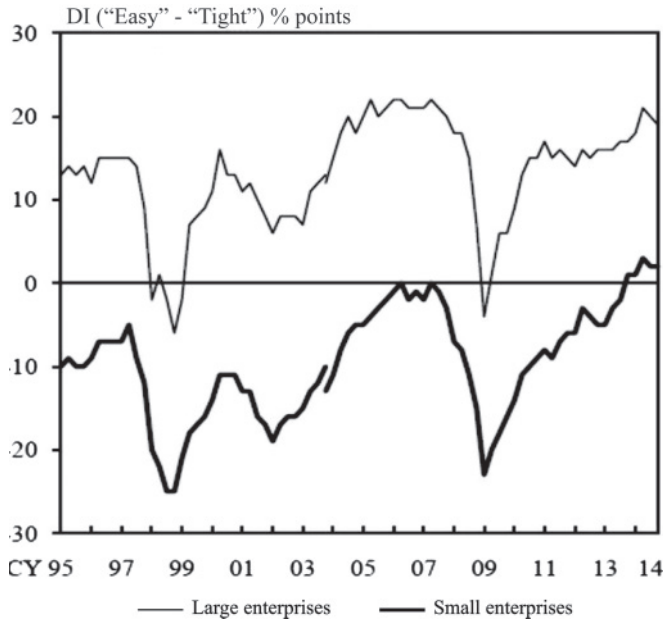
Note: Data include micro enterprises.

Source: ADB 2014.

revenues and 60% of GDP. They also provided 80% of urban job opportunities, introduced 75% of new products, and accounted for 65% of patents and inventions in the PRC (ADB 2014).

The Indonesian economy has grown resiliently amid rapid changes in the global economy, backed by strong domestic demand and driven by the micro, small, and medium-sized enterprise (MSME) sector. In Indonesia, there were 56.5 million MSMEs, accounting for 99.9% of total enterprises in 2012. The MSME sector has regularly recorded about 2% y-o-y growth in terms of number of enterprises, even during and after the 2008/09 global financial crisis. Primary industries such as agriculture, forestry, and fisheries accounted for about 50% of MSMEs in 2011, followed by wholesale and retail trade and the hotel and restaurant sector with a combined share of 28.8%. The MSME sector employed about 97% of the total workforce, accounting for 107.7 million employees in 2012 on 5.8% y-o-y growth. The sectors employing the greatest number of MSME workers in 2011 were primary industries (42.4% of all MSME employees), followed by trade (21.7%), manufacturing (11.7%), and services (10.5%). These sectors have underpinned the national economy, regularly contributing about 60% of GDP (Figure 3); the trade sector contributes the most at 26.7% of MSMEs' GDP contribution in 2011. Indonesian MSMEs accounted for 14.1% of total export value in 2012. Small-scale, export-oriented manufacturers, such as handicrafts and wooden furniture industries, exist across Indonesia and often organize in clusters, which helps to make their production

Figure 4. Access to Finance—Small and Medium-Sized Enterprise and Large Firms in Japan



CY = commercial year, DI = diffusion index.

Note: The diffusion index is a method of summarizing the common tendency of a group of statistical series.

Source: Bank of Japan. 2014. *Financial System Report October 2014*. Tokyo.

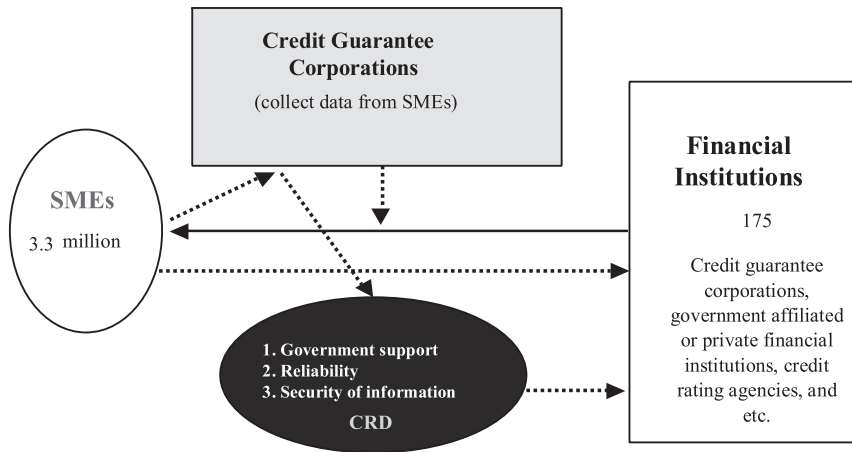
processes more efficient. MSME exports were directly affected by the 2008/09 global financial crisis, registering a sharp decrease of 8.9% in 2009. Although the business environment has gradually recovered since then, the growth of MSME exports remains volatile, as evidenced by the 11.1% y-o-y decrease in 2012 (ADB 2014).

### C. Small and Medium-Sized Enterprises' Difficulties in Raising Money

Figure 4 shows the level of difficulty in raising money depending on firm size: the thick line shows the difficulties faced by SMEs, and the thin line shows the relative ease for large enterprises. Data points below zero indicate that companies are finding it difficult to raise money from either banks or the capital market. SMEs appear to face a more difficult situation in raising money when compared with large firms.<sup>2</sup>

<sup>2</sup>There are also nonbank financial institutions that can finance SMEs. For example, the coauthor of this paper, Naoyuki Yoshino, proposed the creation of Hometown Investment Trust Funds (HITs). HITs are new forms of financial intermediation that have been adopted as a national strategy in Japan. For more information on HITs, see Yoshino (2013) and Yoshino and Taghizadeh-Hesary (2014a, 2014b, and 2015).

Figure 5. Credit Risk Database of Small and Medium-Sized Enterprises



CRD = Credit Risk Database; SME = small and medium-sized enterprise.  
Source: Authors and CRD website.<sup>3</sup>

### III. Small and Medium-Sized Enterprise Database

Considering the importance of SMEs to many dimensions of Asian economic activity, further efforts need to be made to offer them access to finance. Their financial and nonfinancial accounts are often difficult to assess, but the Credit Risk Database (CRD) in Japan shows how SMEs can be rated based on financial and nonfinancial data. The CRD includes a huge amount of data that can be used to rate SMEs through statistical analysis.

#### Database Provided by the CRD Association

The CRD Association was established in 2001 as an initiative of the Japanese Ministry of Economy, Trade and Industry and the Small and Medium Enterprise Agency. The initial membership was 52 credit guarantee corporations as well as financial and nonfinancial institutions. Its aim was to facilitate fundraising for SMEs and to improve their operational efficiency. The association's membership increased from 73 institutions at the end of March 2002 to 175 by 1 July 2015.

The CRD covers SMEs exclusively (Figure 5). As of March 31, 2015 it included 2,210,000 incorporated SMEs and 1,099,000 sole-proprietor SMEs, and it is by far the largest SME database in Japan. The database for enterprises in default covered 500,000 incorporated and sole-proprietor SMEs. The CRD Association receives active support from both the private and public sectors, which has contributed

<sup>3</sup>[www.crd-office.net](http://www.crd-office.net)

to its success. For example, the Small and Medium Enterprise Agency nominates representatives of the CRD Association to government councils, which gives the association an opportunity to promote its activities and increase its membership. Credit guarantee corporations and private financial institutions use the CRD when they create a joint guarantee scheme.<sup>4</sup> Before the CRD was formally established, the government invested ¥1.3 billion from the supplementary budgets for fiscal years 1999 and 2000 to finance the setting up of the CRD's computer system and other operational costs. The association provides sample data and statistical information, and scoring services.

Member financial institutions use scoring models to evaluate creditworthiness, check the validity of internal rating systems, and align loan pricing with credit risk. In addition, the CRD Association provides consulting services to support the management of SMEs on the assumption that if SMEs are better managed, this will reduce the credit risk for member financial institutions and strengthen SME business operations. Consulting services have also been offered to member financial institutions to help them promote implementation of Basel II.

If such systems could be established in other parts of Asia to accumulate and analyze credit risk data, and to measure each SME's credit risk accurately, SMEs would not only be able to raise funds from the banking sector, they could also gain access to the debt market by securitizing their claims.

#### **IV. Analysis of Small and Medium-Sized Enterprise Credit Ratings Using Asian Data**

Credit ratings are opinions expressed in terms of ordinal measures, reflecting the current financial creditworthiness of issuers such as governments, firms, and financial institutions. These ratings are conferred by rating agencies—such as Fitch Ratings, Moody's, and S&P—and may be regarded as a comprehensive evaluation of an issuer's ability to meet their financial obligations in full and on time. Hence, they play a crucial role by providing participants in financial markets with useful information for financial planning. To conduct rating assessments of large corporates, agencies resort to a broad range of financial and nonfinancial pieces of information, including domain experts' expectations. Rating agencies usually provide general

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<sup>4</sup>A credit guarantee system would make it easier for banks to lend money to SMEs. For example, in the case of an SME default, a percentage of the losses would be met by the credit guarantee corporation, which is a governmental organization. For example, assuming a credit guarantee corporation sets 80% as the guarantee ratio, if an SME went into bankruptcy, a bank could recover 80% of its loan. If there were no credit guarantee system in place and an SME went into bankruptcy, the bank would lose its entire loan. Research is needed into the optimal level of partial credit guarantees; that is, the percentage at which a credit guarantee corporation can encourage lending yet ensure that banks have an incentive to carefully assess the creditworthiness of borrowers. Arráiz, Meléndez, and Stucchi (2014) have provided a framework for a partial credit guarantee system.



guidelines on their rating decision-making process, but detailed descriptions of the rating criteria and the determinants of banks' ratings are generally not provided (Orsenigo and Vercellis 2013). In search of more objective assessments of the creditworthiness of large corporate and financial institutions, there has been a growing body of research into the development of reliable quantitative methods for automatic classification according to their financial strength.

Extensive empirical research devoted to analyzing the stability and soundness of large corporates dates back to the 1960s. Ravi Kumar and Ravi (2007) provided a comprehensive survey of the application of statistical and intelligent techniques to predicting the likelihood of default among banks and firms. Despite its obvious relevance, however, the development of reliable quantitative methods for the prediction of large corporates' credit ratings has only recently begun to attract strong interest. These studies are mainly conducted within two broad research strands focusing on statistical and machine learning techniques, and may address both feature selection and classification. Poon, Firth, and Fung (1999) developed logistic regression models for predicting financial strength ratings assigned by Moody's, using bank-specific accounting variables and financial data. Factor analysis was applied to reduce the number of independent variables and retain the most relevant explanatory factors. The authors showed that loan provision information, and risk and profitability indicators added the greatest predictive value in explaining Moody's ratings. Huang et al. (2004) compared support vector machines and back-propagation neural networks to forecast the rating of financial institutions operating in the United States and Taipei, China, respectively. In each case, five rating categories were considered based on information released by S&P and TRC, respectively. The analysis of variance was used to discard noninformative features. In this study, support vector machines and neural networks achieved comparable classification results. However, the authors found that the relative importance of the financial variables used as inputs by the optimal models were quite different between the two markets.

In a more recent study, Yoshino, Taghizadeh-Hesary, and Nili (2015) used two statistical analysis techniques on various financial variables taken from bank statements for the classification and credit rating of 32 Iranian banks. The underlying logic of both techniques—principal component analysis (PCA) and cluster analysis—is dimension reduction; that is, summarizing information on numerous variables in just a few variables. While the two techniques achieved this in different ways, their results both classified 32 banks into two groups and sorted them based on their credit ratings.

While the aforementioned examples are for credit ratings of large corporate and financial institutions, the story is different for SMEs because of the lack of data. In Japan and other Asian economies, rating SMEs is regarded as a difficult action when compared to rating large corporates; data is available for large corporates

because of official auditing, while for SMEs, there are no such auditing requirements. As mentioned earlier, the CRD Association started to compile a database on SMEs, which made it much easier to evaluate SMEs since the huge datasets tell us the normal distribution of SME data. In Japan, SMEs have been categorized since 2012 into one of five rating classifications based on the CRD.

In this section, we present an efficient and comprehensive scheme for rating the creditworthiness of SMEs. First, we examine various financial ratios that describe the characteristics of SMEs and which enable banks to categorize their SME customers into different groups based on their financial health. The data for this statistical analysis were provided by an Asian bank for 1,363 SMEs.

### A. Selection of the Variables

A large number of possible ratios have been identified as useful in predicting a firm's likelihood of default. Chen and Shimerda (1981) show that out of more than 100 financial ratios, almost 50% were found useful in at least one empirical study. Some have argued that quantitative variables are not sufficient to predict SME defaults and that including qualitative variables—such as the legal form of the business, the region where the main business is carried out, and industry type—improves a model's predictive power (Lehmann 2003; Grunert, Norden, and Weber 2004). However, the data used here are based on firms' financial statements, which do not contain such qualitative variables.

We have followed Altman and Sabato (2007) and Yoshino and Taghizadeh-Hesary (2014b) who proposed five categories to describe a company's financial profile: (i) liquidity, (ii) profitability, (iii) leverage, (iv) coverage, and (v) activity. For each of these categories, they created a number of financial ratios identified in the literature. Table 2 shows the financial ratios selected for this survey.

The firms considered as being unsound in this study are those whose risk-weighted assets are greater than their shareholders' equity.

In the next stage, two statistical techniques are used: PCA 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. PCA 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 PCA and then run the cluster analysis in order to group the SMEs.

### B. Principal Component Analysis

PCA is a standard data-reduction technique that extracts data, removes redundant information, highlights hidden features, and visualizes the main relationships

Table 2. Examined Variable

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

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

that exist between observations.<sup>5</sup> PCA is a technique for simplifying a dataset, by reducing multidimensional datasets to lower dimensions for analysis. Unlike other linear transformation methods, PCA does not have a fixed set of basis vectors. Its basis vectors depend on the dataset, and PCA has the additional advantage of indicating what is similar and different about the various models created (Bruce-Ho and Dash-Wu 2009). Through this method, we reduce the 11 variables listed in Table 2 to determine the minimum number of components that can account for the correlated variance among SMEs.

In order to examine the suitability of these data for factor analysis, the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity were performed. KMO is a measure of sampling adequacy that indicates the proportion of common variance that might be caused by underlying factors. High KMO values (larger than 0.6) generally indicate that factor analysis may be useful, which is the case in this study as the KMO value is 0.71. If the KMO value is less than 0.5, factor analysis will not be useful. Bartlett's test of sphericity indicates whether the correlation matrix is an identity matrix, indicating that variables are unrelated. A significance level less than 0.05 indicates that there are significant relationships among the variables, which is the case in this study as the significance of Bartlett's test is less than 0.001.

<sup>5</sup>PCA can be also called the Karhunen–Loève transform (KLT), named after Kari Karhunen and Michel Loève.

Table 3. Total Variance Explained

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

Source: Authors' calculations.

Table 4. Factor Loadings of Financial Variables after Direct Oblimin Rotation

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

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

Source: Authors' calculations.

Next, we determine how many factors to use in our analysis. Table 3 reports the estimated factors and their eigenvalues. Only those factors accounting for more than 10% of the variance (eigenvalues > 1) are kept in the analysis. As a result, only the first four factors were finally retained. Taken together, Z1 through Z4 explain 71% of the total variance of the financial ratios.

In running the PCA, we used direct oblimin rotation. Direct oblimin 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 revealed PCA information, the pattern matrix must then be studied. Table 4 presents the pattern matrix of factor loadings by the use of the direct oblimin rotation method, where variables with large loadings, absolute value (>0.5) for a given factor, are highlighted in bold.

Table 5. **Component Correlation Matrix**

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

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

Source: Authors' calculations.

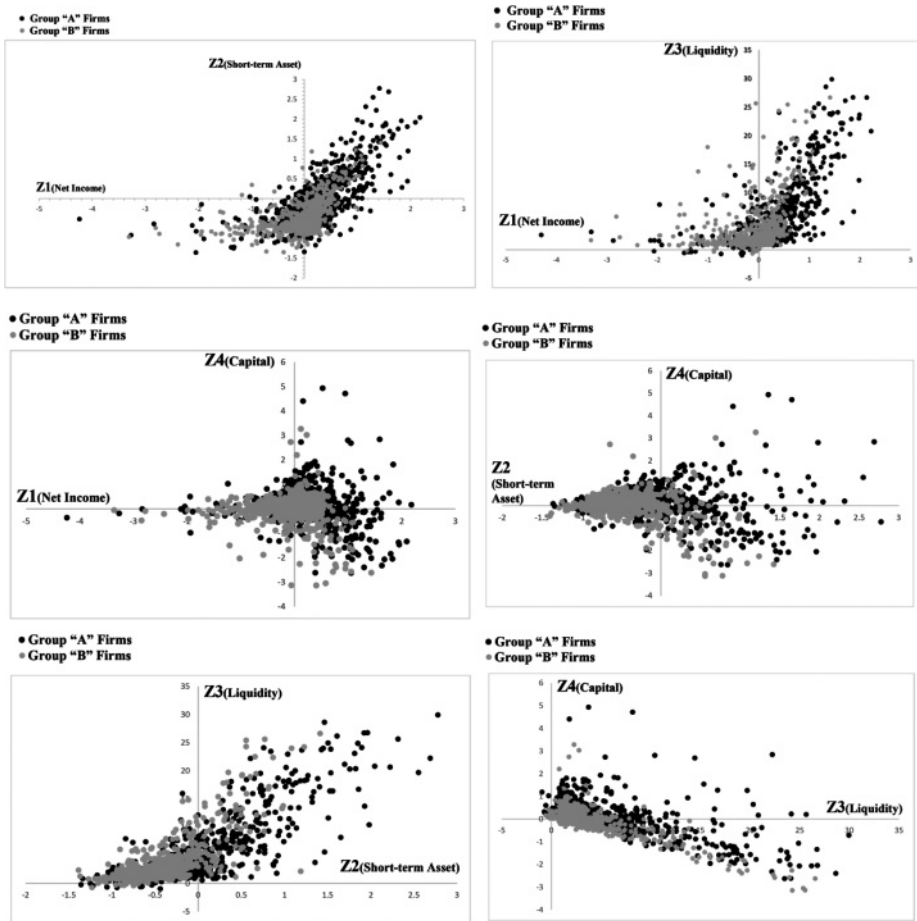
As can be seen in Table 4, the first component, Z1, has four variables with an absolute value ( $>0.5$ ), of which two are positive (ebit/sales and net income/sales) and two are negative (cash/net sales and account payable/sales). For Z1, the variables with large loadings are mainly net income and earnings. Hence, Z1 generally reflects the net income of an SME. As this factor explains the most variance in the data, it is the most informative indicator of an SME's overall financial health. Z2 reflects short-term assets. This component has three major loading variables: (i) liabilities/total assets, which is negative, meaning that an SME has few liabilities and mainly relies on its own assets; (ii) working capital/total assets, which is positive, meaning an SME has short-term assets; (iii) retained earnings/total assets, which is positive, meaning an SME has some earnings that it keeps with the company or in the bank. These three variables indicate an SME whose reliance on borrowings is small and which is rich in working capital and retained earnings, and therefore has plenty of short-term assets. Z3 reflects the liquidity of SMEs. This factor has two variables with large loadings (cash/total assets and ebit/interest expenses), both with positive values, which shows an SME that is cash-rich and has high earnings. Hence, it mainly reflects an SME's liquidity. The last factor, Z4, reflects capital. This factor has two variables with large loadings, both with positive values: equity (book value)/total liabilities and accounts receivable/total liabilities, meaning an SME with few liabilities that is rich in equity.

Table 5 shows the correlation matrix of the components and shows there is no correlation between these four components. This means we could have used a regular orthogonal rotation approach to force an orthogonal rotation, although in this survey, we used an oblique rotation method, which still provided basically an orthogonal rotation factor solution because these four components are not correlated with each other and are distinct entities.

Figure 6 shows the distribution of the four components (Z1, Z2, Z3, and Z4) for Group A, which comprises financially sound SMEs, and Group B, which comprises unsound SMEs.

It is clear from all six graphs in this figure that Group A SMEs can generally be found in the positive areas of the graphs and Group B SMEs in the negative areas in most cases. This is evidence that these four defined components (Z1, Z2, Z3, and Z4) are able to separate SMEs, suggesting they represent a good measure for showing the financial soundness of SMEs.

Figure 6. Distribution of Factors for SME Groups A and B



SME = small and medium-sized enterprise.

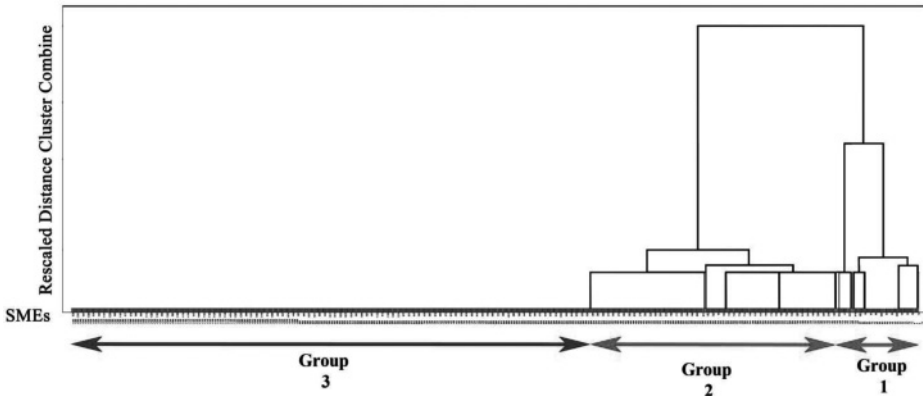
Notes: Group A = sound SMEs, group B = unsound SMEs. The firms considered to be unsound in this study have risk-weighted assets greater than their shareholders' equity.

Source: Authors' calculations.

### C. Cluster Analysis

In this section we take the four components that were used in the previous section and identify those SMEs that have similar traits. We then generate clusters and place the SMEs in distinct groups. To do this, we employ cluster analysis, which organizes a set of data into groups so that observations from a group with similar characteristics can be compared with those from a different group (Martinez and Martinez 2005). The result of the cluster analysis tells us how much each individual SME is close to others and it looks at the distance between two companies based on their financial statements. If they are close to each other in the cluster analysis, it

Figure 7. Dendrogram Using Average Linkage



SME = small and medium-sized enterprise.  
Source: Authors' calculations.

means their financial statements are similar; if two SMEs are different, it means their financial statements are completely different. Thus, the similarities and differences between two companies are statistically analyzed.

In this case, SMEs were organized into distinct groups according to the four components derived from the PCA used in the previous section. Cluster analysis techniques can themselves be broadly grouped into three classes: hierarchical clustering, optimization clustering, and model-based clustering.<sup>6</sup> We used the most prevalent method of these in the literature, hierarchical 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 (or divided) from the previous partition according to some adequacy criterion. 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 called the dendrogram (Figure 7). Agglomerative hierarchical clustering proceeds by a series of successive fusions of the  $n$  objects into groups. By 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). Below, we use the average linkage method, which is a hierarchical clustering technique.

<sup>6</sup>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 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 criterion (Feger and Asafu-Adjaye 2014).

### The Average Linkage Method

The average linkage method defines the distance between clusters as the average distance from all observations in one cluster to all points in another cluster. In other words, it is the average distance between pairs of observations, where one is from one cluster and one is from the other. The average linkage method is relatively robust and also takes the cluster structure into account (Martinez and Martinez 2005, Feger and Asafu-Adjaye 2014, and Yoshino and Taghizadeh-Hesary 2014b, 2014c). The basic algorithm for the average linkage method can be summarized in the following manner:

- $N$  observations start out as  $N$  separate groups. The distance matrix  $D = (d_{ij})$  is searched to find the closest observations, for example,  $Y$  and  $Z$ .
- The two closest observations are merged into one group to form a cluster ( $YZ$ ), producing  $N - 1$  total groups. This process continues until all observations are merged into one large group.

Figure 7 shows the dendrogram that results from this hierarchical clustering.

The resultant dendrogram (hierarchical average linkage cluster tree) provides a basis for determining the number of clusters by sight. In the dendrograms shown in Figure 7, the horizontal axis shows 1,363 SMEs. Because of the large number of SMEs in this survey, they have not been identified by number in the dendrogram, although this is how they are identified in this survey. Rather, the dendrogram categorizes the SMEs in three main clusters (Groups 1, 2, and 3), but it does not show which of these three clusters contains the financially healthy SMEs, which contains unhealthy SMEs, and which contains intermediate SMEs. Hence, there is one more step to go.

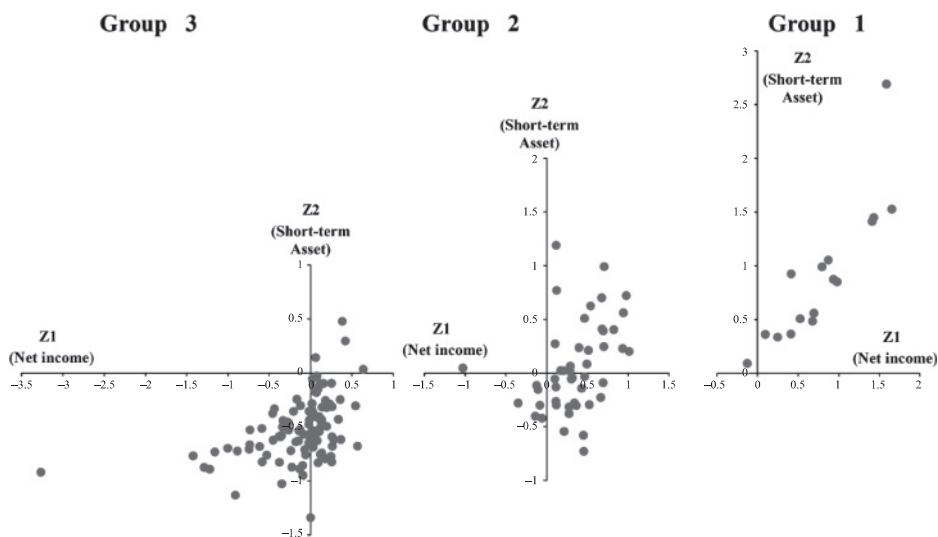
Figure 7 shows the 1,363 SMEs categorized into three major clusters. Using their components, which were derived from the PCA described in Section IV.B, we can plot the distribution of factors for each member of the three major clusters. Figure 8 shows the distribution of  $Z1-Z2$  for these three cluster members separately.<sup>7</sup>

As it is clear in Figure 8, Group 1 comprises the healthiest SMEs, Group 3 the least healthy SMEs, and Group 2 the in-between SMEs. Interestingly, when we do this grouping using the other components ( $Z1-Z3$ ,  $Z1-Z4$ ,  $Z2-Z4$ ,  $Z2-Z3$ , and  $Z3-Z4$ ), the grouping is similar in most cases, which implies that this analysis is an effective way of grouping SMEs.

<sup>7</sup>The dendrogram shows us the major and minor clusters. One useful feature of this tree is that it identifies a representative SME of most of the minor groups, which has the average traits of the other members of the group. For simplification, in Figure 8, we have only used data from these representative SMEs, which explains the whole group's traits. This is why the total number of observations in Figure 8 is lower than the 1,363 observations in this survey.



Figure 8. Grouping Based on Principal Component Analysis (Z1–Z2) and Cluster Analysis



Notes: Group 1 comprises the healthiest SMEs. Group 2 represents the in-between SMEs. Group 3 represents the least healthy SMEs.

Source: Authors' calculations.

Table 6. Average of Financial Ratios for Each Group of SMEs

Variables (Financial Ratios)	SME Groups		
	Group 1	Group 2	Group 3
Equity_TL	1.11	0.77	0.33
TL_Tassets	0.56	0.62	0.78
Cash_Tassets	0.08	0.03	0.05
WoC_Tassets	0.15	0.11	0.04
Cash_Sales	0.06	0.05	0.05
EBIT_Sales	0.24	0.26	0.13
Rinc_Tassets	0.28	0.17	0.06
Ninc_Sales	0.20	0.25	0.18
EBIT_IE	22.88	7.74	2.04
AP_Sales	0.49	0.50	0.60
AR_TL	0.61	0.44	0.41

SME = small and medium-sized enterprise.

Notes: Group 1 comprises the healthiest SMEs. Group 2 represents the in-between SMEs. Group 3 represents the least healthy SMEs. For the definition of each variable (financial ratios) see Table 2.

Source: Authors' calculations.

For a robustness check of classifications based on the aforementioned method, we have done one more step and the results are summarized in Table 6.

Table 6 shows the average of the 11 financial ratios based on our classifications, which categorized 1,363 SMEs into three groups. The healthiest group of SMEs (Group 1) in all ratios had a relatively better performance in comparison with

the two other groups. The performance of the in-between SMEs (Group 2) in most cases was better than the least healthy SMEs (Group 3). On the other hand, 59% of firms in Group 3 are unsound firms, which means they have risk-weighted assets greater than their shareholders' equity. This percentage is higher than the share of unsound SMEs in either Group 1 or Group 2, demonstrating that the rationale of our method is acceptable and we can retain the results.

## V. Concluding Remarks

SMEs play a significant role in all Asian economies. They are responsible for very high shares of employment and output. However, they find it difficult to borrow money from banks and other financial institutions. Using accumulated data on SMEs, we can carry out statistical analysis on their quality in a way that can facilitate bank financing for SMEs.

We applied 11 financial variables of 1,363 SMEs who are customers of Asian banks and subjected them to PCA and cluster analysis. The results showed that four variables (net income, short-term assets, liquidity, and capital) are the most important for describing the general characteristics of SMEs. Three groups of SMEs were then differentiated based on financial health.

The policy implications of this research are that if Asian governments can provide a comprehensive SME database—such as the CRD in Japan—and apply analytical techniques similar to those presented in this paper, then a comprehensive and efficient credit rating system for SMEs can be created. Accordingly, financially healthy SMEs could borrow more money from banks at lower interest rates because of their lower default risk, while SMEs in poor financial health would have to pay higher interest rates and have a lower borrowing ceiling. By using such a credit rating mechanism, banks could reduce the amount of nonperforming loans made to SMEs, which would improve the creditworthiness of the financial system and help healthy SMEs to raise money more easily from banks while contributing to economic growth.

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