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Small Business Credit Scoring: Evidence from Japan

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Abstract

This paper studies the Japanese credit scoring market using data on 2,000 SMEs and a small business credit scoring model widely used in the market. After constructing a model for determining a bank's profit maximization, we find the optimum loan sizes and profit levels, and point out some lending pitfalls based on small business credit scoring. We show that solving the problems of adverse selection and window dressing are the most important things to do to increase the profitability of SBCS lending. In addition, omitted variable bias and transparency of financial statements are also important.

Key words: small business credit scoring, adverse selection, window dressing

JEL classification: G21, G30

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1 Introduction

Small business credit scoring (SBCS) has been widely used in Japanese SME's fundraising since the 2000s. Mega banks and regional banks started using SBCS in 2002–2003. Mega banks accumulated 5 trillion yen of SBCS loans, about 5% of their loan outstanding to small businesses, by the end of 2005. Regional banks made more than 8 trillion yen of SBCS loans, also about 5% of their loan outstanding to small businesses, by the end of 2006.[1] Moreover, Japan Finance Corporation, the government-affiliated financial institution, has provided a Securitization Support Program since 2004. The Program securitizes SME loans, including SBCS loans with regional banks. The new public loan guarantee system that began in 2006 uses SBCS to compute its guarantee fees.

Support for the rapid increase in SBCS use includes development of SME databases, the FSA's regulatory encouragement, and the introduction of Basel II reserve rules. First, SBCS came into practical use in the early 2000s because advances in information technology made it possible to create the large SME databases essential in building these models. Second, the FSA has since 2003 been encouraging adoption of lending technologies that do not require borrowers to pledge collateral.[2] Third, the Basel II rules requiring relatively high capital reserve ratios for SMEs have led banks to develop technology for quantitatively measuring credit risks of SMEs (see Altman and Sabato, 2005, 2007).

Even though we have no recent public statistics regarding the levels of outstanding SBCS loans, all commercial banks have tended to decrease the volume of outstanding SBCS loans over the last few years. That was triggered by the huge SBCS loan losses of many banks using the SBCS technology. The typical case is the losses incurred by the Shinginko (= "new bank", in Japanese) Bank Tokyo established by the Tokyo Metropolitan Government in 2005. Shinginko Bank Tokyo lost nearly 80% of its capital by the end of 2007. Such huge losses are the result of the relatively high default rates and

[1]Data are reported by the FSA and the *Nikkei Newspaper*.

[2]This is called the "Action Program to Promote Further Enhancement of Region-based Relationship Banking Functions".

low profitability of SBCS loans.

Academic literature on SBCS focuses on how SBCS is applied and the effect of SBCS on the volume of small business credit. Berger and Udell (2002, 2006) and Uchida, Udell, and Yamori (2007) examine the choice of lending technology by banks. Frame, Srinivasan, and Woosley, (2001), Cowan and Cowan (2006), and Ono (2005) show survey results about the use of SBCS by financial institutions. Frame, Srinivasan, and Woosley, (2001), Frame, Padhi, and Woosley (2004), Berger, Frame, and Miller (2005), Agarwal and Hauswald (2008), and Berger, Cowan, and Frame (2009) find that SBCS can enhance credit availability for SMEs. Berger, Frame, and Miller (2005) and Agarwal and Hauswald (2008) discuss the prices of small business credits made by banks using credit scoring.

Our objective is somewhat different from that of the literature. This paper evaluates the profitability of SBCS loans in Japan. Discussion on the profitability of SBCS loans has been burgeoning. The Bank of Japan (2007) suggests the particular importance of assessing the quality of the scores used in the case of Japan's SBCS lending.[3] The *Wall Street Journal* (Maltby, 2010) says, "Even entrepreneurs with high business credit scores may have trouble getting financing. This is partly because business credit scores as well as personal credit scores have become a weak indicator of repayment ability..." in the United States. Even though the discussion is lively, to the best of our knowledge there is no empirical research on profitability relative to risks of default.[4]

This paper computes some quantitative profitability measures for SBCS lending by using a practically used scoring model and actual SMEs' data. We show (1) why SBCS loan losses arise, and (2) how financial institutions can profit from SBCS loans. In addition, this paper runs simulations of (3) how Shinginko Tokyo made its huge losses from SBCS lending.

[3]Bank of Japan (2007) considers "the credit scoring models used by Japanese banks are not sufficiently reliable and observed default rates at some banks exceed the default rates projected by the models."

[4]This paper is also aimed at enhancing the secondary market for SBCS loans, as currently "no significant secondary market for small business credits has emerged" in the United States (Berger and Frame, 2007) and that is also the case with Japan.

It should be noted that this paper's first priority is not the evaluation of scoring models themselves but the evaluation of the profitability of SBCS loans. Therefore, we construct a simple profit maximization problem of a bank using the SBCS technology.

The remainder of the paper is as follows. Section II explains the SBCS market in Japan and the data used in this paper. Section III describes the model and the empirical results. Section IV shows our simulation results of the Shinginko Bank's lending policies. Section V concludes the paper.

2 Japanese SBCS and the Data Used

2.1 Japanese SBCS

Japanese SBCS is somewhat different from that in the United States. According to Berger and Frame (2007) and many others, SBCS is a technology for computing small business applicants' propensity to repay their loans, and is one of the most widely used lending technologies. SBCS models for computing scores are constructed using econometric methods. Hard information such as both quantitative and qualitative data are used for estimating the default probability (= score) of loan borrowers. SBCS in Japan differs from that in the US in regard to the use of consumer data on SME owners. Given the incomplete combination of the consumer information and business information databases, Japanese SBCS only uses business information in general.

There is a variety of Japanese SBCS models, and the one considered in this paper is RiskCalc Ver. 1 developed by Moody's KMV (the "RiskCalc"). The RiskCalc is created using pooled data on 41,577 SMEs between 1994 and 2000. Released in December 2001 by Moody's KMV, it is one of the most widely used first-generation credit scoring models for evaluating unlisted companies' creditworthiness in Japan. Typical SBCS models use latent variable regression techniques and the RiskCalc employs probit regression. The RiskCalc is also typical in regard to its independent and dependent variables. Its independent variables comprise quantitative data about firms' ordinary profit/total assets, liabilities/total assets, cash/current assets, retained earnings/current liabilities, gross profit/total interest expense, sales, and total inventories/sales. They do not include any qualitative or consumer data on SME owners. The dependent variable represents the default risk (the "score") and would be "0" in the case of survival and "1" in the case of default.

It should be noted that this paper focuses not on the absolute level of the scores but rather on the relative level of the scores. When the RiskCalc was created, the estimation sample data were mainly those of the late 1990s, a time of weakening confidence in the Japanese financial system. This period corresponds to the Heisei financial crisis, a time when Japanese credit markets became keenly sensitive to credit risks for the first time (at least) since 1980. In fact, the series of failures among financial institutions was accompanied by a string of bankruptcies among general business firms, including those in 1997 of Tokai Kogyo, Tada Corporation, and Yaohan. The number of bankruptcies among SMEs began to trend upwards from the late 1990s. In this period, it was very difficult to obtain information on overall default rates of SMEs in Japan. According to Moody's KMV, the average annual default rate of the RiskCalc is assumed to be 1.2%. Judging from subsequent actual overall default rates (1.5%), this level was somewhat optimistic. The RiskCalc also estimates a "Dot PD rating" that maps the score to a rating. This Dot PD rating cannot be directly compared to Moody's long-term bond rating, but as far as SMEs are concerned, the model assigns too high ratings to them. As explained later, of 2000 SMEs there were 225 Aa rated firms, followed by A: 246 firms, Baa: 465 firms, Ba: 467 firms, and B: 597 firms. Based on those facts, the level of long-term average default rates was initially set too low compared with actual default rates, and then the absolute level of default rates (the rating) may be a comparatively low value (resulting in a higher rating).

2.2 Dataset

Our sample consists of SMEs in business for two consecutive years in 2001 and 2002. We see those companies as if they had applied to a bank for SBCS loans in the beginning of 2003, when the SBCS loans were introduced in Japan.[5] Firms in business in 2001 and 2002 were sampled from the database of Tokyo Shoko Research (TSR). TSR, one of Japan's oldest major credit reporting and information provision companies, regularly collects corporate data nationwide. We can find an adequate number of Japanese typical SMEs in the TSR database.

The analysis focuses on a total of two thousand incorporated but unlisted SMEs in three industries, including 496 in manufacturing, 504 in wholesale, and 1,000 in construction. Sample companies were chosen in the following way. First, for each industry, we sample the companies (1) in business in 2001 and 2002 and (2) whose survival or default information at the end of 2005 is available. In other words, the loan period is assumed to be three years and the defaulting (or surviving) companies were companies that did (or did not) default within three years after the loans were made. Second, we choose the industries with a sufficient number of defaulting companies' data as well as those industries conforming to the RiskCalc.[6] Third, out of the two thousand companies, the numbers of surviving companies and defaulting companies were equal in 2005. For example, 500 defaulting (surviving) SMEs in construction were chosen from all defaulting (surviving) companies in construction by random sampling from the TSR database. In short, the number of surviving companies in each industry equals the number of defaulting companies. This was done for two reasons. The first reason was to avoid problems that might otherwise arise if sampling were made in a simple fashion, possibly resulting in the defaulting companies being too few in number. The second reason was that we can change the default rate of loan

[5] A firm is assumed to submit the latest financial statements to a financial institution.

[6] There are some differences between the definitions of "default" used in the TSR Data and by the RiskCalc. The TSR Data defines default as being subject to the application of the Corporation Reorganization Law, taking procedures under the Civil Rehabilitation Law, application for bankruptcy, application for special liquidation, suspension of transactions with banks, internal (voluntary) liquidation, and the like. The RiskCalc defines a borrower as being in default when it has been in arrears for ninety days, when it files for bankruptcy, when it is classified by the lending financial institution as being in danger of bankruptcy or when the borrower's loan is written off by the lender. Since it is impossible to make them completely consistent, definitions of default are assumed to be the same for the sake of convenience.

applicants, as explained later.

2.3 Descriptive Statistics

Table 1 shows the distribution of the scores and the medians of the principal financial ratios for two thousand companies in the TSR database. The score (the default rate) seems to function as a better signal of default than these individual indicators. A comparison of the median scores of surviving companies and those of defaulting companies shows a significant difference.

An interesting point is the fact that default rates do not necessarily decline as company size increases, and that default rates decline as profitability or financial viability increases. If one looks at companies in wholesale and construction in terms of sales, the defaulting companies tend to be the larger ones. When companies are compared in terms of financial ratios used as indicators of profitability (operating margin) or financial viability (capital asset ratio), on the other hand, there is a wide gap between surviving companies and defaulting companies.

3 SBCS Loans and Bank Profitability

In this section, we construct a simple profit maximization model of SBCS lending a la Hasumi and Hirata (2010) to evaluate empirically the profitability of the SBCS lending business.

3.1 Profit Maximization of Scoring Lending

Suppose that a risk-neutral bank uses a SBCS technology. If a borrower survives and repays, the bank earns r yen. If a borrower defaults and does not repay, the bank loses $l(> r)$ yen. The procedure for scoring lending is as follows: the bank ranks the loan applicants by their scores and lends to the applicants with the top $z\%$ scores. The amount of each loan is assumed to be the same across borrowers and the bank can change the level of z from 0 to 100. When the bank chooses $z\%$, the profit $\pi(z)$ is:

$$\pi(z) = rN_A(z) - lN_D(z) \tag{1}$$

where $N_A(z)$ and $N_D(z)$ are the numbers of surviving and defaulting borrowers, respectively. The profit-maximizing bank chooses $z\%$ to maximize its $\pi(z)$. Suppose that $N_A(z)$ is differentiable with respect to z and the total number of loan applicants is N_M, which means $N_A(z)+N_D(z) = N_M \times 0.01z$, the first-order condition is:

$$\pi'(z) = rN'_A(z) - l\left(\frac{N_M}{100} - N'_A(z)\right) = 0 \tag{2}$$

In addition, suppose that $\pi'(z)$ is monotonically decreasing z satisfying the following equation given the maximum of $\pi(z)$.

$$N'_A(z) = \frac{l}{r+l}\frac{N_M}{100} \tag{3}$$

3.2 Empirical Models and the Assumptions

We next transform the theoretical model into the empirical model. We quantitatively compute $\pi(z)$ for any z, as we know the survive/default information for all sample SMEs. We define $\pi(z_M)$ as the maximized $\pi(z)$ at $z = z_M$. This z_M is the measure of the availability of small business credit by using the SBCS technology. There are N SMEs seeking credit (= loan applicants) and $S_D + S_A = N$, where S_D and S_A are the number of defaulting SMEs and that of surviving SMEs. Let $n_A(n)$ be the number of surviving borrowers in the top n borrowers in terms of scores. We have

$$z = f(n) = \left\{(1-P_D)\frac{n_A(n)}{S_A} + P_D\frac{n - n_A(n)}{S_D}\right\} \times 100 \tag{4}$$

where z indicates what percentage of SMEs can borrow in the case that n out of N loan applicants borrow, given the default rate P_D. We give the default rate of loan applicants P_D exogenously, as no banks know that number. An increase in this number can be considered as the degree of the adverse selection problem.

Function f is monotonic to n and the inverse function f^{-1} is described as follows:

$$n = f^{-1}(z) \tag{5}$$

The number of defaulting SMEs in the top n borrowers, $n_D(n)$, is:

$$n_D(n) = \frac{P_D}{1-P_D}\frac{S_A}{S_D}(n - n_A(n)) \tag{6}$$

and thus:

$$n_A(N) : n_D(N) = S_A : \frac{P_D}{1-P_D}\frac{S_A}{S_D}(N - S_A) = 1 - P_D : P_D \tag{7}$$

Now the profit function π_n is

$$\pi_n = rn_A(n) - ln_D(n) \tag{8}$$

By plugging equation (5) into equation (8), the bank has its objective function for z, which is the empirical version of equation (1). The derivative of (8) is:

$$\frac{d\pi_n}{dz} = \frac{d\pi_n}{dn}\frac{dn}{dz} \tag{9}$$

As $\frac{dn}{dz} > 0$ is obvious, whether π_n increases or decreases depends upon the sign of:

$$\frac{d\pi_n}{dn} = r\frac{dn_A}{dn} - l\frac{P_D}{1-P_D}\frac{S_A}{S_D}\left(1 - \frac{dn_A}{dn}\right) \tag{10}$$

If $\frac{dn_A}{dn}$ is smaller than the constant value $x = l\frac{P_D}{1-P_D}\frac{S_A}{S_D}\left(r + l\frac{P_D}{1-P_D}\frac{S_A}{S_D}\right)^{-1}$, then π_n goes down.

Some parameters and data are calibrated for the benchmark simulation. First, the bank is assumed to order the loan applicants by the scores computed by the RiskCalc. Second, based on analysis of the Japanese SBCS loans surveyed by RIETI (2009), we assume that the terms of the contract are three years and that the contracted annual interest rates on SBCS loans are 2.7% (assuming simple interest just for simplicity). Second, the three-year default rate of loan applicants P_D is assumed to be 5% based on the Small Enterprise Default Ratio (i.e., default rates of SMEs) by the Risk Data Bank of Japan. In this case, the adverse selection problem (discussed later) does not exist, as the default rate for loan applicants is assumed to be the same as the default rate for overall SMEs. Third, the recovery ratio is set at zero for simplicity. Fourth, the amount of each loan is assumed to be the same across borrowers. Fifth, fixed costs of developing the SBCS technology and other costs, such as interest rates on deposit and labor costs, are assumed to be zero.[7]

In sum, we set $P_D = 0.05$, $r = \frac{100}{S_A}$, and $l = \frac{100}{2.7\times 3}r$. r is set to normalize the maximized value of π_n, rS_A at 100 in the case that the SBCS technology completely discriminates between surviving / defaulting firms. $l = \frac{100}{2.7\times 3}r$ is computed from the fact that l/r = (loss when a SME defaults)/(profit when a SME survives) $= 100/(2.7 \times 3)$. Looking at the marginal changes in π_n:

$$s_k = \frac{n_A(n_k) - n_A(n_{k-1})}{n_k - n_{k-1}}(k = 1, 2, \ldots, K) \tag{11}$$

where $n_0 = 0 < n_1 < \cdots < n_K = N$, is computed as the approximation of dn_A/dn. s_k indicates the portion of surviving SMEs that exists in the kth bin, when the loan applicants are sorted by the scores and divided into K bins.

3.3 Empirical Results

The bold solid line in Figure 1 shows the relationship between z and π_n. The bar graph represents the relationship between z_k and s_k. The entire sample of SMEs is divided into 20 (=K) bins. z_k is equal to $k/K \times 100$. The horizontal dotted line is the threshold, i.e., a bar is lower (higher) than the horizontal dotted line, and π_n decreases (increases). The downward-sloping bar graph implies that the share of defaulting SMEs increases as the ranking

[7] In this case, profit π_n corresponds to gross margin. Note that the interest rates on deposits were close to zero in 2003–2005 (interests on checking accounts: 0.001%, interests on three-year saving accounts: 0.05%) given the Japan's quantitatively easing monetary policy.

score goes down.

The kinked line in the upper left shows π_n in the *perfect* case. It increases from the origin to (z, π_n)=(95,100) linearly and decreases to (100, π_n(=35.2)) linearly. Note that the SBCS can evaluate the true PDs of the loan applicants and the SBCS can order them in order of default if the model is *perfect*. As the model is not *perfect* in reality, the bold solid line is located below the straight kinked line of the *perfect* case. The shaded area between the bold solid line and the kinked line displays the *inefficiency* of SBCS loans. The larger the shaded area is, the more *inefficient* (= less profitable) SBCS lending is. Table 2 reports the maximized π_n and the corresponding values including the *inefficiency* for each industry.

There are various points worth mentioning. First, profit is maximized in the neighborhood of $z = 75$ for the three industries. In other words, without the adverse problem, the bank using the SBCS technology can maximize its profit by lending to 75% of the loan applicants. If the bank lends more ($z > 75$), the profit becomes smaller.

Second, SBCS lending is relatively profitable compared with more informationally rich "relationship lending". "Relationship lending" uses not only hard information but also soft information to solve the information opacity problem of SMEs. As a proxy for the credit decisions of a relationship lending bank, we have the TSR ratings ranging from 0 to 100.[8] The standards of the TSR ratings are identical across TSR's officers' ratings of firms and they should do in-person interviews with the owners of each firm to carry out a subjective credit assessment.[9] The same experiment as the benchmark one is conducted for the TSR ratings and the results are shown in Figure 2. The maximized $\pi(z)$ ($= \pi(z_M)$) and the associated z ($= z_M$) are ($\pi(z_M)$,

[8] Given a lack of data availability, we only have data on the TSR ratings for 160 firms, 116 surviving, and 44 defaulting firms. The simulation is done by using those 160 firms' data.

[9] According to the TSR, the score consists of four components: (i) management ability (such as the business experience of the owner) and outstanding assets that can be collateralized (20 points); (ii) the growth potential of sales and profits (25 points); (iii) stability factors such as firm age, the amount of capital outstanding, and the payment and credit history of the firm (45 points); and (iv) reputation and disclosure (10 points). The TSR ratings are subjective in the sense that each TSR officer grades the firms for which he or she is responsible.

z_M)=(84.7, 60.5) if the scores are used and ($\pi(z_M)$, z_M)=(87.3, 63.2) if the TSR ratings are used. Given the differences in the richness of the information, we can say that the SBCS is quite a powerful tool for profitable lending.

Third, SBCS fits best for wholesale and fits worst for construction, judging from $\pi(z_M)$, the *inefficiency*, and z_M. The profit peak is the lowest and the bar graph shows an unsmooth curve for construction, while the profit peak is the highest and the bar graph shows a smooth downward-sloping curve for the wholesale industry.

4 The Pitfalls of SBCS Lending

To sum up, SBCS lending can be considered a profitable business to some extent for those banks using the SBCS technology.[10]

We also find some pitfalls with SBCS lending. In this section, we try to answer two questions to understand the sources of the pitfalls: first, what causes the *inefficiency* in the benchmark simulation; second, why large losses were made in practice.

4.1 Causes of the *Inefficiency*

In consideration of the empirical result in the previous section, various types of factors cause the *inefficiency*.

First, *inefficiency* is, of course, what caused the accumulation of the loan losses. The vertical difference between the bold solid line and the kinked line in the profit curve should widen with respect to z. Thus, the higher the number of SMEs with higher scores go bankrupt, the greater the *inefficiency*. Figure 2 suggests that relationship lending is *less inefficient* than SBCS lending in the sense that the marginal changes in π_n is smaller for relationship lending than for SBCS lending in the range between $z = 0$ and $z = 50$ (or smaller).

[10] We examined another commercial SBCS model for checking the sensitivity and all results were very similar to those in this paper.

Second, the SBCS models have an omitted variable bias. There are difficulties in predicting the future performance of an enterprise depending only on its financial statements. In the case of the RiskCalc, only seven pieces of hard data are used and any soft data are excluded as independent variables that might influence the dependent variable. In fact, the *inefficiency* is relatively large in the case of construction, as this industry is heavily affected by the amount of public works projects in Japan, and these are not covered by the SBCS models.

Third, econometric methods applied to general SBCS models in the market would be less sophisticated.[11]

Fourth, there is a difference between the distribution of independent variables in the estimation sample and the prediction sample. The differences in the periods cause an extrapolation bias. Particularly, loans to SMEs are quite sensitive to swings in business cycles and the bias cannot be negligible.[12]

Fifth, the transparency of financial statements of SMEs is doubtful in Japan. According to the *White Paper on Small and Medium Enterprises in Japan in FY 2007*, the Small Business Agency is trying to increase the number of firms making quality financial statements, but only a limited number of them can do so. Lack of high quality hard data makes the SBCS models less accurate, and a low quality prediction sample worsens the scores. Note that low quality can be caused not only by the (unintentional) lack of accounting knowledge but also by (intentional) window dressing.

4.2 Simulating the Shinginko Bank's Business Model

Many Japanese banks incurred huge SBCS loan losses in 2007–2008, and many of those banks, including Shinginko Bank Tokyo, often applied SBCS to not current but new customers whose loan applications had been rejected by other banks using relationship lending. Those losses cannot be explained

[11] As described, focusing on econometric issues with the SBCS technology is not this paper's primary objective. Please refer to Rommer (2005) and many other papers working on the estimation issues of SBCS for further discussion.

[12] Since the RiskCalc was constructed using data for the period when credit risks were rising, the scores might be rather conservative. Note that the latest SBCS technologies used in Japan generally control for the business cycle factor.

by the already mentioned causes of *inefficiency*.

In this section, we examine the case of Shinginko Bank established by Tokyo Metropolitan Government in 2005. Shinginko Bank's main lending technology was SBCS, but it was saddled with huge bad loans within three years of opening. It was faced with the loss of nearly 80% of its capital by the end of 2007 and was forced to increase its capital by 40 billion yen in April, 2008.

Figure 3 illustrates the abstract of Shinginko Bank's original business model. The governor of the Tokyo Metropolitan Government said that Shinginko Bank sought to provide financial intermediation services for insolvent SMEs, i.e., provide unsecured and uncollateralized loans for insolvent SMEs, which could not easily borrow from other banks. In reality, the vast majority of the Shinginko Bank's loan applicants were firms rejected by other banks, which generally did not use the SBCS technology but chose relationship lending instead.

We mimic the Shinginko Bank's business model and simulate that in the following way. In the first stage, profit-maximizing banks using relationship lending make loan decisions. Some SMEs can borrow and the others cannot. In the second stage, Shinginko Bank, using the SBCS technology, makes loan decisions but all of its applicants are those rejected by banks using relationship lending. For simulating the first stage, we assume banks using relationship lending maximize their profit.[13] For simulating the second stage, loans are assumed to be made uniformly by profit-maximizing Shinginko Bank and its interest rate on SBCS loans is assumed to be 7%. Although 7% is much higher than 2.7% used in the benchmark experiment, that rate is the average really applied by Shinginko Bank according to the financial press.

Figure 4 draws the profit curve of the Shinginko simulation.[14] It sug-

[13]We use both the TSR ratings and the scores computed by the non-Moody's SBCS model to mimic the first stage. Using the TSR ratings is more consistent with the theory but the results do not show any significant differences. In Figure 4, the results using the latter scores are displayed, as the TSR ratings are only available for 160 firms and the scores computed by the a non RiskCalc SBCS model are available for 2000 firms. Note that we were given access to the non RiskCalc model, one of the most popular SBCS models in Japan, after signing a confidentially agreement.

[14]The figure's horizontal axis is normalized, i.e., z takes 100 in the case that Shinginko

gests that the Shinginko Bank's business model is surprisingly profitable and the result contradicts the fact that it is relatively less profitable than the benchmark experiment.[15] Judging from this simulation result, good borrowers remain even after the first stage and the SBCS technology with higher interest rates can work even in the second stage.

What produces such a puzzling result? One possible hypothesis is that the adverse selection and window-dressing problems take place simultaneously, and those problems undermine the performance of SBCS loans. In this simulation, the default rate of loan applicants P_D is assumed to be 5% in three years. This number, however, is not predetermined and not known when loans are made. This level of P_D is just the average default rate of Japanese SMEs, and this simulation implicitly assumes that almost no adverse selection happens. In addition, the data used in this simulation are randomly sampled and the number of window-dressing SMEs might be limited.

We can simulate the impact of adverse selection by increasing the value of P_D. The value of P_D is changed from the benchmark simulation. Figure 5 shows $(\pi(z_M),\, z_M)$ with respect to P_D. When P_D rises, maximum profit significantly decreases and the credit availability for SMEs also substantially decreases. The SBCS models themselves seem to be weak against the adverse selection problem and Shinginko Bank suffered from this problem.

Finding any evidence of window dressing only from its financial statements is difficult, and we explore the possibility of window dressing in a casual manner. We compute the debt ratios, the ratios of total liabilities at the time when firms became bankrupt to those in 2002, i.e., the time when loans were made. We also compute the sales ratios, the ratios of sales at the time when firms became bankrupt to those in 2002. Those two ratios are compared with the analogue ratios for surviving firms.[16] The results suggest that the medians of the debt ratios and the sales ratios are almost unity across industries but the distribution of the debt ratios of defaulting firms

Bank lends to all of the applicants rejected by banks using relationship lending.

[15]If 2.7% is applied, the Shinginko Bank's business model is not profitable and makes large losses.

[16]For surviving firms, we compute the ratios of total liabilities or sales at the time when loans were repaid (in 2005) to those at the time when loans were made (in 2002).

has a thicker right tail than that of surviving firms. At the 90% percentile, the sales ratios of the defaulting firms and of the surviving firms are 1.48 and 1.54, while the debt ratios of the defaulting firms and of the surviving firms are 2.50 and 1.65, respectively. In particular, the debt ratio of the defaulting construction firms exceeds 3.0 at the 90% percentile. Large changes in stock data such as total liabilities might be a good signal of window dressing, because they are generally much less volatile than flow data.[17] For a robustness check, Table 3 shows the Spearman's rank-order correlation coefficients for the scores' ranking and the debt ratios' ranking for the defaulting firms. This result indicates that the defaulting construction firms with the higher scores (lower default possibilities) tend to increase their debt more significantly than the surviving firms do, suggesting the possibility of window dressing.

5 Conclusions

This paper studies the Japanese credit scoring market using data on 2,000 SMEs in business between 2001 and 2002. After constructing a model for a bank's profit maximization, we find the optimum loan sizes and profit levels, and demonstrate some pitfalls of SBCS lending.

Now we can answer the questions raised in the Introduction. The first question is why SBCS loan losses occur, and the most important answers are the combination of adverse selection problem and window-dressing problems. This paper quantitatively shows that, given the presence of adverse selection, it is difficult to make profits from SBCS lending. This paper also confirms quantitatively that about half of the companies that defaulted despite having a high score (= low default probability) defaulted following a sharp increase in liabilities. There tends to be many such problems in the construction industry. These findings are consistent with those of the Bank of Japan (2007). In addition, needless to say, statistically refining the SBCS models to reduce the omitted variable bias and making SMEs increase the transparency

[17] Of course, a firm close to bankruptcy tends to borrow more to survive. However, we focus on not a gradual increase but a jump in total liabilities to determine the (intentional) window-dressing cases.

of financial statements are also important for reducing the *inefficiency*.

The second question is how financial institutions could profit from SBCS lending. The first thing to do is to solve the adverse selection and the window-dressing problems, although that would be costly. In so doing, greater stress should be placed on interviews with management and on company visits, as indicated by Ono (2005). Unfortunately, however, it would be too early to assume that U.S. models could be readily applied in Japan, as only a limited number of financial institutions are in a position that enables them to use consumer data about the owners. For this reason, it seems reasonable that, in most cases, lenders request prior interviews with company owners and request personal guarantees from them.[18] It is also important to identify the idiosyncrasies of the model through a scrupulous analysis of track record data to establish the telltale signs of window dressing.

Finally, several points in regard to this study should be mentioned. First, fixed costs and variable costs involved in credit scoring were not considered. Second, the SBCS models are now in their second or third generation, but these newer models have not been analyzed. Third, this paper did not explicitly consider the demand function of SBCS loans. Fourth, this paper's analysis is partial in the sense that it does not consider substitutes for credit scoring. These issues are for future studies.

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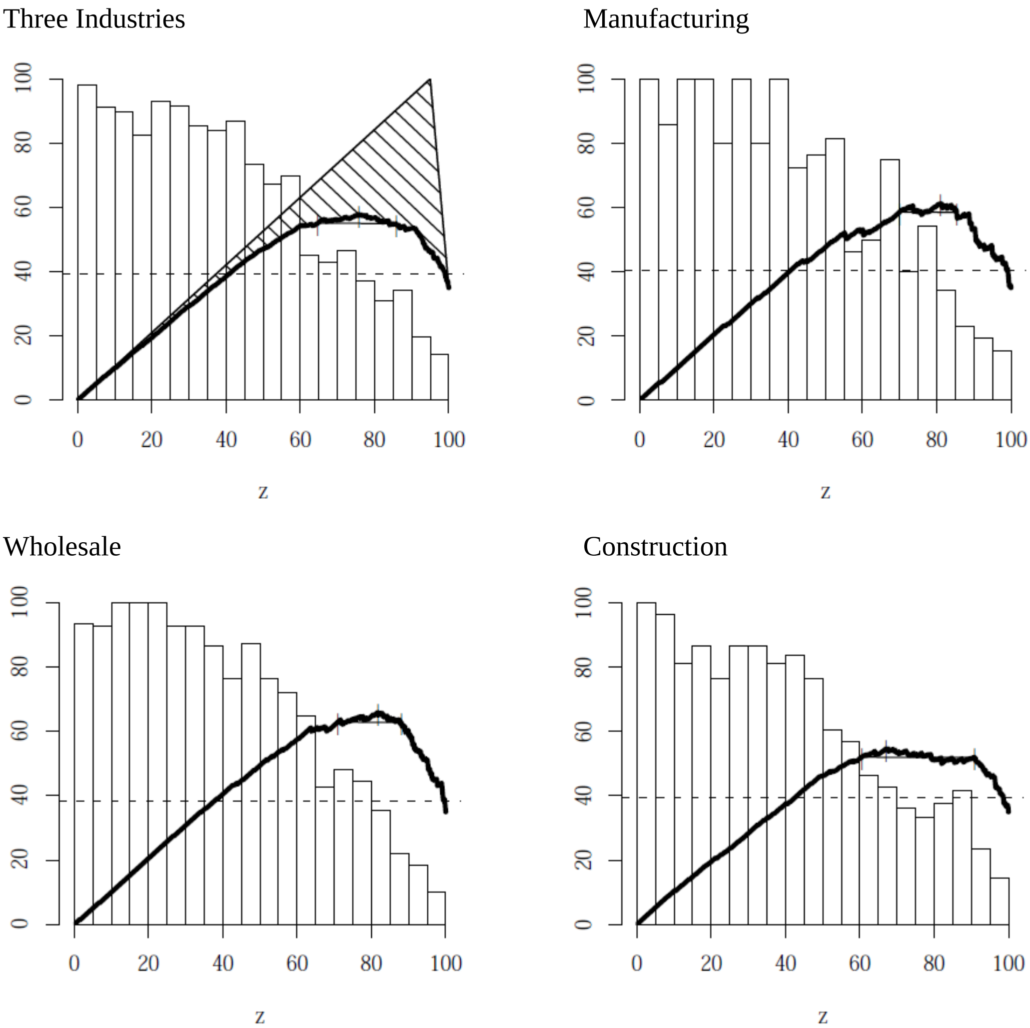
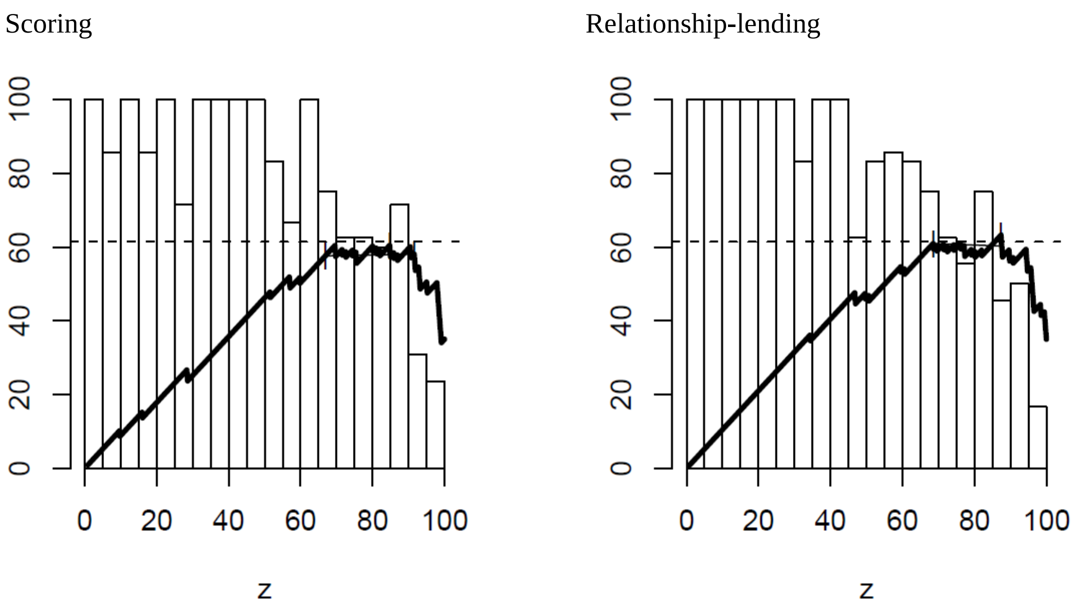
Figure 1. Profit Curves



Notes: The bold solid line is the profit curve when the SBCS technology is used. The solid kinked line shows the profit curve when the examination of loans is perfect. The shaded area is the inefficiency. The bar graph represents the relationship between z_k and s_k. Profit decreases when a bar is lower than the horizontal dotted line.

Figure 2. Comparison of Scoring and Relationship Lending



Note: See Figure 1.

Figure 3. The Business Model of Shinginko Bank Tokyo

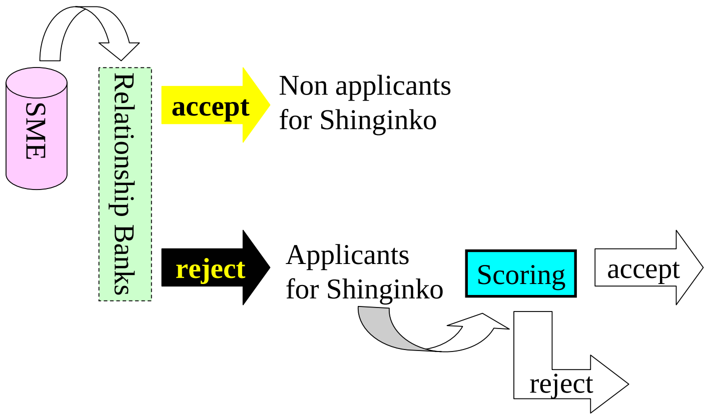
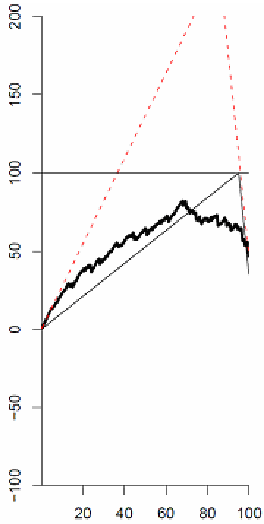


Figure 4. Simulation of the Business Model of Shinginko Bank Tokyo



Notes: See Figure 1. This figure is comparable with Figure 1. The dotted kinked line shows the profit curve when the examination of loans is perfect in the second stage.

Figure 5. Adverse Selection and Profitability

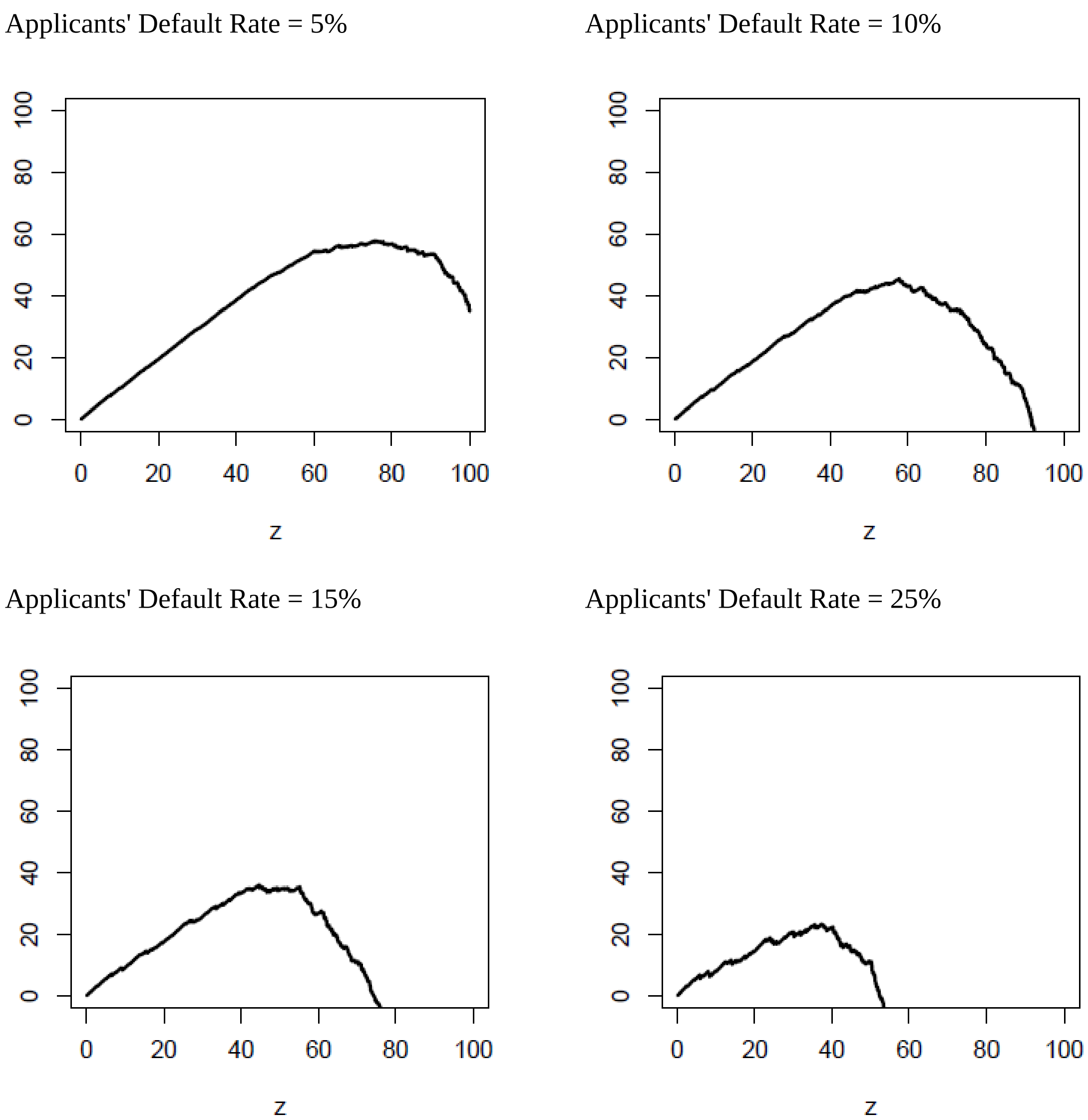


Table 1. Descriptive Statistics

		# of Sample	# of Employees	Sales (million yen)	Interest Rates Paid (%)	Operating Margin (%)	Capital Asset Ratio (%)	RiskCalc Scores
Three Industries		2,000	14	498	2.68	0.92	13.4	0.91
	Surviving	1,000	14	482	2.42	1.07	22.9	0.23
	Defaulting	1,000	14	504	2.95	0.81	7.7	3.02
Manufacturing		485	30	702	2.56	1.46	11.4	1.33
	Surviving	248	32	725	2.28	2.14	21.0	0.34
	Defaulting	237	26	617	2.83	1.09	6.2	4.07
Wholesale		515	13	812	2.50	0.55	11.8	0.85
	Surviving	252	14	760	2.14	0.61	19.6	0.23
	Defaulting	263	13	877	2.80	0.53	5.9	2.47
Construction		1,000	11	338	2.88	0.96	15.2	0.84
	Surviving	500	11	308	2.61	1.10	25.7	0.20
	Defaulting	500	12	374	3.11	0.91	9.8	2.65

Table 2. Benchmark Results

	Maximized profit	n	z	*Inefficiency*
Three Industries	57.9	1092	75.8	1235
Manufacturing	61.3	288	81.0	1155
Wholesale	66.0	288	81.7	911
Construction	54.7	460	67.1	1379

Table 3. Spearman's Rank-order Correlation Coefficients

	Debt Ratios	Sales Ratios
Defaulting firms	0.24 (0.00)	0.07 (0.04)
Those in Manufacturing	0.16 (0.01)	0.11 (0.09)
Those in Wholesale	0.17 (0.01)	0.04 (0.55)
Those in Construction	0.31 (0.00)	0.05 (0.25)
Surviving firms	-0.01 (0.84)	0.21 (0.00)

Notes: Numbers in the brackets are the p-values (Null hypothesis is the correlation coefficient equals 0).