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ESTIMATION OF FIRMS' DEFAULT RATES IN TERMS OF INTANGIBLE ASSETS*

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ABSTRACT

This paper quantitatively analyzes how firms' default rates are affected by intangible assets, which play a crucial role in business management but are difficult to assess objectively. We use intangible assets such as firms' technological capability and the qualifications of senior management, for which numerical data from each firm are available. The results are as follows: (1) intangible assets have statistical explanatory power for firms' default rates in addition to financial data; (2) a model that incorporates intangible assets has greater accuracy in estimating default rates than one that incorporates only financial data, and the difference in the accuracy is statistically significant; and (3) the impact of changes in intangible assets on firms' default rates is comparable with that of changes in financial data. Based on our analysis, it may be effective to take into consideration intangible assets to enhance the accuracy in estimating firms' default rates. Therefore, in assessing firms' credit risk, it is important to enhance the information on intangible assets to objectively assess these assets.

Keywords: Estimated default rates; Intangible assets; Logit model; Bootstrap method

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I. Introduction

It is important for financial institutions to quantitatively assess firms' credit risk in their lending operations. They need to gauge credit risk with a uniform standard through quantitative assessment in order to appropriately set the conditions for loan extension and conduct follow-up monitoring of existing loans. Furthermore, the Basel requirements allow financial institutions to adopt their own methods for measuring credit risk in calculating capital adequacy ratios. This point also raises the importance of quantitatively assessing credit risk.

Many studies on quantitative assessment of credit risk have estimated default rates using financial indicators. The study by Altman (1968) that used multivariate discriminant analysis is a typical example of an early study. Ando and Yamashita (2004) briefly introduced a typical analysis method for default forecast using financial indicators and research results following the study by Altman (1968). A characteristic of recent studies is that empirical analysis using large-scale data has become possible due to further improvements in the database. The number of subjects in the risk calculation has increased to include unlisted small and medium-sized firms. For example, Takahashi and Yamashita (2002) and Fujii and Takemoto (2010) analyzed the relationship between financial data and the default forecast by using small and medium-sized firms' Credit Risk Database (CRD). The series of research results verified that firms' financial data are effective in estimating their default rates.

On the other hand, it is widely recognized that there is a certain limit in estimating future default rates by using financial data that reflect only past outcomes in firms' economic activity. Therefore, some researchers have used data other than financial data in estimating default rates. Hibiki, Ogi, and Toshiro (2012) and Moridaira and Okazaki (2009) examined whether firms' common macro factors affect the accuracy of default forecast besides firms' financial data. In addition, Saito and Tachibanaki (2004) verified that the forecast of firm’s default rates is improved by using qualitative information such as the financial institutions from which firms borrowed funds, whether firms have submitted collateral, and whether firms are subcontractors.

Furthermore, some have pointed out that intangible assets, which play a crucial role in business management but are difficult to assess in numerical terms, should be taken into consideration in default forecast. Intangible assets cover a range of factors such as firms' technological capability, branding power, and the qualifications of senior management as well as intangible assets in terms of accounting. According to the estimation in Miyakawa, Takizawa, and Kim (2010), such a broad range of intangible assets has become all the more important for firms' profitability in recent years. Miyata (2003) concluded that senior management's qualifications significantly affect profits and the size of firms.

Nevertheless, the accumulation of research on the relationship between a broad range of intangible assets and estimation on firms' default has hardly been observed. A few examples are Grunert, Norden, and Weber (2005) and Teikoku Databank (2009). Grunert, Norden, and Weber (2005), which conducted empirical analysis using data on firms' creditworthiness provided by German major banks, explained that nonfinancial information such as the qualifications of senior management and market share enhances the accuracy of default forecast, in addition to financial data. Teikoku Databank (2009) showed that Japanese firms' technological capability significantly reduces future default rates. In financial practices, some financial institutions in Japan take account of soft information such as borrowing firms' potential growth and senior management's qualifications when deciding on loan extension and assigning internal credit ratings. However, it seems that small financial institutions are behind the curve in such initiatives (Nemoto, Ogura, and Watanabe [2013]).

Based on the above discussion, we will analyze the effects of a broad range of intangible assets on firms' credit risk. Our analysis is similar to the two early studies discussed above. However, it differs from the study by Grunert, Norden, and Weber (2005) in that we use data -- namely, nonfinancial information assessed by a third party -- instead of banks' internal credit information. It also differs from the study by Teikoku Databank (2009) in that, although we use the same indicator for firms' technological capability, we incorporate senior management's qualifications.

In Section II, we will discuss in detail the variables used in our analysis. We will estimate firms' default rates in two cases using only financial data and using both financial data and intangible assets, and compare the estimation accuracy of each model. We will then calculate the magnitude of the effects of intangible assets on firms' default rates. In Section III, we will draw a conclusion.

II. Estimation of Firms' Default Rates in terms of Intangible Assets

A. Outline of the Analysis

In this section, we estimate firms' default rates in terms of intangible assets by using a logit model, which is widely used not only in empirical research but also in financial practices.[1] We use the database provided by Teikoku Databank, which includes items such as firms' financial data and senior management's qualifications.[2] We also use the database of patents and information services on firms' value provided by Kudo & Associates, which includes items such as firms' technological capability. The sample is 3,509 firms identified by data matching in these databases, mainly comprising small and medium-sized firms in the manufacturing industry. The estimation period is from fiscal 2003 to fiscal 2011.[3]

B. Variables Used in the Estimation

We use firms' possible default as an independent variable in the logit model. We use major financial variables and indicators for firms' technological capability and senior management's qualifications as dependent variables. The details are described below. Chart 1 shows the descriptive statistics of each variable.

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[1] Dimitras, Zanakis, and Zopounidis (1996) indicated that many studies from 1981 used a logit model for estimating default rates according to the comprehensive survey results.

[2] We used data such as "Corporate Credit Research," "Corporate Financial Database (COSMOS1)," and "Corporate Profile Database (COSMOS2)" provided by Teikoku Databank.

[3] In Japan, the fiscal year starts in April and ends in March of the following year.

Firms' default

The variable of firms' default shows whether a firm defaults within three years. If the firm defaults within three years, the variable is one, and if not, the variable is zero. As shown in Chart 1, firms' default rate in our sample is 3.2 percent. The default is basically defined to occur when a firm goes bankrupt as defined by Teikoku Databank. Specifically, this happens when firms experience voluntary liquidation (suspension of transactions with banks due to the second dishonor and internal liquidation) or legal liquidation (a request to the court regarding application of the Corporate Reorganization Act, commencement of the process under the Civil Rehabilitation Act, and special liquidation).[4] We set the period until default at three years because it takes a certain period of time for intangible assets such as technological capability to affect firms' business conditions. In fact, the National Institute of Science and Technology Policy (2012) found based on its survey of firms that approximately three years are required on average for firms to develop new products and services and introduce them in the markets.[5]

Indicators for firms' financial conditions

As variables for firms' financial conditions, we used five ratios indicated in the table below, from the viewpoint of firms' profitability, steadiness, liquidity, payment

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[4] Firms' default includes firms that were deleted from the database as well as firms that were confirmed to have experienced voluntary liquidation or legal liquidation based on credit research. This was because we might underestimate the number of bankrupt firms if we only take account of the latter case. The major reason behind the former case was bankruptcy, but some firms that were dormant, out of business, or had undergone mergers or acquisitions might be included. In financial institutions' credit risk management, firms are considered to be in default when they are in a severe business condition with no prospect for reconstruction or when they are delinquent for a certain period in regard to principal and interest repayments.

[5] In a recent empirical analysis, Hasumi, Hirata, and Ono (2011) used the default rate three years after the base date and Fujii and Takemoto (2010) used the rates two years and three years after the base date. Many studies other than these also set the estimation period at one year to five years after the base date, and three years are considered as the average.

capability, and efficiency. When selecting the variables, we referred to the studies conducted by Kocagil and Akhavein (2001), Chua, Dwyer, and Zhang (2009), and Fujii and Takemoto (2010). We used the ratio of current profits to total assets as the variable for profitability, the ratio of cash and deposits to total assets as the variable for liquidity, and the ratio of operating profits to interest payments as the variable for payment capability. A higher value for these variables means higher levels of profitability, liquidity, and payment capability.[6] On the other hand, we used the ratio of total liabilities to total assets as the variable for steadiness and the ratio of inventories to sales as the variable for efficiency. A lower value for these variables means higher levels of steadiness and efficiency. The parentheses in the table below show the sign conditions. The average figures in Chart 1 indicate that the ratios of current profits to total assets, cash and deposits to total assets, and operating profits to interest payments are lower at defaulted firms than at surviving firms, while the ratios of total liabilities to total assets and inventories to sales are higher.[7]

Classification	Independent variables
Profitability (-)	Current profits / total assets
Steadiness (+)	Total liabilities / total assets
Liquidity (-)	Cash and deposits / total assets
Payment capability (-)	Operating profits / interest payments
Efficiency (+)	Inventories / sales

[6] We defined operating profits as operating profits including interest and dividends received.

[7] We used the logarithmic value when estimating the ratios of operating profits to interest payments and inventories to sales. Since there were some antilogarithms that were negative figures, we conducted logarithmic conversion of the values including negative ones by employing negative logarithmic transformation in line with the estimation of default rates conducted by Altman and Sabato (2007) and Moridaira and Okazaki (2009).

$$ngl(x) = \begin{cases} +\log(1+x) & if\ x > 0 \\ -\log(1-x) & if\ x \leqq 0 \end{cases}$$

Indicators for firms' technological capability

As an indicator for firms' technological capability, we used the YK value, which is an indicator for the objective assessment of a firm's patents.[8] The YK value estimates the economic value of a patent in terms of how competitors evaluate it. There are many procedures governing the application of a patent and its expiration, such as the publication of an unexamined application, requests for validation, substantive examination, a decision of refusal, and a decision of registration. If a firm judges that registration of another firm's patent is a threat to its business, the firm might seek to prevent the patent registration or make a request for invalidation of the patent. Such actions incur costs, since the firm needs to provide information to examiners or request a patent invalidation. Nevertheless, if the patent is crucial, the competitor will take action to prevent the patent registration or seek to make the registered patent invalid despite high costs. The YK value is an indicator that calculates the costs a competitor may incur in preventing a patent registration or requesting a patent invalidation, estimated by using data released by the Japan Patent Office.[9] The YK value covers all patents in Japan.

A number of studies used the numbers of patent applications and registrations or the amount of research and development expenses recorded on balance sheets as indicators for gauging firms' technological capability. However, as many have often pointed out, these indicators are insufficient to a degree in gauging firms' technological competitiveness. For example, if a firm obtains a patent for a unique innovation but demand for the innovation is small, the patent might not contribute to the firm's growth. In addition, no product will enhance a firm's growth if it is never launched despite the large cost in R&D. The YK value -- the actual costs incurred by a competitor -- reflects a firm's technological competitiveness, that is, the firm's potential value.

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[8] The source is an indicator for patents and information services on firms' value provided by Kudo & Associates.

[9] Adjustments have been made by, for example, multiplying the rate of obsolescence in each technological field in accordance with the passage of time.

Mizuta, Kudo, and Kobayashi (2009) and Ide (2013) showed that a firm with a higher YK value increases the future returns on its stock. The average YK value (an indicator for firms' technological capability) in Chart 1 is higher for surviving firms than defaulted firms.

Indicators for senior management's qualifications

We used the survey results of Teikoku Databank as the indicator for senior management's qualifications. Teikoku Databank surveys, as part of its corporate credit research, the personality of firms' senior management through interviews with firms. Specifically, the score of senior management's qualifications was the sum of scores on 25 items related to senior management such as "decisiveness," "high planning capability," "vision," "a wide network of contacts," "a high degree of activity," "a strong sense of responsibility," and "verbal ability."[10] The score was one if qualified and zero otherwise on a 25-point scale based on the investigators' interviews.[11] The average was 4.3 points, with a standard deviation of 1.6 points. Many firms fell within the range of 1-8 points. The average for surviving firms was 4.3 points, higher than that for defaulted firms of 4.1 points.

Information on senior management is an important factor among intangible assets for determining firms' growth potential. However, such information is difficult to collect and costs are entailed in evaluating the collected information. Therefore, senior management's information used in earlier empirical analyses was limited to areas such as name, academic background, and whether the senior management included the founder. The indicators we use in this paper incorporate information on senior management that relates directly to business management as compared with the indicators used in the past studies.

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[10] Teikoku Databank provides on its website the survey results that include some survey categories mentioned in this paper.

[11] The survey also contained an item termed "poor at calculation." For this item, as an exceptional case, the score was zero if qualified and one otherwise.

Since the indicator shows the subjective evaluation of investigators, better business conditions of firms may lead to higher scores, regardless of the true picture of senior management. In such a case, the indicator merely reflects firms' financial indicators and thus loses its significance in forecasting default. Nonetheless, as shown in Chart 2, the indicator is weakly related to firms' profitability (current profits / total assets). The correlation coefficient of the indicator and financial indicators used in our estimation in Chart 3 is small at 0.045 at a maximum, and investigators' evaluation is not necessarily affected by firms' business conditions.

C. Estimation Results

Chart 4 shows the results of estimation conducted under the framework mentioned above. In the case of using only financial data (Model 1), all financial variables were statistically significant and also met expected sign conditions. In other words, when the profitability, steadiness, liquidity, payment capability, and efficiency increase, firms' default rates may decline.

In the case of using both financial data and intangible assets (Model 2), all financial variables were statistically significant as in Model 1, and these variables met sign conditions. As for intangible assets, both indicators for firms' technological capability and for senior management's qualifications were statistically significant. The signs of these variables were negative, and the larger value led to a decrease in firms' default rates.

From the above estimation results, we confirmed that not only financial data but also intangible assets such as firms' technological capability and senior management's qualifications had significant effects on firms' default rates.

D. Estimation Accuracy of Models

1. Indicators for assessing models

Here we examine whether the inclusion of intangible assets improves the performance of default forecast, that is, how much of a disparity in estimation accuracy occurs between Model 1 and Model 2. There are a range of indicators for evaluating models. In this paper, we use the detection rate such as McFadden's coefficient of determination, the Brier score, Type I error, and Type II error in line with Grunert, Norden, and Weber (2005). In addition, we calculate the accuracy ratio (AR), which is often used in credit risk management operations.

McFadden's coefficient of determination

In the logit model, we cannot use ordinary coefficients of determination such as those used in an ordinary least squares (OLS) regression model, and thus we use McFadden's coefficient of determination. The coefficient is also called a likelihood ratio, and is calculated by $1-\log L_u / \log L_r$. The estimation accuracy is high when the likelihood ratio is high. $\log L_u$ is the logarithm likelihood of the estimation model, and $\log L_r$ is the logarithm likelihood of a model that only contains constant terms.[12]

Brier score

The Brier score is an indicator for estimation accuracy used mainly in the fields of meteorology and medical science, and the formula is $1/\mathrm{n} \sum_{i=1}^{n}(\theta_i - p_i)^2$. θ_i is set at one at the time of default and zero in other cases. p_i is set at the estimated default rate. A lower level of the Brier score means higher accuracy.

Detection rate, Type I error, and Type II error

The detection rate shows the proportion of correct default detection, and the higher rate indicates higher accuracy. We set firms' actual average default rate as a threshold for detecting default. We also calculate the Type I error and the Type II error as a

[12] As evident from the estimation method, we cannot simply compare the level of McFadden's coefficient of determination with that of ordinary coefficients of determination. For more details, see Domencich and McFadden (1975).

partial detection rate. The Type I error is the proportion of firms that actually defaulted even though the model did not forecast their defaults, and the Type II error is the proportion of firms that did not actually default even though the model forecast their defaults. A lower level of these indicators means higher accuracy.

Accuracy ratio

AR is an indicator that determines whether a firm with an estimated high default rate has actually defaulted. Specifically, firms are listed in order from the estimated highest default rate, and the number of defaulted firms is added up from the top of the list. If the model's estimation accuracy is high, the accumulated number of defaulted firms should reach the total number of defaulted firms at an early stage.[13] And on the contrary, if the accuracy is low, then the accumulated number of defaulted firms does not reach the total number of defaulted firms until a later stage. AR evaluates the accuracy of models in accordance with the accumulated number of defaulted firms at a certain stage, and is shown in the range of 0-100 percent. AR is close to 100 percent when the accuracy of the model is high. AR only evaluates the accuracy of models by order of default, and does not take into account the estimated value of default rates.

2. Comparison of model accuracy

Chart 5 calculates the above six evaluation indicators for Model 1 (using only financial data) and Model 2 (using both financial data and intangible assets). As mentioned earlier, the models' accuracy is considered high when McFadden's coefficient of determination, the detection rate, and AR are higher and when the Brier score, Type I error, and Type II error are lower. The calculation results show the difference in the degree of accuracy between Model 1 and Model 2, in that the accuracy of the indicators is higher in Model 2 than in Model 1.

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[13] For more details on the calculation method of AR, see Yamashita, Tsuruga, and Kawaguchi (2003).

The question is whether such a difference is statistically significant. The right-hand column of Chart 5 shows the test results whether or not there is a significant difference between the two indicators. The distribution of the difference between Model 1 and Model 2 is calculated by the bootstrap method.[14] The test rejects the null hypothesis that there is no difference between Model 1 and Model 2 at a significance level of 1 percent in terms of McFadden's coefficient of determination, the Brier score, the detection rate, and AR. In terms of the Type II error, the test rejects the null hypothesis at a significance level of 5 percent. However, we cannot reject the null hypothesis for the Type I error. All indicators except for the Type I error support the hypothesis that the estimation accuracy of Model 2 is higher than that of Model 1.[15] Chart 6 plots the combination of indicators calculated using Model 1 and Model 2 by conducting the bootstrap method 1,000 times. Although the accuracy in Model 2 is relatively low for the Type I error, the accuracy in Model 2 exceeds that in Model 1 for all cases for McFadden's coefficient of determination, for 996 cases for the Brier score, for 993 cases for the detection rate and the Type II error, and for 998 cases for AR. These results prove that the accuracy of Model 2 is higher than that of Model 1.

E. Sensitivity of Independent Variables

Next, we examine the magnitude of the effects on firms' default of changes in intangible assets such as firms' technological capability and senior management's qualifications compared with changes in financial data. In Chart 7, we calculated by

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[14] We conducted the bootstrap method with the following steps based on the study by Davidson and MacKinnon (2004): (1) calculate estimation errors for the default of each firm at each period using the estimation model; (2) randomly resample estimation errors and allocate them to each firm at each period; (3) add the allocated estimation errors to the default rate and calculate a new default rate; (4) conduct estimation on Model 1 and Model 2 by using the new default rate and calculate each evaluation indicator; and (5) repeat the above four steps 1,000 times and derive an empirical distribution of each indicator.

[15] Grunert, Norden, and Weber (2005) conducted a similar test on firms in Germany and proved that there was a significant difference in McFadden's coefficient of determination, the Brier score, and the detection rate, but none was observed in the Type I error and Type II error.

using Model 2 how much the estimated default rate changed in accordance with changes in each factor (sensitivity). We assumed a firm with average values for all independent variables and a firm where one independent variable was higher by one standard deviation from the averages, and regarded the difference in the default rates as sensitivity. We confirmed that financial indicators related to liquidity had the largest effect on the firm's estimated default rate.[16] The second-largest effect was estimated to be the firm's technological capability. As with other financial indicators, senior management's qualifications also had some effects on the default rate. Therefore, we verified the importance of financial data in the process of evaluating firms' credit risk, and concluded that data on intangible assets have substantial effects.

III. Conclusion

In this paper, we quantitatively analyzed the effects on firms' default rates of intangible assets such as firms' technological capability and senior management's qualifications that were broadly defined and hence were difficult to evaluate objectively. The summary of our analysis is as follows. First, we found that not only financial data but also intangible assets such as firms' technological capability and senior management's qualifications have statistically significant effects on firms' default rates. Second, the accuracy of estimating default rates turned out to be high with a model that used both financial data and information on intangible assets compared with a model that used only financial data. The difference in the accuracy was generally significant. And third, based on the analysis of sensitivity, we discovered that the magnitude of the effects on firms' default rates of data on intangible assets was comparable with that of the effects of financial data. We estimate that the indicator on firms' technological capability has large effects on firms' default rates, being second to financial indicators on liquidity.

There are many kinds of intangible assets other than the ones we discussed in this

[16] This result is consistent with the analysis done by Fujii and Takemoto (2010) in which they estimated the default rates of small and medium-sized firms by using financial indicators.

paper that may affect firms' default rates, but many of them are difficult to quantify. In light of the results of our analysis, devising ways to quantify intangible assets that are important for business management is effective in evaluating firms' credit risk.

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Chart 1: Descriptive statistics

	Averages			Standard deviation		
	All firms	Surviving firms	Defaulted firms	All firms	Surviving firms	Defaulted firms
Default (percentage)	0.0316	0.0000	1.0000	0.1750	0.0000	0.0000
Firms' technological capability (% pts)	12.1048	12.2328	8.1862	53.8837	54.0496	48.4128
Senior management's qualifications (pts)	4.2515	4.2563	4.1053	1.5862	1.5869	1.5617
Current profits / total assets (percentage)	0.0370	0.0383	-0.0022	0.0749	0.0716	0.1359
Total liabilities / total assets (percentage)	0.6735	0.6661	0.9017	0.4102	0.3976	0.6518
Cash and deposits / total assets (percentage)	0.1406	0.1423	0.0878	0.1117	0.1118	0.0953
Operating profits / interest payments (times)	590.8342	602.6854	228.0963	11,780.795	11,935.176	5,161.671
Inventories / sales (percentage)	0.1467	0.1449	0.2030	0.1481	0.1436	0.2413

Note: The estimation period is from fiscal 2006 to fiscal 2011 for default and from fiscal 2003 to fiscal 2008 for other variables. Operating profits are the total of operating profits and interest and dividends received.

Chart 2: Indicator for senior management's qualifications and firms' profitability

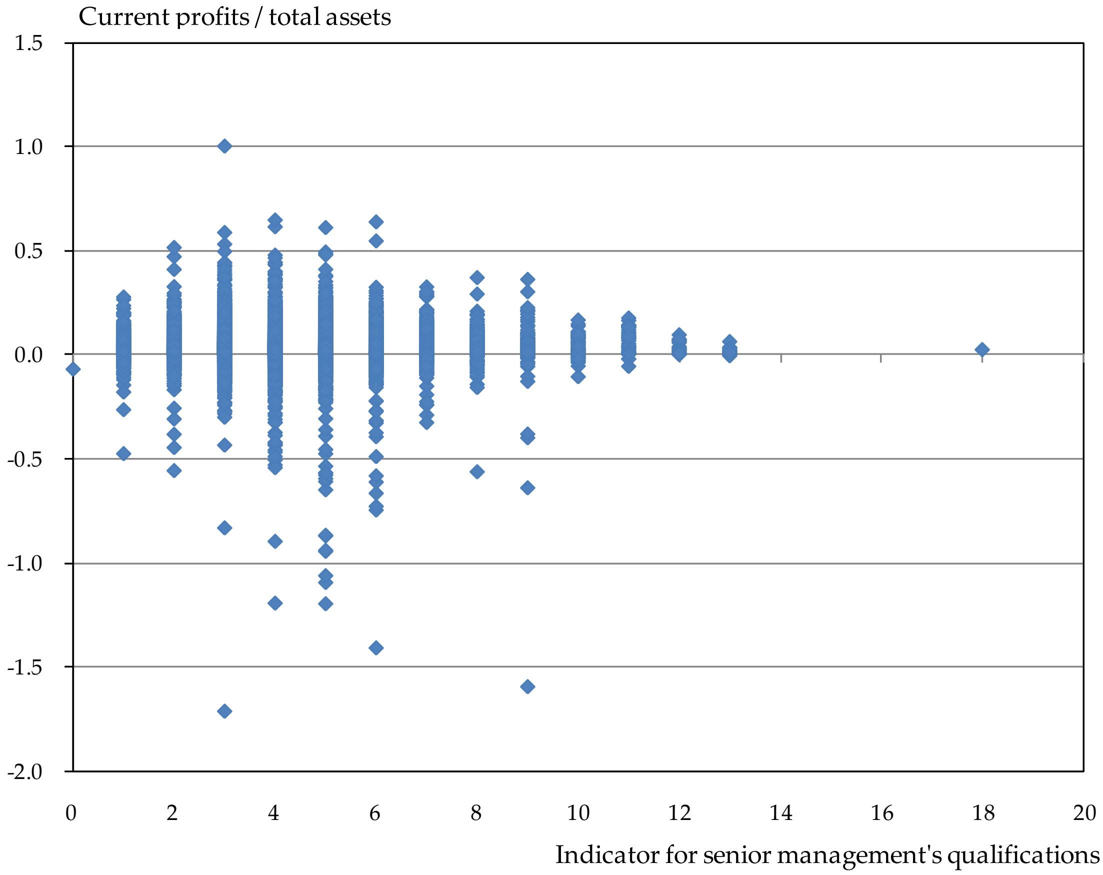


Chart 3: Correlation coefficient of the indicator for senior management's qualifications and financial indicators

Current profits / total assets	Total liabilities / total assets	Cash and deposits / total assets	Operating profits / interest payments	Inventories / sales
-0.0163	0.0269	0.0454	0.0030	0.0092

Chart 4: Estimation results

	Model 1 (only financial data)		Model 2 (financial data and intangible assets)	
	Estimated value	Standard error	Estimated value	Standard error
Firms' technological capability	--	--	-0.172***	0.040
Senior management's qualifications	--	--	-0.065**	0.029
Current profits / total assets	-1.622***	0.454	-1.669***	0.455
Total liabilities / total assets	0.341***	0.066	0.331***	0.066
Cash and deposits / total assets	-5.545***	0.580	-5.434***	0.578
Operating profits / interest payments	-0.098***	0.024	-0.089***	0.024
Inventories / sales	1.473***	0.300	1.520***	0.300
Constant terms	-3.101***	0.110	-2.738***	0.158
Number of samples	17,479			
Number of defaults	553			

Note: Dependent variables are the default rates three years after the base date. *** and ** indicate statistical significance at the 1 percent and 5 percent levels, respectively.

Chart 5: Indicators for evaluating models using financial data and intangible assets

	Model 1 (only financial data)	Model 2 (financial data and intangible assets)	Difference between Model 1 and Model 2
McFadden's coefficient of determination	0.0622	0.0676	0.0054*** <0.000>
Brier score (%)	2.9775	2.9721	0.0054*** <0.008>
Detection rate (%)	60.4211	61.2964	0.8753*** <0.006>
Type I error rate (%)	0.8811	0.8582	0.0229 <0.382>
Type II error rate (%)	38.6979	37.8454	0.8525** <0.010>
AR (%)	44.3031	45.7273	1.4242*** <0.000>

Note: *** and ** indicate statistical significance at the 1 percent and 5 percent levels, respectively. Figures in angular brackets are preliminary. Regarding McFadden's coefficient of determination, the detection rate, and AR, the difference is derived by subtracting Model 1 from Model 2, whereas for the Brier score, Type I error, and Type II error, Model 2 is subtracted from Model 1.

Chart 6: Combination of Model 1 and Model 2 based on the bootstrap method

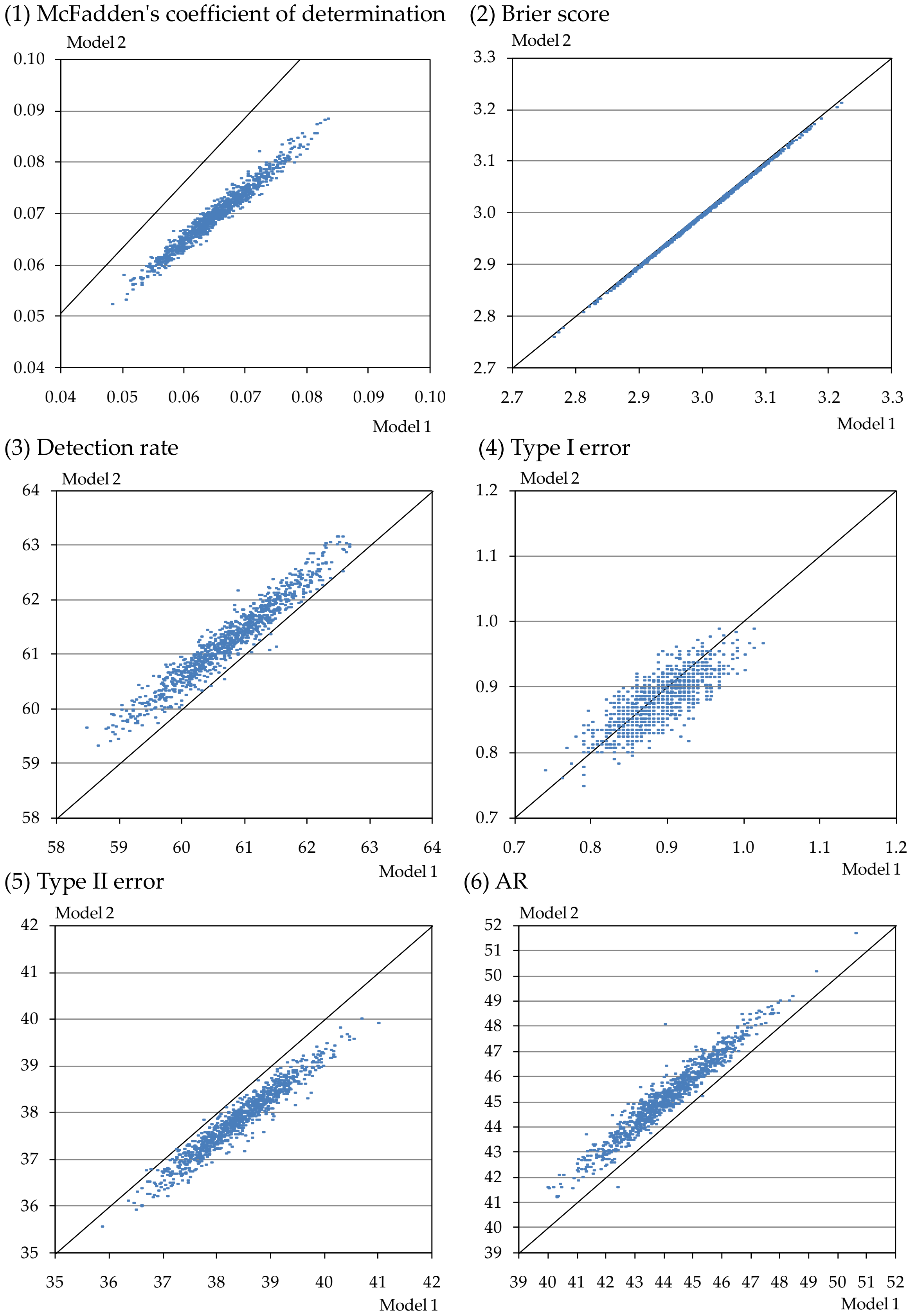
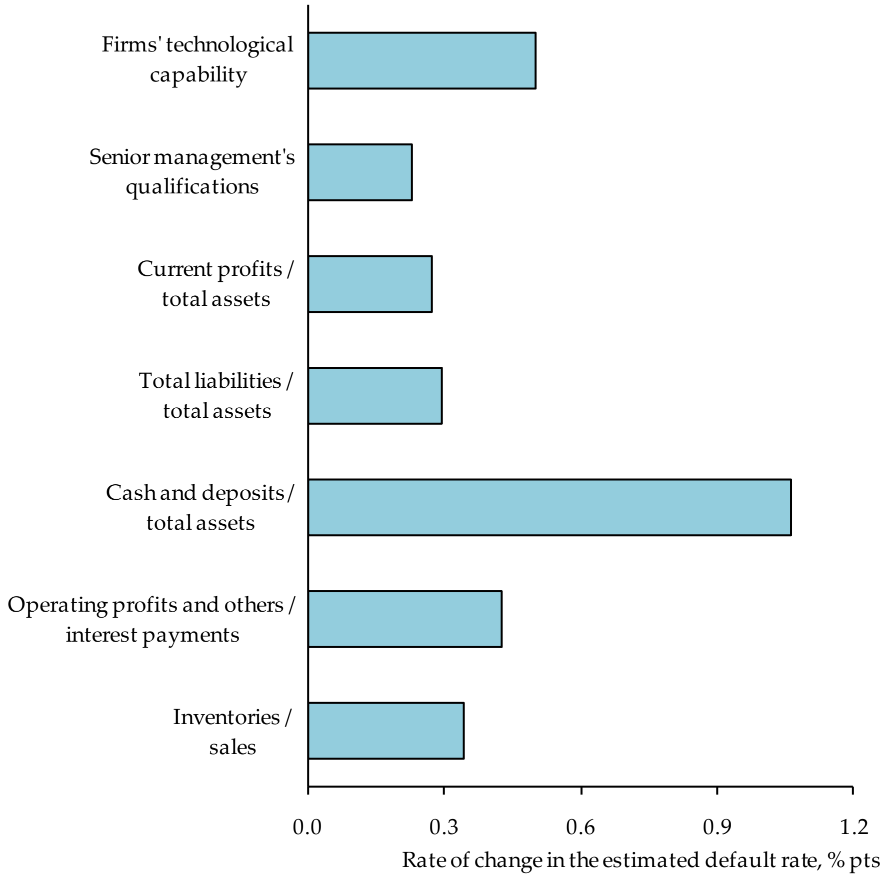


Chart 7: Magnitude of effects on the default rate of financial data and intangible assets



Note: We assumed a firm with average values for all variables and a firm where one independent variable was higher by one standard deviation from the averages. The difference in the estimated default rates was calculated for each variable.