

# MOODY'S KMV RISKCALC™ V3.2 JAPAN

## MODELING METHODOLOGY

### ABSTRACT

#### AUTHORS

Lee Chua

Douglas W. Dwyer

Andrew Zhang

Moody's KMV RiskCalc is the Moody's KMV model for predicting private company defaults.. It covers over 80% of the world's GDP, has more than 20 geographic specific models and is currently used by over 200 institutions worldwide. While using the same underlying framework, each model reflects the domestic lending, regulator, and accounting practices of its specific region.

In April 2008, Moody's KMV introduced its newest RiskCalc model for Japan, RiskCalc v3.2 Japan. By incorporating both market- (systematic) and company-specific (idiosyncratic) risk factors along with newest default data reflecting the recent credit cycle development, the RiskCalc modeling framework is in the forefront of modeling middle-market default risk.

This document outlines the underlying research, model characteristics, data, and validation results for the RiskCalc v3.2 Japan model.

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# 1 INTRODUCTION

The Moody's KMV RiskCalc™ v3.2 Japan model is built using the result of extensive research of Moody's KMV including:

- Moody's KMV RiskCalc™ v3.1, v1.0 and the Moody's KMV Private Firm Model® (PFM)
- Moody's KMV Credit Research Database™ (CRD), the world's largest and cleanest private company default database
- Industry sector information, market information, and industry specific default rates.

RiskCalc v3.2 incorporates the structural and market-based comparables approach (used in PFM), and the localized financial statement-based approach (used in RiskCalc v1.0). This allows RiskCalc v3.2 to blend market-based (systematic) information with detailed firm-specific financial statement (idiosyncratic) information to enhance the model's predictive power. In addition, RiskCalc v3.2 incorporates the newest data (from 2001 through 2005) reflecting the recent credit environment in Japan.

## 1.1 RiskCalc Modes

RiskCalc v3.2 allows you to assess the risk of a private firm in two ways: Financial Statement Only (FSO) and Credit Cycle Adjusted (CCA).

The FSO mode delivers a firm's default risk based only on financial statements and sector information, adjusted to reflect differences in credit risk across industries.

The CCA mode adjusts the default risk by taking into account the current stage of the credit cycle. The CCA is a sector-specific adjustment derived directly from Moody's KMV public firm model's distance-to-default (DD). The CCA model reflects the market's current assessment of the credit cycle and is a forward-looking indicator of default.

The CCA mode is specific to the firm's sector and country or region and is updated monthly. The CCA mode also has the ability to stress test Moody's KMV EDF™ (Expected Default Frequency) credit measures under different credit cycle scenarios—a proposed requirement under Basel Capital Accord (BIS II).

## 1.2 Differences between RiskCalc v3.2 Japan and RiskCalc v3.1 Japan

Since the release of RiskCalc v3.1, Moody's KMV has significantly increased the size of the Japanese database. We compare the risk factors in RiskCalc v3.1 and RiskCalc v3.2 Japan and the corresponding model weights. More details on the selection of these drivers and the corresponding weights can be found in Sections 3.1 and 3.2, respectively. The RiskCalc v3.2 has new calibration and central default tendency, which will be described in detail in Section 2.4 and 4.5..

# 2 DATA DESCRIPTION

The source of the data for RiskCalc v3.2 Japan is Moody's KMV Credit Research Database (CRD). Our CRD group collects data from participating financial institutions, working closely with them to understand the strengths and weaknesses of the data. Moody's KMV uses this data for both model development and testing purposes.

## 2.1 Data Exclusions

### Excluded Companies

The goal of the RiskCalc model is to provide an EDF credit measure for private Japanese companies in the middle market. The firms and industries covered in the model must have similar default characteristics. To create the most powerful model for Japanese middle-market companies, companies that did not reflect the typical company characteristics in this market were eliminated. The following types of companies are not included in the model development:

- **Small Companies**—For companies with assets of less than ¥12 million, their future success is often linked to the finances of the key individuals. For this reason, they are not reflective of a typical middle-market company and are excluded from the database.
- **Financial Institutions**—The balance sheets of financial institutions (banks, insurance companies, and investment companies) exhibit higher leverage than the typical private firm. The regulation and capital requirements of these institutions make them dissimilar to the typical middle market company and, therefore, they are excluded from the database.
- **Real Estate Development Companies**—The annual accounts of a real estate development and investment companies provide only a partial description of the dynamics of the firm and, therefore, its likelihood of default. This is because its financial health often hinges on a particular development.<sup>1</sup>
- **Public Sector and Non-profit Institutions**—Government-run companies' default risks are influenced by the states' or municipalities' unwillingness to allow them to fail. Therefore, their results are not comparable to other private firms. Not-for-profit financial ratios are different from for-profit firms, particularly with regard to variables relating to net income, as they do not have a profit maximization objective.

### Excluded Financial Statements

The financial statements in the CRD are cleaned to eliminate highly suspect financial statements. Plausibility checks of financial statements are conducted, such as assets not equal liabilities plus net worth, and financial statement covering a period of less than twelve months. If errors are detected, those statements are excluded from the analysis.

## 2.2 Descriptive Statistics of the Data

### Overview of the Data

The extensive data on both non-defaulting and defaulting companies contained in Moody's CRD has increased substantially since RiskCalc v3.1.

Table 1 provides a summary of the data set used in development, validation, and calibration of the RiskCalc v3.2 Japan model. The number of financial statements, firms, and defaults utilized in the recent version is considerably larger than v3.1. There has been more than a 49% increase in the number of unique firms, and more than a 37% increase in the number of financial statements. In addition, there has been more than 100% increase in the number of defaults. The current data set is also based on a longer time period.

Figure 1 presents the distribution of Japanese financial statements and defaults by year.

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<sup>1</sup> The success of many types of project finance firms depends largely on the outcome of a particular project. We recommend using separate models for such firms. This characteristic is explicitly recognized by the Basel Capital Accord.

TABLE 1 Japanese Private Firm Sample Data

Japanese Private Firms	RiskCalc v3.1 Japan	RiskCalc v3.2 Japan	Credit Research Database Growth
Financial statements	699,000+	955,000+	↑37%
Unique number of firms	135,000+	201,000+	↑49%
Defaults	5,500+	12,000+	↑118%
Time period	1993-2002	1992-2005	↑ + 4 years

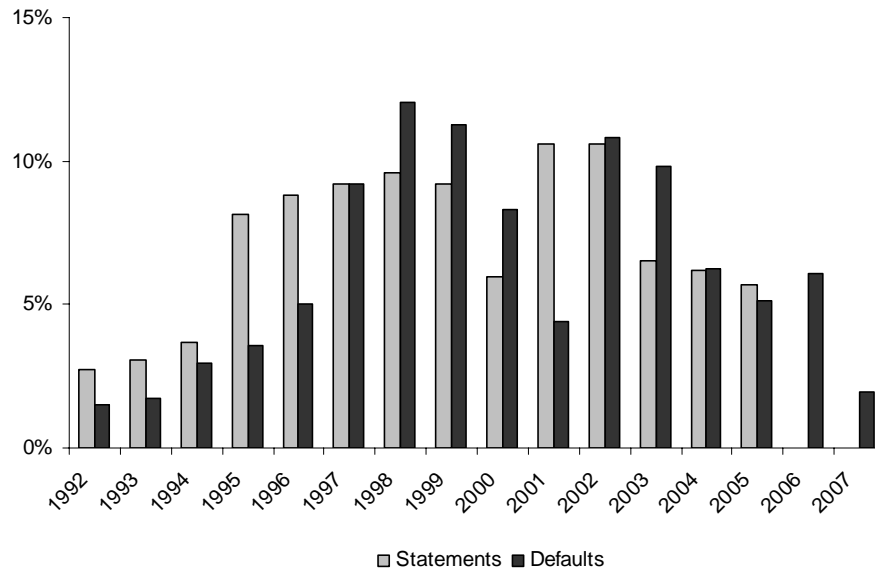


FIGURE 1 Date Distribution of Financial Statements and Default Data

### Robustness of the Data

In building a model potential database weaknesses need to be examined. Not only does the database need to cover a large number of firms and defaults, but the defaults also need to be distributed among industries and company types covered. For example, if the database has significant numbers of small firms or firms in one particular industry without sufficient defaults in those areas, the model may not be a good default predictor. The CRD used in developing the RiskCalc models has addressed both of these issues.

Figure 2 and Figure 3 present the distribution of defaults and firms by industry and size classification, respectively. These figures show that the proportion of defaults in any one size group or industry is comparable to the number of firms in these groupings. Firm size as measured by assets range from ¥12 million to over ¥5 billion (Figure 3), with the range between ¥120 million and ¥750 million accounting for approximately half of the sample.

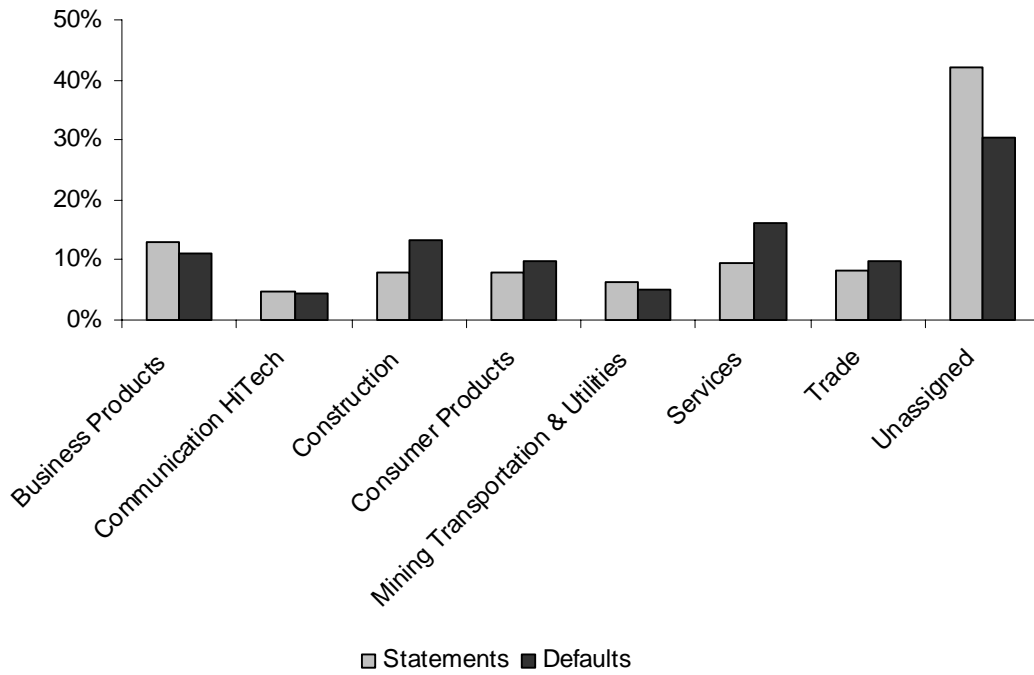


FIGURE 2 Distribution of Defaults and Firms by Industry

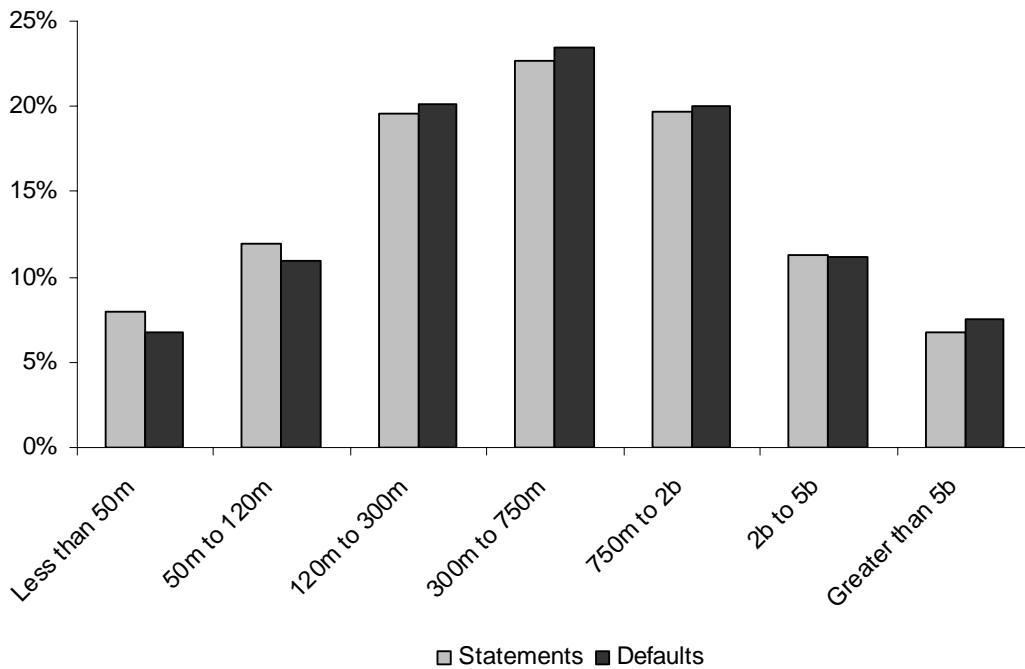


FIGURE 3 Size Distribution of Defaults and Firms

## 2.3 Definition of Default

RiskCalc provides assistance to institutions and investors for determining the risk of default, missed payments, or other credit events. The proposals for BIS II have stimulated debates about what constitutes an appropriate definition of default. RiskCalc applies the criteria used by most of the advanced economies in the world. The events which we defined as defaults include special attention, in danger of bankruptcy, and bankrupt/de facto bankrupt.

## 2.4 Central Default Tendency

Because most companies do not default, companies that do default are relatively rare and thus more valuable in building a default prediction model. Much of the lack in default data comes from data storage issues within financial institutions (e.g., defaulting companies being purged from the system after troubles begin), not all defaults being captured, or other sample errors. Also, if the date of default is uncertain, the financial statement associated with the firm may be excluded from model development, depending on the severity of the problem. This can result in a sample that has lower default rates than what actually occurs in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true central default tendency (CDT). When default definitions used in the data sample may understate the defaulting population, as is the case with Japan, the CDT can be used to realign the default rates.

The estimate of long-run aggregate probabilities of default (i.e., CDT) is important as an anchor for a model. The best estimation of the default probability is a ratio that reflects the number of obligors that defaulted in one year compared with the total obligors at the beginning of that year. Often these types of data are not available.

The estimate of the central default tendency for Japan is based on several sources.

- Loan loss provision data from the Organization for Economic Co-operation and Development (OECD).
- Provisioning data gathered from financial statements of large Japanese banks.
- Data for major city and regional banks gathered from the *Banking Statistics Supplement: Japan*, published by Moody's Investors Service.
- Statistics on total credit charges from the Japanese Bankers Association.
- Confirmation of the CDT exceeding the default rates observed in our development sample.

Based on these discussions and data review, 2.0% is used as the CDT figure. In calibrating RiskCalc v3.2 for Japanese private companies, a central tendency of 2.0% is used for the 1-year PD, The corresponding central tendency rate used for the 5-year is 7.7% .<sup>2</sup>

To test the 1-year mean default rate, bank loan provisions are used. Financial institutions make provisions for bad loans that are representative of their expectations for write-offs. From the volume of losses and the volume of loans, an average default rate can be calculated by making an assumption regarding loss given default (LGD):

$$\text{Volume of Losses} = \text{Volume of Loans} \times \text{Probability of Default} \times \text{LGD}$$

Therefore,

$$\text{Probability of Default} = \text{Volume of Losses} / (\text{Volume of Loans} \times \text{LGD})$$

The foundation approach to capital allocation as described in Basel II uses a loss given default rate of 50%, so this assumption can be used to calculate the implied default rates.

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<sup>2</sup> The 5-year to 1-year mean default ratio of 3.9 is close to the previous version of RiskCalc v1.0 Japan.

### 3 MODEL COMPONENTS

The RiskCalc v3.2 model incorporates several components to determine the EDF credit measure. The inputs to the model include selection of the financial ratios, transforms of those ratios, the inclusion of industry information, and the Credit Cycle Adjustment.

The development of a RiskCalc model involves the following steps:

1. Choosing a limited number of financial statement variables for the model from a list of possible variables.<sup>3</sup>
2. Transforming the variables into interim probabilities of default using non-parametric techniques.
3. Estimate the preliminary weightings of the financial statement variables, using a probit model, combined with industry variables.
4. Creating a (non-parametric) final transform that converts the probit model score into an actual EDF credit measure.

In FSO mode, the models are based on the following functional form:

$$FSO\ EDF = F \left( \Phi \left( \sum_{i=1}^N \beta_i T_i(x_i) + \sum_{j=1}^K \gamma_j I_j \right) \right) \quad (1)$$

Where

$x_1, \dots, x_N$  are the input ratios,

$I_1, \dots, I_K$  are indicator variables for each of the industry classifications,

$\beta$  and  $\gamma$  are estimated coefficients,

$\Phi$  is the cumulative normal distribution,

$F$  and  $T_1, \dots, T_N$  are non-parametric transforms,

and FSO EDF is the financial statement-only EDF credit measure.<sup>4</sup>

The  $T$ s are the transforms of each financial statement variable, which capture the non-linear impacts of financial ratios on the default likelihood, as shown in Figure 4 and discussed in detail later in the document. We refer to  $F$  as the final transform (i.e., the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. We describe the final transform as calibrating the model score to an actual EDF value. The difference between the FSO EDF and the CCA EDF credit measure is that in CCA mode the final transform is adjusted to reflect our assessment of the current stage of the credit cycle, while in FSO mode it remains constant.

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<sup>3</sup> These variables are often ratios of two (or more) financial statement items, but do not always have to be ratios. For example, one measure of profitability is Gross Profit to Total Assets, which is a ratio, and one measure of size is inflation adjusted Net Sales, which is not a ratio.

<sup>4</sup> By non-parametric, we mean that the  $T(x)$  is a continuous function of  $x$  not requiring a specification of a specific closed (or parametric) functional form. We estimate these transforms using a variety of local regression and density estimation techniques.

## 3.1 Financial Statement Variables

### Selecting the Variables

Our variable selection process starts with a list of possible financial statement variables addressing various risk factors. The working list of ratios is divided into groups that represent different underlying concepts regarding a firm's financial status (Table 2). A model is then built with at least one variable per group. When it is possible to enrich the scope of the model in a given category and increase model performance while maintaining model robustness, several variables from each group will be used in the model.

We ask the following questions when deciding which variables to include in the final model:

1. Is the variable readily available?
2. Are the definitions of the inputs to the variable unambiguous?
3. Is the meaning of the variable intuitive?
4. Does the variable predict default activity?
5. Is the variable not highly correlated with other variables in the model?

TABLE 2 Groupings of Financial Statement Ratios

Profitability ratios include net income, net income less extraordinary items, EBITDA, EBIT, and operating profit in the numerator; and total assets, tangible assets, fixed assets and sales in the denominator. → High profitability reduces the probability of default.

Leverage ratios include liabilities to assets and long-term debt to assets. → High leverage increases the probability of default.

Debt coverage is the ratio of cash flow to interest payments or some other measure of liabilities. → High debt coverage reduces probability of default.

Growth variables are typically the change in ROA and sales growth. These variables measure the stability of a firm's performance. → Both rapid growth and rapid decline (negative growth) will increase a firm's default probability.

Liquidity variables include cash and marketable securities to assets, the current ratio and the quick ratio. These variables measure the extent to which the firm has liquid assets relative to the size of its liabilities. → High liquidity reduces the probability of default.

Activity ratios include inventories to sales and accounts receivable to sales. These ratios may measure the extent to which a firm has a substantial portion of assets in accounts that may be of subjective value. For example, a firm with a lot of inventories may not be selling its products and may have to write off these inventories. → A large stock of inventories relative to sales increases the probability of default; other activity ratios have different relationships to default.

Size variables include sales and total assets. These variables are converted into a common currency as necessary and then are deflated to a specific base year to ensure comparability (e.g., total assets are measured in 2001 U.S. dollars). → Large firms default less often.

We choose the same set of variables as RiskCalc v3.1 Japan. Table 3 presents the variables used in the final version of RiskCalc v3.2 Japan. They differ from the variables chosen for RiskCalc Japan v1.0 in three important ways.

- Unlike v3.1, RiskCalc v3.2 Japan contains dynamic factors. As a result, we include two variables that require inputs from the previous year's financial statements: Net Sales Growth and Previous Year's Net Income to Sales.<sup>5</sup> In our experience to date, Net Sales Growth acts as a two-sided indicator, where both declining sales and rapidly increasing sales increase the likelihood of default. Further, including Previous Year's Net Income to Sales controls for the stability of the firm's profits; consistent profitability lowers the probability of default. By including inputs from the previous year's financial statement, the new model uses more information than the previous model, which increases the model's power.
- For the debt coverage variable, we use EBITDA to Interest Expense instead of Gross Profit, as EBITDA is more representative of the firm's actual profitability.
- We include a new variable, Trade Receivables to Net Sales. This variable measures the extent to which the firm carries debt associated with product sales to its customers. A large ratio of trade receivables to sales could indicate a problem associated with collecting on these debts. Trade Receivables is the sum of accounts receivable and notes receivable. In Japan, the classification of trade receivables into one of these groups is somewhat arbitrary and differs by industry. Therefore, we combine accounts receivable and notes receivable in the construction of this ratio.

TABLE 3 Financial Statement Variables used in RiskCalc v3.2 Japan

Category	Variable
Activity	Inventory to Net Sales Trade Receivables to Net Sales
Debt coverage	EBITDA to Interest Expense
Growth	Net Sales Growth
Leverage	Total Liabilities less Cash to Total Assets Retained Earnings to Total Liabilities
Liquidity	Cash to Total Assets
Profitability	Gross Profit to Total Assets Previous Year Income to Previous Year Net Sales
Size	Real Net Sales

### Variable Transforms

After the variables are selected, they are transformed into a preliminary EDF value, Figure 4 presents the transformations used in the model. The horizontal axis gives the percentile score of the ratio, and the vertical axis gives the default probability of that ratio in isolation (univariate). The percentile score represents the percent of the database that had a ratio or level below that of the company (e.g., if ROA is in the 90th percentile, then 90% of the sample had an ROA lower than that firm).

The shape of the transformation indicates how significantly a change in level impacts the EDF value. If the slope of the transform is steep, a small change will have a larger impact on risk than if the slope were flat.

- For the **Profitability** group, we include Gross Profit to Total Assets and Previous Year Net Income to Sales. The Gross Profit to Total Assets transform is downward-sloping, and the slope becomes smaller as Gross Profit to Total Assets becomes large. This transform indicates that more profitable firms have lower default probabilities, but the impact of Gross Profit to Total Assets on default probabilities diminishes as Gross Profit to Total Assets increases. Previous Year Net Income to Previous Year's Sales has more of an S-shaped transform, implying that low levels of profitability in the previous year can increase default likelihood, and that a higher level of previous year profitability reduces the default likelihood. In addition, there is a range between the 40<sup>th</sup>–60<sup>th</sup> percentiles where the default likelihood is highly sensitive to the previous year's profitability.

<sup>5</sup> More precisely, the variable is previous year's net income to previous year's sales.

- For the **Leverage** group, we include two variables: Total Liabilities less Cash to Total Assets and Retained Earnings to Total Liabilities. Large values of Retained Earnings to Total Liabilities lower default probabilities, while large values of Total Liabilities less Cash to Total Assets increase default probabilities.
- For the **Liquidity** group, Cash to Assets is downward-sloping, indicating that higher values of this ratio are associated with lower default probabilities.
- For the **Activity** group, the ratios are Inventories to Sales and Trade Receivables to Sales. Both are upward-sloping, indicating that high values of these ratios are associated with higher default probabilities. Both of these variables exhibit a threshold effect. Increases in these variables do not have significant impact on the likelihood of default until around the 60<sup>th</sup> percentile.
- The **Size** variable is Sales. This variable's transformation is downward-sloping.
- The **Debt Coverage** variable is EBITDA to Interest Expense. This variable is downward-sloping, indicating that large values of EBITDA relative to interest expense lower the probability of default.
- The **Growth** variable is Sales Growth. It is U-shaped, indicating that large increases or decreases in sales are associated with higher default probabilities.

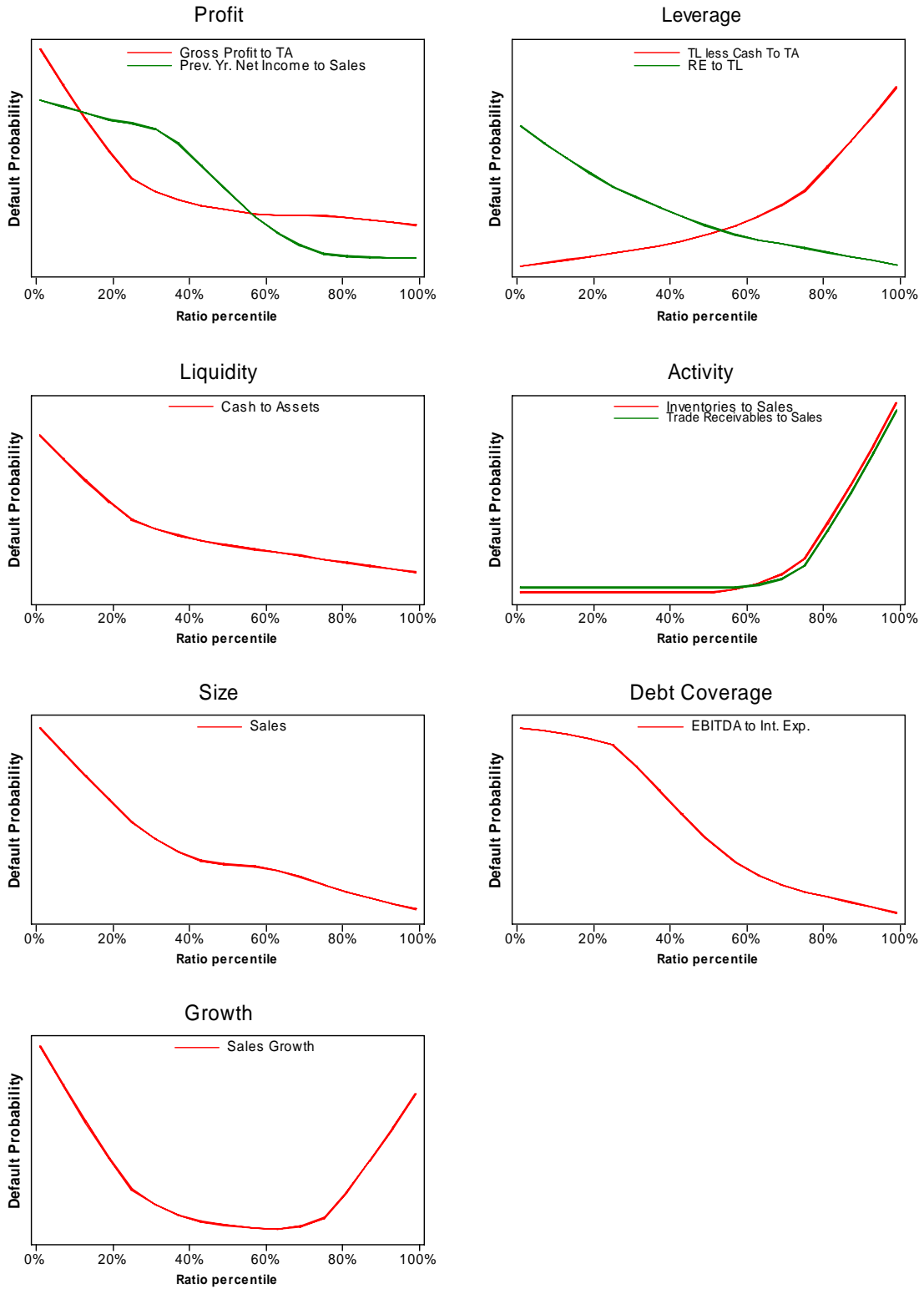


FIGURE 4 Transformations of Financial Statement Variables in RiskCalc v3.2 Japan

## 3.2 Model Weights

### Importance

Financial analysts are interested in the relative importance of different factors that comprise the model (e.g., profitability vs. liquidity, and leverage vs. debt coverage). Due to the non-linear nature of the model, describing the relative importance of different variables in the model is complicated. For example, the EDF value of a firm is very sensitive to Gross Profit to Total Assets if the firm has low levels of profitability. If the firm has high levels of Gross Profit to Total Assets, however, the sensitivity of its EDF to profitability is considerably smaller (Figure 4).

### Calculation of Weights

We developed the following methodology to describe the relative importance of a variable in the model on average. After transforming the variables using the transforms in Figure 4, we compute the EDF value for a theoretical firm with all its variables at the average values. The variables are then increased one at a time by one standard deviation. The EDF level change for each variable (in absolute value) is computed. The relative weight of each variable is then calculated as this change divided by the sum of the changes for each variable. This gives the variable with the largest impact on the EDF level the largest weight, and the variable with the smallest impact on the EDF level the smallest weight. The weights of each variable sum to 100% by construction. The weight of each category is the sum of the weights of each variable in that category.

In developing the RiskCalc v3.2 Japan model, we keep the same variables and inputs as v3.1 after examining the robustness of each ratio's prediction power in the new data. The new model has been "re-weighted" according to the new data, reflecting the new credit environment that is beyond the coverage of the RiskCalc v3.1 Japan development data. As shown in Table 1, the new model has an additional four years of data, including the period between 2003 and 2005.

Table 4 presents the weights in RiskCalc v3.1 Japan and RiskCalc v3.2 Japan. The most important categories continue to be Leverage and Debt Coverage, whose importance increased, as did that of the Growth group. The importance of Liquidity, Profitability, and Activity decreased, while Size remained approximately the same.

TABLE 4 Risk Factors: RiskCalc v3.1 Japan vs. RiskCalc v3.2 Japan

RiskCalc v3.1 Japan		RiskCalc v3.2 Japan	
Risk Factors	Weight	Risk Factors	Weight
<b>Leverage</b> Liabilities less Cash to Assets Retained Earnings to Total Liabilities	26%	<b>Leverage</b> Liabilities less Cash to Assets Retained Earnings to Total Liabilities	28%
<b>Debt Coverage</b> EBITDA to Interest Expense	22%	<b>Debt Coverage</b> EBITDA to Interest Expense	25%
<b>Activity</b> Inventory to Net Sales Trade Receivables to Net Sales	13%	<b>Activity</b> Inventory to Net Sales Trade Receivables to Net Sales	12%
<b>Liquidity</b> Cash to Total Assets	16%	<b>Liquidity</b> Cash to Total Assets	16%
<b>Profitability</b> Gross Profit to Total Assets Previous Year's Net Income to Sales	12%	<b>Profitability</b> Gross Profit to Total Assets Previous Year's Net Income to Sales	11%
<b>Growth</b> Net Sales Growth	8%	<b>Growth</b> Net Sales Growth	9%
<b>Size</b> Net Sales	3%	<b>Size</b> Net Sales	3%

### 3.3 Industry Adjustments

While the variables included in the RiskCalc model explain most of the risk factors, the relative importance of the variables can be different among industries. In the FSO mode of RiskCalc v3.2 Japan, the EDF value is adjusted for industry effects. Table 5 presents the increase in model power and accuracy from introducing industry controls into the FSO model. Both the power and the accuracy of the EDF credit measure increase, as measured by the accuracy ratio (AR) and the gain in log likelihood. The significance of the gain in likelihood indicates that the industry controls are especially important in producing an accurate EDF credit measure. Table 6 presents the average EDF value by industry for the development sample.

TABLE 5 Increase in Model Power and Accuracy from Introducing Industry Controls

FSO Mode	1-year model		5-year model	
	Accuracy Ratio	P-value of Relative Gain in Log Likelihood	Accuracy Ratio	P-value of Relative Gain in Log Likelihood
Without industry controls	59.6%	---	47.3%	---
With industry controls	61.0%	<0.0001	49.3%	<0.0001

In this table, and hereafter, AR is the measure of the model's ability to rank order credits. Increases in log likelihood, on the other hand, measures the extent to which the model's EDF values match observed default rates.<sup>6</sup>

TABLE 6 Average EDF in Development Sample by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Business Products	1.25%	5.12%
Construction	1.49%	6.27%
Consumer Products	2.51%	9.50%
Communication and High Tech	1.87%	7.80%
Mining, Transportation, and Utilities	1.51%	6.07%
Services	2.32%	9.08%
Trade	1.54%	6.31%
Unassigned	2.32%	8.57%

### 3.4 Credit Cycle Adjustment

The existence of a credit cycle is a known factor to market participants and can easily be observed by episodes of elevated default activity. Further, elevated rates of default activity are generally associated with recessions.

The CCA mode of the RiskCalc v3.2 Japan model includes a Credit Cycle Adjustment factor in addition to the FSO component. The CCA is designed to incorporate an assessment of the current stage of the credit cycle into our estimate of private firm default risk.

<sup>6</sup> For further details, see Dwyer and Stein (2004), Technical Document on RiskCalc v3.1 Methodology.

## Selecting an Adjustment Factor

Incorporating a Credit Cycle Adjustment into the model is challenging for several reasons. There are many possible indicators of the credit cycle, but there is no conclusive evidence about which ones to choose. Further complicating this task is the fact that there are few credit cycles with which to test these indicators.

In building our Credit Cycle Adjustment, we draw on the Moody's KMV public firm model to provide a forward-looking measure of default risk. For public firms throughout the world, our model provides an option-theoretic assessment of its default risk by calculating its distance-to-default. This measure is specifically designed to be a forward-looking indicator of default risk. It extracts signals of default risk from the stock market performance of individual firms, and has been extensively validated.<sup>7</sup>

A calculation of DD measure necessitates the availability of equity prices at the firm level, so we cannot calculate it directly for private firms. Accordingly, we implement the Credit Cycle Adjustment in the following way: if the level of DD for public firms in a given industry group increases, then private firms' EDF values in the industry are adjusted downward. Conversely, if the level of DD for the public firms in an industry decreases vis-à-vis the historical average for that industry, the private firms' EDF values in that industry are adjusted upward.

## Adjustment Factor Used in the Model

To elaborate, the fitting of CCA is based on empirical data. For the RiskCalc v3.2 Japan model, the DD factor is based on an aggregation of all public Japanese firms in the corresponding industry. If a firm cannot be associated with a specific industry, the model uses a Credit Cycle Adjustment that is based on an aggregation of all public Japanese firms for that firm.

When the Credit Cycle Adjustment factor is neutral, the CCA EDF coincides with the FSO EDF. This relationship does not necessarily imply that the average of the CCA EDF on any particular sample will equal the average of the FSO EDF, as the relationship between CCA and FSO is nonlinear, and the selected sample may not cover a sufficient historical window to contain a complete credit cycle.

Figure 5 presents the DD factor for public Japanese firms against the real GDP growth rates (blue line). The DD factor increases with the growth of GDP. Grey areas indicate business cycle peak-to-trough dates from ECRI.

Figure 6 presents the inverted DD factor against the median of the option-adjusted spreads on Japanese bonds. The DD factor has been inverted so that large positive factors are associated with elevated risk. The spreads generally coincide with the DD factor, but for 2006–2009, the DD factor increases in anticipation of the spreads.

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<sup>7</sup> cf. Bohn and Crosbie, 2003, and Dwyer and Korablev, 2007.

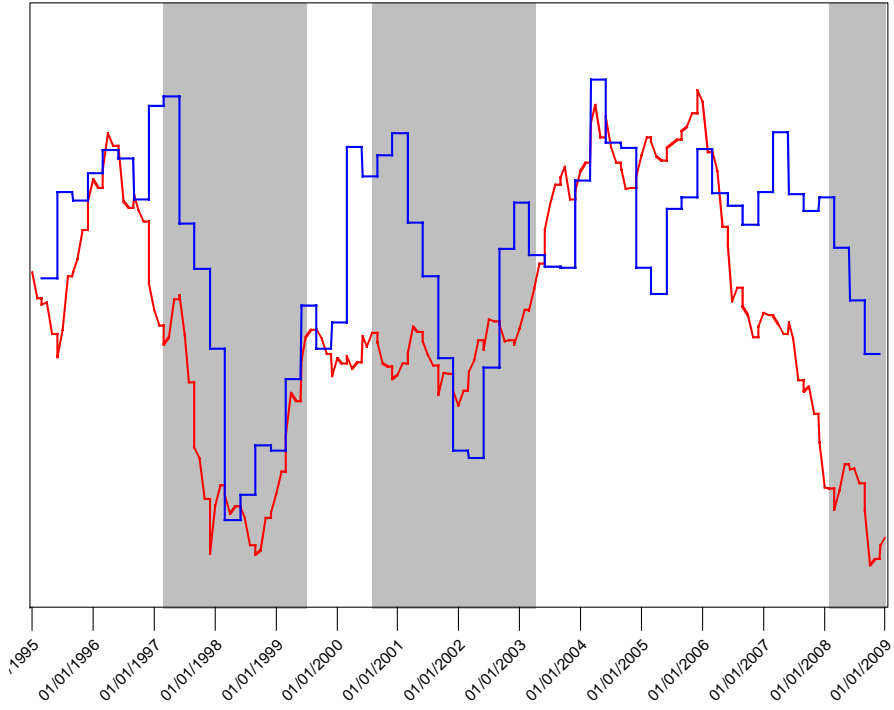


FIGURE 5 DD Factor in Japanese and the GDP Growth Rates:1995–2009

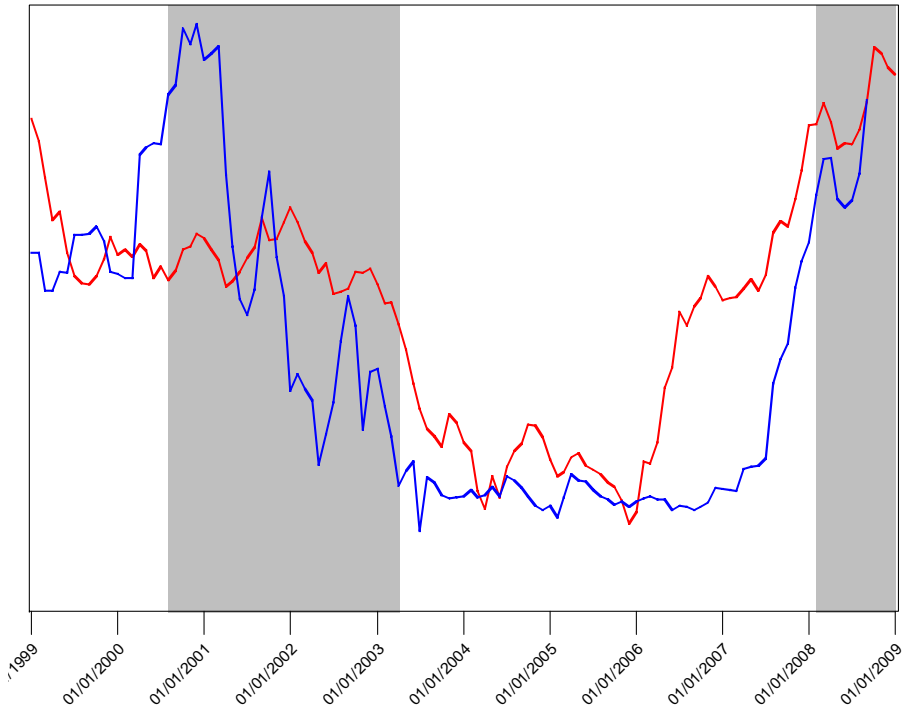


FIGURE 6 Inverted DD Factor in Japanese & Option-adjusted Spreads on Japanese Bonds: 1999–2009

## 4 VALIDATION RESULTS

In this section, we present testing results on the model's ranking power, and the accuracy of its predicted EDF credit measure over two sets of samples: the new data sample and the overall full sample. We also present the results of Moody's KMV model robustness and stability tests. These tests examine the independent variable correlation matrices and variance inflation factors to ensure that the model does not contain excessive multicollinearity.

The results show that the model is uniformly more powerful than other models across different time periods, sectors, and size classifications.

### 4.1 Model Power and Accuracy

In Japan, we performed rank order validation of the model in both CCA and FSO modes. As in other countries, data issues can complicate the interpretation of AR differences between these modes. Therefore, we focus on whether the new model outperforms the old model and other benchmarks in both modes. Changes in the DD, the legal environment, or simply the process of collecting defaults can skew AR difference between the two modes. Also, during 2001–2005 in Japan, loans that had been performing poorly for an extended period were written off. We present the overall AR for the power tests across periods, sectors, and size classifications. We also present AR for the FSO model relative to RiskCalc v3.1 FSO and Z-score. Power comparisons by cut are often more robust to data issues described above when done in the FSO mode of the model.

Table 7 presents the in-sample overall measures of power for RiskCalc v3.2 Japan versus alternative models over the new data sample.<sup>8</sup> Table 7 also contains p-values for the statistical test showing how the difference between the accuracy ratio from v3.2 and the benchmark is less than or equal to zero. A p-value of less than .05 indicates we can reject the hypothesis that the difference in the accuracy ratios is less than or equal to zero with 95% confidence.

The new RiskCalc v3.2 model outperformed the Z-score model by more than 30 percentage points at the 1-year horizon, and 23 percentage points at the 5-year horizon.<sup>9</sup>

TABLE 7 Overall Power of the New RiskCalc v3.2 Japan Model—New Data Sample

Mode	1-year Model		5-year Model	
	Accuracy Ratio	P-value of Relative Gain of v3.2 over alternatives	Accuracy Ratio	P-value of Relative Gain of v3.2 over alternatives
RiskCalc v3.2	58.0%	---	48.5%	---
RiskCalc v3.1	56.6%	<.0001	46.9%	<.0001
RiskCalc v1.0	54.3%	<.0001	44.4%	<.0001
Z-score	27.2%	<.0001	25.5%	<.0001

Figure 7 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 7. It shows the power improvements of RiskCalc v3.2 FSO, RiskCalc v3.1, and the Z-score. These power improvements are uniformly significant across different regions of the distribution relative to Z-score.

<sup>8</sup> With the credit cycle adjustment, the model's performance improves by three percentage points of accuracy ratio at the 5-year horizon (51.6 versus 48.5), but loses almost five percentage points at the 1-year horizon compared with RiskCalc v3.2 FSO (53.1 versus 58.0).

<sup>9</sup> Altman, Hartzell and Peck, 1995.

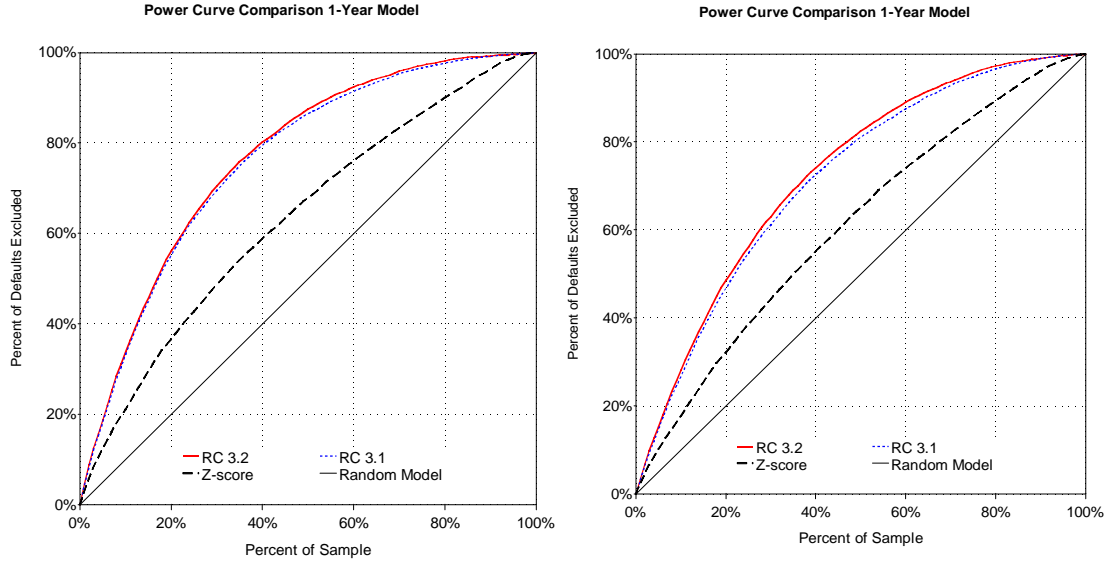


FIGURE 7 Power of Alternative Models (1- and 5-year)—Japan New Data Sample

Table 8 presents the in-sample overall measures of power for the RiskCalc v3.2 Japan model versus alternative models over the full sample. With the Credit Cycle Adjustment, model performance improves by about one percentage point of accuracy ratio at the 5-year horizon. However, compared with RiskCalc v3.2, there is approximately a one percentage point loss at the 1-year horizon. Table 8 also contains p-values for the statistical test showing how the difference between the accuracy ratio from v3.2 and the benchmark is less than or equal to zero.

For the overall sample, the new RiskCalc v3.2 model outperformed the Z-score model by more than 30 percentage points at the 1-year horizon, and t25 percentage points at the 5-year horizon.<sup>10</sup>

TABLE 8 Overall Power of the new RiskCalc v3.2 Japan Model—Full Sample

Mode	1-year Model		5-year Model	
	Accuracy Ratio	P-value of Relative Gain over v3.2 in Log Likelihood	Accuracy Ratio	P-value of Relative Gain over v3.2 in Log Likelihood
RiskCalc v3.2	61.0%	---	49.3%	---
RiskCalc v3.1	60.9%	0.1152	47.7%	<.0001
RiskCalc v1.0	59.0%	<.0001	48.6%	<.0001
Z-score	29.7%	<.0001	24.7%	<.0001

Figure 8 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 8. It shows the power improvement of RiskCalc v3.2, RiskCalc v3.1, and the Z-score. These power improvements are uniformly significant across different regions of the distribution relative to Z-score.

<sup>10</sup> Altman, Hartzell and Peck, 1995.

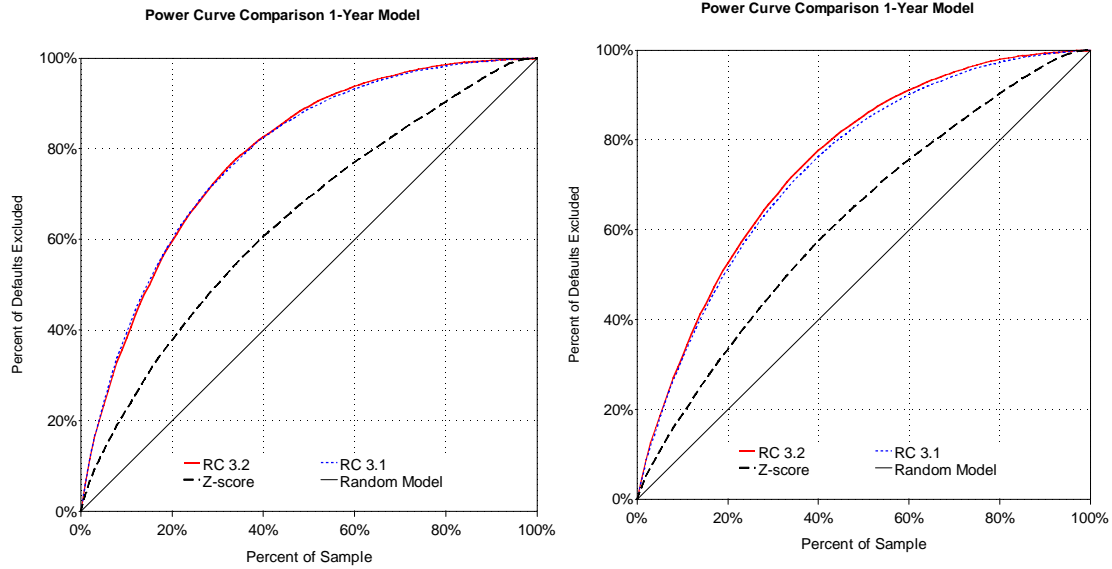


FIGURE 8 Power of Alternative Models (1- and 5-year)—Japan, Full Sample

## 4.2 Correlations and Variance Inflation Factors

In this section, we present the correlation coefficients (Table 9) for the model ratios and the variance inflation factors (Table 10). These analyses check for excessive multicollinearity in the model.<sup>11</sup>

Table 9 displays the Spearman Rank correlation coefficients computed on the transformed variables as they enter into the probit regression (Figure 4). The highest correlation coefficient is between Retained Earnings to Total Liabilities and Total Liabilities less Cash to Total Assets. The correlation coefficient is 0.66. The second highest (0.34) is between Retained Earnings to Total Liabilities and Previous Year Net Income to Net Sales. Such coefficients are below what we would consider indications of multicollinearity that would typically cause concern. This is also verified by the Variance Inflation Factors (VIF) analysis below.

<sup>11</sup> For further details on the definitions and how to interpret these analyses, refer to the Technical Document.

TABLE 9 Correlations Among the Transformed Input Factors (Spearman Rank)

	Inventory to Net Sales	EBITDA to Interest Expense	Sales Growth	TL less Cash to TA	Cash to TA	Gross Profit to TA	RE to TL	Trade Receivables to Sales	Prev. Yr Net Income to Sales	Real Net Sales
Inventory to Net Sales	1.00									
EBITDA to Interest Expense	0.18	1.00								
Net Sales Growth	0.13	0.17	1.00							
Total Liabilities less Cash to Total Assets	0.06	0.26	0.08	1.00						
Cash to Total Assets	0.06	0.12	0.02	0.61	1.00					
Gross Profit to Total Assets	0.14	0.19	0.09	0.17	0.29	1.00				
Retained Earnings to Total Liabilities	0.06	0.37	0.11	0.66	0.27	0.12	1.00			
Trade Receivables to Net Sales	0.09	0.07	0.08	0.05	0.08	0.11	0.05	1.00		
Previous Year Net Income to Net Sales	0.06	0.33	0.06	0.22	0.07	0.02	0.34	0.04	1.00	
Real Net Sales	-0.02	0.21	0.14	0.30	0.27	0.12	0.30	0.02	0.00	1.00

Table 10 presents the Variance Inflation Factors for the financial statement variables in the model. The VIF values represent how much of the variation in one independent variable can be explained by all other independent variables in the model, which is in contrast to the pair-wise correlation coefficients in Table 9 that show how closely two variables move together. As Table 10 illustrates, in the case of all model variables the estimated VIF values are notably below 4, thus below the commonly used threshold levels in VIF analysis when testing for presence of multicollinearity.<sup>12</sup> Thus, the findings strongly indicate that the model variables do not present any substantial multicollinearity.

<sup>12</sup> As Woolridge (2000) shows VIF is inversely related to the tolerance value ( $1-R^2$ ), such that a VIF of 10 corresponds to a tolerance value of 0.10. Clearly, any threshold is somewhat arbitrary and depends on the sample size. Nevertheless, if any of the  $R^2$  values are greater than 0.75 (so that VIF is greater than 4.0), we would typically suspect that multicollinearity might be a problem. If any of the  $R^2$  values are greater than 0.90 (so that VIF is greater than 10) we then conclude that multicollinearity is likely a serious problem.

TABLE 10 Variance Inflation Factors

Variable	VIF
Total Liabilities less Cash to Total Assets	2.78
Retained Earnings to Total Liabilities	2.13
Cash to Total Assets	1.86
EBITDA to Interest Expense	1.35
Real Net Sales	1.33
Gross Profit to Total Assets	1.26
Lag Net Income to Lag Net Sales	1.24
Inventory to Net Sales	1.13
Net Sales Growth	1.07
Trade Receivable to Net Sales	1.03

### 4.3 Model Power by Industry and Size Groups

It is important to test the power of a model not only overall, but also among different industry segments and firm sizes. To address these issues, we conduct a series of model power tests by industry and size. We also include the power of Z-score for reference. The results are summarized for short- and long-term horizons in Table 11 through Table 14.

Table 11 and Table 12 present the power comparisons by sector for the 1-year and 5-year models, respectively. At both horizons, RiskCalc v3.2 outperforms both RiskCalc v3.1 and Z-score across industries. The highest power in the 1-year model (Table 11) is found in Business Products and Construction (66.0%), while the lowest is found in Services (55.6%). At the 5-year horizon (Table 12), the highest power is in Business Products (53.8%) and the lowest is in Services (45.6%).

TABLE 11 Model Power by Industry: 1-Year model

	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
Business Products	11.2%	66.0%	62.8%	35.9%
Construction	4.4%	66.0%	64.8%	44.4%
Consumer Products	13.6%	60.6%	59.7%	21.5%
Communication and High Tech	10.1%	63.1%	61.5%	30.4%
Mining, Utilities, and Transportation	5.3%	64.5%	62.1%	31.0%
Services	16.3%	55.6%	55.5%	30.6%
Trade	9.8%	63.2%	62.0%	26.6%

TABLE 12 Model Power by Industry: 5-Year model

	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
Business Products	11.2%	53.8%	51.1%	32.0%
Construction	4.5%	49.8%	49.3%	32.4%
Consumer Products	13.6%	46.6%	46.2%	18.4%
Communication and High Tech	10.3%	47.3%	46.1%	25.4%
Mining, Utilities, and Transportation	5.2%	53.0%	52.3%	28.8%
Services	16.1%	45.6%	44.7%	27.3%
Trade	9.8%	50.4%	49.8%	22.3%

Table 13 and Table 14 present the power comparisons by Total Assets (in 2002 Japanese yen) for the 1-year and 5-year models, respectively. At both horizons, RiskCalc v3.2 outperforms both RiskCalc v3.1 and Z-score in all size groups except the smallest one, with total assets less than 150 million Japanese yen. At both the 1-year and 5-year horizons, the highest power is found in the largest firms, and the lowest power is in the smallest firms under ¥150 million in assets. This finding is not surprising because the quality of financial statements generally increases with firm size. For example, larger firms are more likely to have audited statements.

TABLE 13 Model Power by Size (Total Assets in 2002 Japanese yen): 1-Year model

Range	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
< 150mm	16.3%	57.9%	59.9%	27.4%
¥150-350mm	21.2%	61.0%	61.2%	30.7%
¥350-1 billion	28.3%	62.6%	61.6%	31.8%
¥1-2.5 billion	18.2%	61.7%	59.8%	26.2%
> ¥2.5 billion	16.0%	62.2%	60.1%	24.3%

TABLE 14 Model Power by Size (Total Assets in 2002 Japanese yen): 5-Year model

Range	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
< 150mm	17.5%	44.9%	44.0%	20.8%
¥150-350mm	22.0%	49.1%	47.2%	23.0%
¥350-1 billion	27.8%	50.7%	48.8%	24.9%
¥1-2.5 billion	18.0%	52.5%	50.1%	27.9%
> ¥2.5 billion	14.6%	53.3%	51.3%	29.1%

Table 15 and Table 16 present the power comparisons by Net Sales (in 2002 Japanese yen) for the 1-year and 5-year models, respectively. Similar to the power cut by total assets, RiskCalc v3.2 outperforms both RiskCalc v3.1 and Z-score in all size groups except the smallest one, with net sales less than 150 million Japanese yen.

TABLE 15 Model Power by Size (Net Sales in 2002 Japanese yen): 1-Year model

Range	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
< 150mm	22.0%	54.3%	56.2%	22.3%
¥150-350mm	19.9%	62.1%	63.1%	27.9%
¥350-1 billion	27.6%	65.1%	64.5%	30.8%
¥1-2.5 billion	17.1%	62.1%	60.1%	30.7%
> ¥2.5 billion	13.3%	61.1%	58.0%	32.6%

TABLE 16 Model Power by Size (Net Sales in 2002 Japanese yen): 5-Year model

Range	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
< 150mm	20.2%	49.4%	48.4%	17.0%
¥150-350mm	20.9%	54.0%	53.1%	24.0%
¥350-1 billion	27.9%	55.2%	53.8%	26.9%
¥1-2.5 billion	18.2%	54.6%	52.5%	30.2%
> ¥2.5 billion	12.8%	50.3%	47.9%	27.3%

#### 4.4 Power Performance over Time

Because models are implemented at various points in time in a business cycle, we conducted model power tests by year to examine whether the model performance is excessively time-dependent or exhibits big swings in power depending on time.

Table 17 and Table 18 present the results from this analysis at the 1- and 5-year horizons, respectively. The AR of RiskCalc v3.2 is compared with RiskCalc v3.1 and Z-score for each year. At the 1-year horizon, RiskCalc v3.2 outperforms both RiskCalc v3.1 except during the period of 1997–2000. It outperforms Z-score by a sizeable margin for all years. At the 5-year horizon, RiskCalc v3.2 consistently outperforms both RiskCalc v3.1 and Z-score for all years.

TABLE 17 Model Power Over Time: 1-Year Horizon

Year	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
1992	0.5%	65.8%	65.8%	26.3%
1993	1.8%	66.9%	64.7%	30.6%
1994	2.3%	66.0%	64.9%	30.8%
1995	5.1%	67.9%	67.0%	32.4%
1996	7.2%	62.6%	62.2%	30.9%
1997	8.3%	60.0%	60.3%	32.3%
1998	7.8%	64.0%	65.2%	35.3%
1999	5.9%	63.2%	66.3%	37.4%
2000	5.9%	58.9%	61.8%	30.5%
2001	16.2%	62.8%	61.9%	28.1%
2002	14.2%	60.6%	59.7%	26.9%
2003	8.0%	54.1%	52.7%	22.1%
2004	8.3%	52.5%	50.6%	24.8%
2005	8.7%	53.9%	51.8%	31.2%

TABLE 18 Model Power over Time: 5-year model

Year	Percentage of Defaults	AR RiskCalc v3.2	AR RiskCalc v3.1	AR Z-score
1992	1.8%	58.6%	56.7%	29.2%
1993	2.6%	56.9%	54.9%	26.6%
1994	3.9%	55.4%	54.1%	26.4%
1995	8.6%	55.9%	54.9%	28.8%
1996	9.3%	55.3%	54.2%	28.6%
1997	9.5%	53.4%	52.3%	30.7%
1998	8.3%	54.0%	53.1%	31.1%
1999	6.5%	53.2%	51.9%	31.6%
2000	4.5%	55.2%	54.0%	30.0%
2001	13.7%	55.9%	54.5%	24.6%
2002	12.7%	50.3%	48.8%	23.1%
2003	8.1%	44.3%	41.4%	19.6%
2004	6.2%	47.4%	44.1%	22.9%
2005	4.3%	54.3%	51.0%	28.8%

## 4.5 Model Calibration and Implied Ratings

As many credit analysts are trained to differentiate credit quality in terms of letter grades, in order to assist the interpretation of an EDF, we map the EDF credit measures to .edf ratings (an EDF-implied letter grade) utilizing Moody's bond default studies. All RiskCalc v3.1 models (or latter versions) to date have used the same mapping. This mapping is designed with the following considerations:

- There is a large range of .edf ratings (as required for economic and regulatory applications).
- No one rating contains too many credits (as required for economic and regulatory applications).
- The distribution of the 5-year ratings is approximately the same as the distribution of 1-year ratings (for consistency with rating-based analysis applications).
- The EDF credit measure associated with an .edf rating is approximately the same as the observed historical default rate associated with a Moody's Bond Rating (for consistency with rating-based analysis applications).

Figure 9 shows the distribution of CRD observations by rating category in the development sample (for the Credit Cycle-Adjusted EDF values over the full time period). Note that 13 categories between A1 and Caa/C are utilized, and that less than 14% of the observations are in any one category. For both the 1-year and 5-year models, the distribution peaks at Ba1. While not reported here, other research has shown that the distribution of the credit cycle adjusted .edf ratings changes over time with the credit cycle while the distribution of the FSO .edf ratings remains relatively stable over time.

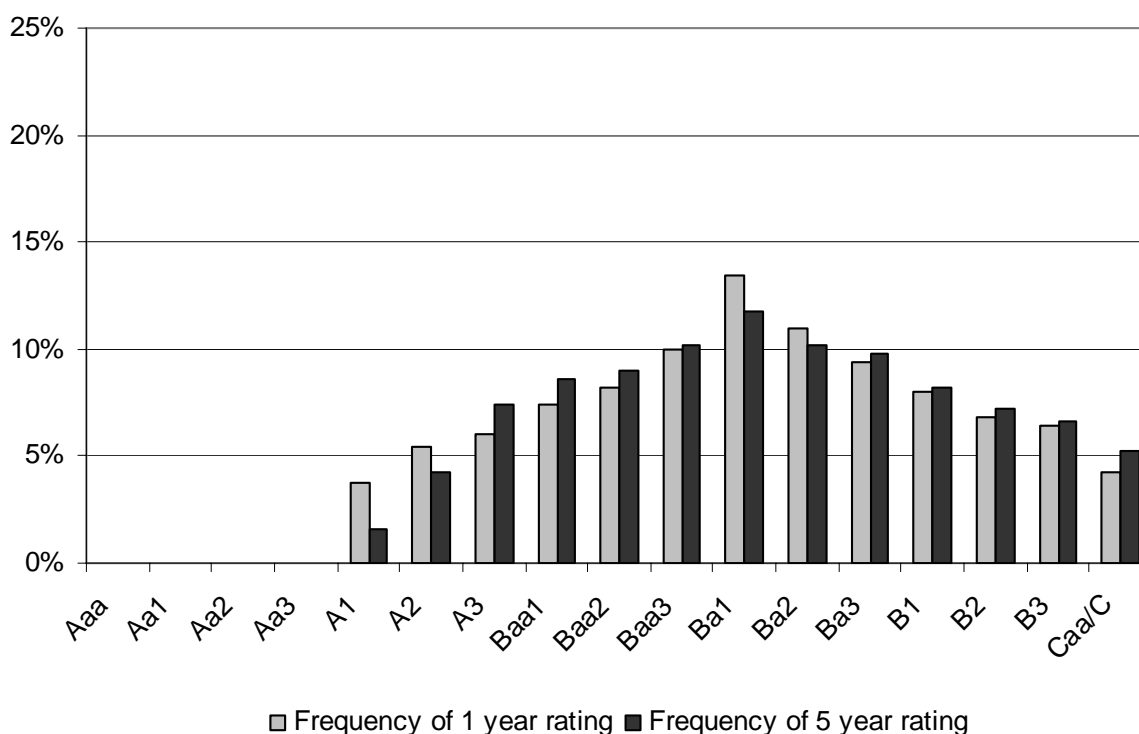


FIGURE 9 EDF-implied Ratings for the 1- and 5-year Models in the Development Sample

## 4.6 New Data Validation

Table 19 compares new data received in October 2008 with the RiskCalc v3.2 Japan development sample information.

TABLE 19 Information on New Private Firm Sample Data

Japanese Private Firms	New Data	RiskCalc v3.2 Japan
Financial statements	36,000+	955,000+
Unique number of firms	33,000+	201,000+
Defaults	420+	12,000+
Time period	2006-2008	1992-2005

We ran the data through both RiskCalc Japan v3.2 and v3.1 in order to examine the performance of v3.2 versus v3.1. Table 20 and Figure 10 shows the overall power performance of v3.2 versus v3.1. The new model has significant power gains over v3.1.

TABLE 20 Overall Power of the RiskCalc v3.2 Japan 1-year Model—New Data

Model	1-year Model	
	Accuracy Ratio	P-value of Relative Gain over v3.2 in Log Likelihood
RiskCalc v3.2	59.5%	---
RiskCalc v3.1	57.9%	<.0001

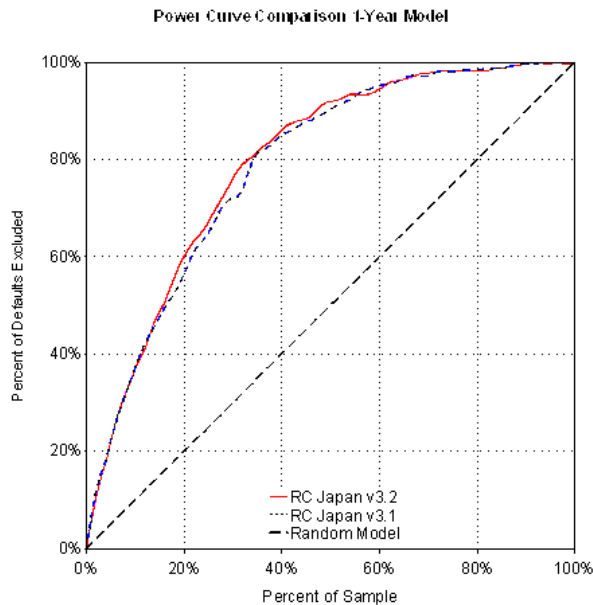


FIGURE 10 Power of Alternative Models (1-year): Newly Received Data

## 5 FURTHER MODEL IMPROVEMENTS

In this section, we briefly outline some other improvements to the model.<sup>13</sup>

### 5.1 Continuous Term Structure

The previous version of the RiskCalc model provided the user two discrete default probability estimates: a 1-year and a 5-year EDF credit measure. In this version, utilizing the two point estimates for 1- and 5-year estimates we fit a Weibull function, and thus achieve a continuous term structure of EDF values for each credit. In other words, users of RiskCalc v3.2 Japan now can obtain EDF values for any point between one and five years. In addition, RiskCalc v3.2 provides EDF values for alternative definitions, such as the Forward EDF and the Annualized EDF (Table 21).

#### Cumulative EDF Credit Measures

A cumulative EDF credit measure gives the probability of default over that time period. For example, a five-year cumulative EDF credit measure of 13.44% means that that company has a 13.44% chance of defaulting over that five-year period. The second column of Table 21 provides an example of the cumulative 1- to 5-year credit measures produced by the model.

#### Forward EDF Credit Measures

The forward EDF is the probability of default between  $t-1$  and  $t$ , conditional upon survival until  $t-1$ . In other words, the 4-year Forward EDF credit measure is the probability that a firm will default between years 3 and 4,

<sup>13</sup> For a detailed discussion of these improvements, refer to the Technical Document.

assuming the firm survived to year 3.<sup>14</sup> The third column of Table 21 displays the forward 1- to 5-year EDF credit measures derived from the cumulative EDF values.

### Annualized EDF Credit Measures

The annualized EDF credit measure is the cumulative EDF value for a given period, stated on a per year basis. For example, a company with a cumulative 5-year EDF credit measure of 13.44% would have a 5-year annualized EDF of 2.84%.<sup>15</sup> This means that the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column of Table 21 presents the annualized EDF credit measures for years 1 to 5. These credit measures are derived from the cumulative EDF values.

TABLE 21 Term Structure of EDF Credit Measures: An Example

EDF	Cumulative	Forward	Annualized
Year 1	4.23	4.23	4.23
Year 2	7.00	2.90	3.57
Year 3	9.37	2.55	3.23
Year 4	11.49	2.34	3.01
Year 5	13.44	2.20	2.84

## 5.2 New Analytical Tools

The RiskCalc v1.0 application provides users an analytical tool to gauge the relative impact of each variable—as a deviation from the mean of each ratio. To equip users with further tools, we developed relative sensitivities (also known as sensitivity multiples), which exhibit the EDF sensitivity to each of the model variables at the point of evaluation. This feature is especially useful when addressing the topic of identifying variables to improve the EDF value of a company.

The relative sensitivity gives the impact of a small change in a variable on the EDF level of the company. It indicates which variables are most sensitive to an increase. A positive number means an increase in the variable will increase risk and a negative number will decrease risk. The percentile is the sensitivity of the variable relative to the average.

For example, a small increase in the activity ratio (Trade Receivables/Net Sales) will change the risk of the company. It is about 300% (1 year) as sensitive as the average variables (Figure 11).

<sup>14</sup> Specifically,  $FEDF_{t,t} = (CEDF_t - CEDF_{t-1}) / (1 - CEDF_{t-1})$ , where  $FEDF_{t,t}$  is the forward EDF credit measure from years  $t-1$  to  $t$ , and  $CEDF_t$  is the cumulative EDF credit measure for year  $t$ .

<sup>15</sup> Specifically,  $AEDF_t = 1 - (1 - CEDF_t)^{1/t}$ , where  $AEDF_t$  is the annualized EDF credit measure for year  $t$ .

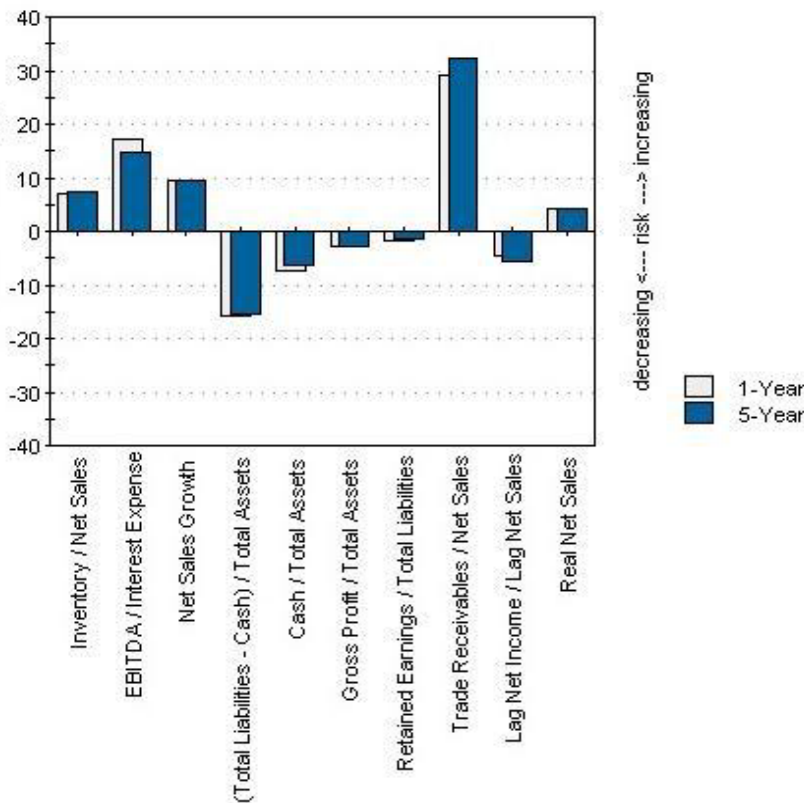


FIGURE 11 Relative Sensitivities for the RiskCalc v3.2 Japan Model

### 5.3 Asset Value and Volatility Calculation

One of the features of the PFM model that is appreciated by users is an implied asset value and an estimate of the firm's volatility. This feature is useful for example in analyzing IPO activities. In order to address this question, as an add-on to the model we estimate the asset volatility of the firm using its industry and size and a methodology that is very similar to the PFM model. We then use a structural model framework to solve for the implied asset value from the estimated EDF value, the estimated volatility, and the firm's liability structure.

### 5.4 Percentile Map

The percentile map feature allows users to quickly isolate the problematic ratios for a given company. As shown in Figure 12, each horizontal bar represents a ratio that is labeled on the left (e.g., Lag Income to Lag Sales). The column on the right displays the actual value of the ratio. The percentage number within the horizontal bar graph represents the percentile of the ratio within the development sample (e.g., 92.6% of the development sample had a prior year Net Income to Sales ratio of less than 4.66%). The shading represents the risk level associated with the ratio: green is low risk, red is high risk and grey is neutral risk. The variables shaded red to green represent “good” ratios for which high values lower risk, while the variables shaded green to red represent “bad” ratios for which high values increase risk. Net Sales growth is shaded red to green to red. This demonstrates that both high and low values of sales growth indicate high risk, while moderate sales growth indicates low risk. For this hypothetical firm, the problematic ratios are EBITDA to Interest Expense, Cash to Assets, Gross Profits to Assets, Net Sales Growth, and Total Liabilities less Cash to Total Assets.

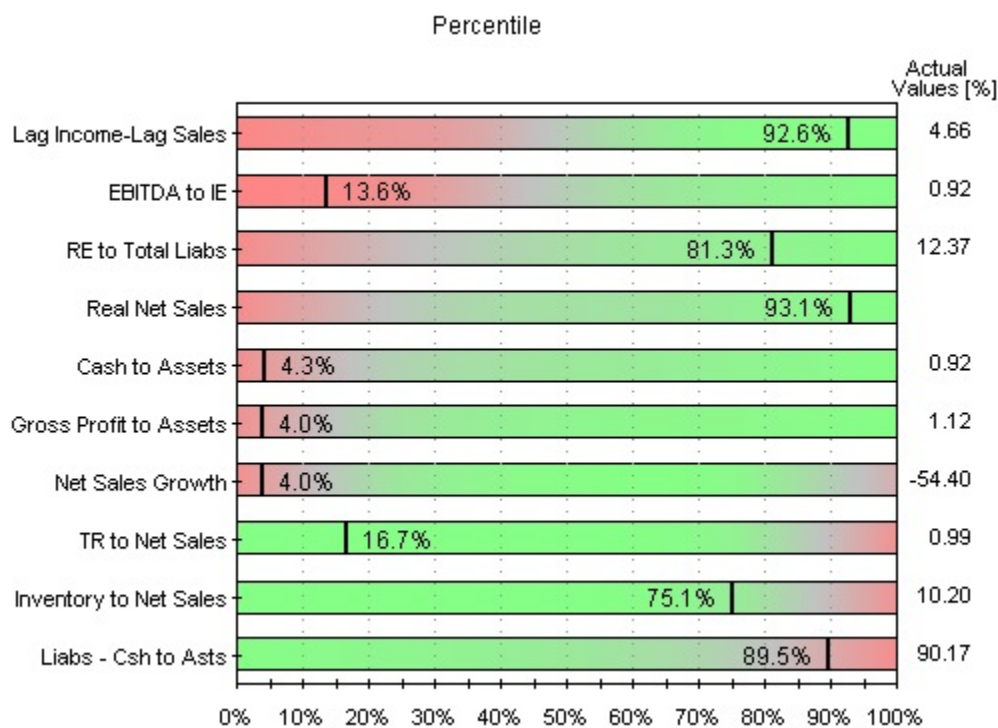


FIGURE 12 Ratio Percentile Analysis for the RiskCalc v3.2 Japan Model

## 6 CONCLUSION

The RiskCalc v3.2 Japan is based on a substantially larger database than RiskCalc v3.1 Japan, with twice as many defaults, 34% increase in the number of firms and 9% increase in the number of financial statements. Furthermore, it has an additional four years of data. The model includes variables from the previous years' financial statements, which capture firm dynamics and improve model power. Improved data coverage has allowed us to further refine our financial statement model and achieve a very robust prediction model of private firm default behavior.

RiskCalc v3.2 Japan represents a substantial advance in default prediction for private Japanese firms. The model is more powerful than any publicly-available alternatives that we have tested. We demonstrated how the increase in power is consistent across industry sectors, size classifications, and regions, as well as for different time periods.

As with RiskCalc v3.1 Japan, the RiskCalc v3.2 model controls for differences in the default risk across industries in the FSO mode. In addition, it also adjusts the EDF level to reflect the current stage of the credit cycle in the given industry. If default risk in a given firm's industry is high, then the EDF level is adjusted upward. Likewise, when default risk in the industry is low, then the EDF level is adjusted downward. This additional feature of the model increases the model power and precision and allows users to monitor their portfolios on a monthly basis.

In addition, the framework for RiskCalc v3.1 and v3.2 models offers further enhancements, such as a continuous term structure, providing EDF values for any point between one and five years, newer analytic tools, and the ability to calculate asset value and volatilities using a structural model framework.

This model is useful for financial institutions seeking to implement quantitative tools for originating loans, managing portfolio risk, and meeting regulatory requirements. It also provides a benchmark of the risk associated with a private firm, useful in securitizing middle-market debt. Finally, as an established objective external benchmark, RiskCalc will enable institutions to communicate between each other about their exposures.

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