MOODY'S KMV RISKCALC™ V3.1 SWITZERLAND

MODELINGMETHODOLOGY

ABSTRACT

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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 used by hundreds of institutions worldwide. While using the same underlying framework, each model reflects the domestic lending, regulator, and accounting practices of its specific region.

In January 2004, Moody's KMV introduced its newest RiskCalc modeling framework, Moody's KMV RiskCalc v3.1. By incorporating both market- (systematic) and company-specific (idiosyncratic) risk factors, RiskCalc v3.1 is in the forefront of modeling middle-market default risk. This modeling approach substantially increases the model's predictive powers.

This document outlines the underlying research, model characteristics, data, and validation results for the RiskCalc v3.1 Switzerland model.

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TABLE OF CONTENTS

1 INTRODUCTION

The Moody's KMV RiskCalc™ v3.1 Switzerland model is built using the results of extensive Moody's KMV research, including:

- Moody's KMV RiskCalc 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 v3.1 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 v3.1 to blend market-based (systematic) information with detailed firm-specific financial statement (idiosyncratic) information to enhance the model's predictive power.

1.1 RiskCalc Modes

RiskCalc v3.1 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. In this mode, the risk assessments produced by the model are relatively stable over time.

The CCA mode adjusts the default risk by taking into account the current stage of the credit cycle. The CCA adjustment is a sector-specific factor derived directly from the 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 adjustment is specific to the firm's sector and country 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).

2 DATA DESCRIPTION

The source of the data for RiskCalc v3.1 Switzerland is the Moody's KMV CRD. Moody's KMV collects data from participating institutions, working closely with them to understand the strengths and weaknesses of the data.

2.1 Definition of Default

RiskCalc provides assistance to institutions and investors for determining the risk of default, missed payments, or other credit events. Proposals for the new 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. In model development, RiskCalc uses the local criteria for default. For the Swiss model development, whenever possible, we flag the first occurrence of 90-days past due as the default event, consistent with BIS II. If past due information is not available, we flag an obligor as defaulted if the obligor's loan(s) reach any stage beyond 90-days past due up to and including insolvency and liquidation.

2.2 Data Exclusions

Excluded Companies

The goal of the RiskCalc model is to provide an EDF credit measure for private Swiss 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 Swiss middle-market companies, companies that did not reflect the typical company in this market were eliminated. The following types of companies are not included in the data:

- Small Companies—For companies with net sales of less than 500,000 CHF (2002 real Swiss francs), future success is often linked to the finances of the key individuals. For this reason, they are not reflective of typical middle-market companies 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. Therefore, they are excluded from the database.
- Real Estate Development Companies—The annual accounts of real estate development and investment companies provide only a partial description of the dynamics of these firms and, therefore, their likelihood to default. This is because their financial health often hinges on a particular development.[1]
- Public Sector and Non-profit Institutions—Government run companies' default risks are influenced by the states' or municipalities' unwillingness to allow them to fail. As a result, their financial 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.
- Start-up companies—Our experience has shown that the financial statements for a company during its first two years are extremely volatile and are a poor reflection of the creditworthiness of the company. The special nature of start-ups is reflected in the fact that many financial institutions have separate credit departments for dealing with these companies.

Excluded Financial Statements

The financial statements of smaller companies can be less accurate and of lower quality than those of larger companies. 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 to Liabilities plus Net Worth, and financial statements covering a period of less than twelve months. If errors are detected, those statements are excluded from the analysis.

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[1] 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. At the time of writing, this characteristic is explicitly recognized within the proposals for the new Basel capital accord.

2.3 Descriptive Statistics of the Data

Overview of the Data

Figure 1 presents the distribution of Swiss financial statements and defaults by year in the CRD. Table 1 summarizes the data used in the development, validation, and calibration of the RiskCalc v3.1 Switzerland model.

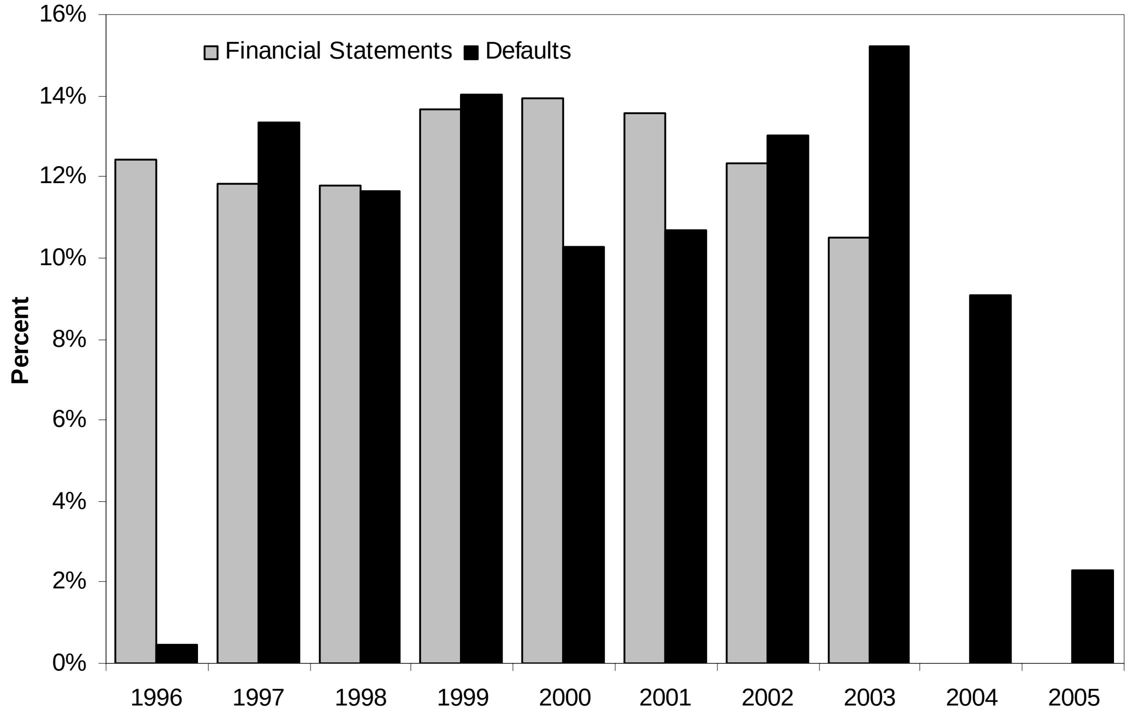

FIGURE 1 Date Distribution of Swiss Financial Statements and Default Data

TABLE 1 Swiss Private Firm Sample Data

Swiss Private Firms	RiskCalc v3.1 Switzerland
Financial statements	100,000+
Unique number of firms	22,000+
Defaults	2,000+
Time period	1996–2005

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 presents the distributions of Swiss defaults and firms by industry and the proportion of defaults in each industry. Figure 2 and Figure 3 present similar distributions by the size of firms measured as real total assets and real net sales in 2002 Swiss Francs, respectively.[2] These figures demonstrate how the proportion of defaults in any one size group or industry group is comparable to the proportion of firms in these groupings. The size distribution shows that about 40% of the firms hold assets less than 1 million, and about 40% hold assets between 1 and 10 million. The proportion of firms between 1 and 10 million in sales is 57% (where firms with less than 500,000 CHF in sales are excluded from the sample).

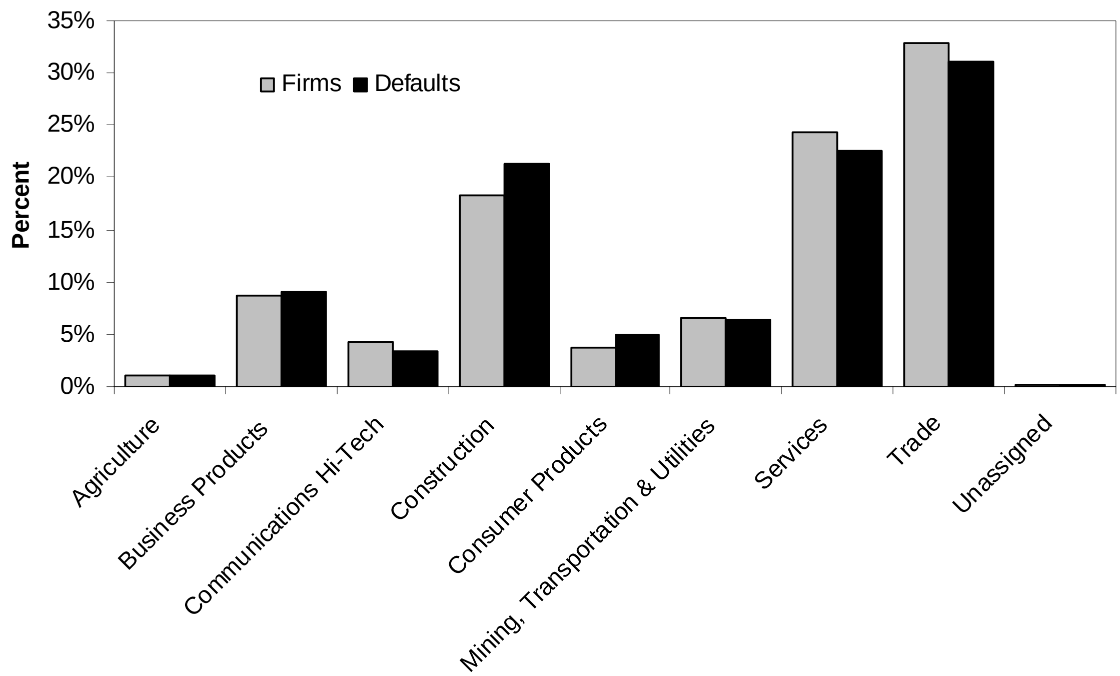

FIGURE 2 Distribution of Swiss Defaults and Firms by Industry

[2] In December 2002, a Swiss Franc was worth approximately 0.68 Euros.

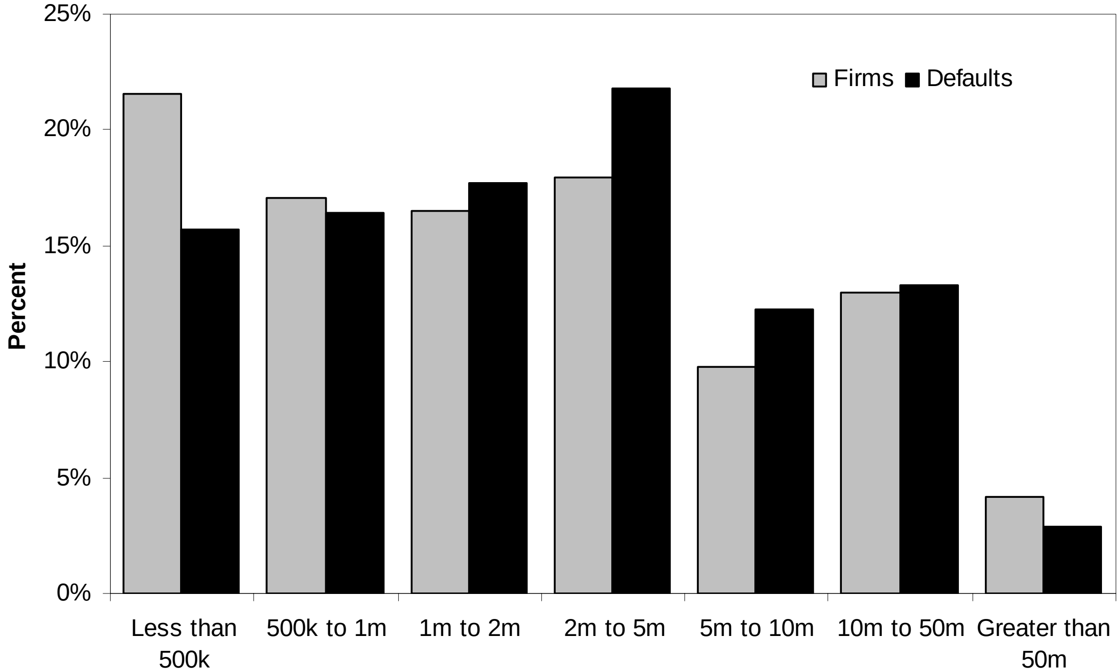

FIGURE 3 Size (as Total Assets) Distribution of Defaults and Firms

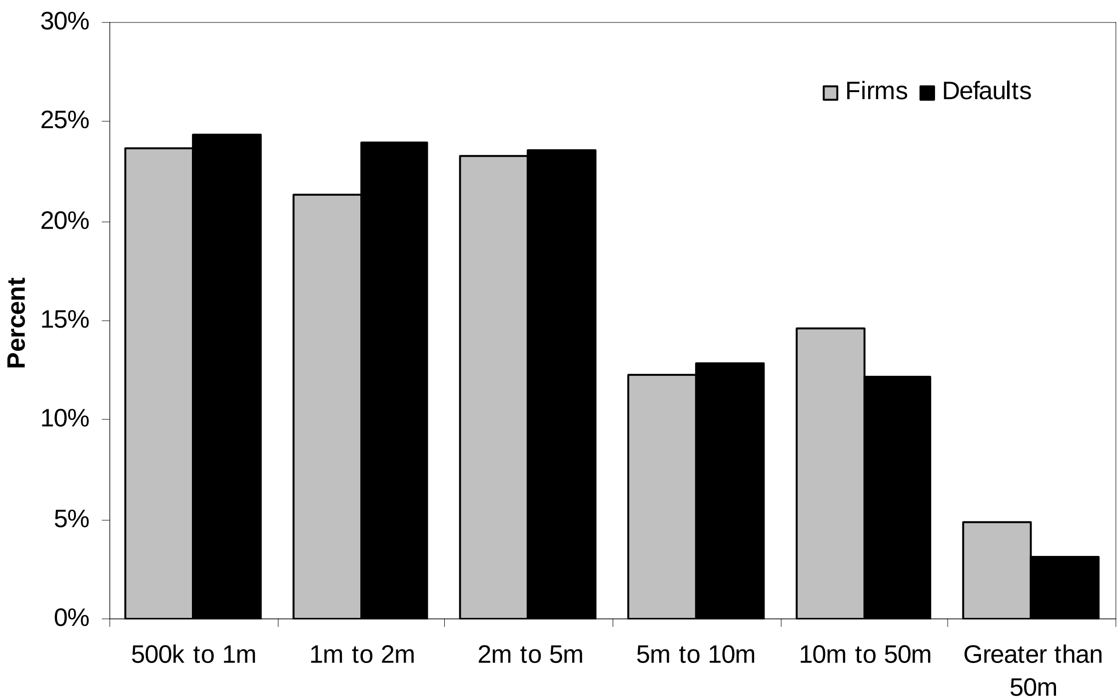

FIGURE 4 Size (as Net Sales) Distribution of Defaults and Firms

2.4 Cleaning the Data

When developing a RiskCalc model, the first step is to collect a large and appropriate database. In addition, data needs to be "cleaned" so that it represents the actual risk of the firms covered. Moody's KMV has developed techniques for cleaning the database to improve the model results.

2.5 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 is because of the 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 occur in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true CDT. When default definitions used in the data sample understate the defaulting population, as is the case with Switzerland, 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 default probability is a ratio that would reflect 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 Switzerland is based on several sources.

- Insolvency rates of Swiss businesses examined over time with data from Creditreform.
- Loan loss provision data from the Organization for Economic Co-operation and Development (OECD) and
- Provisioning data gathered from financial statements of large Swiss banks.
- Public debt market default rates.
- The relative calibrations of other RiskCalc models within the region.
- Confirmation of the CDT exceeding the default rates observed in our development sample.

The multiple sources of external data lead us to an estimate of 1.8% as the CDT figure for the 1-year model.

Calculating a 5-year Central Default Tendency

There is a lack of publicly-available data for direct calculation of the CDT of a cumulative 5-year default probability. Based on extensive Moody's KMV research, a 5-year cumulative default tendency is derived from the 1-year estimate. This research, combined with the information provided by the CRD, shows that the 5-year cumulative default rate is, on average, four times the level of the 1-year default rate. Therefore, 7.2% is used as the CDT for the 5-year model.

Central Default Tendency in FSO and CCA Modes

In FSO mode, the CDT remains constant over time. In CCA mode, the central default tendency is equal to the central default tendency of the FSO mode when the effects of the credit cycle are neutral. When the forward-looking prediction of the credit cycle indicates increasing default risk, the central default tendency of the CCA mode will be larger; when the effects of the credit cycle indicate reducing default risk, the central default tendency will be smaller.

3 MODEL COMPONENTS

The RiskCalc v3.1 model incorporates various components to determine the EDF credit measure. The inputs to the model include a selection of the financial ratios and 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.[3]
2. Transforming the variables into interim probabilities of default using non-parametric techniques.
3. Estimating the 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 $x_1,...,x_N$ are the input ratios.

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

β and γ are estimated coefficients,

Φ is the cumulative normal distribution,

F and $T_1,..., T_N$ are non-parametric transforms,

and FSO EDF is the financial-statement-only EDF credit measure.[4]

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 is shown in Figure 5 and discussed in detail later in the document. *F* is 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 credit measure. The difference between the FSO EDF and the credit cycle adjusted EDF 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.

[3] These variables are often ratios, but not always. For example, one measure of profitability is Net Income to Total Assets, which is a ratio, and one measure of size is Inflation Adjusted Total Assets, which is not a ratio.
[4] By non-parametric, we mean that the $T(x_i)$ 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 long list of possible financial statement variables. The working list of ratios is divided into groups that represent different underlying concepts regarding a firm's financial status (Table 3). A model is then built with at least one variable per group. When it is possible to 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

Examples of ratios in the profitability group 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.
Examples of ratios in the leverage (or gearing) group 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 the probability of default.
Growth variables are typically the change in Return on Assets (ROA) and sales growth. These variables measure the stability of a firm's performance. → Growth variables behave like a double-edged sword: both rapid growth and rapid decline (negative growth) will tend to 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 2002 Euros). → Large firms default less often.

TABLE 3 Financial Statement Variables used in RiskCalc v3.1 Switzerland

Category	Definition
Activity	**Short Term Debt to Net Sales** [Accounts Payable to Credit Institutions (< 1 YR) + Accounts Payable from Trade (< 1 YR) + Notes Payable (< 1 YR) + Other Accounts Payable (< 1 YR)] to Net Sales
Debt Coverage	**Debt Coverage** [Net Profit and Loss + Depreciation] to [Interest and Similar Expenses + Total ST Financial Liabilities + Notes Payable (< 1 YR)]
Growth	**Sales Growth** Sales(t)/Sales(t-1) - 1
Leverage /Gearing	**Equity to Adjusted Liabilities** [Total Equity + LT Liabilities to Shareholders – LT Loans to Shareholders – Intangible Assets] to [Total Liabilities - LT Liabilities to Shareholders]
Liquidity	**Cash to Current Assets** Cash and Marketable Securities to Current Assets **Quick Ratio** (Current Assets – Inventory) to Current Liabilities
Profitability	**ROA** Net Income to Total Assets **Average of Ordinary Profit to Sales** .5*[Ordinary Profit (t) to Net Sales (t)] + .5*[Ordinary Profit (t-1) to Net Sales (t-1)]
Size	**Size** Inflation adjusted Net Sales (2002 CHF)

Variable Transforms

After the variables are selected, they are transformed into a preliminary EDF value. Figure 5 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 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, the transforms for ROA and Average Ordinary Profit to Sales are both downward-sloping. For both profitability ratios, the slope of the transform decreases as profitability becomes large (Figure 5). Such a transform indicates that more profitable firms have lower default probabilities, but the impact diminishes as profitability increases.

- For the **Leverage** group, the transform for Equity to Adjusted Liabilities is downward-sloping, since increasing Equity relative to Liabilities lowers default risk. For this transform, the slope is fairly constant, implying that the changes in risk are uniform across the transform (Figure 5).

- For the **Liquidity** group, both transforms downward-sloping. The slope of the transform for Cash to Current Assets is mostly constant, while the slope of the transform for the Quick Ratio is steeper for low levels of the ratio and flattens out as the ratio increases (Figure 5).

- For the **Activity** group, the transform for ST Debt to Sales Ratio is upward-sloping. The slope of the transform is flat and then becomes steeper (Figure 5). This shape indicates that risk levels are fairly insensitive to movements in the ratio below the 40th percentile. This definition of Short Term Debt does not include debts that can be viewed as unrelated to activities. Specifically, this definition excludes current liabilities that should not trigger default since there is no payment. Examples include: Dividends, Deferred Income, and Advances from Customers[5].

- The **Size** variable is Net Sales (2002 CHF). This variable's transformation is downward-sloping, and becomes steeper as sales increases (Figure 5). This indicates that the impact on default risk increases as size increases, consistent with empirical evidence.

- The **Debt Coverage** variable is Net Income before Depreciation to Interest Expense plus Debt Due. The transformation of this variable is backward-S-shaped. This shape indicates that the impact of changes in debt coverage is small when debt coverage is already relatively high or low (Figure 5).

- For the **Growth** group, the transform for Sales Growth is U-shaped. This indicates that large increases or decreases in sales are associated with higher default probabilities, while stable sales year upon year decrease the probability of default (Figure 5).

[5] For example, if a company is paid before goods and services are delivered, the cash is recorded as deferred revenue or income, a liability on the balance sheet. Such items are not likely to cause financial distress.

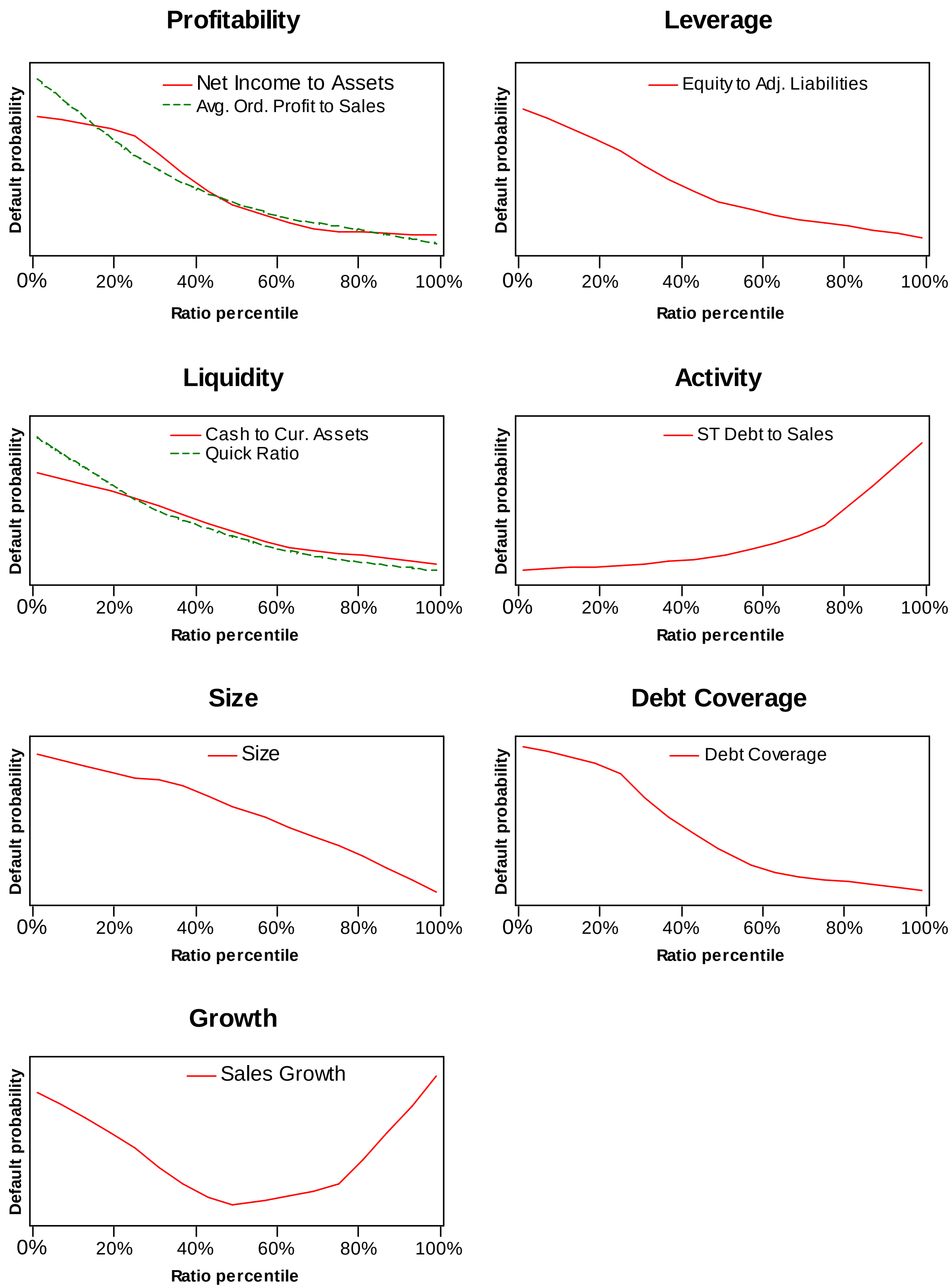

FIGURE 5 Transformations of Financial Statement Variables Used in RiskCalc v3.1 Switzerland

3.2 Model Weights

Importance

The relative value of each variable used in calculating an EDF credit measure is important in understanding a company's risk. The non-linear nature of the model makes the weight of the variables more difficult to determine, because the actual impact on the risk depends on the coefficient, the transformation shape, and the percentile ranking of the company. The model weights, therefore, are calculated based on the average EDF value for the transformation and its standard deviation. A variable with a flat transformation could have a low weight, even if the coefficient is large (Figure 5).

Calculation of Weights

To calculate the weighting of a variable, the EDF credit measure is computed for a theoretical firm with all its variables at the average transformation values. The variables are then increased one at a time by one standard deviation. The EDF change for each variable (in absolute value) is computed and added together. The relative weight of each variable is then calculated as the EDF level change for that variable as a percent of the sum of EDF level changes across all variables. This gives the variable with the biggest impact on the EDF level the biggest weight, and the variable that has the smallest impact on the EDF level the smallest weight. Since the weights are a percentage of the total change in EDF levels, they sum to 100%. The weight of each category is the sum of the weights of each variable in that category.

Table 4 presents the weights in RiskCalc v3.1 Switzerland. The most important categories are Activity, Liquidity, and Leverage/Gearing.

TABLE 4 Risk Drivers in RiskCalc v3.1 Switzerland

Risk Drivers	Weight
Activity Short Term Debt to Net Sales	25%
Liquidity Cash and Securities to Current Assets Quick Ratio	19%
Leverage/Gearing Equity to Adjusted Liabilities	17%
Profitability Net Income to Assets Average of Ordinary Profit to Sales	12%
Debt Coverage Debt Coverage	16%
Growth Sales Growth	6%
Size Size	5%

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 v3.1 Switzerland, 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 large gain in likelihood indicates that the industry controls are especially important in producing an accurate EDF. 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	One-year Model		Five-year Model	
	Accuracy Ratio	Relative Increase in Log Likelihood	Accuracy Ratio	Relative Increase in Log Likelihood
Without industry controls	72.3%	---	60.1%	---
With industry controls	72.5%	51***	60.5%	96***

*** Indicates a P-value of less than 0.01 percent.

In this table, and hereafter, Accuracy Ratio (or AR) is the measure of the model's ability to rank order credits. Increases in log likelihood measure the extent to which the model's EDF values match observed default rates.[6]

TABLE 6 Average EDF Credit Measure by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Agriculture	1.90%	6.34%
Business Products	1.92%	6.98%
Communications and High Tech	1.58%	5.56%
Construction	2.45%	9.38%
Consumer Products	2.31%	8.78%
Mining, Transportation, Utilities, and Natural Resources	2.07%	7.83%
Services	2.19%	7.54%
Trade	1.79%	6.31%

[6] For further details, see Dwyer and Stein (2004), Technical Document on RiskCalc v3.1 Methodology (Technical Document).

3.4 Credit Cycle Adjustment

EDF credit measures are impacted not only by the financials of a company, but also by the general credit cycle in the economy. To capture this effect, RiskCalc v3.1 Switzerland includes a credit cycle adjustment (CCA) factor. The CCA is designed to incorporate the current credit cycle into the estimate of private firm default risk.

Selecting an Adjustment Factor

The RiskCalc v3.1 model uses the distance-to-default calculation from the Moody's KMV public firm model. 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.[7] This measure was chosen because it is available for a large universe of industries and it has been extensively validated.

If the DD for public firms in an industry indicates a level of risk above the historical average for that industry, then the private firms' EDF values in that industry are adjusted upward. Conversely, if the level of risk is below the historical average, then the private firms' EDF values are adjusted downward. When the credit cycle adjustment factor is neutral, the CCA EDF value coincides with the FSO EDF value.

Adjustment Factor used in the Model

For the Swiss model, the DD factor for each industry is a weighted average of two indices. The average is based on the aggregation of DD in each industry for all Swiss firms, and firms in a basket of nine other countries. [8] These nine countries have relatively liquid public debt markets and are trading partners with Switzerland The weight on the Swiss factor is industry-specific and determined by the value (assets) of Swiss firms in each industry relative to all firms in the basket. If a firm cannot be associated with a specific industry, the model uses a credit cycle adjustment based on an aggregation of all public firms in Switzerland and the associated countries.

The DD factor is meant to be a forward-looking indicator of default risk. One way to measure the market's current assessment of credit risk is to examine credit spreads on corporate bonds. When the market expects higher levels of default on public debt, the yield spread over a riskless bond will increase to compensate for the extra risk. Figure 6 presents the evidence of the Swiss DD factor and yield spreads on western European Corporate Bonds. The DD factor is inverted when graphed so that higher values on the graph indicate higher probabilities of default for Swiss public firms. We would expect a concurrent relationship between the series, since both are forward-looking (Figure 6). The inverted Swiss DD factor tracks credit spreads in this sample with a correlation of .86.

Figure 7 shows the relationship between the DD factor and public default rates in continental Europe, as measured by Moody's KMV.[9] The factor is a forward-looking measure of the probability of default for public European firms. Overall, the evidence shows that the DD factor is a predictor of economic conditions in each industry, and will adjust the probabilities default to reflect the position in the credit cycle.

[7] cf., Bohn and Crosbie, 2003.

[8] The nine additional countries used to compute the distance-to-default factor include: Austria, Belgium, France, Germany, Italy, the Netherlands, Spain, the UK, and the USA.

[9] In this context, a public company is a company with publicly traded equity. For the default rate calculation, Continental Europe includes: Austria, Belgium, Denmark, France, Switzerland, Greece, France, Luxembourg, the Netherlands, Portugal, Spain, and Switzerland

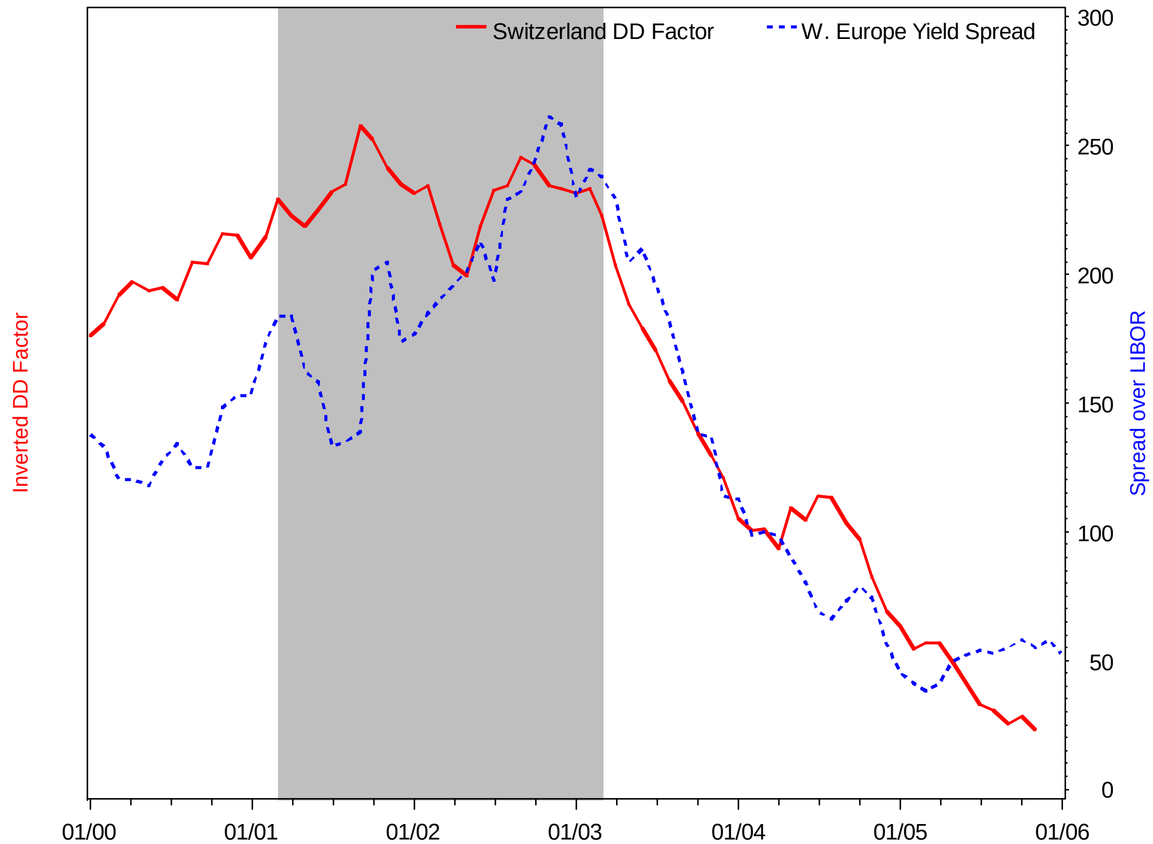

FIGURE 6 Swiss DD Factor and Western Europe Corporate Credit Spreads: Jan. 2000–Jan. 2006

Figure 6 shows the DD factor (red solid line) against the historical credit spread levels (blue dotted line). Bond prices and yields are from Reuters EJV, and the yield spread is over the benchmark LIBOR rate. The spread statistics are complied using Moody's KMV CreditEdge for the Western European Corporate Bond Group. The grey shaded area denotes a recession as defined by the Economic Cycle Research Institute.

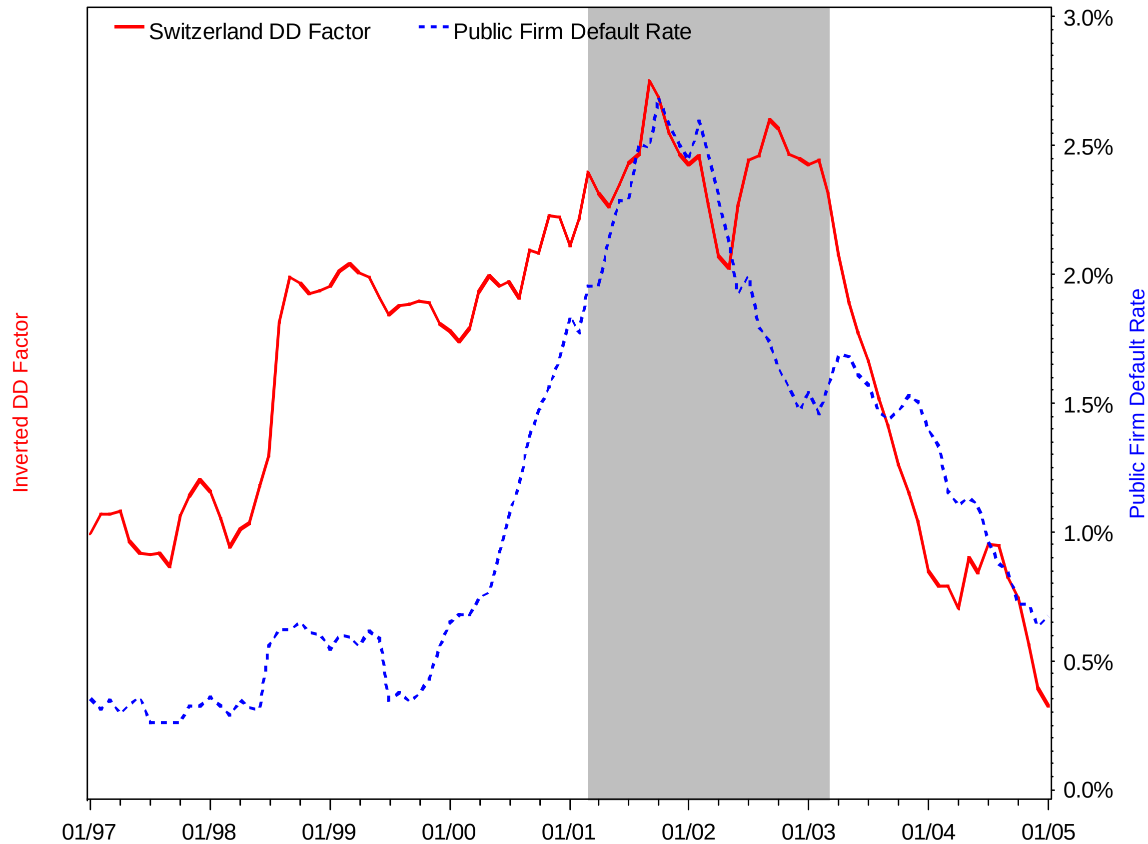

FIGURE 7 Switzerland DD Factor and Continental Europe Public Default Rates: 1997–2004

Figure 7 displays the Swiss DD factor (red solid line) against the historical public firm default rate for continental Europe (blue dotted line). The DD factor increases in anticipation of the increase in default activity. The grey shaded area denotes a recession as defined by the Economic Cycle Research Institute.

4 VALIDATION RESULTS

After a model is developed, it must be proven effective in predicting defaults. In this section, we present testing results on the model's ranking power (the model's ability to sort credits from worst to best).

The tests need to check not only the model effectiveness, but also its robustness and how well it works on data outside the sample. Both *k*-Fold and walk-forward analyses were performed for out-of-sample testing. The results of the testing show that the model is uniformly more powerful than other models across different time periods, sectors, and size classifications.

4.1 Increase in Overall Model Power

Table 7 presents the in-sample overall measures of power for RiskCalc v3.1 Switzerland versus alternative models.

We present the accuracy ratios for three neighboring countries with RiskCalc models and for Z-score. With the credit cycle adjustment, the accuracy ratio is 8.6% and 7.5% greater than with RiskCalc v1.0 Germany, at the 1- and 5-year horizon, respectively.

Relative to other available alternatives, the results were more dramatic. The new RiskCalc v3.1 model outperformed the Z-score model.[10] It did so by more than 15 percentage points at the 1- and 5-year horizon.[11]

TABLE 7 Power of the RiskCalc v3.1 Switzerland Model

	One-year Model		Five-year Model	
	Accuracy Ratio	**p-value of Difference in AR***	**Accuracy Ratio**	**p-value of Difference in AR***
RiskCalc v3.1	72.4%	---	59.6%	---
RiskCalc Italy v3.1 FSO	63.5%	<.001	50.3%	<.001
RiskCalc Italy v1.0	63.4%	<.001	48.6%	<.001
RiskCalc Germany v1.0	63.8%	<.001	52.1%	<.001
RiskCalc Austria v1.0	61.1%	<.001	46.1%	<.001
Z-score	54.6%	<.001	44.4%	<.001

* p-values indicate the statistical significance of the gain in accuracy ratio of RiskCalc v3.1 Switzerland model over alternatives. Lower p-values indicate higher confidence levels in the statistical test.

Figure 8 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 7, including only the RiskCalc German v1.0 model with Z-score.[12] The profiles show a power gain throughout the entire distribution relative to Germany v1.0, particularly for the 1-year model. This shows that RiskCalc Switzerland v3.1 identifies high, medium, and low risk firms better than the alternative models.

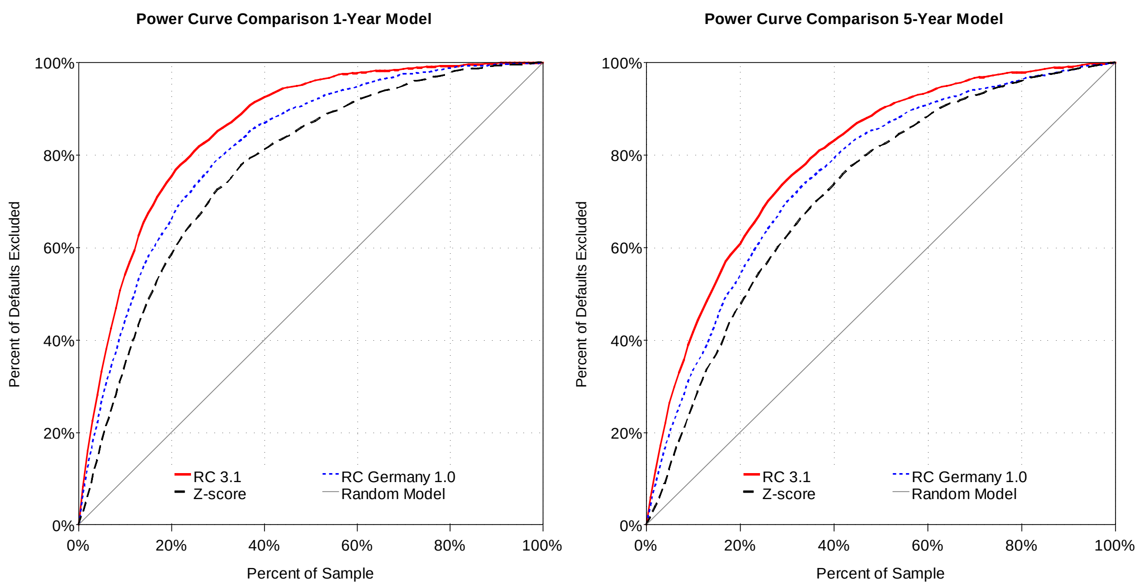

FIGURE 8 Power of Alternative Models (1- and 5-year)—Switzerland

[10] cf. Altman, Hartzell and Peck, 1995.

[11] The corresponding Financial Statement Only accuracy ratios are 72.0% (FSO) for the one-year horizon and 60.5% (FSO) for the 5-year horizon.

[12] For the remaining validation statistics, we present the accuracy ratio of Z-score and RiskCalc Germany v1.0 as benchmarks. Germany is used since it has the next highest accuracy ratio of RiskCalc v1.0 alternatives. All following validation results are qualitatively similar when using RiskCalc Italy v1.0 as the benchmark.

4.2 Correlations and Variance Inflation Factors

To ensure model robustness, the model must be tested for excessive multicollinearity, which occurs if a number of the variables used in the model are highly correlated. Excessive multicollinearity can cause instability in parameter estimates. To check for this issue, the correlation coefficients in **Error! Reference source not found.** for the financial statement ratios in the model and the variance inflation factors (VIF) in Table 9 are computed on the transformed variables displayed in Figure 5.[13]

Model Results

The highest correlation coefficient is between the two profitability ratios at 0.64. The next highest coefficient is between Debt Coverage and Net Income to Assets at 0.63. Such coefficients are below what we typically consider indications of multicollinearity, and this finding is also verified by the VIF analysis.

TABLE 8 Correlations Among the Transformed Input Factors (Spearman Rank)

	Debt Coverage	Short Term Debt To Net Sales	Cash and Securities to Current Assets	Quick Ratio	Net Income to Assets	Average Ordinary Profit to Sales	Equity to Adjusted Liabilities	Size	Sales Growth
Debt Coverage	1.0								
Short Term Debt To Net Sales	0.49	1.0							
Cash and Securities to Current Assets	0.46	0.40	1.0						
Quick Ratio	0.47	0.56	0.44	1.0					
Net Income to Assets	0.63	0.25	0.21	0.24	1.0				
Average Ordinary Profit to Sales	0.49	0.20	0.21	0.24	0.64	1.0			
Equity to Adjusted Liabilities	0.37	0.42	0.26	0.55	0.23	0.25	1.0		
Size	0.16	0.07	0.02	0.06	0.13	0.14	-0.02	1.0	
Sales Growth	0.06	0.07	0.02	0.00	0.05	0.04	0.01	0.06	1.0

[13] For further definitions and technical discussion of the testing procedures in Section 4 please refer to the Technical Document.

The VIF levels displayed in Table 9 for the financial statement variables represent how much of the variation in one independent variable can be explained by all the other independent variables in the model. The correlation coefficient, however, measures only the relationships between two variables. As shown in Table 9, the three highest VIF levels are on the Debt Coverage and two Profitability ratios. This is consistent with the correlation analysis. The estimated VIF values in the Swiss model are notably below the threshold levels of 4 to 10 that are commonly used in VIF analysis when testing for presence of multicollinearity.[14] These findings indicate that the model is not likely to be negatively impacted by multicollinearity. Additional out-of-sample testing also shows that the statistical and economic significance of the model is similar on subsections of the data, as described in Sections 4.5 and 4.6.

TABLE 9 Variance Inflation Factors

Variable	VIF
Debt Coverage	2.31
Net Income to Assets	2.13
Average of Ordinary Profit to Sales	1.78
Quick Ratio	1.74
Short Term Debt to Net Sales	1.60
Equity to Adjusted Liabilities	1.45
Cash and Securities to Current Assets	1.34
Size	1.18
Sales Growth	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.

Table 10 and Table 11 present the power comparisons by sector for the 1-year and 5-year models, respectively. RiskCalc v3.1 Switzerland outperforms both RiskCalc v1.0 Germany and Z-score in all sectors. The highest power in the 1-year model is found in Construction (79.9%) while the lowest is found in Services (63.3%). At the 5-year horizon, the highest power is in Consumer Products (66.8%), and the lowest is in Services (51.8%).

TABLE 10 Model Power by Industry: 1-year Model

	Percentage of Defaults	AR RiskCalc v3.1 Switzerland	AR RiskCalc v1.0 Germany	AR Z-score
Business Products	10.2%	77.3%	70.3%	53.1%
Communications and High Tech	3.6%	76.5%	75.2%	64.1%
Construction	20.1%	79.4%	69.4%	62.0%
Consumer Products	5.1%	77.9%	74.3%	60.0%
Mining, Transportation, Utilities and Natural Resources	7.4%	73.8%	60.6%	63.0%
Services	21.9%	63.3%	56.6%	46.1%
Trade	31.6%	70.8%	61.9%	54.6%

[14] 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 could 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 to be a serious problem.

TABLE 11 Model Power by Industry: 5-year Model

	Percentage of Defaults	AR* RiskCalc v3.1 Switzerland	AR RiskCalc v1.0 Germany	AR Z-score
Business Products	10.1%	58.2%	57.0%	39.0%
Communications and High Tech	3.6%	61.8%	59.8%	50.2%
Construction	20.0%	63.7%	56.8%	51.4%
Consumer Products	5.0%	66.8%	59.8%	43.8%
Mining, Transportation, Utilities and Natural Resources	7.2%	64.1%	52.8%	51.6%
Services	22.5%	51.8%	45.2%	37.2%
Trade	31.5%	60.7%	51.5%	46.4%

Table 12 and Table 13 present the power comparisons by firm size for the 1-year and 5-year models, respectively. RiskCalc v3.1 Switzerland outperforms both RiskCalc v1.0 Germany and Z-score in all size groups. The highest power in the 1-year model is found in the 5mm to 10mm CHF group of firms, and the lowest is in the smallest firms with less than 500,000 CHF in assets. The highest power in the 5-year model is found in the 2mm to 5mm CHF group, and the lowest is in the under 500k CHF group. A similar relationship is often found between model power and size in other countries. Such performance improvements are likely to reflect the higher quality of financial statements among larger firms.

TABLE 12 Model Power by Size: 1-year model

	Percentage of Defaults	AR RiskCalc v3.1 Switzerland	AR RiskCalc v1.0 Germany	AR Z-score
< 500,000 CHF	14.1%	58.1%	56.7%	46.0%
500,000 to 1mm CHF	16.2%	69.2%	65.4%	55.3%
1mm to 2mm CHF	19.1%	70.4%	63.7%	49.4%
2mm to 5mm CHF	22.8%	75.5%	67.3%	62.3%
5mm to 10mm CHF	12.2%	77.2%	64.4%	55.4%
10mm to 50mm CHF	13.0%	76.8%	63.3%	56.8%
> 50mm CHF	2.6%	67.9%	50.8%	38.6%

TABLE 13 Model Power by Size: 5-year model

	Percentage of Defaults	AR RiskCalc v3.1 Switzerland	AR RiskCalc v1.0 Germany	AR Z-score
< 500,000 CHF	14.6%	44.3%	40.8%	34.9%
500,000 to 1mm CHF	17.3%	55.0%	52.4%	46.5%
1mm to 2mm CHF	18.8%	62.7%	58.4%	44.9%
2mm to 5mm CHF	22.3%	65.5%	59.5%	53.3%
5mm to 10mm CHF	12.5%	62.2%	53.0%	41.8%
10mm to 50mm CHF	11.8%	63.8%	53.4%	44.8%
> 50mm CHF	2.7%	60.6%	46.0%	36.2%

4.4 Power Performance over Time

Since models are implemented at various points in a business cycle by design, power tests by year were conducted to examine whether the model performance is excessively time dependent.

Table 14 and Table 15 present the results from this analysis at the 1- and 5-year horizons, respectively. The AR of RiskCalc v3.1 Switzerland is compared with RiskCalc v1.0 Germany and Z-score for each year. RiskCalc v3.1 consistently outperforms both by a considerable margin.

TABLE 14 Model Power over Time: 1-year Horizon

Year	Percent of Defaults	AR RiskCalc v3.1 Switzerland	AR RiskCalc v1.0 Germany	AR Z-score
1997	17.4%	66.9%	60.4%	52.1%
1998	13.8%	68.4%	60.6%	49.8%
1999	14.7%	68.6%	57.7%	47.9%
2000	18.1%	66.4%	57.3%	45.4%
2001	18.5%	67.3%	58.0%	49.1%
2002	13.6%	66.0%	58.4%	51.1%
2003	3.9%	75.3%	67.0%	63.3%

TABLE 15 Model Power over Time: 5-year Horizon

Year	Percent of Defaults	AR RiskCalc v3.1 Switzerland	AR RiskCalc v1.0 Germany	AR Z-score
1997	20.8%	61.1%	52.9%	43.2%
1998	20.0%	58.5%	49.4%	41.9%
1999	18.8%	57.6%	48.2%	40.6%
2000	18.0%	57.9%	49.7%	41.5%
2001	12.8%	61.2%	52.6%	43.4%
2002	7.5%	65.8%	58.1%	51.0%
2003	2.1%	75.0%	66.9%	63.3%

4.5 Out of sample Testing: *k*-Fold Tests

The model exhibits a high degree of power in distinguishing good credits from bad ones (Table 7), but whether this power is attributable to the overall model effectiveness or the impact of a particular sub-sample also needs to be tested. A standard test for evaluating this is the "*k*-Fold test," which divides the defaulting and non-defaulting companies into *k* equally sized segments. This yields *k* equally sized observation sub-samples that exhibit the identical overall default rate and are temporally and cross-sectionally independent. The model is then run on *k-1* sub-samples and these parameter estimates are used to score the *k-th* sub-sample. We repeat this procedure for all possible combinations, and put the *k* scored "out-of-sample" sub-samples together to calculate an accuracy ratio on this combined data set.

Table 16 summarizes the *k*-Fold test results (with *k*=5). The reported figures are the accuracy ratios by the corresponding sample and time horizons. The out-of-sample model consistently out-performs RiskCalc v1.0 Germany. Figure 9 presents the cumulative accuracy profiles associated with the overall out-of-sample results against the in-sample results. The model performance is maintained both in- and out-of-sample in the *k*-Fold analysis.

Results

The in- and out-of-sample plots are virtually indistinguishable at both the 1- and 5-year horizons in Figure 9. The difference in AR between the overall in-sample and out-of-sample results is not larger than 20 basis points in both cases. Furthermore, RiskCalc v3.1 Switzerland outperforms RiskCalc v1.0 Germany in an out-of-sample context at both the 1- and 5-year horizons (Table 16).

TABLE 16 RiskCalc v3.1 Switzerland *k*-Fold Test Results

	Out of Sample AR		RiskCalc v1.0 Germany	
	1-year AR	5-year AR	1-year AR	5-year AR
Subsample 1	67.8%	61.7%	59.2%	51.1%
Subsample 2	69.9%	62.0%	61.4%	53.6%
Subsample 3	67.8%	59.7%	58.9%	52.2%
Subsample 4	69.1%	60.7%	59.8%	51.4%
Subsample 5	69.2%	62.2%	59.1%	52.0%
K-Fold Overall	72.4%	59.5%	---	---
In-sample AR	72.6%	59.7%	63.8%	52.1%

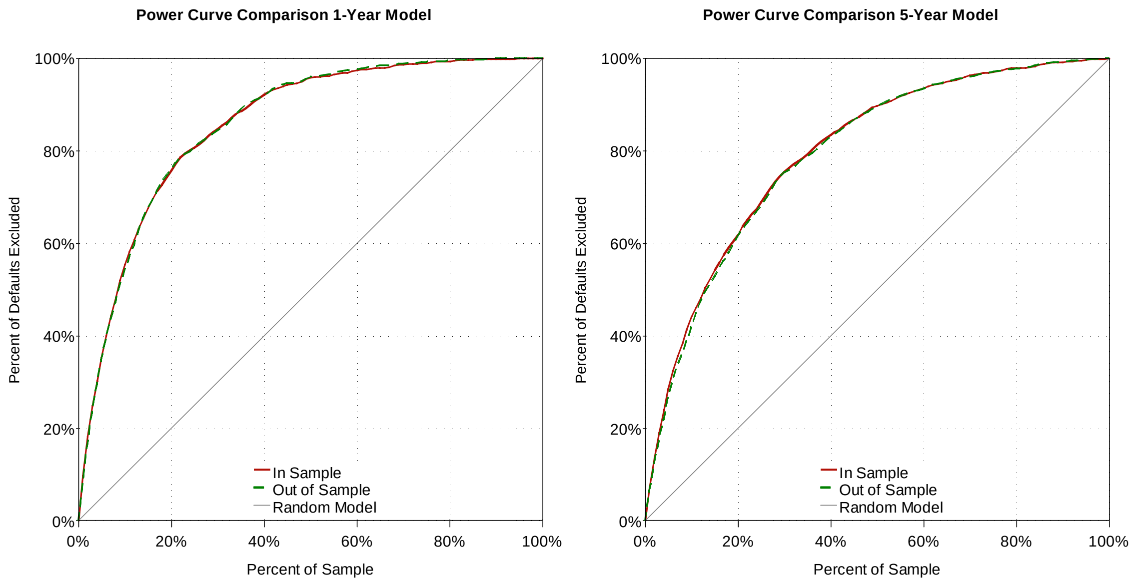

FIGURE 9 RiskCalc v3.1 Switzerland *k*-Fold

The *k*-Fold testing does not control for time-dependence. Each of the *k* subsamples contains data from all periods. As a result, if there were a particularly high period of default rates, this would be included in each of the *k* samples. Such testing does not give a true sense of the how the model would have performed during those volatile periods because the model is estimated with full information on those time periods.

4.6 Walk-Forward Tests

An alternative out-of-sample test developed by Moody's KMV is a walk-forward analysis, which is designed along similar lines as the *k*-Fold test, except that it controls for the effects of time. The model is estimated up to a certain year, and the parameter estimates are then used to score the observations in the next year. These model scores are out-of-time. The model is re-estimated including one more year of data and we repeat the analysis for the next year and continue until the end of the sample. These out-of-sample out-of-time scores are combined into a single prediction set so that the accuracy ratio and the power curve can be calculated for the combined set. The out-of-sample accuracy ratio is then compared to the corresponding in-sample accuracy ratio and power curve.

No data from a future period is used in fitting the model, and only data from future periods is used for testing it. The parameter estimates are checked for stability across the different samples. Figure 10 presents the results from this analysis.

Results

Similar to the *k*-Fold results, the in- and out-of-sample plots for the walk-forward results are virtually indistinguishable at both the 1- and 5-year horizons in Figure 10. The difference in AR between the in-sample and out-of-sample results is no more than 0.9% in both cases. Furthermore, RiskCalc v3.1 Switzerland outperforms RiskCalc v1.0 Germany in an out-of-time context at both the 1- and 5-year horizons.[15]

[15] The out-of-sample AR is 72.9% for the 1-year model and 58.7% for the 5-year model. The 1-year out-of-sample power is .1% more than the in-sample power, while the 5-year power is .9% less out-of-sample than in-sample. These out-of-sample ARs are 9.1 and 9.3 points higher than RiskCalc v1.0 Germany, for the 1- and 5-year models respectively—on the same sample.

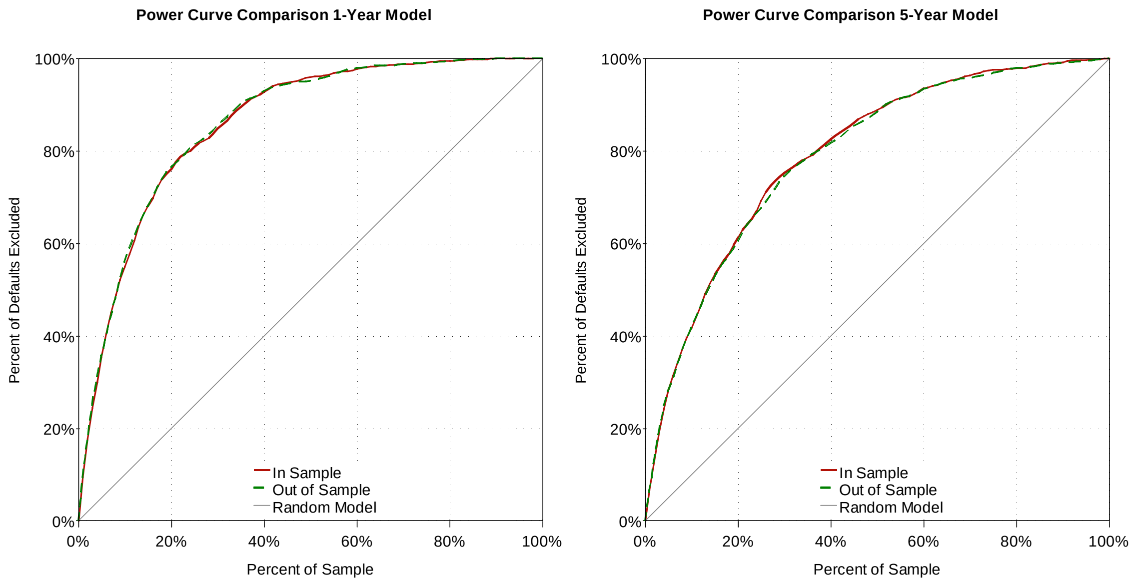

FIGURE 10 Out-of-sample Performance (1- and 5-year) Switzerland Walk-forward

4.7 Model Calibration and Implied Ratings

The model maps an EDF value to an .edf rating (i.e., an EDF-implied rating) to help interpret an EDF credit measure. All RiskCalc v3.1 models 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 value 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 11 shows the distribution of CRD observations by rating category in the development sample for the Credit Cycle Adjusted EDF credit measures over the full time period. Note that 14 categories between Aa3 and Caa/C are utilized, and that less than 15% of the observations are in any one category. Both the 1- and 5-year distributions peak at Baa3. While not reported here, other research has shown that the distribution of the CCA EDF-implied ratings changes over time with the credit cycle, while the distribution of the FSO EDF-implied ratings remains relatively stable over time.

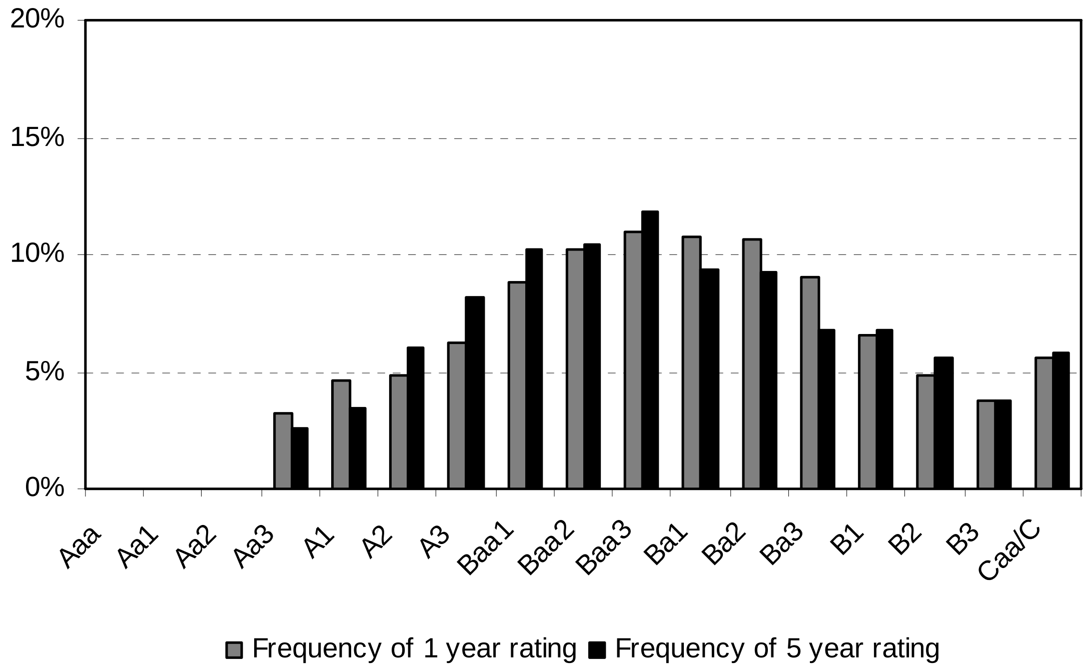

FIGURE 11 EDF-implied Ratings for the 1- and 5-year Models in the Development Sample

5 FURTHER MODEL IMPROVEMENTS

This section outlines some other improvements to the model.[16]

5.1 Continuous Term Structure

The previous version of the RiskCalc model provided 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 fits a Weibull function, and thus achieves a continuous term structure of EDF values for each credit. In other words, users of RiskCalc v3.1 Switzerland can obtain EDF estimates for any point between one and five years. In addition, RiskCalc v3.1 provides EDF estimates for alternative definitions, such as the forward EDF value and the annualized EDF value (Table 17).

Cumulative EDF Credit Measures

A cumulative EDF credit measure gives the probability of default over that time period. For example, a 5-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 17 provides an example of the cumulative 1- to 5-year credit measures produced by the model.

[16] For a detailed discussion of these improvements, refer to the Technical Document.

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 is the probability that a firm will default between years three and four assuming the firm survived to year 3.[17] The third column of Table 17 displays the forward 1- to 5-year EDF credit measures that are 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 value of 13.44% would have a 5-year annualized EDF value of 2.84%.[18] This means that the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column of Table 17 presents the annualized EDF credit measures for years 1 to 5 that are derived from the cumulative EDF values.

TABLE 17 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: Relative Sensitivity

The RiskCalc v1.0 interface provides an analytical tool to gauge the relative impact of each variable—as a deviation from the mean of each ratio. 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 Debt Coverage reduces the risk of the company. It is about 250% (1-year) as sensitive as the average variable (Figure 12).

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[17] Specifically, $FEDF_{t-1,t} = (CEDF_t - CEDF_{t-1})/(1-CEDF_{t-1})$, where $FEDF_{t-1,t}$ is the forward EDF from years *t-1* to *t,* and $CEDF_t$ is the cumulative EDF for year *t*.

[18] Specifically, $AEDF_t = 1 - (1-CEDF_t)^{1/t}$, where $AEDF_t$ is the annualized EDF for year *t*.

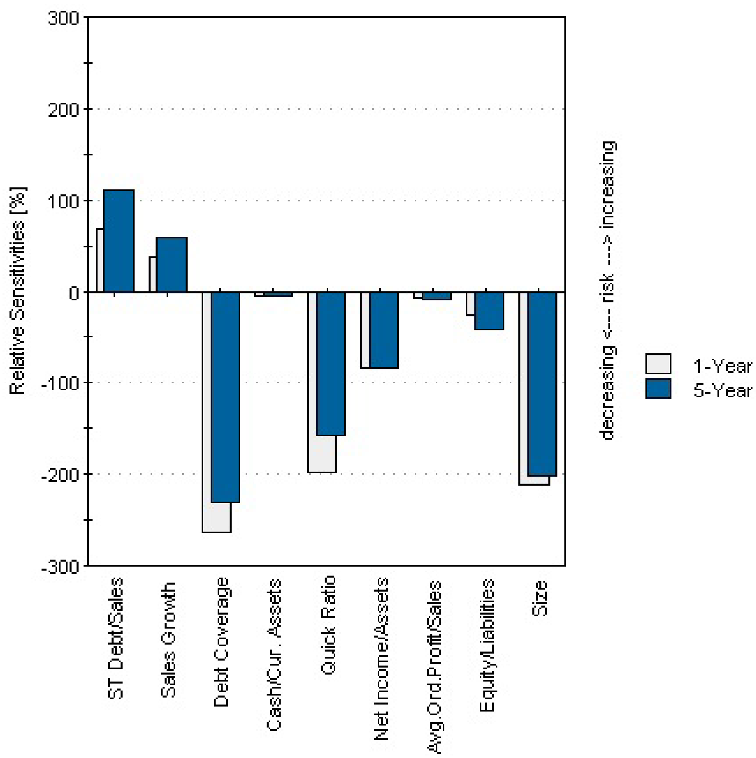

FIGURE 12 Relative Sensitivities for the RiskCalc v3.1 Switzerland Model

5.3 Asset Value and Volatility Calculation

One useful feature of RiskCalc v3.1 is that it provides an implied asset volatility. Credit Monitor and CreditEdge clients can use this volatility to analyze IPO activities. After a firm is public, the Moody's KMV PFM should be used. However, this model requires an asset volatility that is derived from the public share price. In RiskCalc v3.1, the asset volatility of the firm is estimated using its industry and size and a methodology that is very similar to PFM. A structural model framework is then used to solve for the implied asset value from the estimated EDF credit measure, the estimated volatility, and the firm's liability structure.

6 CONCLUSION

The RiskCalc v3.1 Switzerland model incorporates actual financial statement and default information provided by Swiss financial institutions.

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 and size classifications as well as for different time periods. We also demonstrated how the power advantage is maintained both in-sample and out-of-sample.

The RiskCalc v3.1 Switzerland model controls for differences in the default risk across industries in the FSO mode. In addition, in the CCA mode, it 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, the EDF level is adjusted upward. Likewise, when default risk is low, 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.

The Moody's KMV RiskCalc v3.1 model is useful for financial institutions seeking to implement quantitative tools for originating loans, managing portfolio risk, and meeting regulatory requirements. It also provides these institutions an objective external benchmark of the risk associated with a private firm, useful in securitizing middle-market debt. Finally, as an established benchmark, RiskCalc v3.1 enables institutions to communicate with one another about their exposures.

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