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MOODY'S KMV RISKCALC™ V3.1 BELGIUM

MODELING**METHODOLOGY**

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, regulatory, and accounting practices of its specific region.

In January 2004, Moody's KMV introduced its newest RiskCalc modeling framework, RiskCalc v3.1. By incorporating both market-based (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 Belgium model.

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1 INTRODUCTION

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

- Moody's KMV RiskCalc v1.0 and 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 on only 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. This mode uses a sector-specific factor derived directly from the Moody's KMV public firm model's distance-to-default (DD). The CCA mode 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, 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 the Basel Capital Accord (BIS II).

1.2 Differences Between RiskCalc v3.1 Belgium and RiskCalc v1.0 Belgium

Since the release of RiskCalc v1.0 Belgium, Moody's KMV significantly increased the size of the database for Belgium and improved its data cleansing technologies. Because of improved data coverage, RiskCalc v3.1 Belgium includes new ratios to expand the coverage on dynamic factors of private firms' credit risk. Furthermore, the new model allows for more granular industry adjustments, credit cycle adjustments, and a complete term structure of EDF credit measures. RiskCalc v3.1 Belgium also provides new analytic tools that increase model usability and transparency. Given the advances in modeling, RiskCalc v3.1 Belgium is a more powerful predictor of default than its predecessor.

2 DATA DESCRIPTION

The source of the data for RiskCalc v3.1 Belgium 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 Basel II 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. Accordingly, in Belgium, the events which we defined as defaults include bankruptcy, insolvency, and liquidation. At the calibration stage, the model outputs are adjusted to ensure a consistent interpretation throughout the world. Specifically, the model outputs are converted into a term structure of actual default probabilities (1- through 5-year EDF credit measures).

2.2 Data Exclusions

Excluded Companies

The goal of the RiskCalc model is to provide an EDF credit measure for private Belgian 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 Belgian middle-market companies, we included only typical middle-market companies. The following types of companies are not included in the data:

- Small companies—For companies with total assets less than € 250,000 (2002 Euros), 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 shows 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 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.

2.3 Descriptive Statistics of the Data

Overview of the Data

The extensive data on both non-defaulting and defaulting companies contained in the CRD increased since RiskCalc v1.0 was developed. Figure 1 presents the distribution of Belgian 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 Belgium model.

[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 was explicitly recognized within the proposals for Basel II.

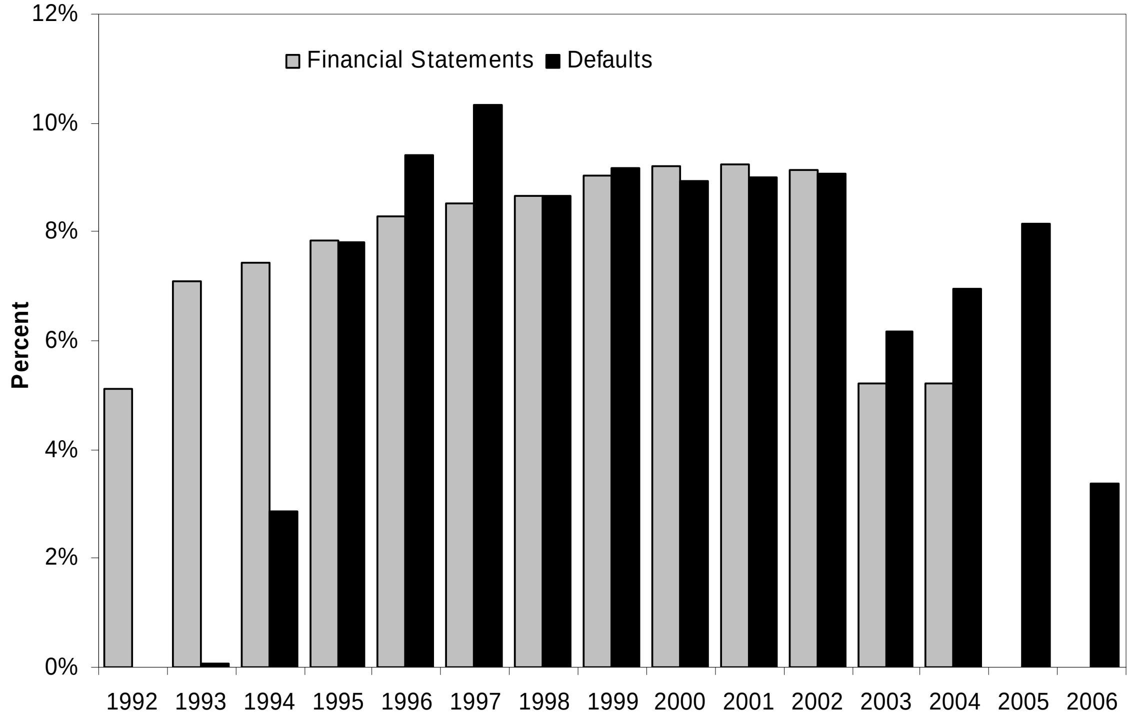

FIGURE 1 Date Distribution of Belgian Financial Statements and Defaults

TABLE 1 Information on Belgian Private Firm Sample Data

Belgian Private Firms	RiskCalc v1.0 Belgium	RiskCalc v3.1 Belgium	Change
Financial statements	523,057	1,094,000+	↑ 109%
Unique number of firms	102,954	139,000+	↑ 35%
Defaults	6,658	14,000+	↑ 110%
Time period	1992–1999	1992–2006	+7 years

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 and there are not sufficient defaults in those areas, the model may not be a good default predictor. The CRD used in developing the RiskCalc models addresses both of these issues.

Figure 2 presents the distributions of Belgian firms by industry and the proportion of defaults in each industry. Trade is the largest sector with about 30% of the sample. Figure 3 presents the distributions by the size of firms measured as Total Assets in 2002 Euros. These figures demonstrate how the proportion of defaults in any one industry group or size group is comparable to the proportion of firms in these groupings. The size distribution shows that about 50% of the firms hold assets less than 0.5 million Euros.

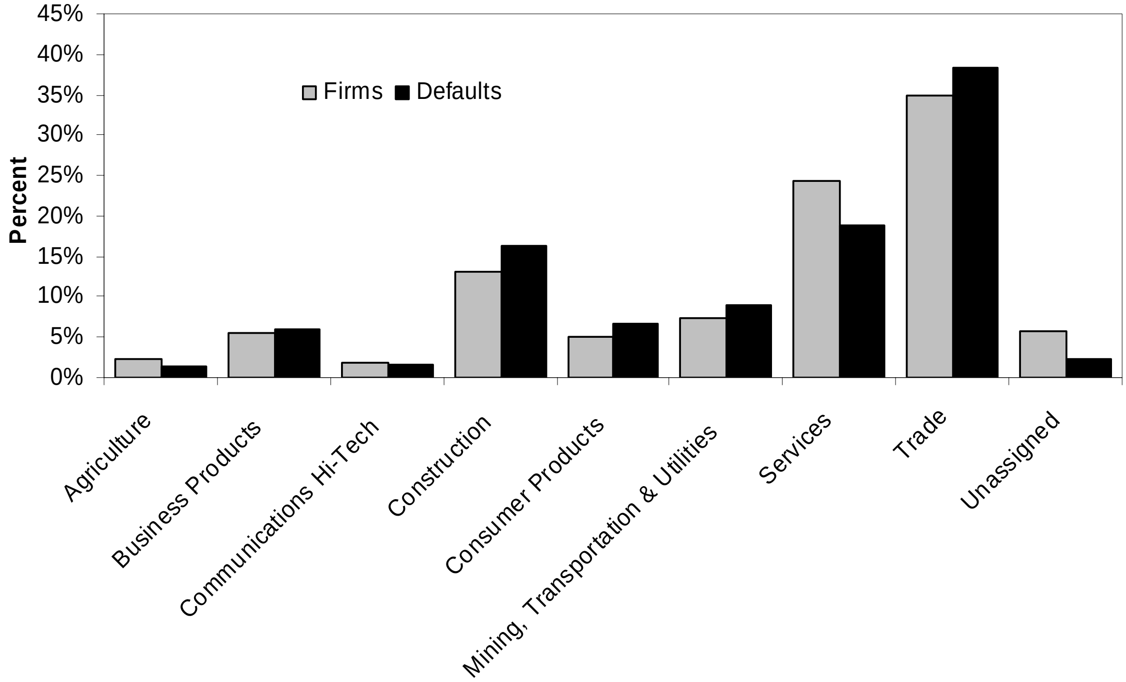

FIGURE 2 Distribution of Belgian Defaults and Firms by Industry

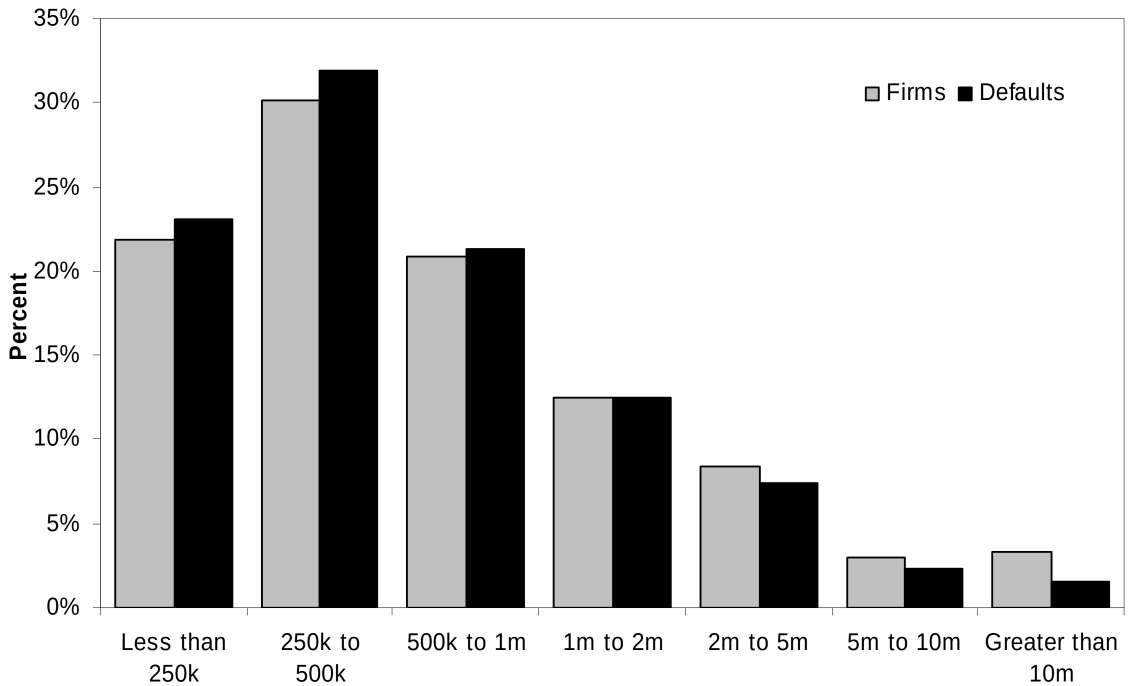

FIGURE 3 Size (as Total Assets in Euros) Distribution of Defaults and Firms

2.4 Cleaning the Data

In the development of a RiskCalc model, the first step is the collection of a large and appropriate database. In addition, data needs to be cleaned so that it is representative of the actual risk of the firms covered. Moody's KMV 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 comes from the data storage issues within financial institutions, such as 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 occurs in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true central default tendency. When default definitions used in the data sample understate the defaulting population, as is the case with Belgium, the central default tendency can be used to realign the default rates.

The estimate of long-run aggregate probabilities of default (or central default tendency) is important as an anchor for a model. The best estimation of 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 Belgium is based on several sources.

- Our examination of loan loss provision data from the Organization for Economic Co-operation and Development (OECD) and provisioning data from financial statements of large Belgian banks
- Our examination of bankruptcy data from Belgium
- Our confirmation that the central default tendency exceeded the default rates observed in our development sample

The multiple sources of external data lead us to an estimate of 1.5% as the central tendency figure for the 1-year model. This estimate is consistent with the average probability of default from the RiskCalc v1.0 Belgium model on the development sample.

Calculating a 5-year Central Default Tendency

There is a lack of publicly available data for direct calculation of the central tendency rate 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, 6.0% is used as the central default tendency for the 5-year model.

Central Default Tendency in FSO and CCA Modes

In FSO mode, the central default tendency 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, and 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.[2]
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:

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(1)

where $x_1,\ldots,x_N$ are the input ratios; $I_1,\ldots,I_K$ are indicator variables for each of the industry classifications; β and γ are estimated coefficients; Φ is the cumulative normal distribution; F and $T_1,\ldots,T_N$ are non-parametric transforms; and FSO EDF is the financial statement only EDF credit measure.[3] The Ts are the transforms of each financial statement variable, which capture the non-linear impacts of financial ratios on the default likelihood (this is shown in Figure 4 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 CCA 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.

3.1 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 2). 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:

- Is the variable readily available?
- Are the definitions of the inputs to the variable unambiguous?
- Is the meaning of the variable intuitive?
- Does the variable predict default activity?
- Is the variable not highly correlated with other variables in the model?

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[2] 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.

[3] 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.

TABLE 2 Groupings of Financial Statement Ratios

Examples of ratios in the profitability group include net income, net income less extraordinary items, profit before tax, 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 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) tend to increase a firm's default probability.
Liquidity variables include pure cash or 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 assets or 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 large 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 normally 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 Belgium

Category	Definition
Activity	Trade Debts Ratio: Trade Debts / Net Sales
Debt Coverage	Interest Coverage Ratio: EBITDA / Financial Charges
Growth	Sales Growth: Net Sales(t) / Net Sales(t-1) – 1 Change in ROA: Net Income(t) / Assets(t) – Net Income(t-1) / Total Assets(t-1)
Leverage/Gearing	Equity Ratio: (Reserves + Retained Earnings)/ Total Liabilities Current Leverage: (Current Liabilities - Cash and Securities) / (Total Assets - Intangible Assets)
Liquidity	Current Assets Structure: Cash and Securities / Current Assets
Profitability	ROA: Pre-Tax Income / Total Assets
Size	Size: Total Real Assets in 2002 Euros

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 below that of the company (e.g., if ROA is in the 90th percentile that means that 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 transform for return on assets is downward sloping. For this ratio the slope decreases as profitability becomes large (Figure 4). Such a transform indicates that more profitable firms have lower default probabilities, but the impact diminishes as profitability increases.
- For the **Leverage/Gearing** group, the transform for the equity ratio is downward sloping and the transform for current leverage is upward sloping (Figure 4). The equity ratio is backwards S-shaped, with less impact on risk from changes at both ends of the distribution of the ratio.
- For the **Liquidity** group, the transform for current assets structure is downward sloping. Current assets structure (cash and securities/current assets) measures the portion of current assets that are immediately available for use. The slope of the transform is similar across the percentile space. Therefore, changes in either direction from the median imply an equal change in risk (Figure 4).
- For the **Activity** group, the transform for the trade debts ratio is upward sloping. The slope of both transforms is mostly constant across the percentiles (Figure 4).
- The **Size** variable is inflation-adjusted total assets (2002 Euros). This variable's transformation is flat until the 40th percentile and then downward sloping (Figure 4). This indicates that larger firms have lower default probabilities. The slope of the transform becomes steep around for the largest firms indicating that the impact of size on risk is higher for the largest firms.
- The **Debt Coverage** variable is EBITDA over financial charges. The slope of the transform declines as the coverage ratio exceeds one. This indicates that once the debt coverage ratio reaches a low level, the risk is sensitive to changes in either direction (Figure 4).
- The **Growth** variables are sales growth and change in ROA. Both of them are U-shaped, indicating that large increases or decreases in sales and ROA are associated with higher default probabilities, while stable sales and ROA year-upon-year decreases the probability of default (Figure 4).

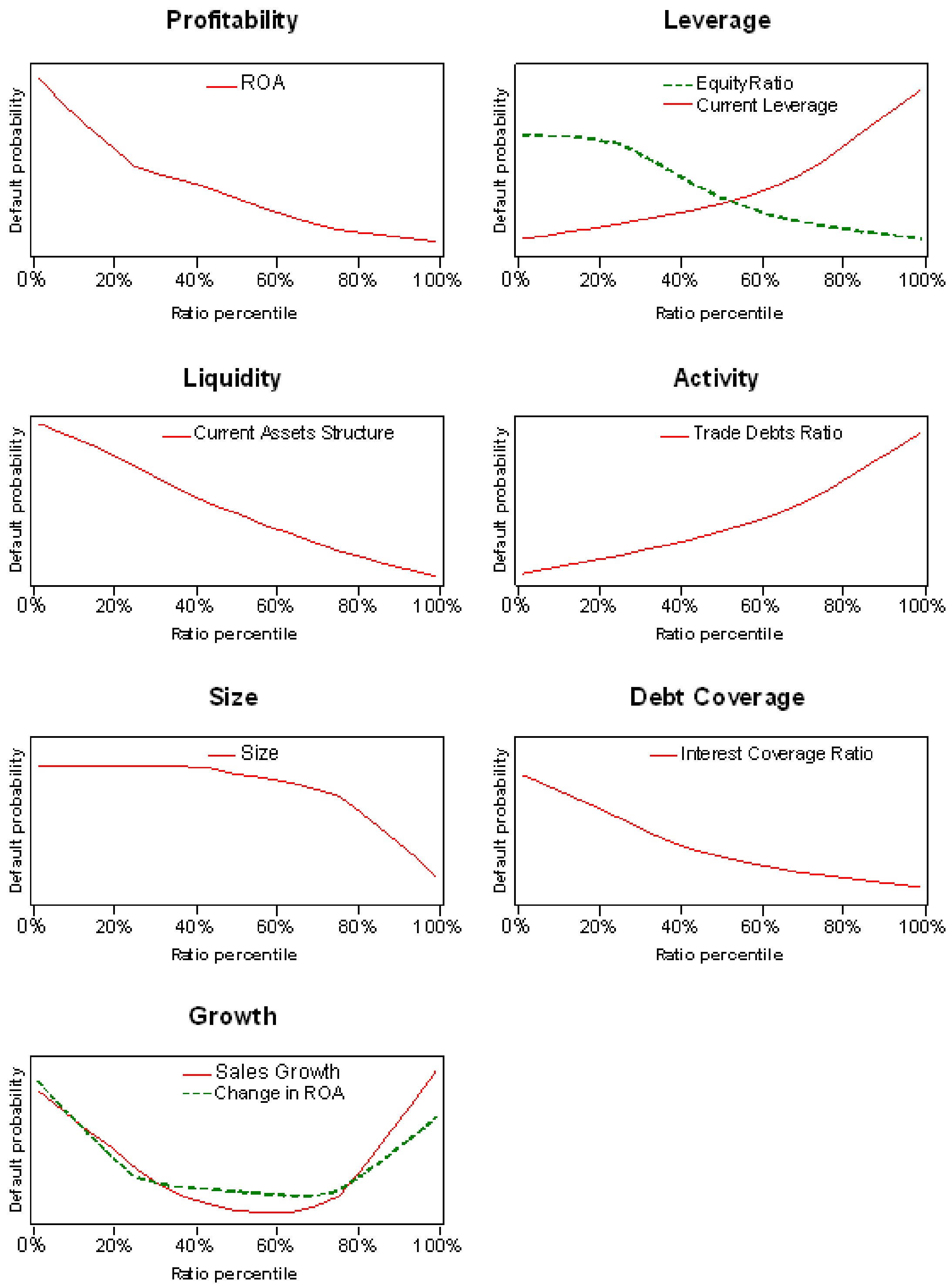

FIGURE 4 Transformations of Financial Statement Variables Used in the Model

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 since 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.[4]

Calculation of Weights

To calculate the weighting of a variable, the EDF credit measure for a theoretical firm with all its variables at the average transformation values is computed. 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 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. Because 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 Belgium. The most important categories are Leverage/Gearing and Liquidity.

TABLE 4 Risk Drivers in RiskCalc v3.1 Belgium

Category	Weights
Leverage/Gearing	35%
Liquidity	22%
Debt Coverage	12%
Profitability	11%
Growth	10%
Activity	5%
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 Belgium, 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 credit measure. Table 6 presents the average EDF value by industry for the development sample.

[4] See Figure 4.

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

	1-year Model		5-year Model	
	Accuracy Ratio	P-value for the Increase in Log Likelihood	Accuracy Ratio	P-value for the Increase in Log Likelihood
FSO mode without industry controls	71.6%		52.7%	
FSO mode with industry controls	72.3%	<.0001	53.7%	<.0001

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.[5] In Table 6, the values show the combined impact of the industry adjustment and the average levels of each ratio for a particular industry. The combination of the two determine the average FSO EDF value for a company.

TABLE 6 Average EDF Credit Measure by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Agriculture	0.96%	3.52%
Business Products	1.83%	6.53%
Telecommunications and High Tech	1.92%	5.77%
Construction	2.00%	7.37%
Consumer Products	2.19%	7.94%
Mining, Transportation, Utilities and Natural Resources	1.77%	6.78%
Services	1.30%	4.71%
Trade	1.55%	5.86%

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 Belgium includes a credit cycle adjustment factor. The credit cycle adjustment 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 DD 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.[6] 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.

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

[6] cf., Bohn and Crosbie, 2003

Adjustment Factor Used in the Model

For the Belgian 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 public firms in Belgium together with the Netherlands and Luxembourg (BeNeLux), and public firms in a basket of eleven continental European countries.[7] The weight on the BeNeLux index is industry-specific and determined by the market value of assets of BeNeLux firms in each industry relative to all firms in the basket. In the event that 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 the associated countries.

The DD factor is meant to be a forward-looking indicator of default risk. One way to measure the markets 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 risk-free bond will increase to compensate for the extra risk. Figure 5 presents the evidence of the Belgian 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 Belgian public firms. We expect a concurrent relationship between the series since both are forward-looking, which is what the figure shows.

Figure 6 provides evidence of the relationship between the DD factor and public default rates in Europe as measured by Moody's KMV.[8] Similar to credit spread evidence, 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 strong predictor of economic conditions in each industry and will adjust the probabilities of default to reflect the position in the credit cycle.

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[7] In this context, a public company is a company with publicly traded equity. The European index includes Austria, Belgium, Denmark, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, and Switzerland.

[8] The public default rate is based on the same eleven countries included in the DD factor calculation.

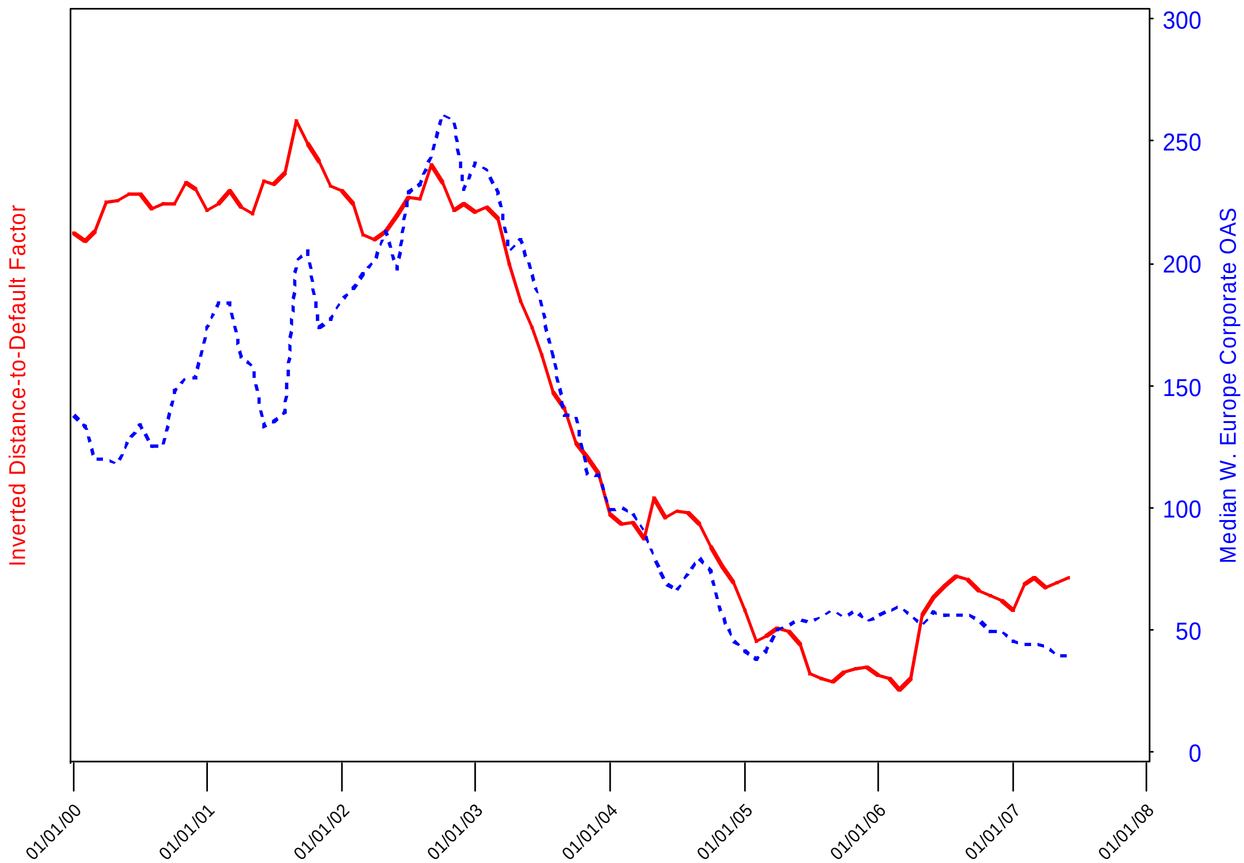

FIGURE 5 Belgian DD Factor and Western Europe Corporate Yield Spreads: Jan. 2000–Jun. 2007

Figure 5 displays the Belgian DD factor (red solid line) against the historical credit spread levels in Western Europe (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 Europe Corporate Bond Group.

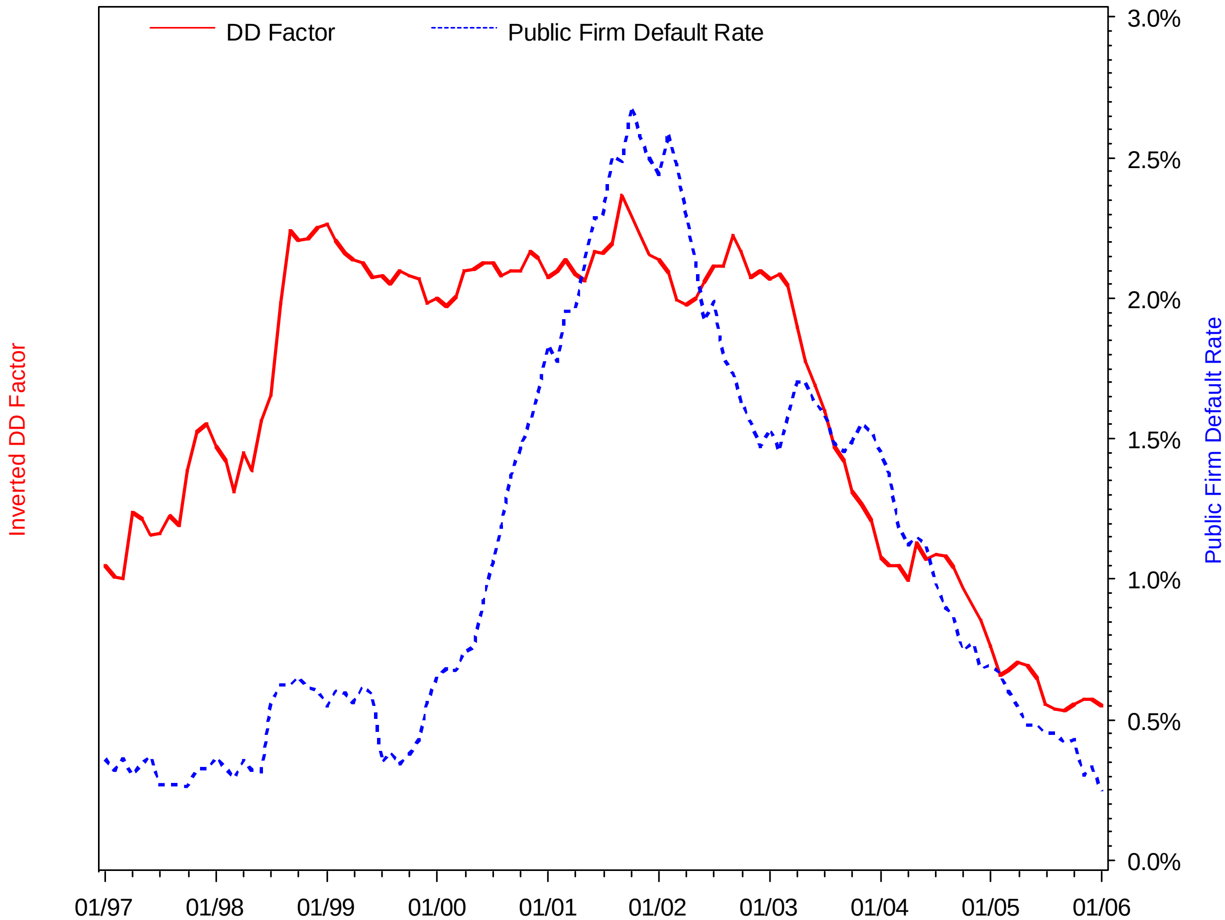

FIGURE 6 Belgian DD Factor and Europe Public Default Rates: 1997–2005

Figure 6 displays the Belgian DD factor (red solid line) against the historical public firm default rate for Europe (blue dotted line). The DD factor increases in anticipation of the increase in default activities.

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. To perform out-of-sample testing, we performed walk forward and *k*-fold analyses. The results of the testing show that the model is uniformly more powerful than other models across different time periods, sectors, and size classifications.

In Belgium, we performed rank order validation of this model in both CCA and FSO mode. As in other countries, data issues can complicate the interpretation of the differences in AR between these modes. Therefore, we chose to focus on whether or not the new model outperforms the old model and other benchmarks in both modes. Changes in the definition of default, legal environment or simply the process of collecting defaults, can skew the difference in AR between the two modes. For purposes of this document, we present the overall AR for both the CCA and FSO model and for the power tests across periods, sectors, and size classifications we present AR for the FSO model relative to v1.0 and Z-score.

4.1 Increase in Overall Model Power and Accuracy

Table 7 presents the in-sample overall measures of power for the RiskCalc v3.1 Belgium model versus alternative models. In FSO mode, the model's performance improves by more than three percentage points of accuracy ratio at the 1-year horizon and 2.7% at the 5-year horizon compared with RiskCalc v1.0 Belgium. Table 7 also contains p-values for the statistical test for which the difference between the accuracy ratio from v3.1 FSO 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[9].

Relative to other available alternatives, the results were more dramatic. The new RiskCalc v3.1 model outperformed the Z-score model (Altman, Hartzell and Peck, 1995) by more than eighteen percentage points at the 1- and 5-year horizon.

TABLE 7 Power Enhancements of the RiskCalc v3.1 Belgium Model

	1-year Model		5-year Model	
	Accuracy Ratio	p-value	Accuracy Ratio	p-value
RiskCalc v3.1 CCA	70.7%		52.4%	
RiskCalc v3.1 FSO	72.3%		53.7%	
RiskCalc v1.0	69.2%	<.0001	51.0%	<.0001
Z-score	54.3%	<.0001	35.0%	<.0001

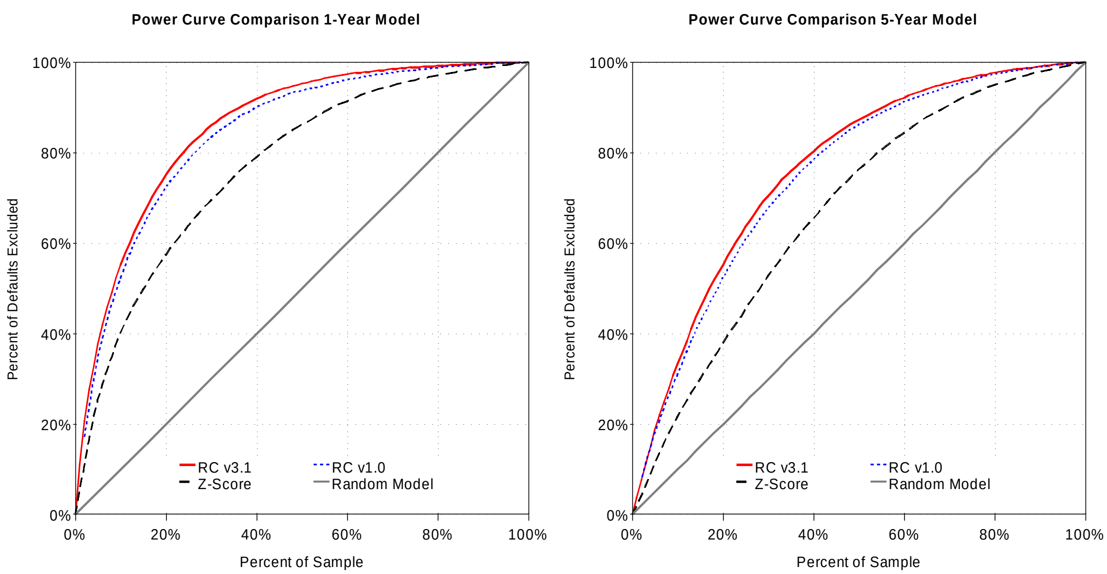

FIGURE 7 Power of Alternative Models (1- and 5-year)—Belgium

Figure 7 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 7. The power improvements are across the middle of the distribution relative to RiskCalc v1.0.

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.

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[9] For more details on the computation of the p-value, see Hood (2007).

To check for this issue, the correlation coefficients (Table 8) for the financial statement ratios in the model and the variance inflation factors (Table 9) are computed on the transformed variables (see Figure 4).[10]

Model Results

This section shows the results of the model, after being tested for excessive multicollinearity. Table 8 displays the correlations among the transformed input factors. Table 9 displays the variance of inflation factors.

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

	Trade Debts Ratio	Interest Coverage Ratio	Sales Growth	Change in ROA	Equity Ratio	Current Leverage	Current Assets Structure	ROA	Size
Trade Debts Ratio	1.0								
Interest Coverage Ratio	0.08	1.0							
Sales Growth	0.06	0.01	1.0						
Change in ROA	-0.02	0.06	0.09	1.0					
Equity Ratio	0.24	0.26	0.00	0.05	1.0				
Current Leverage	0.12	0.37	0.06	0.13	0.53	1.0			
Current Assets Structure	0.18	0.24	-0.01	-0.02	0.57	0.27	1.0		
ROA	0.12	0.49	0.05	0.11	0.30	0.50	0.24	1.0	
Size	-0.10	-0.02	0.10	0.21	-0.05	0.09	-0.10	0.02	1.0

The Variance Inflation Factors (VIF) (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. The VIF levels are all below 2, indicating that the collinearity between the variables is low.[11] The two ratios with the highest correlation are the equity ratio and current assets structure in Table 8.

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

[11] As Woolridge (2000) shows, VIF is inversely related to the tolerance value (1-R2), 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 R2 values are greater than 0.75 (so that VIF is greater than 4.0), we typically suspect that multicollinearity could be a problem. If any of the R2 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 9 Variance Inflation Factors

Variable	VIF
ROA	1.81
Current Leverage	1.71
Equity Ratio	1.66
Interest Coverage Ratio	1.58
Current Assets Structure	1.38
Trade Debts Ratio	1.17
Change in ROA	1.14
Size	1.09
Sales Growth	1.06

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- and 5-year models, respectively.

RiskCalc v3.1 Belgium outperforms both RiskCalc v1.0 Belgium and Z-score in all sectors. The power gain over the v1.0 model is statistically significant for 8 of the 9 sectors. The highest power in the 1-year model (Table 10) can be found in Business Products (75.8%), while the lowest is found in the Telecommunications and High Tech group (68.0%). At the 5-year horizon (Table 11), the highest power other than Unassigned is in Business Products (55.9%), and the lowest is in the Telecommunications and High Tech group (49.1%).

TABLE 10 Model Power by Industry 1-year Model

	Percentage of Defaults	AR* v3.1	AR v1.0	v3.1-v1.0* p-value	AR* Z-score
Agriculture	1%	70.0%	62.9%	0.0003	51.4%
Business Products	6%	75.8%	73.6%	0.0001	61.8%
Telecommunications and High Tech	2%	68.0%	66.3%	0.0967	55.9%
Construction	17%	73.5%	70.0%	<.0001	57.3%
Consumer Products	7%	72.0%	69.7%	<.0001	55.3%
Mining, Transportation, Utilities and Natural Resources	9%	69.8%	69.1%	0.1525	55.8%
Services	18%	72.3%	69.8%	<.0001	54.5%
Trade	38%	71.0%	67.5%	<.0001	54.9%
Unassigned	2%	74.7%	71.4%	0.0025	52.6%

*AR = accuracy ratio

TABLE 11 Model Power by Industry 5-year Model

	Percentage of Defaults	AR* v3.1	AR* v1.0	v3.1-v1.0 p-value	AR* Z-score
Agriculture	1%	49.9%	44.9%	0.0010	37.5%
Business Products	6%	55.9%	53.9%	0.0005	42.5%
Telecommunications and High Tech	2%	49.1%	47.5%	0.2499	35.6%
Construction	16%	52.7%	49.1%	<.0001	36.1%
Consumer Products	7%	53.2%	51.3%	0.0003	36.4%
Mining, Transportation, Utilities and Natural Resources	9%	50.9%	50.6%	0.5467	39.0%
Services	19%	55.5%	53.6%	<.0001	37.2%
Trade	38%	51.5%	49.5%	<.0001	34.5%
Unassigned	2%	63.1%	58.7%	<.0001	35.2%

*AR = accuracy ratio

Table 12 and Table 13 present the power comparisons by firm size (Total Assets in 2002 Euros) for the 1- and 5-year models, respectively. RiskCalc v3.1 Belgium outperforms both RiskCalc v1.0 Belgium and Z-score in all size groups but one at the 5-year horizon. The highest power in the 1-year model is found in the over 0.5 to 1 mm group of firms. The highest power in the 5-year model is found in the 1 to 2 mm group, and the lowest is in the under 250,000 group.

TABLE 12 Model Power by Size (Total Assets in 2002 Euros) 1-year Horizon

	Percentage of Defaults	AR* v3.1	AR* v1.0	v3.1-v1.0 p-value	AR* Z-score
< € 250,000	22%	69.6%	65.6%	<.0001	58.2%
€ 250,000 to € 0.5mm	31%	71.6%	68.7%	<.0001	52.8%
€ 0.5mm to € 1mm	22%	74.6%	71.9%	<.0001	54.7%
€ 1mm to € 2mm	13%	74.5%	72.3%	<.0001	52.9%
€ 2mm to € 5mm	8%	73.9%	70.7%	<.0001	54.0%
€ 5mm to € 10mm	2%	72.2%	71.0%	0.1908	55.2%
Over € 10mm	2%	68.9%	68.9%	0.9725	46.1%

*AR = accuracy ratio

TABLE 13 Model Power by Size (Total Assets in 2002 Euros) 5-year Horizon

	Percentage of Defaults	AR* v3.1	AR v1.0	v3.1-v1.0 p-value	AR Z-score
< € 250,000	22%	51.4%	49.4%	<.0001	37.3%
€ 250,000 to € 0.5mm	32%	59.7%	56.3%	<.0001	39.8%
€ 0.5mm to € 1mm	22%	61.8%	58.6%	<.0001	40.9%
€ 1mm to € 2mm	13%	62.1%	59.0%	<.0001	41.3%
€ 2mm to € 5mm	7%	59.5%	55.7%	<.0001	40.0%
€ 5mm to € 10mm	2%	57.2%	55.0%	0.0097	41.9%
Over € 10mm	1%	51.5%	54.4%	0.0169	29.7%

*AR = accuracy ratio

4.4 Power Performance Over Time

Because models are implemented at various points in a business cycle by design, power tests by year (Table 14 and Table 15) 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 Belgium is compared with RiskCalc v1.0 Belgium and Z-score for each year. As shown in these tables, RiskCalc v3.1 consistently outperforms both. In addition, the power of the model is consistent across the years with no single year having an accuracy ratio below 60% for the 1-year model.

TABLE 14 Model Power over Time: 1-year Horizon

	Percentage of Defaults	AR* v3.1	AR* v1.0	v3.1-v1.0 p-value	AR* Z-score
1992	2%	63.7%	60.7%	<.0001	44.1%
1993	9%	72.9%	69.5%	<.0001	54.1%
1994	10%	72.6%	70.1%	<.0001	55.3%
1995	10%	72.2%	69.0%	<.0001	54.0%
1996	9%	71.5%	69.4%	<.0001	55.0%
1997	9%	71.9%	69.0%	<.0001	53.5%
1998	8%	71.8%	68.1%	<.0001	53.2%
1999	9%	69.9%	68.4%	0.0042	51.3%
2000	9%	71.0%	69.8%	0.0128	53.8%
2001	7%	70.0%	67.7%	<.0001	52.3%
2002	7%	61.8%	58.7%	<.0001	41.5%
2003	7%	68.6%	64.1%	<.0001	49.5%
2004	5%	70.5%	66.5%	<.0001	51.3%

*AR = accuracy ratio

TABLE 15 Model Power over Time: 5-year Horizon

	Percentage of Defaults	AR* v3.1	AR* v1.0	v3.1-v1.0 p-value	AR* Z-score
1992	7%	54.8%	51.5%	<.0001	36.9%
1993	10%	61.7%	58.4%	<.0001	43.0%
1994	10%	62.7%	58.8%	<.0001	43.5%
1995	10%	62.0%	58.2%	<.0001	43.0%
1996	10%	60.2%	57.4%	<.0001	41.9%
1997	10%	58.7%	56.1%	<.0001	39.9%
1998	9%	59.2%	57.1%	<.0001	40.0%
1999	9%	58.5%	56.4%	<.0001	38.6%
2000	9%	57.6%	55.7%	<.0001	38.2%
2001	8%	58.6%	56.2%	<.0001	39.1%
2002	5%	59.8%	56.6%	<.0001	39.0%
2003	3%	65.6%	61.2%	<.0001	46.7%
2004	2%	70.8%	66.3%	<.0001	51.4%

*AR = accuracy ratio

4.5 Power Performance on Luxembourg Data

While we did not include data from Luxembourg firms in our model development sample, we validated the v3.1 model on firms from Luxembourg. We have approximately 17,000 financial statements, and more than 150 defaults from Luxembourg firms from 1992–2005. Table 16 presents the AR for v3.1 vs. v1.0 and Z-score, and Figure 8 shows the power plots for the tests. The v3.1 model performs very well on Luxembourg firms, even though this data was not included in the model building process.

TABLE 16 Power of the RiskCalc v3.1 Belgium Model on Luxembourg Firms

	1-year Model		5-year Model	
	Accuracy Ratio	p-value	Accuracy Ratio	p-value
RiskCalc v3.1	78.2%		60.7%	
RiskCalc v1.0	76.1%	.17	57.7%	.02
Z-score	61.6%	<.0001	41.2%	<.0001

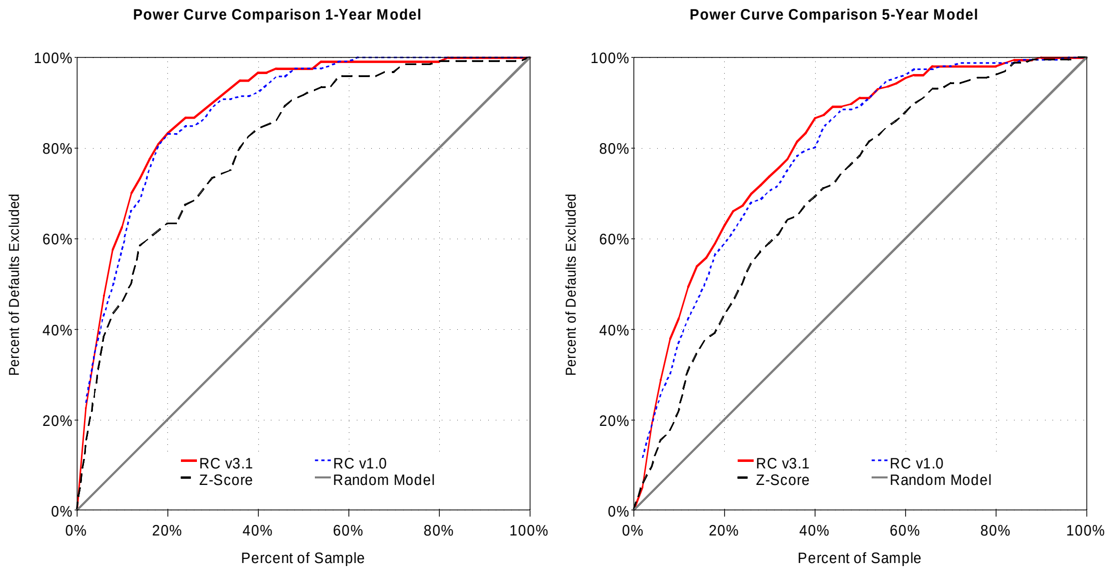

FIGURE 8 Power of Alternative Models (1- and 5-year) — Luxembourg Data

4.6 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 17 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 outperforms RiskCalc v1.0 Belgium. 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.

TABLE 17 RiskCalc v3.1 Belgium *k*-fold Test Results

	Out-of-Sample AR*		RiskCalc v1.0	
	1-year AR	5-year AR	1-year AR	5-year AR
Subsample 1	70.8%	58.8%	67.9%	56.1%
Subsample 2	71.1%	58.9%	67.7%	55.9%
Subsample 3	69.6%	58.8%	67.3%	56.3%
Subsample 4	71.7%	58.9%	69.0%	56.3%
Subsample 5	71.0%	58.5%	68.2%	55.9%
k-fold Overall	72.1%	53.7%		
In-sample AR	72.3%	53.7%	69.2%	51.0%

*AR = accuracy ratio

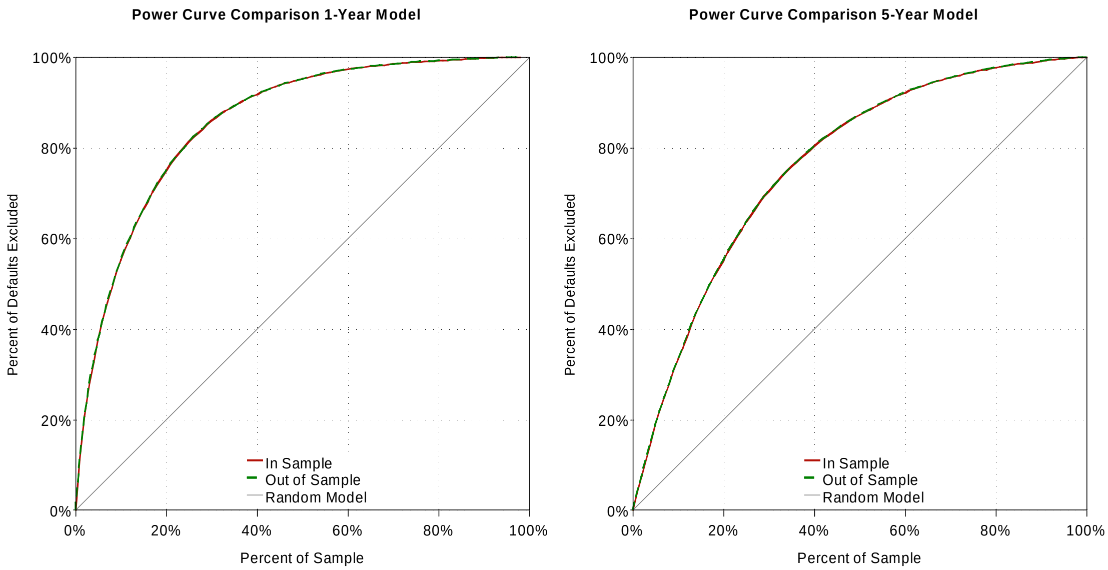

FIGURE 9 RiskCalc v3.1 Belgium *k*-fold

The *k* -fold testing does not control for time dependence. Each of the *k* sub-samples contains data from all periods. As a result, if there was 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.

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 10 bps in both cases. Furthermore, the RiskCalc v3.1 Belgium model outperforms RiskCalc v1.0 Belgium in an out-of-sample context at both the 1- and 5-year horizons (Table 17).

4.7 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. We then 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.

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 0.7% in both cases. Furthermore, the RiskCalc v3.1 Belgium model outperforms RiskCalc v1.0 Belgium in an out-of-time context at both the 1- and 5-year horizons.[12]

[12] The out-of-sample ARs are 73.3% and 57.8% for the 1-year and 5-year models, respectively. These out-of-sample ARs are 3.1 and 2.9 points higher than RiskCalc v1.0 Belgium for the 1- and 5-year models respectively—on the same sample.

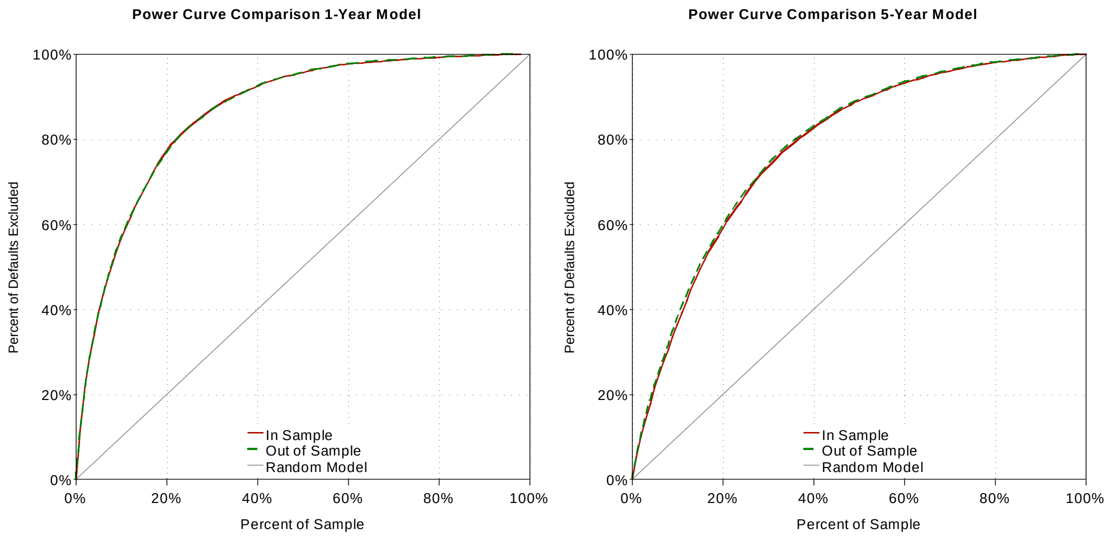

FIGURE 10 Out-of-sample Performance (1- and 5-year) Belgium Walk Forward

4.8 Model Calibration and Implied Ratings

To aid in the interpretation of an EDF credit measure, an EDF value is mapped to an EDF-implied rating. 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 CCA 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. The distributions peak at Ba1 for both the 1-year, and Baa2 for the 5-year. While not reported here, other research shows 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.

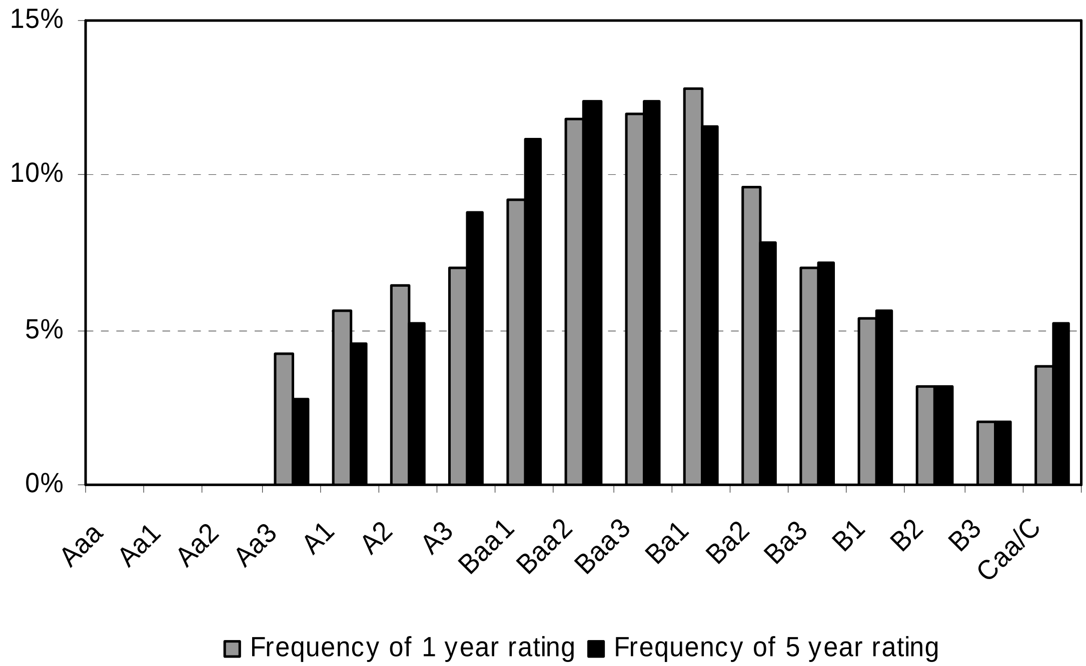

FIGURE 11 EDF-implied Ratings for the 1- and 5-year Models in the Development

5 FURTHER MODEL IMPROVEMENTS

In this section, we briefly outline some other improvements to the model. For a detailed discussion of these improvements, refer to the Technical Document.

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 v3.1 Belgium now can obtain EDF values for any point between 1 and 5 years. In addition, RiskCalc v3.1 provides EDF values for alternative definitions, such as the Forward EDF and the Annualized EDF (Table 18).

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 5-year period. The second column of Table 18 provides an example of the cumulative 1- to 5-year credit measures produced by the model.

Forward EDF Credit Measures

The forward EDF credit measure 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 three and four assuming the firm survived to year three.[13] The third column of Table 18 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 of 13.44% would have a 5-year annualized EDF of 2.84%.[14] This means that the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column of Table 18 presents the annualized EDF credit measures for years 1 to 5. These credit measures are derived from the cumulative EDF values.

TABLE 18 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 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 trade debts ratio will change the risk of the company. It is about 400% (1 year) as sensitive as the average variables (Figure 12).

[13] 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.

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

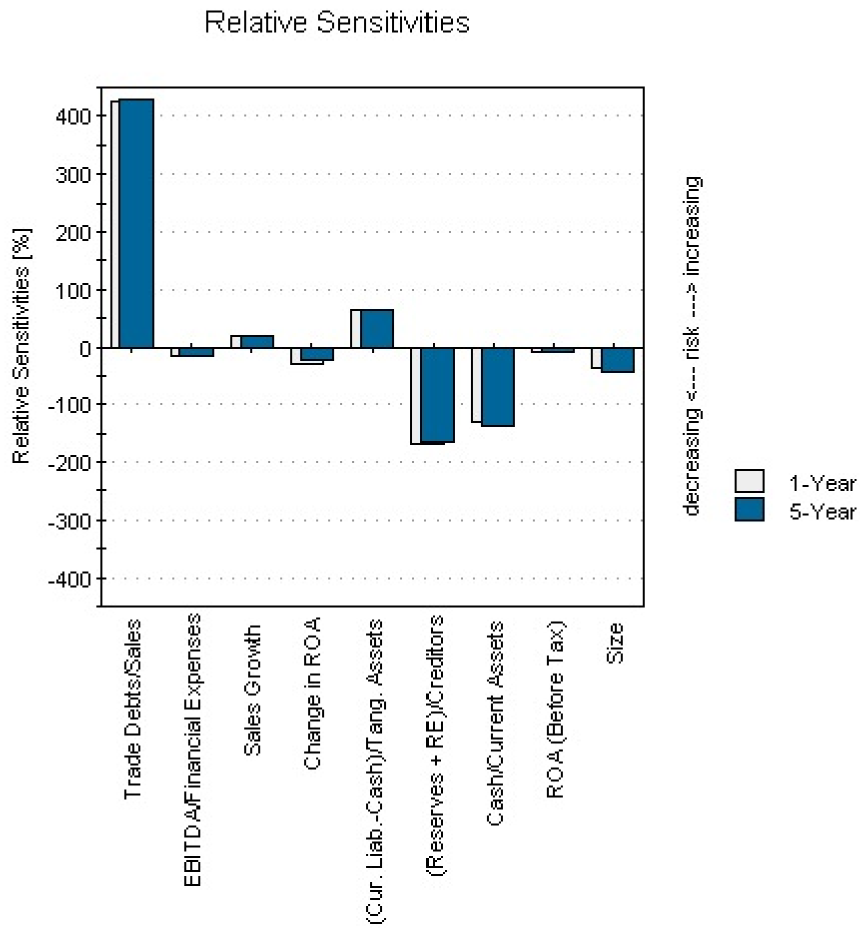

FIGURE 12 Relative Sensitivities for the RiskCalc v3.1 Belgium Model

5.3 Asset Value and Volatility Calculation

One of the features of the RiskCalc v3.1 model is that it provides an implied asset volatility. Clients of Credit Monitor® and CreditEdge can use this volatility to analyze a private firm that is to go public through an IPO. After the firm is public, the public firm model should be used. However, this model requires an asset volatility derived from the public share price. In the RiskCalc v3.1 model, the asset volatility of the firm is estimated using its industry and size and a methodology that is similar to the Private Firm Model. 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 Belgium model is based on a substantially larger database than RiskCalc v1.0 Belgium and has an additional three years of data. Improved data coverage has allows us to refine our financial statement model and achieve a robust prediction model of private firm default behavior.

The model is more powerful than any publicly available alternatives that we 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- and out-of-sample.

The RiskCalc v3.1 Belgium model controls for differences in the default risk across industries in FSO mode. In addition, in 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 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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