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MOODY'S KMV RISKCALC™ V3.1 NETHERLANDS

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.

Moody's KMV RiskCalc v3.1 incorporates both market- (systematic) and company-specific (idiosyncratic) risk factors. This document outlines the underlying research, model characteristics, data, and validation results for the RiskCalc v3.1 Netherlands model.

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1 INTRODUCTION

The Moody's KMV RiskCalc™ v3.1 Netherlands 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 Netherlands and RiskCalc v1.0 Netherlands

Since the release of RiskCalc v1.0 Netherlands, Moody's KMV significantly increased the size of the database for the Netherlands and improved its data cleansing technologies. Because of improved data coverage, RiskCalc v3.1 Netherlands 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 Netherlands also provides new analytic tools that increase model usability and transparency. Given the advances in modeling, RiskCalc v3.1 Netherlands is a more powerful predictor of default than its predecessor.

2 DATA DESCRIPTION

The source of the data for RiskCalc v3.1 Netherlands 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 the Netherlands, the events which we defined as defaults include bankruptcy 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 Dutch 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 Dutch 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 Net Sales 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.

The number of financial statements in the CRD increased substantially since 1999 in the Netherlands database. However, many of these firms are exempt from disclosing and publishing certain items from the annual report because of Dutch law. The exemption status in the Netherlands is dependent upon a three-way classification system based on size. The three different measures of size include Total Assets, Net Turnover, and number of employees. The exemptions for the small- and medium-sized firms are related to the details of the Profit and Loss (Income) statement. Therefore, a proportion of the increase in statement coverage after 1999 will have missing income statement items. While these statements are not eliminated from the CRD, we choose to exclude these firms from the model building process. We do, however, test the performance of the model on these firms in the validation portion of the document (sections 4.1, 4.3, and 4.4).

[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.

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 Dutch financial statements and defaults by year in the development sample only. Table 1 summarizes the total data used in the development, validation, and calibration of the RiskCalc v3.1 Netherlands model.

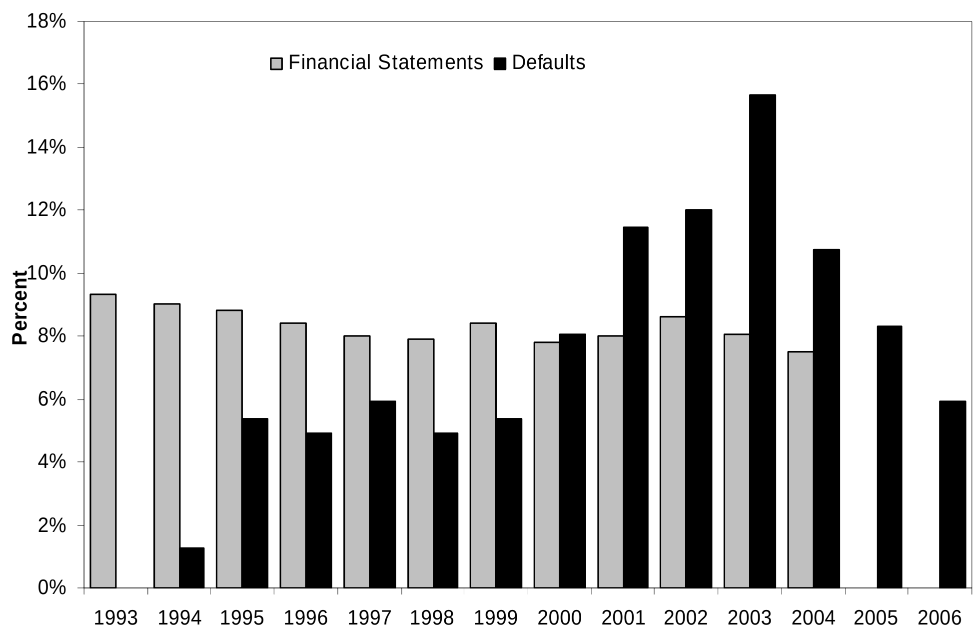

FIGURE 1 Date Distribution of Dutch Financial Statements and Defaults—Development Sample

TABLE 1 Information on Dutch Private Firm Sample Data

Dutch Private Firms	RiskCalc v1.0 Netherlands	RiskCalc v3.1 Netherlands	Change
Financial statements	79,696	400,000+	↑ 402%
Unique number of firms	19,327	90,000+	↑ 366%
Defaults	436	1,300+	↑ 198%
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 Dutch 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 20% of the development sample hold assets less than 1 million Euros.

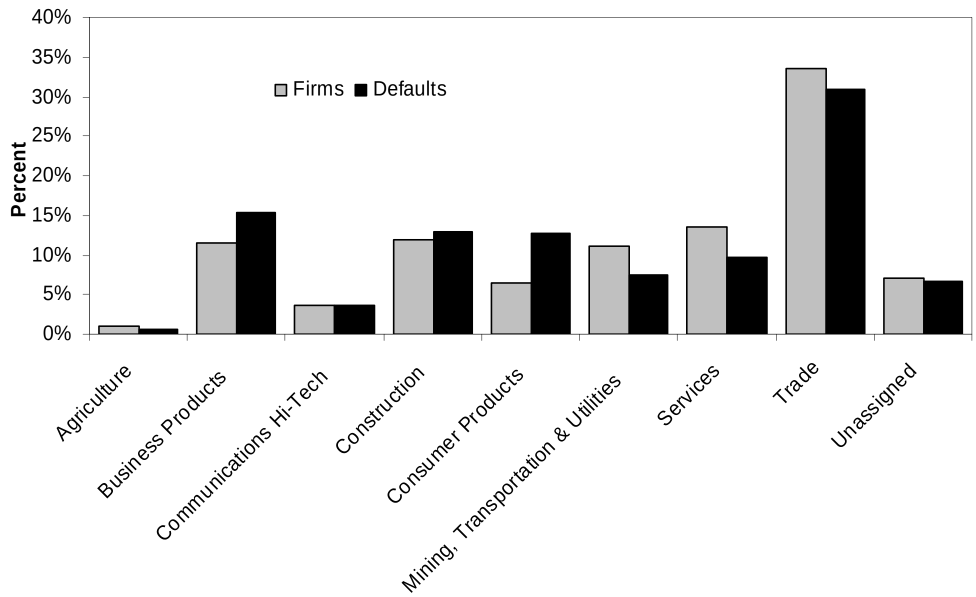

FIGURE 2 Distribution of Dutch Defaults and Firms by Industry—Development Sample

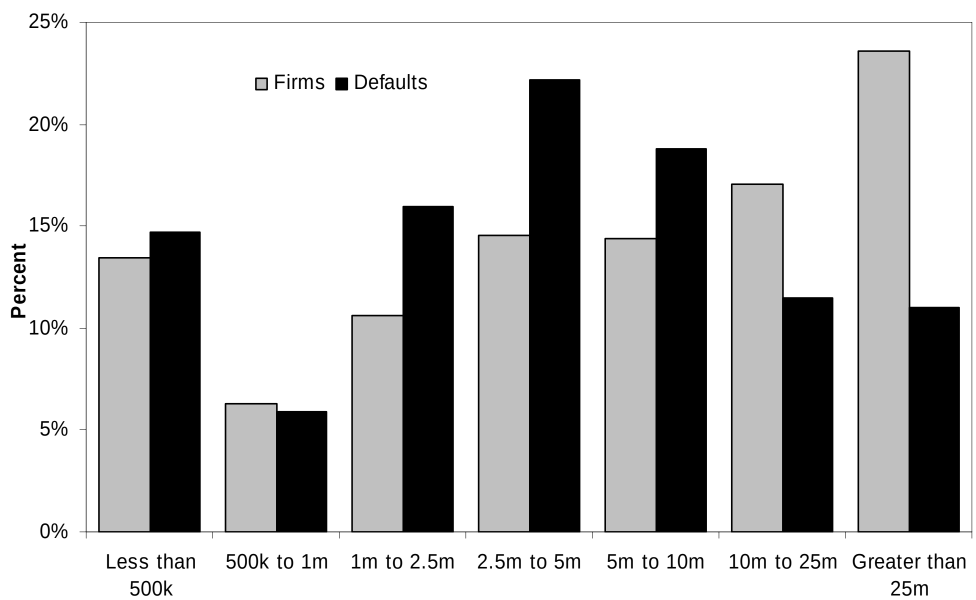

FIGURE 3 Size (as Total Assets in Euros) Distribution of Defaults and Firms—Development Sample

2.4 Central Default Tendency

Because most companies do not default, companies that do default are relatively rare and thus more valuable in building a default prediction model. Much of the lack in default data comes from 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 the Netherlands, 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 the Netherlands 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 Dutch banks
- Our examination of bankruptcy and insolvency data from Statistics Netherlands
- 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 1.65% as the central tendency figure for the 1-year model. This estimate is consistent with the average probability of default to which the RiskCalc v1.0 Netherlands model was calibrated.

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, 6.6% 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:

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

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 Netherlands

Category	Definition
Activity	Trade Creditors / Net Sales Accounts Receivable (t) / Sales (t) – Accounts Receivable (t-1) / Sales (t-1)
Debt Coverage	Cash Flow / Interest Expense
Growth	Net Sales(*t*) / Net Sales(*t*-1) – 1
Leverage/Gearing	Total Liabilities / (Total Assets – Intangible Assets) (Current Liabilities - Cash and Securities) / (Total Assets - Intangible Assets)
Liquidity	Cash and Securities / Current Liabilities
Profitability	Net Income / Total Assets
Size	Size: Total Real Sales 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, 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 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 transforms for both the Liabilities to Tangible Assets ratio and the Current Liabilities less Cash to Tangible Assets ratio are upward sloping (Figure 4). The slope of both ratios is increasing as leverage increases. This indicates that high leverage firms are more sensitive to changes in leverage.
- For the **Liquidity** group, the transform for Cash to Current Liabilities is downward sloping. This ratio measures the amount of liquid assets available to cover short term obligations. The slope of the transform is flat as Cash approaches zero and becomes negative as the ratio increases (Figure 4).
- For the **Activity** group, the transform for the Trade Creditors ratio is upward sloping. The slope of the transform is flat at low levels of the ratio and becomes increasingly positive as the ratio increases. The transform for change in AR to Sales is u-shaped. This indicates that stable levels of Accounts Receivable to Sales are less risky that large changes in either direction (Figure 4).
- The **Size** variable is inflation-adjusted Net Sales (2002 Euros). This variable's transformation is flat until the 20th percentile and then downward sloping (Figure 4). This indicates that larger firms have lower default probabilities. The slope of the transform becomes flat again for the largest firms indicating that the marginal impact of size on risk is small for the largest firms.
- The **Debt Coverage** variable is Cash Flow over Interest Expense. 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 of default is high and constant (Figure 4).
- The **Growth** variable is Sales Growth. The shape of the transform is U-shaped, indicating that large increases or decreases in Sales are associated with higher default probabilities, while stable Sales year-upon-year decreases the probability of default (Figure 4).

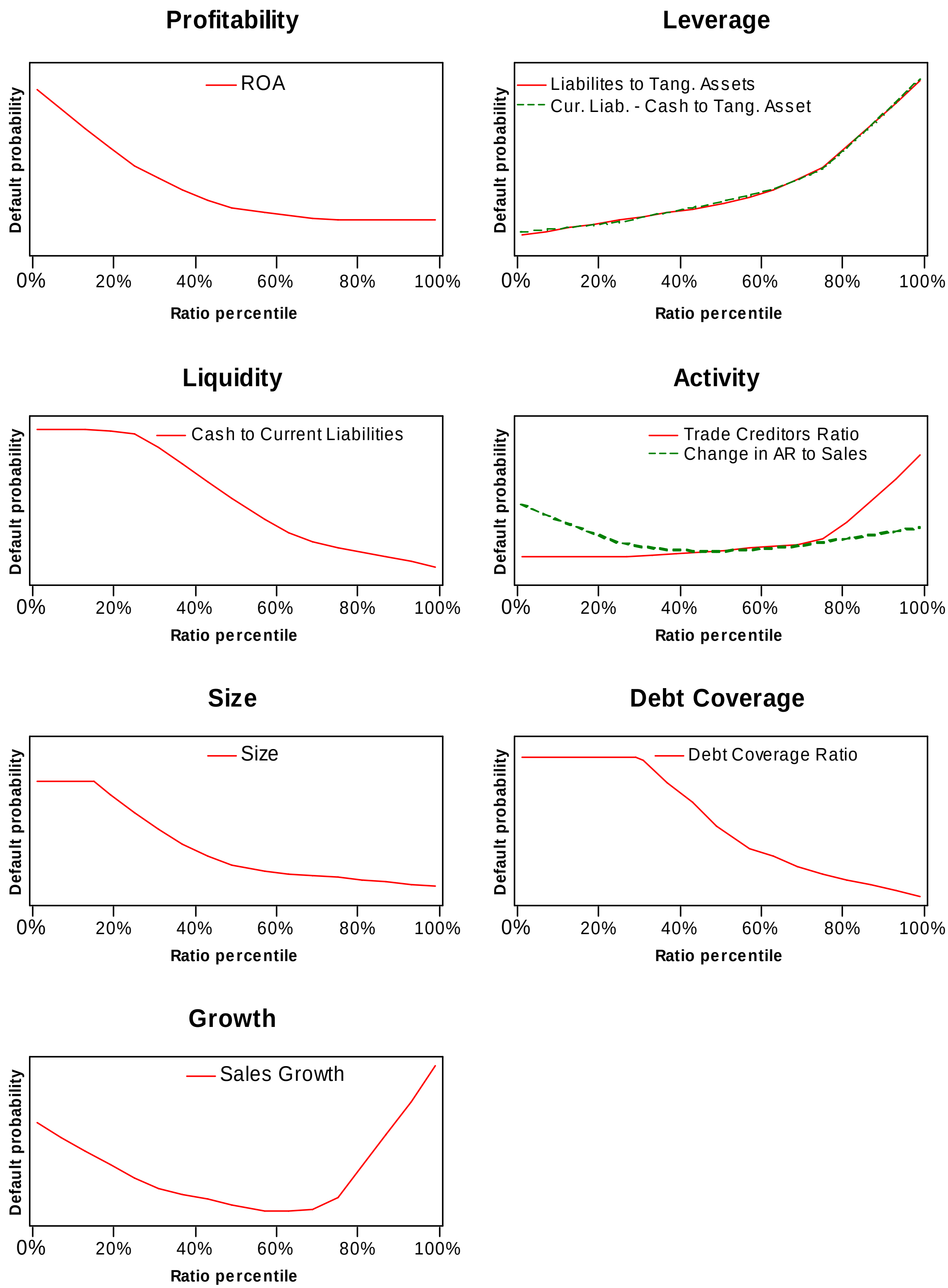

FIGURE 4 Transformations of Financial Statement Variables Used in the Model

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, 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.[4]

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 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 with 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 Netherlands. The most important categories are Leverage/Gearing, Liquidity, and Profitability with weights all close to 20%.

TABLE 4 Risk Drivers in RiskCalc v3.1 Netherlands

Category	Weights
Leverage/Gearing	22%
Liquidity	21%
Profitability	20%
Debt Coverage	12%
Activity	11%
Size	8%
Growth	6%

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 Netherlands, 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. A 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	69.2%		49.5%	
FSO mode with industry controls	70.2%	<.001	51.4%	<.001

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 Netherlands 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.

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

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

Adjustment Factor Used in the Model

For the Dutch 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 the Netherlands together with Belgium 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 Dutch 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 Dutch public firms. We expect a concurrent relationship between the series, because 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.

[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.

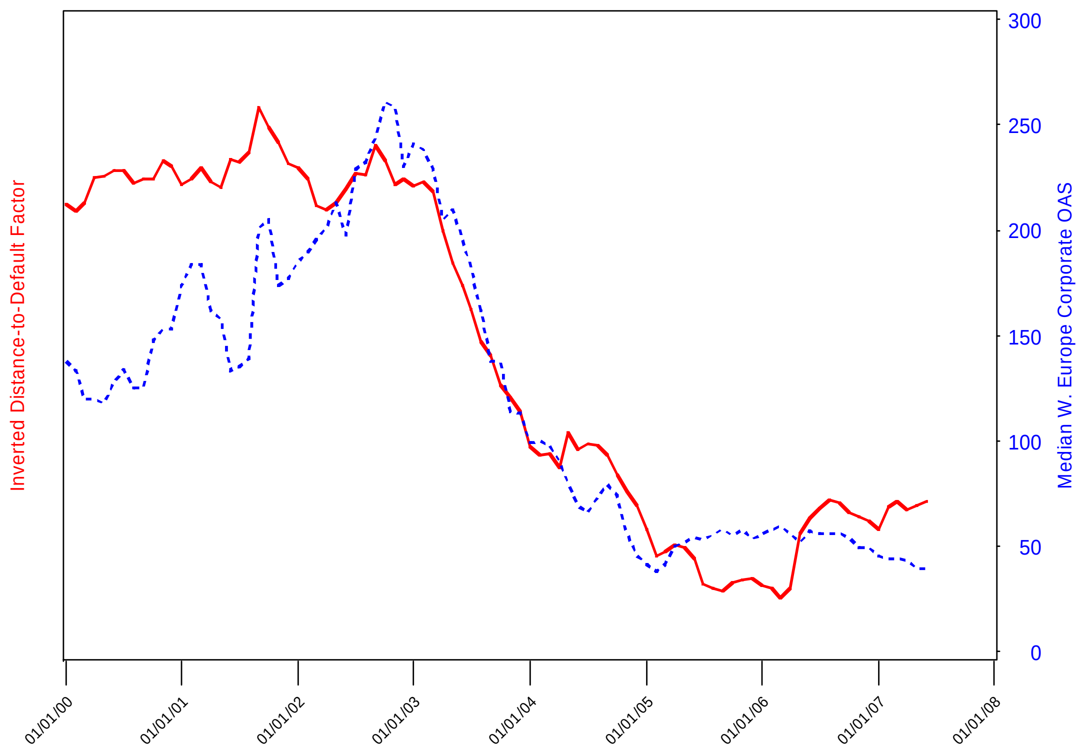


FIGURE 5 Dutch DD Factor and Western Europe Corporate Yield Spreads: Jan. 2000–Jun. 2007

Figure 5 displays the Dutch 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.

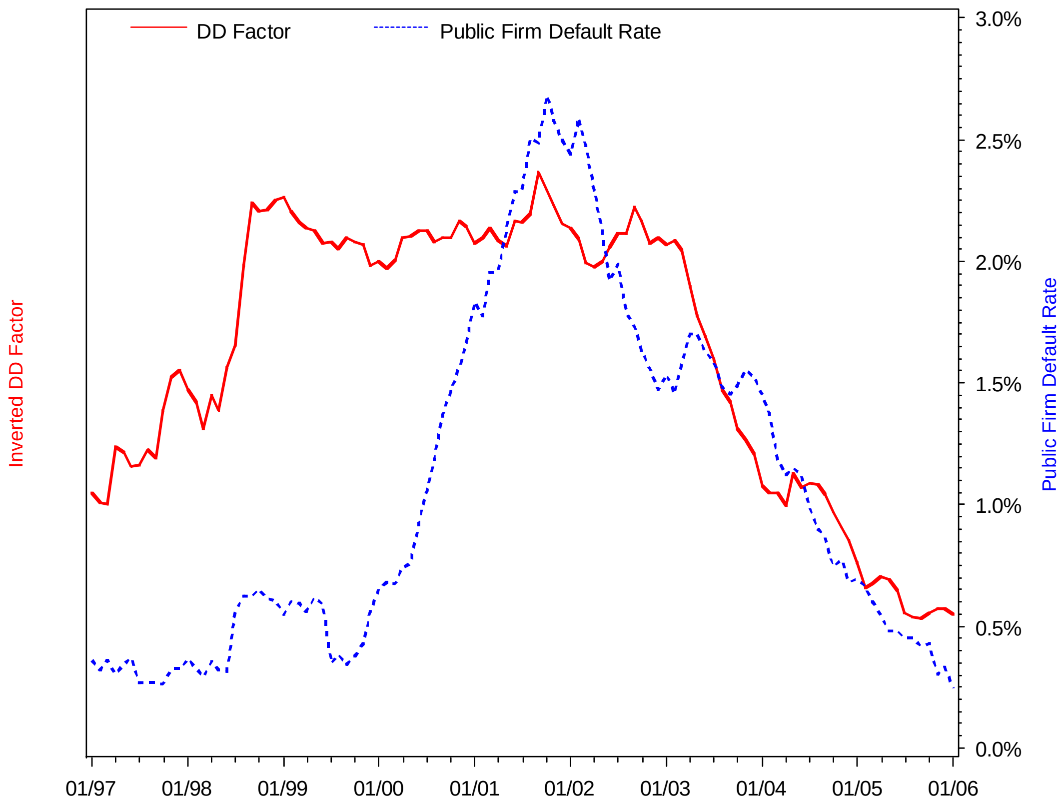


FIGURE 6 Dutch DD Factor and Europe Public Default Rates: 1997–2005

Figure 6 displays the Dutch 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 the Netherlands, we performed rank order validation of this model in both CCA and FSO modes. 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 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 models and for the power tests across periods, sectors, and size classifications we present AR for the FSO model relative to RiskCalc v1.0 and Z-score.

4.1 Increase in Overall Model Power and Accuracy

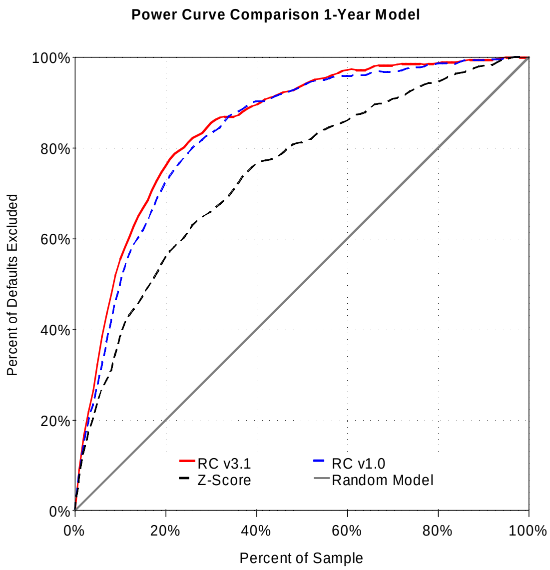
In the Netherlands sample, we filtered the data for the development sample to ensure that each ratio could be populated sufficiently to build the model. There are many cases of missing income statement data for small firms in the Netherlands because of reporting exemptions for small- and medium-sized firms. To ensure the models performance is robust to missing data items, we test the RiskCalc v3.1 model on the sample without missing data filters applied. When we drop the restriction on missing data, the number of defaults increases by over 100% and the number of financial statements increases by 400%. The number of statements and defaults increase dramatically in the later years of the sample. This causes distortions in the CCA accuracy, so we test only the FSO model on the validation (full) sample. We do present the AR for the CCA EDF in the development sample because of the sample stability over time.

Table 7 presents the in-sample overall measures of power for the RiskCalc v3.1 Netherlands model versus alternative models for the development sample. Table 8 contains the AR for the validation sample. For the development sample, in CCA mode, the model's performance improves by more than three percentage points of accuracy ratio at the 1-year horizon and 1.3% at the 5-year horizon compared with RiskCalc v1.0 Netherlands. 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 by more than eighteen percentage points at the 1- and 5-year horizons.[10]

TABLE 7 Power Enhancements of the RiskCalc v3.1 Netherlands Model—Development Sample

	1-year Model		5-year Model	
	Accuracy Ratio	p-value	Accuracy Ratio	p-value
RiskCalc v3.1 CCA	70.5%		51.3%	
RiskCalc v3.1 FSO	70.2%		51.4%	
RiskCalc v1.0	67.3%	.0029	50.0%	.1938
Z-score	48.6%	<.0001	33.2%	<.0001

[9] For more details on the computation of the p-value, see Hood (2007).
[10] Altman, Hartzell, and Peck, 1995.



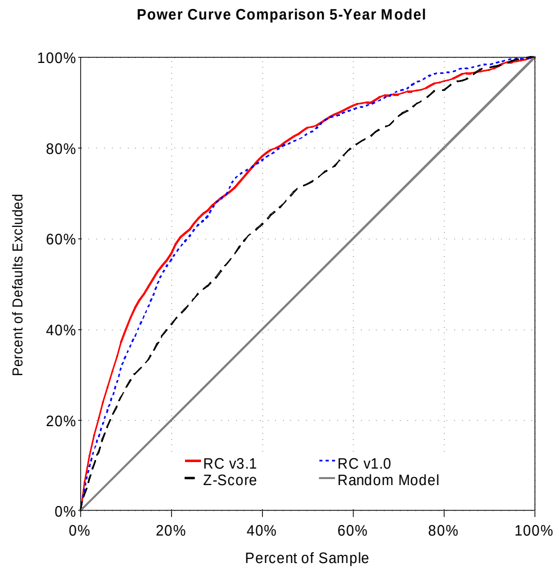


FIGURE 7 Power of Alternative Models (1- and 5-year)—Netherlands Development Sample

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.

For the validation sample, the v3.1 model performs similarly to the development sample (Table 8), while the RiskCalc v1.0 model power drops substantially for both the 1- and 5-year models. As the power plots show in Figure 8, the gain in power is uniform across the distribution of the data and not concentrated at any one end of the graph. Overall, the results show that the RiskCalc v3.1 model is a robust predictor of default in the presence or absence of income statement information. In the following sections, we present results for both the development and validation samples.

TABLE 8 Power Enhancements of the RiskCalc v3.1 Netherlands Model—Validation Sample

	1-year Model		5-year Model	
	Accuracy Ratio	**p-value**	**Accuracy Ratio**	**p-value**
RiskCalc v3.1 FSO	66.4%		44.6%	
RiskCalc v1.0	56.0%	<.0001	34.7%	<.0001
Z-score	44.8%	<.0001	28.5%	<.0001

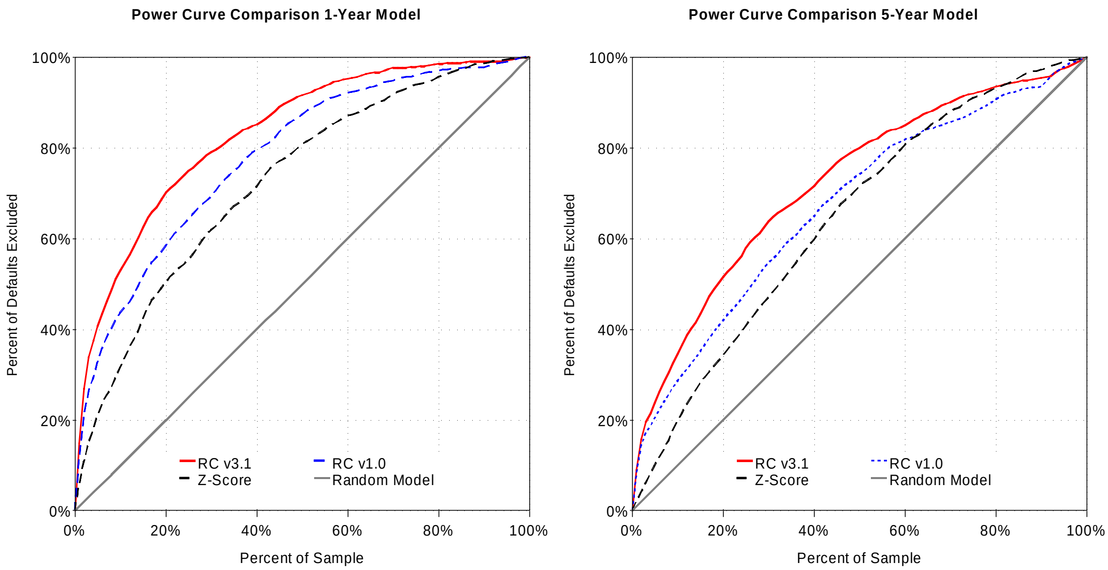


FIGURE 8 Power of Alternative Models (1- and 5-year)—Netherlands Validation Sample

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 (Table 9) for the financial statement ratios in the model and the variance inflation factors (Table 10) are computed on the transformed variables (see Figure 4).[11]

Model Results

This section shows the results of the model, after being tested for excessive multicollinearity. Table 9 displays the correlations among the transformed input factors. Table 10 displays the variance of inflation factors.

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

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

	Trade Creditors Ratio	Change in AR to Sales	Debt Coverage	Liabilities to Tang. Assets	Current Liabilities – Cash to Tang. Assets	Sales Growth	Current Liabilities to Sales	ROA	Size
Trade Creditors Ratio	1.0								
Change in AR to Sales	0.18	1.0							
Debt Coverage	0.02	0.00	1.0						
Liabilities to Tang. Assets	0.09	0.04	0.29	1.0					
Current Liabilities – Cash to Tang. Assets	0.10	0.00	0.20	0.69	1.0				
Sales Growth	0.07	0.32	0.02	0.06	0.04	1.0			
Current Liabilities to Sales	0.07	-0.03	0.25	0.33	0.61	-0.04	1.0		
ROA	0.10	0.04	0.48	0.37	0.27	0.04	0.24	1.0	
Size	0.16	0.26	-0.01	0.08	0.01	0.22	-0.07	0.03	1.0

The variance inflation factors (Table 10) for the financial statement variables represent how much of the variation in one independent variable can be explained by all other independent variables in the model. The correlation coefficient, however, measures only the relationships between two variables. The variance inflation factor levels are all below 3, indicating that the collinearity between the variables is low.[12] The two ratios with the highest correlation are the two Leverage ratios in Table 9.

[12] 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 the variance inflation factor level 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 the variance inflation factor level is greater than 10) we then conclude that multicollinearity is likely to be a serious problem.

TABLE 10 Variance Inflation Factors

Variable	VIF
Current Liabilities – Cash to Tangible Assets	2.55
Liabilities to Tangible Assets	2.23
Cash to Current Liabilities	1.47
Return on Assets	1.44
Debt Coverage	1.32
Change in AR to Sales	1.19
Sales Growth	1.15
Size	1.13
Trade Creditors to Sales	1.09

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. Tables 11 through 14 present the power comparisons by sector for the 1- and 5-year models for both samples.

In the development sample, RiskCalc v3.1 Netherlands outperforms both RiskCalc v1.0 Netherlands and Z-score in 6 of 8 sectors at the 1-year level, and 5 of the 8 sectors at the 5-year level. The highest power in the 1-year model (Table 11) can be found in Business Products (76.8%), while the lowest is found in the Telecommunications and High Tech group (53.1%). At the 5-year horizon (0), the highest power other than Unassigned is in Business Products (54.4%), and the lowest is in the Telecommunications and High Tech group (39.6%).

In the validation sample, RiskCalc v3.1 Netherlands outperforms both RiskCalc v1.0 Netherlands and Z-score in 7 out of 8 sectors at the 1-year level, and 6 of the 8 sectors at the 5-year level. Given the sample size increase and the gain in AR is larger, the difference in industries is statically significant for all 7 positive accuracy ratio gains. At the 5-year level, 5 of the 6 industries differences are statically significant. This shows that model performs very well across different sector definitions, without populated income statement data.

TABLE 11 Model Power by Industry 1-year Model—Development Sample

	Percentage of Defaults	AR* v3.1	AR v1.0	v3.1–v1.0 p-value	AR Z-score
Business Products	15%	76.8%	72.2%	0.0597	58.9%
Telecommunications and High Tech	5%	53.1%	54.2%	0.8294	36.9%
Construction	13%	68.5%	63.4%	0.0811	44.3%
Consumer Products	13%	67.8%	66.1%	0.4046	50.8%
Mining,Transportation, Utilities and Natural Resources	8%	79.5%	80.6%	0.6837	64.6%
Services	9%	63.0%	59.4%	0.2570	42.9%
Trade	32%	68.7%	67.3%	0.3531	46.5%
Unassigned	6%	77.6%	74.9%	0.3093	60.4%

*AR = accuracy ratio