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MOODY'S KMV RISKCALC™ V3.1 FRANCE

MODELING**METHODOLOGY**

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ABSTRACT

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

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

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

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1 INTRODUCTION

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

- Moody's KMV RiskCalc™ v1.0 and the Moody's KMV Private Firm Model®
- 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 the MKMV Private Firm Model), 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.

RiskCalc Modes

RiskCalc v3.1 allows a user to assess the risk of a private firm in two ways: Financial Statement Only (FSO) and Credit Cycle Adjusted (CCA).

The Financial Statement Only (FSO) mode delivers a firm's default risk based only on financial statements and sector information, adjusted to reflect differences in credit risk across industries. In this mode, the risk assessments produced by the model are relatively stable over time.

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

The CCA adjustment is specific to the firm's sector and country and is updated monthly. The CCA mode also has the ability to stress test EDF credit measures under different credit cycle scenarios – a requirement under Basel II.

RiskCalc v3.1 France versus RiskCalc v1.0 France

Since the release of RiskCalc v1.0 France, Moody's KMV has significantly increased the size of the database for France and has substantially improved its data cleansing technologies. Furthermore, the new model includes additional financial statement variables, industry adjustments, and a credit cycle adjustment. We have also made substantial advances in our model development and testing techniques. As a result, the new model is more powerful and precise than its predecessor. It also includes additional analytic tools that increase model usability and transparency.

2 DATA DESCRIPTION

The source of the data for RiskCalc v3.1 France is Moody's KMV Credit Research Database™ (CRD). Moody's KMV collects data from participating institutions, working closely with them to understand the strengths and weakness of the data. In countries like France, where financial statement data is publicly available, the CRD includes this information as well. As of May 2004, the CRD contained 6.5 million financial statements, over 1.5 million unique private firms, and more than 97,000 default events worldwide. Moody's KMV uses this data for model development and testing purposes.

2.1 Definition of Default

Moody's KMV RiskCalc™ provides assistance to institutions and investors in determining the risk of default, missed payment, or other credit events. The proposals for the new Basel Capital Accord (BIS II) have stimulated debates about what constitutes an appropriate definition of default. RiskCalc applies the criteria used by most of the advanced economies in the world. In model development, RiskCalc uses the local criteria for default, which in France is defined as the date of the initiation of legal proceedings of the following types: liquidation, under legal regulation, or ceasing of activities or payments. At the calibration stages, the model outputs are adjusted to ensure consistent interpretation throughout the world. Specifically, model outputs are converted to 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 Expected Default Frequency™ (EDF) for private French 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 French middle-market companies, companies that did not reflect the typical company in this market were eliminated. The following types of companies are not included in the data:

- **Small companies** – For companies with net sales of less than €500,000 (2002 real 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 of 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 very different from for-profit firms, particularly with regard to variables relating to net income.
- **Start-up companies –** Our experience has shown that the financial statements for a company during its first two years are extremely volatile and are a poor reflection of the creditworthiness of the company. The special nature of start-ups is reflected in the fact that many financial institutions have separate credit departments for dealing with these companies.

[1] There are many types of "project finance" firms whose success depends largely on the outcome of a particular project. We recommend using separate models for such firms. This characteristic is explicitly recognized in the new Basel capital accord.

Excluded Financial Statements

The financial statements of smaller companies can be less accurate and of lower quality than those of larger companies. The financial statements in the CRD are cleaned to eliminate highly suspect financial statements. Plausibility checks of financial statements are conducted, such as assets not equal 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 Moody's CRD has increased substantially since RiskCalc v1.0 was developed. In addition to the increase in time-series data, there has been an increase in the number of participants in the CRD.

Figure 1 presents the distribution of French 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 France model.

FIGURE 1 Date Distribution of French Financial Statements and Default Data

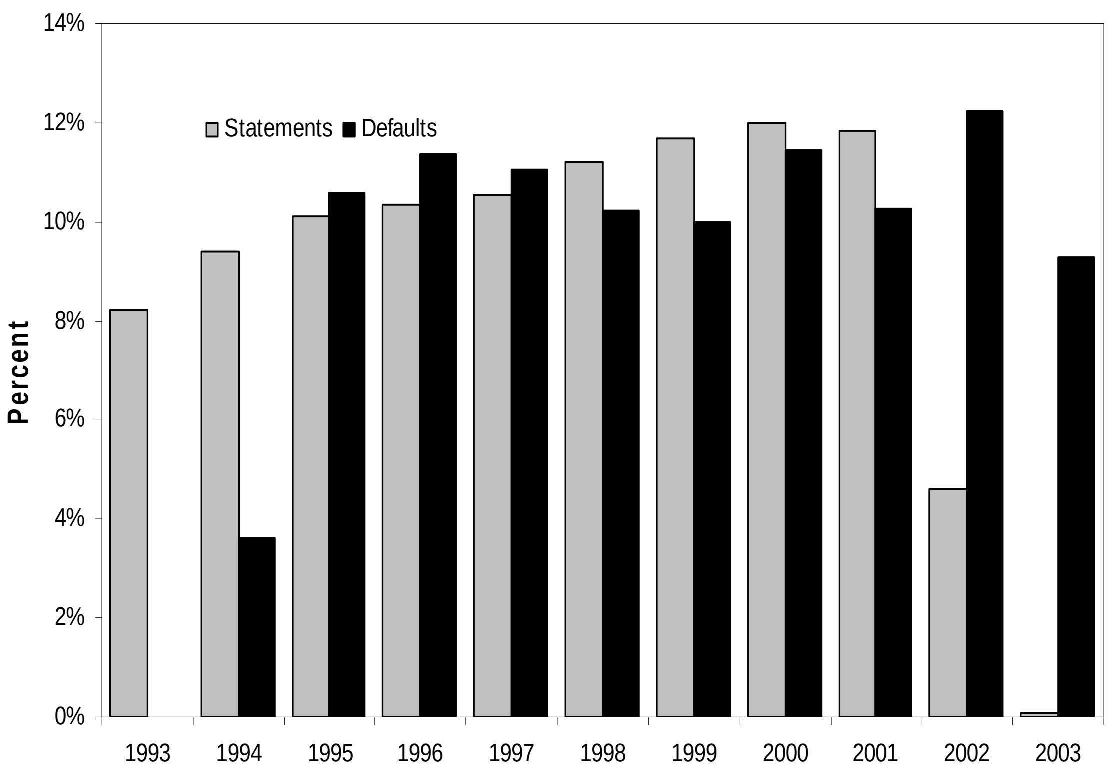


TABLE 1 Information on French Private Firm Sample Data

French Private Firms	RiskCalc v1.0 France	RiskCalc v3.1 France	Credit Research Database Growth
Financial statements	1,323,000+	1,714,000+	↑30%
Unique number of firms	253,000+	297,000+	↑17%
Defaults[2]	25,000+	35,000+	↑40%
Time period	1990-1999	1990-2002	↑ 3 additional 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 has addressed both of these issues.

Figure 2 presents the distributions of French defaults and firms by industry and the proportion of defaults in each industry. Figure 3 and Figure 4 present similar distributions by the size of firms measured as real total assets and real net sales in 2002 Euros, respectively. These figures demonstrate that the proportion of defaults in any one size group or industry group is comparable to the proportion of firms in these groupings. The size distribution shows that the majority of firms (65%) hold between 200 thousand and 1 million in assets. The proportion of firms between 500 thousand and 2 million in sales is 76% (where firms with less than €500,000 in sales are excluded from the sample).

FIGURE 2 Distribution of French Defaults and Firms by Industry

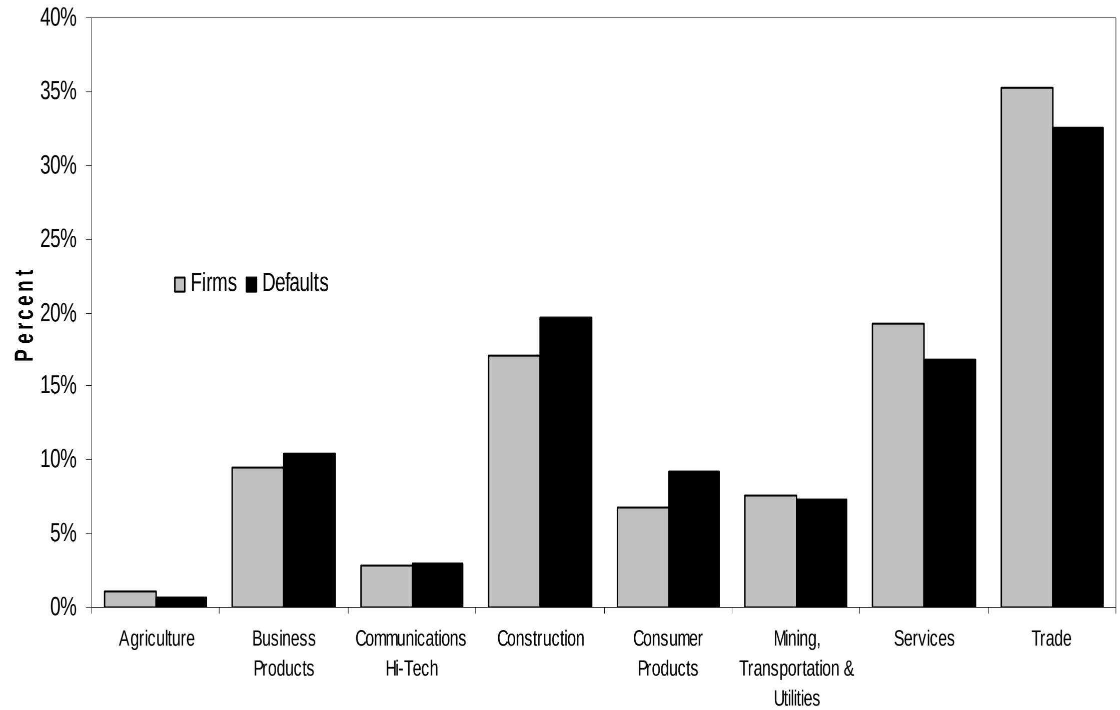


FIGURE 3 Size (as Total Assets) Distribution of Defaults and Firms

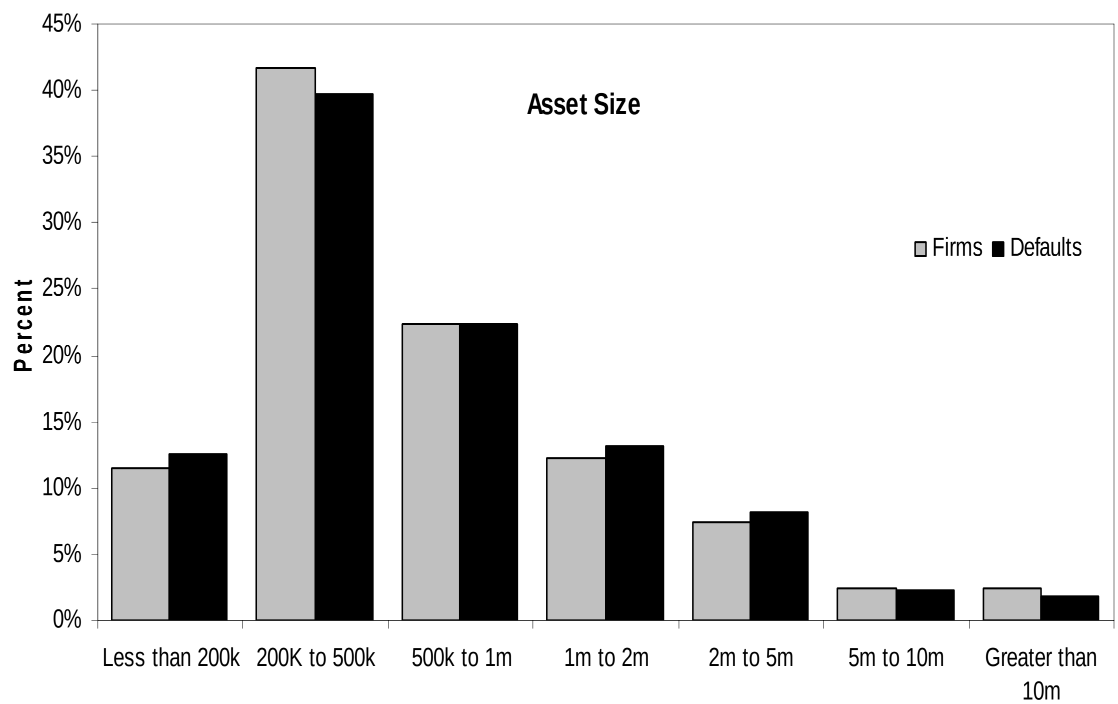
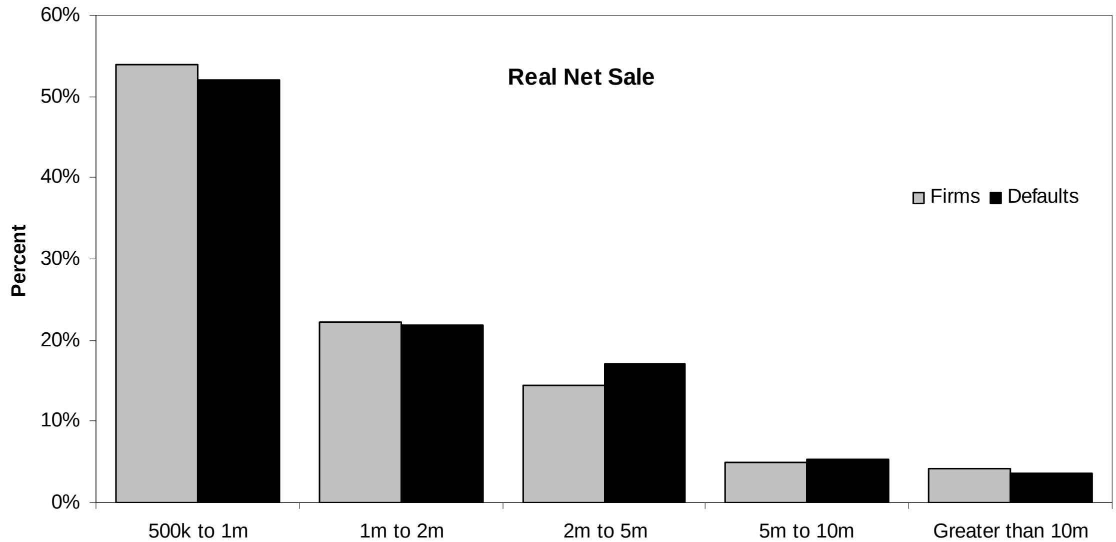


FIGURE 4 Size (as Net Sales) Distribution of Defaults and Firms



2.4 Cleaning the Data

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. MKMV has developed techniques for cleaning the database to improve the model results.

2.5 Central Default Tendency

Since most companies do not default, defaulting companies are relatively rare and thus more valuable in building a default prediction model. Much of the lack in default data is due to 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. Often times, certain types of defaults are not included. Publicly available sources of default data generally only reflect bankruptcy related events and therefore do not capture all default events. These issues can result in a sample that has lower default rates than occur in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true central default tendency.

In order to calculate the overall population default rate, the RiskCalc model uses an approach that integrates information from both private and public records. The central default tendency is typically estimated using two different approaches:

- Reference to reliable third-party data sources
- Analysis of bank charge-offs and provisions

By verifying the central default rate from a variety of sources, the central tendency estimate is more accurate than that inferred directly from the development sample.

Reliable Third-Party Data Sources

In order to determine the central tendency used in RiskCalc, MKMV analyzed data provided by the Institut National de la Statistique et des Etudes Economiques (INSEE). This data indicated an average yearly default rate of approximately 2.2% for France.

Bank Charge-Offs

An alternative approach we implement in determining the mean default rate is based on provisioning or write-off data from banks. Banks make provisions for bad loans that are estimates of their expected write-offs. From the volume of losses and the volume of loans, an average default rate can be inferred given the loss given default (LGD):

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

therefore,

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

In an analysis of the provisions for all French commercial banks from 1992-2001 as reported by the OECD (2002) we found that the implied probability of default was approximately 2.2% assuming an LGD of 50%.[2]

Accordingly, in calibrating RiskCalc v3.1 for French private companies, a central tendency of 2.2% was used for the one-year model, which coincides with the calibration of RiskCalc v1.0 France (Bech, et al, 2002).

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 MKMV 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, 4 times the level of the 1-year default rate. Therefore, 8.8% is used as the central default tendency for the 5-year model.

Central Default Tendency in FSO and CCA Modes

In the Financial Statement Only mode, the central default tendency remains constant over time. In Credit Cycle Adjusted 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 selection of the financial ratios and transforms of those ratios, the inclusion of industry information, and the credit cycle adjustment.

The development of a RiskCalc model involves the following steps:

1. Choosing a limited number of financial statement variables for the model from a list of possible variables.[3]

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[2] Basel II uses 45% for senior claims and 75% for subordinated claims (paragraph 287 & 288 of *The International Convergence of Capital Measurement and Capital Standards* June 2004) in the foundation approach.

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:

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

where $x_1,...,x_N$ are the input ratios; $I_1,...,I_K$ are indicator variables for each of the industry classifications; β and γ are estimated coefficients; Φ is the cumulative normal distribution; F and $T_1,...,T_N$ are non-parametric transforms; and FSO EDF is the financial-statement-only EDF credit measure.[4] The *T*s are the transforms of each financial statement variable, which capture the non-linear impacts of financial ratios on the default likelihood. (This is shown in Figure 5 on page 14 and discussed in detail later in the document.) *F* is the final transform (i.e., the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. We describe the final transform as calibrating the model score to an actual EDF credit measure. The difference between the FSO EDF and the credit cycle adjusted EDF is that in CCA mode the final transform is adjusted to reflect our assessment of the current stage of the credit cycle, while in FSO mode it remains constant.

3.1 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 (see 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. Criteria that must be met for variables to be included in the final model are:

- 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 generally uncorrelated with other variables in the model?

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[3] These variables are often ratios but are not always ratios. For example, one measure of profitability is Net Income to Total Assets, which is a ratio, and one measure of size is Inflation Adjusted Total Assets, which is not a ratio.

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

TABLE 2 Groupings of Financial Statement Ratios

Examples of ratios in the **profitability** group include: net income, net income less extraordinary items, EBITDA, EBIT, and operating profit in the numerator; and total assets, tangible assets, fixed assets, and sales in the denominator. → *High profitability reduces the probability of default.*
Examples of ratios in the **leverage (or gearing)** group include liabilities to assets and long-term debt to assets. → *High leverage increases the probability of default.*
Debt coverage is the ratio of cash flow to interest payments or some other measure of liabilities. → *High debt coverage reduces the probability of default.*
Growth variables are typically the change in ROA and sales growth. These variables measure the stability of a firm's performance. → *Growth variables behave like a double-edged sword: both rapid growth and rapid decline (negative growth) will tend to increase a firm's default probability.*
Liquidity variables include cash and marketable securities to assets, the current ratio, and the quick ratio. These variables measure the extent to which the firm has liquid assets relative to the size of its liabilities. → *High liquidity reduces the probability of default.*
Activity ratios include inventories to sales and accounts receivable to sales. These ratios may measure the extent to which a firm has a substantial portion of assets in accounts that may be of subjective value. For example, a firm with a lot of inventories may not be selling its products and may have to write off these inventories. → *A large stock of inventories relative to sales increases the probability of default; other activity ratios have different relationships to default.*
Size variables include sales and total assets. These variables are converted into a common currency as necessary and then are deflated to a specific base year to ensure comparability (e.g., total assets are measured in 2002 Euros). → *Large firms default less often.*

TABLE 3 Financial Statement Variables used in RiskCalc v3.1 France*

Category	Variable
Activity	Accounts Payable to Sales
	Change in Accounts Receivable Turnover
Size	Total Assets
Cost	Financial Charges to Sales
Debt Coverage	(Net Income plus Depreciation) to (Liabilities less Cash)
	Cash Flow to Financial Charges
Leverage	Equity to Assets
Growth	Sales Growth
	Change in ROA
Liquidity	Cash to Assets
Profitability	EBIDTA to Sales

* ROA is net income to total assets. Change in ROA is the difference between ROA and ROA in the previous year; change in Accounts Receivable Turnover is defined in the same manner. Cash Flow is operating cash flow and is implemented as EBITDA plus changes in accounts payable less changes in accounts receivable less changes in inventories.

Variable Transforms

Once the variables are selected, they are transformed into a preliminary EDF value. Figure 5 presents the transformations used in the model. The horizontal axis gives the percentile score of the ratio and the vertical axis gives the default probability of that ratio in isolation (univariate). The percentile score represents the percent of the database that had a ratio below that of the company (e.g., if liquidity is in the 90th percentile that means that 90% of the sample had lower liquidity 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 EBITDA to Sales is downward sloping, but the slope becomes flatter as profitability increases (Figure 5). Such a transform indicates that more profitable firms have lower default probabilities, but the impact diminishes as profitability increases.

- For the **Leverage** group, the transform for Equity to Assets is downward sloping since leverage increases as the ratio decreases. Large leverage corresponds to low levels of Equity to Assets and high default risk. The slope becomes less negative as the ratio increases, which implies that a small increase in leverage, when leverage is high and equity is low, will increase the default likelihood by a larger amount than when leverage is low and equity is high (Figure 5).

- For the **Liquidity** group, the transform for Cash to Assets is downward sloping, which means the more liquidity (higher cash to asset ratio) a firm has, the lower its default risk. (Figure 5).

- For the **Activity** group, two ratios are included. Accounts Payable to Sales is upward sloping indicating that high values of this ratio are associated with higher default probabilities (Figure 5). Change in Account Receivables Turnover is "U shaped," indicating that large positive values or large negative values are associated with higher default probabilities, while stable current receivables turnover is associated with lower default probabilities.

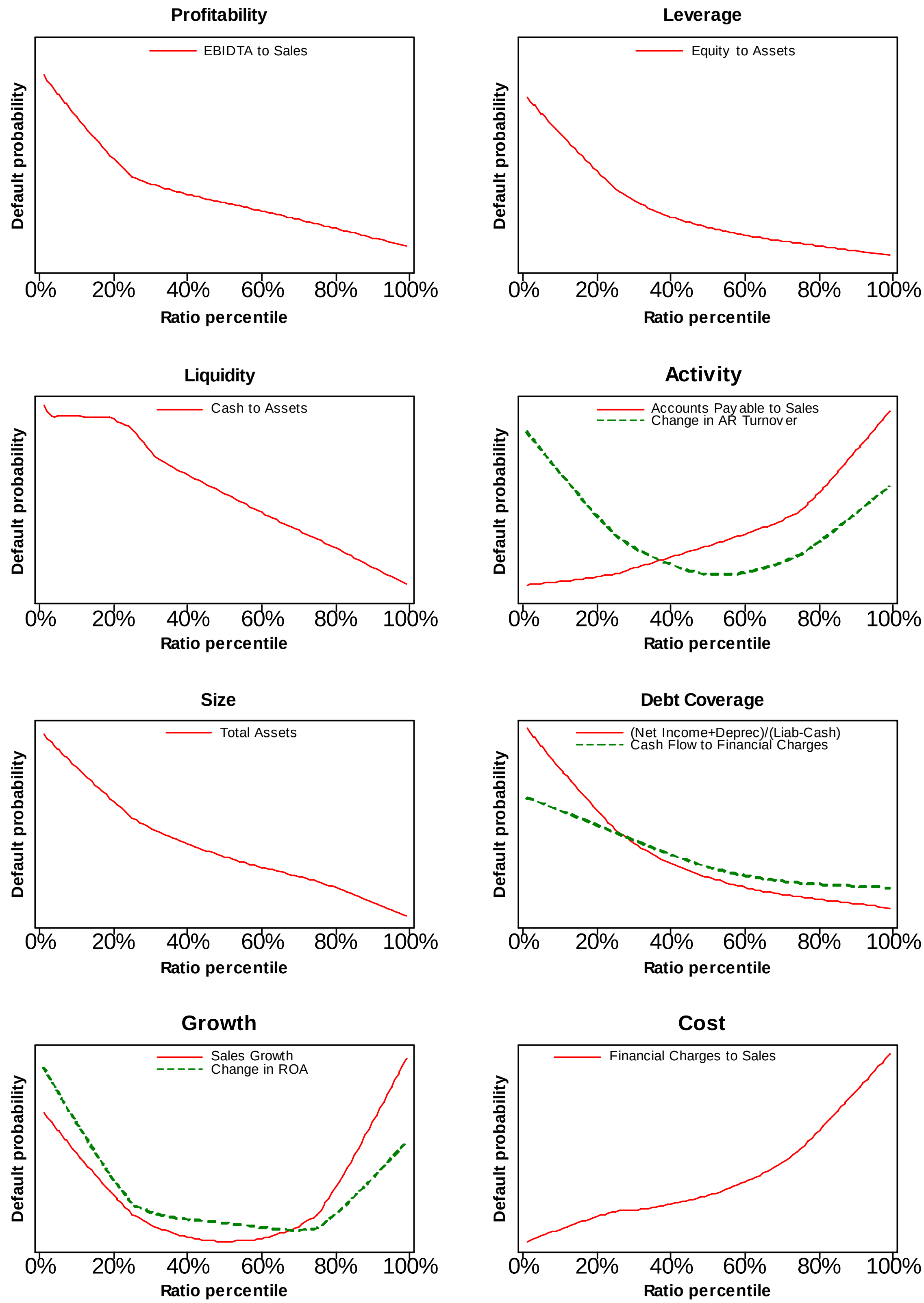
- The **Size** variable is Total Assets. This variable's transformation is downward sloping, but the slope becomes smaller as size becomes large (Figure 5). This indicates that larger firms have lower default probabilities, but the impact of size on default probabilities diminishes as firm size increases.

- The **Debt Coverage** variables are [(Net Income plus Depreciation) to (Liabilities minus Cash)] and [Cash Flow to Financial Charges]. These variables are downward sloping, indicating that large values of debt coverage lower the probability of default. The slopes become flatter as debt coverage ratios increase, indicating the impact of debt coverage diminishes when debt coverage ratios are big. (Figure 5).

- The **Growth** variables are Sales Growth and Change in ROA. These are "U shaped," indicating that large increases or decreases in sales or ROA are associated with higher default probabilities, while stable sales or ROA year upon year indicates lower probability of default (Figure 5).

- The **Cost** variable is Financial Charges to Sales. The variable is upward sloping, indicating that high financial charges lead to high default probabilities. (Figure 5).

FIGURE 5 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 (Figure 5).

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 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 changes for that variable as a percent of the total change in EDF level. This gives the variable with the biggest impact on the EDF level the biggest weight, and the variable that has the smallest impact on the EDF level the smallest weight. Since the weights are a percentage of the total EDF value, 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 France.

TABLE 4 Risk Drivers in RiskCalc v3.1 France*

RiskCalc v3.1 France	
Risk Drivers	Weight
Leverage Equity/Assets	21.6%
Profitability EBITDA/Sales	13.5%
Debt Coverage (Net Income + Depreciation)/(Liabilities – Cash) Cash Flow/Financial Charges	16.4%
Liquidity Cash & Equivalents/Assets	9.6%
Growth Sales Growth Change in ROA	16.9%
Activity Accounts Payable/Sales Changes in AR/sales	8.3%
Cost Financial Charges/Sales	8.0%
Size Total Assets	5.7%

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 France, 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 and the gain in log likelihood. The large gain in likelihood indicates that the industry controls are especially important in producing an accurate EDF value. Table 6 presents the average EDF value by industry for the development sample in April of 2003.

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

	One-year Model		Five-year Model	
	Accuracy Ratio	Relative increase in Log Likelihood	Accuracy Ratio	Relative increase in Log Likelihood
FSO mode without industry controls	60.9%		51.0%	
FSO mode with industry controls	61.3%	519***	51.7%	1,713***

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

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

TABLE 6 Average EDF Credit Measure in April 2003 by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Agriculture	1.02%	4.42%
Business Products	2.10%	8.81%
Communications and Hi Tech	2.05%	8.58%
Construction	1.55%	6.31%
Consumer Products	2.36%	10.16%
Mining, Transportation, Utilities and Natural Resources	1.53%	6.45%
Services	1.52%	6.22%
Trade	1.30%	5.87%
Unassigned	1.23%	5.48%

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 France 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 distance-to-default calculation from the Moody's KMV public firm model. This measure is specifically designed to be a forward-looking indicator of default risk. It extracts signals of default risk from the stock market performance of individual firms (cf. Bohn and Crosbie, 2003). This measure was chosen because it is available for a large universe of industries and it has been extensively validated.

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

Adjustment Factor used in the Model

For the French model, the distance-to-default factor for each industry is a weighted average of two indices. The average is based on an aggregation of distance-to-default for all French and continental European firms in each industry.[5] The weight on the French factor is industry specific and determined by the value (assets) of French firms in each industry relative to all of continental Europe. 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 French and continental European firms.

Figure 6 provides evidence of the relationship between the distance-to-default factor and public default rates in continental Europe as measured by Moody's KMV.[6] Similar to private firm defaults, the factor is a *forward-looking* measure of the probability of default for public European firms. Table 7 shows that including the credit cycle adjustment factor increases the power of the model.

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[5] Continental European countries used to compute the distance-to-default factor are as follows: Austria, Belgium, Denmark, France, Germany, Greece, France, Luxembourg, the Netherlands, Portugal, Spain, and Switzerland.

[6] In this context, a public company is a company with publicly traded equity. There are too few public firm defaults in France to construct a meaningful default rate at this time.

FIGURE 6 Continental Europe DD Factor and Public Default Rates: 1997-2003

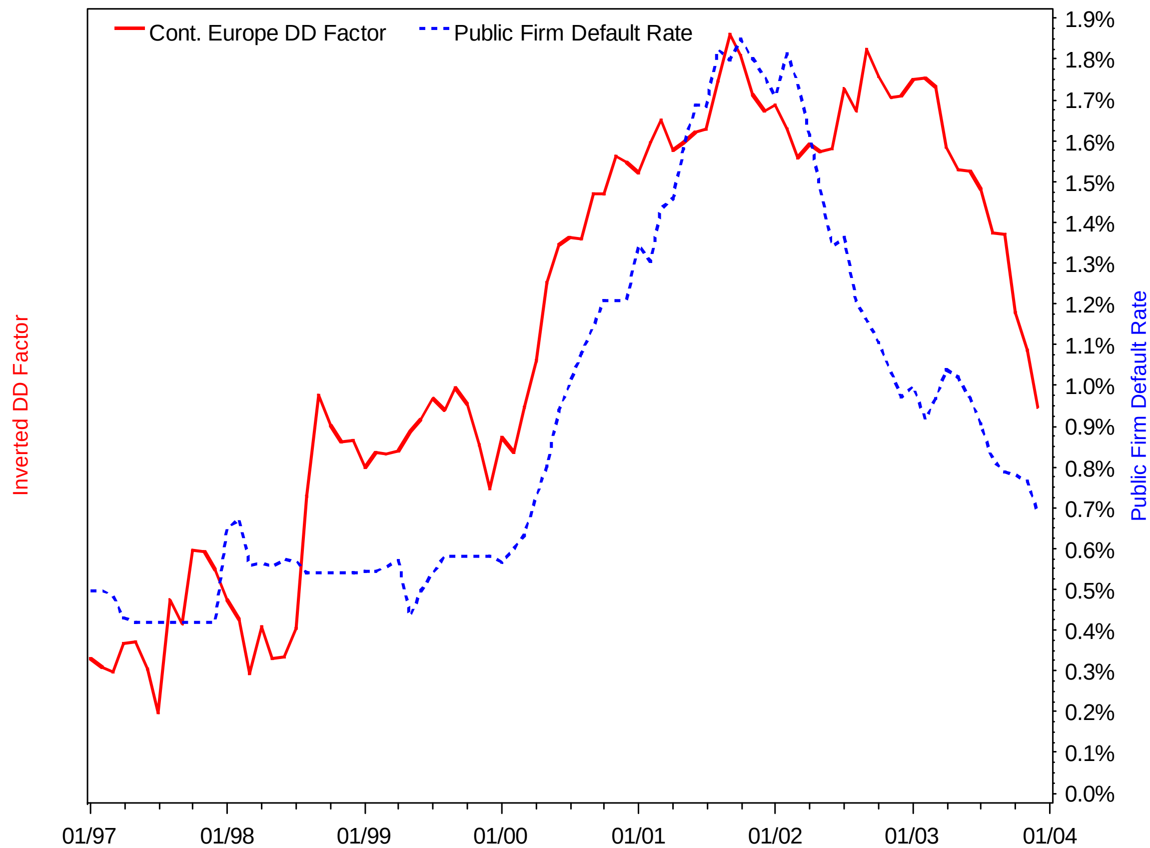


Figure 6 gives the DD factor (solid line) against the historical public bond default rate for continental Europe (dashed line). The DD factor increases in anticipation of the increase in default activity.

4 VALIDATION RESULTS

Once a model is developed, it must be shown to be 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) and the accuracy of its predicted EDF credit measure (the model's ability to estimate correctly the level of EDF).

The tests need to check not only the model's effectiveness, but also its robustness and how well it works on data outside the sample. To do 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.

4.1 Increase in Overall Model Power and Accuracy

Table 7 presents the in-sample overall measures of power and likelihood for RiskCalc v3.1 France versus alternative models. With the credit cycle adjustment, the model's performance improves by 3.4 percentage points of accuracy ratio at the 1-year horizon and 3.6 percentage points at the 5-year horizon compared with RiskCalc v1.0 France. 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 points at both the 1-year and 5-year horizons. The Financial Statement Only (FSO) mode outperforms the old model by 2.7 percentage points at the 1-year horizon and 4.0 percentage points at the 5-

year horizon.[7] RiskCalc v3.1 France is also more accurate than alternative models as measured by the log-likelihood differences.[8]

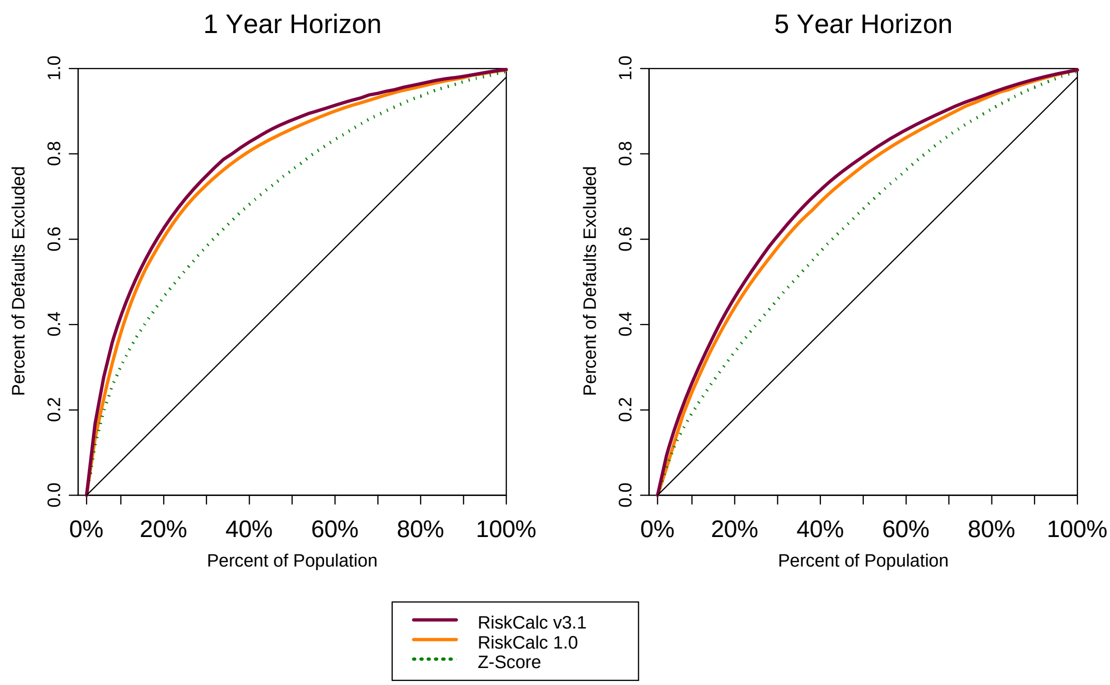
TABLE 7 Power Enhancements of the New RiskCalc v3.1 France Model

	One-year Model		Five-year Model	
	Accuracy Ratio	Lead in Log Likelihood*	Accuracy Ratio	Lead in Log Likelihood*
RiskCalc v3.1 Model CCA	61.7%		47.0%	
RiskCalc v1.0	58.3%	2,515	43.4%	1,626
Z-score	43.5%	16,219	29.4%	22,716

*Presents the increase in log likelihood of RiskCalc v3.1 over the alternative model. Larger values indicate that levels of RiskCalc v3.1 are better calibrated vis-à-vis the alternative model.

Figure 7 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 7. The power improvements are largely in the middle of the distribution relative to RiskCalc v1.0. This result implies that both very good and very poor credits are correctly identified by both RiskCalc v1.0 and RiskCalc v3.1. The added discriminatory power is assessing the credit quality of credits that fall in the middle range.

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



[7] The corresponding accuracy ratios are 61.0% (FSO) vs 58.3% (RiskCalc v1.0) for the one-year horizon and 47.4% (FSO) vs 43.4% (RiskCalc v1.0) for the five-year horizon.

[8] The log likelihood can be thought of as a measure of closeness of the predicted EDF values to the actual default rates.

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 8) for the financial statement ratios in the model and the variance inflation factors (Table 9) are computed on the transformed variables (see Figure 5).

Model Results

The highest correlation coefficient is between [EBITDA / Sales] and [(Net Income + Depreciation)/ (Liabilities – Cash)] (0.625). The next highest coefficient is between [Equity /Assets] and [(Net Income + Depreciation)/ (Liabilities – Cash)] (0.509). Such coefficients are below what we would typically consider indications of multicollinearity. This finding is also verified by the VIF analysis.

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

	Accounts Payable to Sales	Change in AR /Sales	Total Assets	Financial Charges / Sales	(Net Income + Depreciation) / (Liabilities – Cash)	Cash Flow / Interest Expense	Equity /Assets	Sales Growth	Change in ROA	Cash & Equivalent /Assets	EBITDA /Sales
Accounts Payable to Sales	1.000										
Change in AR /Sales	0.160	1.000									
Total Assets	-0.256	-0.089	1.000								
Financial Charges / Sales	0.131	0.031	-0.170	1.000							
(Net Income + Depreciation)/ (Liabilities – Cash)	0.320	0.063	-0.040	0.203	1.000						
Cash Flow / Interest Expense	0.126	0.005	0.016	0.338	0.454	1.000					
Equity /Assets	0.305	0.036	0.138	0.295	0.509	0.353	1.000				
Sales Growth	0.121	0.234	0.015	0.005	0.110	0.091	0.103	1.000			
Change in ROA	-0.034	0.070	0.147	0.023	0.108	0.092	0.110	0.174	1.000		
Cash & Equivalents /Assets	0.146	0.056	-0.133	0.394	0.307	0.351	0.261	0.043	0.035	1.000	
EBITDA /Sales	0.153	-0.056	0.195	-0.115	0.625	0.388	0.393	0.076	0.134	0.116	1.000

The Variance Inflation Factors (Table 9) for the financial statement variables represent how much of the variation in one independent variable can be explained by all the other independent variables in the model. The correlation coefficient, however, measures only the relationships between two variables. As shown in Table 9, the estimated VIF values in the France model are notably below the threshold levels of 4 to 10 that are commonly used in VIF analysis when testing for presence of multicollinearity.[9] These findings indicate that the model variables do not present any substantial multicollinearity.

TABLE 9 Variance Inflation Factors

Variable	VIF
EBITDA /Sales	2.26
(Net Income + Depreciation)/ (Liabilities – Cash)	2.09
Equity /Assets	1.59
Financial Charges / Sales	1.49
Cash Flow / Interest Expenses	1.46
Accounts Payable /Sales	1.33
Total Assets	1.28
Cash & Equivalents /Assets	1.28
Change in ROA	1.18
Chg in AR /Sales	1.16
Sales Growth	1.14

4.3 Model Power by Industry and Size Groups

It is important to test the power of a model not only overall, but also among different industry segments and firm sizes. Table 10 and Table 11 present the power comparisons by sector for the 1-year and 5-year models, respectively.

RiskCalc v3.1 France outperforms both RiskCalc v1.0 France and Z-score in all sectors. The highest power in the 1-year model is found in Construction (68.7%) while the lowest is found in Services (53.7%). At the 5-year horizon (Table 11) the highest power is in Mining, Transportation, Utilities and Natural Resources (51.0%) and the lowest is in Services (41.8%).

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

TABLE 10 Model Power by Industry: 1-year Model

	Percentage of Defaults	AR* RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Agriculture	0.7%	57.6%	56.3%	37.6%
Business Products	11.5%	66.4%	63.3%	54.8%
Communications and Hi Tech	3.0%	61.1%	60.0%	48.3%
Construction	20.9%	68.7%	64.1%	50.5%
Consumer Products	10.1%	63.8%	61.3%	46.2%
Mining, Transportation, Utilities and Natural Resources	7.9%	64.7%	62.5%	48.4%
Services	15.7%	53.7%	50.0%	33.9%
Trade	30.2%	57.8%	55.1%	41.9%

*AR = accuracy ratio

TABLE 11 Model Power by Industry: 5-year Model

	Percentage of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Agriculture	0.6%	50.1%	46.4%	33.0%
Business Products	11.2%	48.9%	47.2%	39.9%
Communications and Hi Tech	3.0%	43.9%	42.9%	30.7%
Construction	19.7%	50.9%	45.3%	32.2%
Consumer Products	10.0%	44.2%	42.8%	29.8%
Mining, Transportation, Utilities and Natural Resources	7.5%	51.0%	47.7%	33.0%
Services	16.1%	41.8%	38.2%	23.8%
Trade	31.9%	45.3%	42.8%	29.7%

Table 12 and Table 13 present the power comparisons by firm size for the 1-year and 5-year models, respectively. RiskCalc v3.1 France outperforms both RiskCalc v1.0 France and Z-score consistently in all size groups.[10] The highest power in the 1-year model is found in the firms with sales between €1 million to €2 million, and the lowest is in the largest firms—over €10 million in sales. A similar power improvement is often found between model power and size in other countries.

[10] The only exception is for the largest firms at the 5-year horizon. Nevertheless, this anomaly does not exist at the 1-year horizon and the number of defaults in this category is relatively small, which suggests that small data problems are at play here.

TABLE 12 Model Power by Size: 1-year Model

	Percentage of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
<€500,000	44.9%	59.6%	56.5%	43.3%
€500,000 to €1mm	24.4%	64.0%	60.1%	43.9%
€1mm to €2mm	15.6%	64.9%	61.4%	44.6%
€2mm to €5mm	9.9%	61.4%	59.5%	42.3%
€5mm to €10mm	3.0%	58.2%	56.6%	39.8%
Over €10mm	2.2%	45.2%	44.4%	30.9%

TABLE 13 Model Power by Size: 5-year Model

	Percentage of Defaults*	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
<€500,000	42.8%	46.3%	42.1%	29.8%
€500,000 to €1mm	26.1%	51.5%	47.6%	32.6%
€1mm to €2mm	16.3%	52.2%	48.3%	32.1%
€2mm to €5mm	9.8%	49.6%	46.5%	30.6%
€5mm to €10mm	3.0%	48.4%	45.3%	29.3%
Over €10mm	1.9%	35.4%	37.9%	23.6%

* The total does not sum to 100% due to rounding

4.4 Power Performance Over Time

Since 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 or not 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 accuracy ratio of RiskCalc v3.1 France is compared with RiskCalc v1.0 France and Z-score for each year. As shown in these tables, RiskCalc v3.1 consistently outperforms both models by a considerable margin.

TABLE 14 Model Power over Time: 1-year Horizon

	Percent of Defaults	AR* RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
1993	7.1%	68.1%	67.0%	48.1%
1994	11.2%	67.2%	65.0%	45.8%
1995	10.2%	63.4%	62.4%	43.5%
1996	11.9%	62.4%	59.8%	44.0%
1997	9.0%	61.1%	58.3%	44.1%
1998	11.9%	59.4%	55.8%	43.3%
1999	11.6%	55.9%	53.6%	41.0%
2000	12.5%	56.0%	52.9%	40.4%
2001	14.6%	55.6%	52.9%	38.7%

*AR = accuracy ratio

TABLE 15 Model Power over Time: 5-year Horizon

	Percent of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
1993	14.9%	51.8%	51.0%	33.2%
1994	16.3%	50.4%	47.1%	32.6%
1995	16.6%	49.0%	46.4%	31.3%
1996	17.1%	47.7%	44.0%	31.5%
1997	17.8%	45.8%	41.6%	30.1%
1998	17.3%	46.7%	42.6%	30.7%

4.5 Out of Sample Testing: K-fold Tests

The model exhibits a high degree of power in distinguishing good credits from bad ones (in 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.

Results

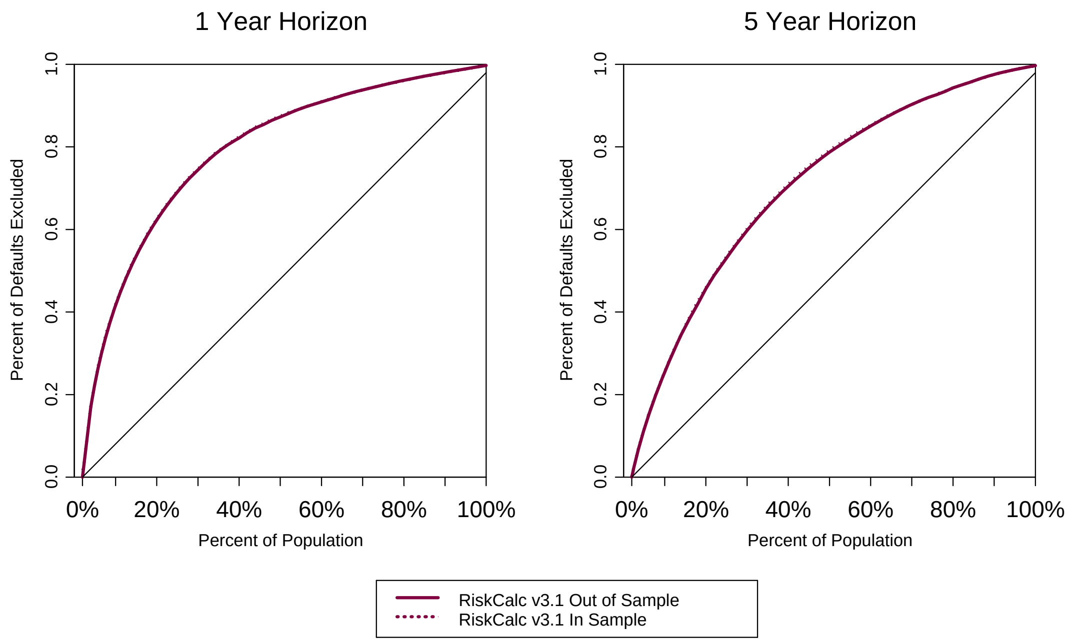
Table 16 summarizes the *k*-fold test results (with *k*=5). The reported figures are the accuracy ratios by the corresponding sample and time horizons. The out-of-sample model consistently out-performs RiskCalc v1.0 France. Figure 8 presents the cumulative accuracy profiles associated with the overall "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: the in- and out-of-sample power curves are indistinguishable.

TABLE 16 RiskCalc v3.1 France 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	60.6%	47.5%	57.6%	44.1%
Subsample 2	60.3%	47.6%	58.0%	44.3%
Subsample 3	60.8%	47.5%	57.9%	44.2%
Subsample 4	60.4%	47.1%	57.4%	43.7%
Subsample 5	61.2%	47.7%	58.7%	44.5%
K-fold Overall	61.8%	45.2%	59.1%	41.1%
In-sample AR	61.8%	45.3%		

*AR = accuracy ratio

FIGURE 8 RiskCalc v3.1 France 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 were a particularly high period of default rates, this would be included in each of the *k* samples. Such testing does not give a true sense of the how the model would have performed during those volatile periods because the model is estimated with full information on those time periods.

4.6 Walk-Forward Tests

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

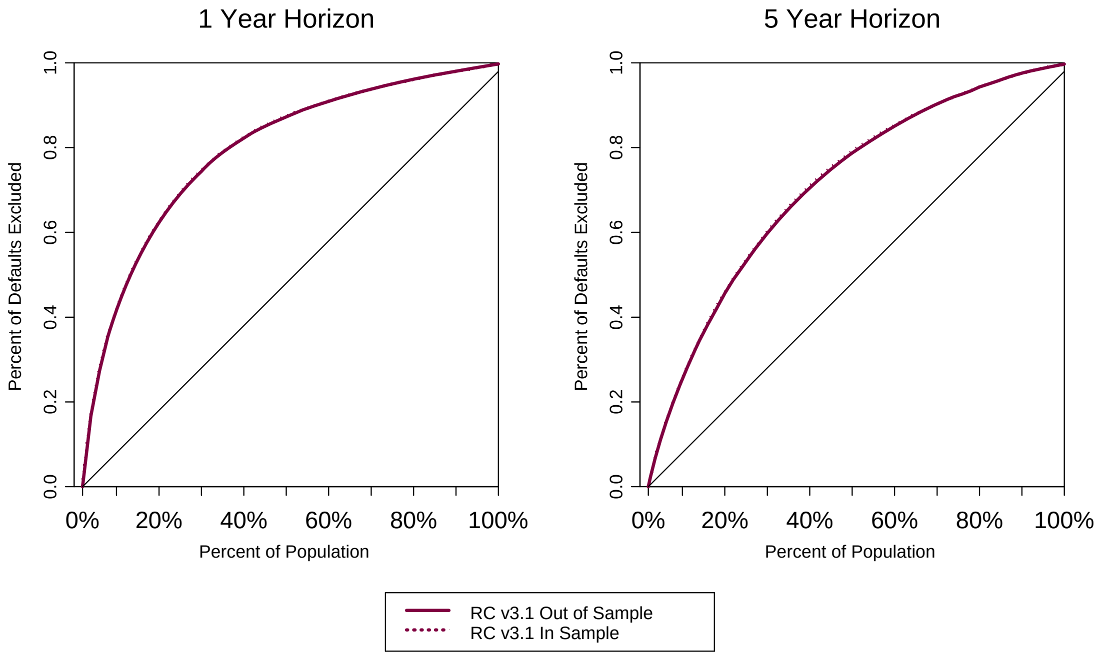
No data from a future period is used in fitting the model and only data from future periods is used for testing it. The parameter estimates are checked for stability across the different samples. Figure 9 presents the results from this analysis.

Results

Similar to the *k*-fold results, the in- and out-of-sample plots for the walk-forward results are virtually indistinguishable at both the 1- and 5-year horizons in Figure 9. The difference in AR between the in-sample and out-of-sample results is no more than 40 basis points in both cases. Furthermore, RiskCalc v3.1 France outperforms RiskCalc v1.0 France in an out-of-time context at both the 1- and 5-year horizons.[11]

[11] The out-of-sample ARs are 60.9% and 45.0% for the 1-year and 5-year models, respectively. The 1-year out-of-sample power is 0.3% less than the in-sample power, while the 5-year power is 0.4% less out-of-sample than in-sample. These out-of-sample ARs are 2.4 and 4.2 points higher than RiskCalc v1.0 France, for the 1- and 5-year models respectively.

FIGURE 9 Out-of-sample Performance (1- and 5-year) France Walk-forward



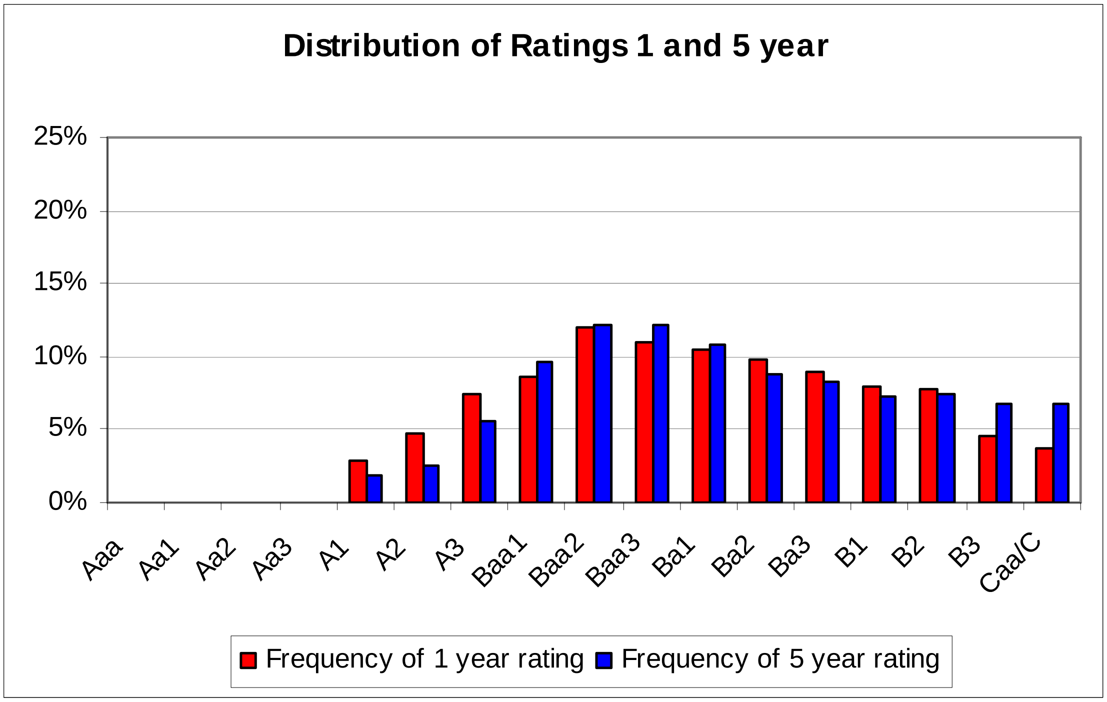
4.7 Model Calibration and Implied Ratings

To aid in the interpretation of an EDF credit measure, an EDF value is mapped to a .edf rating (an EDF-implied rating). All RiskCalc v3.1 models to date have used the same mapping. This mapping is designed so that:

- 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 a .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 10 shows the distribution of CRD observations by rating category in the development sample (for the Credit Cycle Adjusted EDF credit measures over the full time period). Note that 14 categories between Aa3 and Caa/C are utilized and that less than 15% of the observations are in any one category. The 1-year and 5-year distributions peak at Ba1. While not reported here, other research has shown that the distribution of the CCA EDF implied ratings change over time with the credit cycle, while the distribution of the FSO EDF implied ratings remains relatively stable over time.

FIGURE 10 EDF-implied Ratings for the 1- and 5-year Models in the Development Sample



5 CONCLUSION

The Moody's KMV RiskCalc v3.1 France model is based on a substantially larger database than RiskCalc v1.0 France and has an additional three years of data. Improved data coverage has allowed us to refine our financial statement model and achieve a very robust prediction model of private firm default behavior.

The model is more powerful than any publicly available alternatives that we have tested. We have demonstrated that the increase in power is consistent across industry sectors and size classifications as well as for different time periods. We have also shown that the power advantage is maintained both in-sample and out-of-sample.

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

The Moody's KMV RiskCalc v3.1 model will be very useful for financial institutions seeking to implement quantitative tools for originating loans, managing portfolio risk, and meeting regulatory requirements. It also provides them with 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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