

MODELING METHODOLOGY

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RiskCalc 4.0 France

Abstract

Moody's Analytics RiskCalc™ suite is a collection of geographic- or industry-specific models designed for private firm default risk measurement. We develop, calibrate, and validate the model using a large dataset of local financial statements and defaults. This document outlines the underlying research, model characteristics, data, and validation results for the RiskCalc France 4.0 model. The model considers the distinctiveness of the French market, and validation results show that the model effectively measures default risk, both in-sample and out-of-sample, across industry, size, and different time periods.

The RiskCalc France 4.0 model builds on our RiskCalc 3.1 France model, originally released in 2004. The new model utilizes an extended dataset, increases the industry granularity within the model, and provides higher accuracy. In addition, we update the credit cycle adjustment mode, which is better aligned with the economic cycle and includes smoothing for sectors with few public companies in France.

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1. Introduction

Financial institutions seek to establish risk assessment processes that most effectively use credit analyst resources. Regulators expect these processes to be transparent and consistent. Additionally, in order to trade private firm credit risk, unrelated parties require an objective measure of risk. The Moody's Analytics RiskCalc model suite provides objectivity and consistency to the credit risk management process for various countries and industry segments throughout the world. The RiskCalc 4.0 version expands the model's scope and granularity.

The RiskCalc model extracts a measure of default risk from financial statements, known as the RiskCalc EDF™ (Expected Default Frequency) credit measure. The model also adjusts for the firm's industry and the current stage of the credit cycle. Any two analysts, anywhere in the world, working with the same set of financial statements, should be able to agree upon what the RiskCalc EDF credit measure is on that firm. In addition, they should be able to come to an agreement on what the EDF measure would have been on a certain date, even if they are working at different points in time. These features make RiskCalc models useful as objective, transparent, and consistent measures of risk.

RiskCalc began with the establishment of the Moody's Analytics Credit Research Database (CRD™) in the late 1990s. We launched the first RiskCalc model for North American firms in 2000, based on actual, private firm data, including 110,000 financial statements, 25,000 firms, and 1,600 defaults.¹ At the time, the concept of a quantitative approach to credit risk management in the "middle-market" was revolutionary. Since then, we have released many models for different regions and asset classes around the world. Several models are in their second or third recalibration.

Over the past years, RiskCalc models have been used in many different contexts to facilitate many different business decisions. Banks often use RiskCalc credit measures as an internal rating input or as a constraint on the bank's internal rating.² Increasingly, corporates use RiskCalc to measure the credit risk of their counterparties and trading partners. RiskCalc can determine the internal transfer price of credit risk within a large multinational. RiskCalc models can also be used to allow the transfer of credit risk between unrelated parties in a variety of contexts, including guarantees and surety bonds. Finally, effective use of RiskCalc models helps ensure that financial institutions have a thorough and consistent monitoring process in place.

1.1 RiskCalc Model Features and Functionality Over Time

Since we introduced the first RiskCalc model, we have continually expanded its scope. In addition, we have added features and increased functionality to the core RiskCalc framework, including the following:

- » Between 2000 and 2004, we launched country-specific models for the large Western European nations, as well as for Japan, Korea, Singapore, and Australia. We also added the RiskCalc U.S. Banks model.
- » In 2004, we introduced the RiskCalc 3.1 model for the U.S., Canada, the UK, and Japan. RiskCalc 3.1 models incorporated a credit cycle adjustment that used the Moody's Analytics Public Firm Model to adjust the risk of a private firm, based on the risk of public firms in comparable industries and countries. Further, the 3.1 model added a complete term structure of EDF credit measures and additional diagnostic tools to facilitate model transparency.
- » Between 2004 and 2012, we launched country-specific 3.1 models in North America, Europe, Asia, and Africa. In addition, we introduced an insurance model and the RiskCalc North America Large Firm Model, which targets specific subpopulation risk assessment. The former applies to private insurance companies, while the latter applies to private companies large enough to have listed equity, but because they do not, they are not covered by the Moody's Analytics Public Firm Model. We also launched the RiskCalc Emerging Markets model, which provides a validated approach for assessing credit risk in countries too small to warrant a country-specific model or in countries that do not yet have a RiskCalc model. Finally, we introduced the Moody's Analytics CMM™ (Commercial Mortgage Metrics) application, which assesses the default risk of a commercial real estate property.
- » In 2012 and 2013, we released the RiskCalc 4.0 model for the United States, with four standalone submodels, covering Corporates, Not-for-Profit companies, Real Estate firms, and Dealerships. The last three sectors were previously not covered by RiskCalc models. In addition, we developed a new framework for assessing the credit risk of banks, and launched a new generation of models for banks: RiskCalc U.S. Banks Model 4.0 and RiskCalc Global Banks Model 4.0. In 2014, we released the RiskCalc 4.0 United Kingdom model, which extends the industry granularity within the model, uses better calibration, and provides higher accuracy.

¹ Falkenstein, 2000.

² The internal rating of a borrower plays a key role in credit approval and underwriting, loan pricing, allowance for loan and lease losses, credit administration, risk reporting, and portfolio management (cf., OCC, 2001).

- » In 2015, we released the European Large Firm model, which covers firms throughout Europe with assets greater than or equal to €50 million.

1.2 Differences Between RiskCalc 4.0 France and RiskCalc 3.1 France

The RiskCalc 4.0 France model evolved from the RiskCalc 3.1 France model and includes several improvements:

- » Since the release of RiskCalc 3.1 France, Moody's has significantly increased the size of its French database and has substantially improved data cleansing technologies. As a result, industry granularity has increased. The new 4.0 France model includes 14 industries instead of the nine included in the 3.1 France model. The expanded dataset covers the most recent financial crisis.
- » The basic RiskCalc 3.1 model structure (ratios and inputs) has proven to be robust. Therefore, we retain the basic structure and implemented the following changes:
 - Included marketable securities in the liquid assets input
 - Replaced Financial Charges to Sales with Interest Expense to Sales
 - Replaced Change in Accounts Receivable Turnover with Personnel Expenses to Sales
 - Replaced EBITDA to Sales with Operating Margin
 - Excluded the Cash Flow to Financial Charges ratio
- » The RiskCalc 4.0 model refines the methodology for the credit cycle adjustment (CCA) factor, based on the Distance-to-Default (DD) from the Moody's Analytics Public Firm model. The new CCA factor is better aligned with the economic cycle and includes smoothing for sectors with few public companies in France.

1.3 Practical Applications of Default Risk

Risk managers, lenders, and portfolio managers can use default risk models such as the RiskCalc model in a wide range of applications, including:

EARLY WARNING AND MONITORING

Obligor credit quality can change quickly, as history has repeatedly demonstrated. Because EDF measures are objective and forward-looking, they can help risk managers allocate resources more effectively for risk assessment and mitigation.

INPUTS TO INTERNAL RISK RATING SYSTEMS

Internal rating systems are the foundation of many business decisions within financial institutions, including credit approval, limit setting, regulatory compliance, risk-based pricing, and active portfolio management. Internal rating systems typically combine quantitative and qualitative factors at both the market/industry-level and the firm-level. RiskCalc models derive measures of default risk, based on a large amount of data and rigorous statistical methods. EDF credit measures can be used as the quantitative input to internal risk rating systems.

BENCHMARKING AND CALIBRATING INTERNAL RISK RATING SYSTEMS

An internal rating system must provide sufficient differentiation of default risk. To calibrate such a system, regulators typically expect a sizeable amount of realized default events data, spanning at least a full economic cycle. Many institutions might not possess enough internal data for this purpose and can benefit from external sources. RiskCalc EDF credit measures are well-suited for benchmarking and calibrating internal risk systems because their development is based on actual defaults, and their usefulness has been demonstrated through extensive validation.

INPUT TO REGULATORY COMPLIANCE

The probability of default associated with an internal rating plays a central role in the calculation of capital requirements in the Basel II framework. Basel II's regulatory capital formula uses the so-called Asymptotic Single-Risk Factor (ASRF) and builds on the probability of default. Many banks use external PD models as part of their internal ratings, either for regulatory capital calculations or for benchmarking and calibrating their internal models during their process of fulfilling regulatory requirements.³

³ See Basel Committee Newsletter No. 8 (2006).

INPUT TO REQUIRED ECONOMIC CAPITAL CALCULATION

Required economic capital (EC) is a concept that financial institutions use to measure their portfolio risk. EC can be thought of as the amount of capital the financial institution must hold to ensure withstanding losses within a given time horizon, consistent with a given solvency probability. Computing EC usually requires a portfolio model with probability of default as a key input. A simulation-based portfolio model builds the distribution of credit losses from Monte Carlo simulations of possible portfolio outcomes. Required EC corresponds to the value of the loss distribution at the target probability of solvency; for example, 99.7%.

LOSS PROVISIONING

Loan loss provisions are expenses charged to a bank's earnings when adding to the allowance for possible bad debt. In estimating the provisioning amount, one can use a default risk model to estimate the likelihood of borrowers defaulting on their loans. The model should respond to changes in the risk environment across the economy as a whole. RiskCalc models incorporate forward-looking information derived from the Moody's Analytics Public EDF model. The models respond to changes in the credit cycle and produce accurate estimates of credit losses over a long period. Therefore, they are appropriate for expected loss-based provisioning calculations.

STRESS TESTING

In the aftermath of the 2007 – 2008 financial crisis, regulators in developed countries substantially increased the requirements for regulatory stress testing. Such policies aim to better understand and anticipate potential crises and require banks to estimate their credit losses under prospective macroeconomic scenarios. Owing to its comparability of scores, objectivity, transparency, and granularity, the RiskCalc model suite continues to be used as an important tool in bank and financial institution stress-testing exercises.

TRANSFER PRICING

Transfer pricing is used to evaluate intercompany arrangements between related business parties. When intercompany transactions span country borders, the "arm's length principal" applies to prevent tax avoidance. According to this principle, the burden falls on the company to prove that the transaction has terms similar to terms that would have occurred between two unrelated entities. RiskCalc models provide an objective framework for determining creditworthiness in a transfer pricing context.

The remainder of this paper is organized as follows:

- » Section 2 describes the data we use to estimate and build the model and to fill inputs.
- » Section 3 describes model components, including a description of model factors.
- » Section 4 reports validation results such as CAP plots, variance inflation factors, accuracy ratios, and out-of-sample testing and descriptive statistics on the calibration.
- » Section 5 describes the model's analytical features.
- » Section 6 provides further discussion and concludes.

2. Data Description

We use the CRD as the data source for the RiskCalc 4.0 France model.

2.1 Definition of Default

In our French data sample, RiskCalc uses the local criteria for default, defined as the date of the initiation of the following types of legal proceedings: liquidation, under legal regulation, ceasing of payments, and continuation plan.

2.2 Data Exclusions

EXCLUDED COMPANIES

The RiskCalc model's goal is to provide an EDF credit measure for private French companies in the middle market. The firms and industries covered must have similar default characteristics. To create the most powerful model for French middle-market companies, we exclude companies that do not reflect the typical company in this market. The following company types are not included in the data:

- » **Small Companies:** For companies with net sales of less than €500,000 (in 2012 Euros) future success is often linked to the finances of the key individuals. Therefore, 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, so they are excluded from the database.
- » **Real Estate Development Companies:** Since the financial health of real estate development and investment opportunities often hinges on a particular development, such as in "project finance,"⁴ the annual accounts of these firms provide only a partial description of their dynamics and, therefore, their likelihood of default. While the RiskCalc 4.0 France model is not optimized for Real Estate companies, we have tested the performance of the model on this class of firms and find the model performs relatively well. Section 4.6 provides more details.
- » **Public Sector and Not-for-Profit Institutions:** The default risk of government-run companies is 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. Financial ratios of Not-for-Profits are different from the financial ratios of for-profit firms, particularly regarding variables related to net income. While the RiskCalc 4.0 France model is not optimized for Not-for-Profit institutions, we have tested the performance of the model on this class of firms and find the model performs relatively well. Section 4.6 provides more details.
- » **Start-Up Companies:** Our experience has shown that the financial statements for a company during its first two years are extremely volatile and are a poor reflection of the creditworthiness of the company. The special nature of start-ups is reflected in the fact that many financial institutions have separate credit departments for dealing with these companies.

EXCLUDED FINANCIAL STATEMENTS

Smaller companies' financial statements can be less accurate and of lower quality than financial statements of larger companies. We clean the financial statements in the CRD to eliminate any suspect financial statements. We conduct plausibility checks of financial statements (for example, assets not equal to liabilities plus net worth and financial statements covering a period of less than twelve months). If errors are detected, we exclude those statements from the analysis.

2.3 Descriptive Data Statistics

DATA OVERVIEW

We use the CRD as the data source for the RiskCalc 4.0 France model. Table 1 presents the data distribution used in the development sample and compares it to the data set used for the previous version, the RiskCalc 3.1 France model. The number of financial statements, firms, and defaults we use for our recent development sample is considerably larger than the development sample of the RiskCalc 3.1 France model. Table 1 and Figure 1 provide an overview of the data used to develop the RiskCalc 4.0

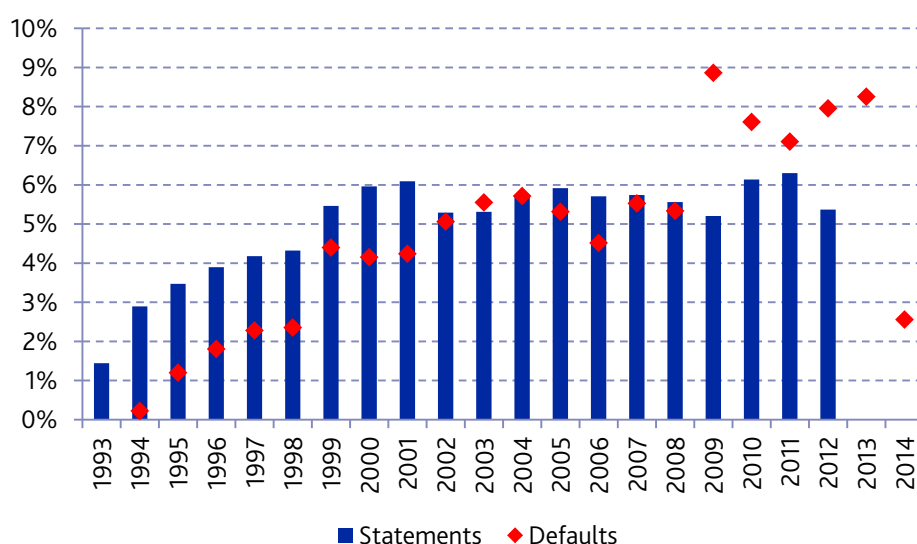
⁴ There are many types of "project finance" firms whose success depends largely on the outcome of a particular project. We recommend using separate models for such firms.

France model. The year on the horizontal axis indicates the year of the financial statement for statements and the calendar year of the default date for defaults.

Table 1

Sample Data Information

MODEL	PERIOD	FIRMS	DEFAULTS	STATEMENTS
RiskCalc 3.1 France	1993–2002	297,000+	22,000+	1,714,000+
RiskCalc 4.0 France	1993–2014	643,000+	76,000+	3,796,000+

Figure 1 Distribution of Statements and Defaults by Year.⁵

DATA ROBUSTNESS

When building a model, we examine potential database weaknesses. Not only should the database cover many firms and defaults, but the defaults should also be distributed among industries and company size. For example, if the database has few firms in a particular size range without sufficient defaults in those groups, the model might not produce good default risk measurements. If the database contains significant numbers of small firms or firms concentrated in one particular industry, and there are not sufficient defaults in those areas, the model might not accurately reflect risk.

Figure 2, Figure 3, and Figure 4 present data distributions based on the full sample, 1993–2014, and highlight how the CRD has sufficient coverage across size and industry.

Figure 2 presents French firm distribution by industry and the proportion of defaults in each industry. Trade and Construction are the largest sectors in our sample.

⁵ Statement year is the calendar year of the statement date and default year is the year of the earliest sign of default for that firm.

Figure 2 Distribution of Statements and Defaults by Industry.

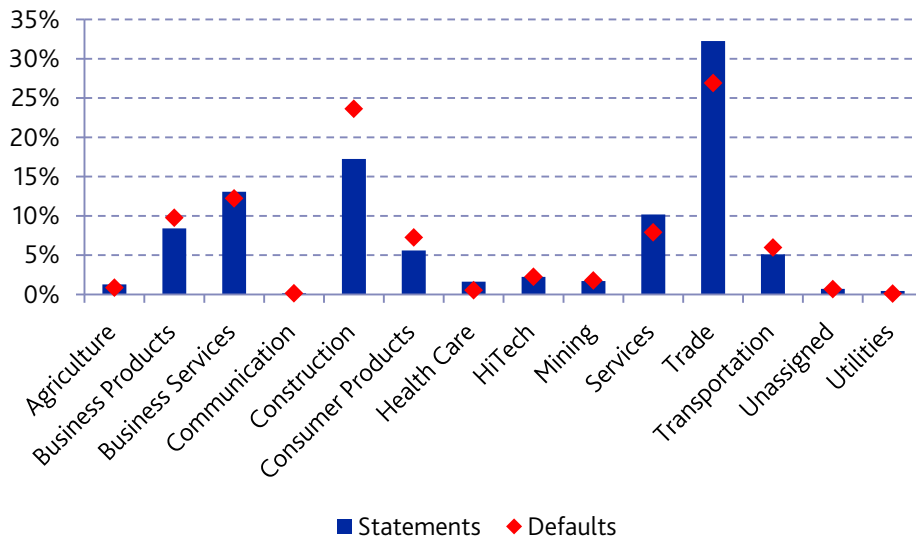


Figure 3 and Figure 4 present distributions by firm size measured in Total Assets and Sales, respectively. Our sample includes a suitable cross-section of both large firms and small firms.

Figure 3 Distribution of Statements and Defaults by Size (Total Assets in 2012 Euros).

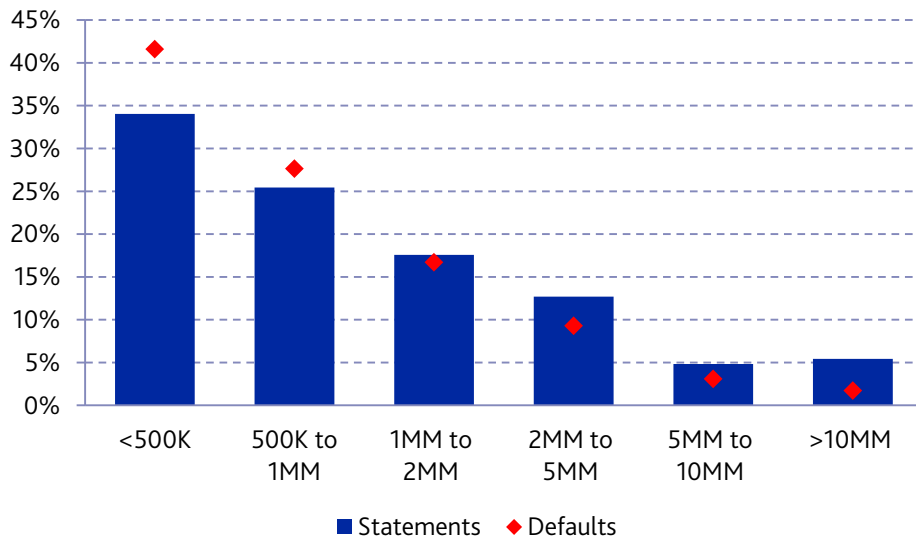
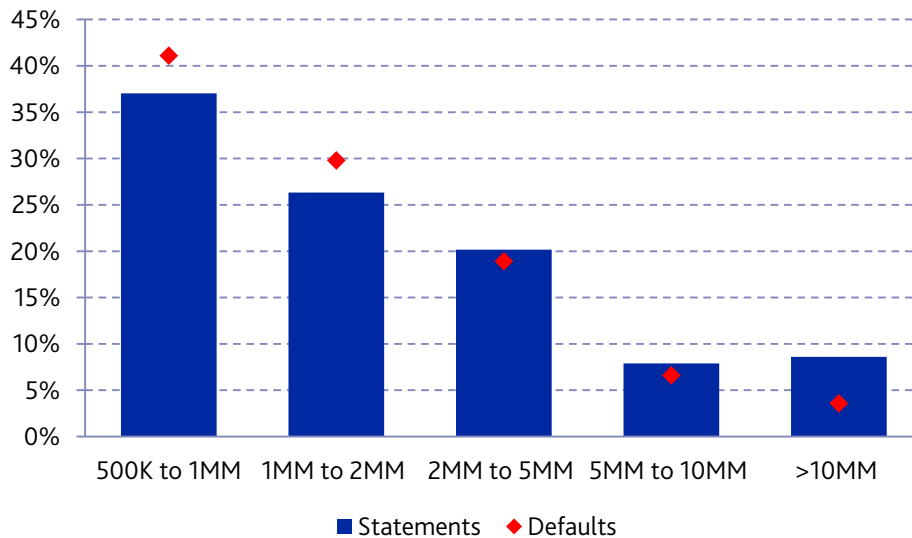


Figure 4 Distribution of Statements and Defaults by Size (Net Sales in 2012 Euros).



2.4 Central Default Tendency

Because most companies do not default, defaulting companies are relatively rare, and are, therefore, more valuable in building a default prediction model. Much of the lack in default data is due to data storage issues within financial institutions, such as defaulting companies being purged from the system after troubles begin, not capturing all defaults, or other sample errors. 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 with lower default rates than occur in the general population. If the underlying sample is not representative, it must be adjusted for the true central default tendency (CDT).

To calculate the overall population default rate, the RiskCalc model uses a triangulation approach that integrates information from both private and public records. The CDT is typically triangulated using two different approaches:

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

By triangulating the central default rate from various sources, the central tendency estimate is more accurate than the estimate inferred directly from the development sample.

We use several sources to determine how the RiskCalc 4.0 France model estimates the CDT:

- » Loan loss provision data from the Organization for Economic Co-operation and Development (OECD) 1999–2009
- » Provisioning data from the financial statements of French banks (2006–2013)
- » Default Rate from the European Banking Authority risk dashboard (2006–2013)
- » Default data from the French CRD sample. We ensure that the CDT exceeds the default rates observed in our development sample.

These multiple external data sources lead us to a CDT estimate of 2.2% for the one-year model, which coincides with the calibration of RiskCalc 3.1 France.

CALCULATING A FIVE-YEAR CENTRAL DEFAULT TENDENCY

There is a lack of publicly available data for directly calculating a CDT for the cumulative five-year default probability. Based on extensive Moody's Analytics research, we derive a five-year cumulative default tendency from the one-year estimate. This research, combined with the information provided by the CRD, shows that the five-year cumulative default rate is, on average, four times the level of the one-year default rate. Therefore, we use 8.8% as the CDT for the five-year model.

CENTRAL DEFAULT TENDENCY IN CCA MODE

The CDT in CCA mode equals the CDT 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 CCA mode CDT is larger; when the effects of the credit cycle indicate decreasing default risk, the CDT is smaller.

3. Model Components

The RiskCalc 4.0 France model incorporates various components to determine the EDF credit measure. Model inputs include selecting financial ratios, transforms of those ratios, the inclusion of industry information, and the credit cycle adjustment.

RiskCalc model development involves the following steps:

1. Choose a limited number of financial statement variables for the model from a list of possible variables.⁶
2. Transform the variables into interim probabilities of default using non-parametric techniques.
3. Estimate financial statement variable weightings using a probit model, combined with industry variables.
4. Create a (non-parametric) final transform that converts the probit model score into an actual EDF credit measure.

In FSO mode, we base models on the following functional form:

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

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

$I_1, \dots, I_K$ are indicator variables for each of the industry classifications (if applicable),

β and γ are estimated coefficients,

Φ is the cumulative normal distribution,

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

FSO EDF is the financial-statement-only EDF credit measure.⁷

The T s are the transforms of each financial statement variable, which capture the non-linear impacts of financial ratios on the default likelihood, as shown in Figure 5 and discussed in detail later. F is the final transform (that is, the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. The final transform is described 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, we adjust the final transform 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 VARIABLES

Our variable selection process begins with a long list of possible financial statement variables. We divide the working list of ratios into groups that represent different underlying concepts regarding a firm's financial status, shown in Table 2.

⁶ These variables are often ratios, but not always. For example, one measure of profitability is Net Income to Total Assets, a ratio, and one measure of size is Inflation Adjusted Total Assets, which is not a ratio.

⁷ By non-parametric, we mean that the $T(x_i)$ is a continuous function of x not requiring a specification of a closed (in other words, parametric) functional form. We estimate these transforms using a variety of local regression and density estimation techniques.

Table 2

Financial Statement Ratio Groupings

RATIO	DESCRIPTION
Activity	These ratios measure a firm's operating efficiency. → For example, a large amount of Accounts Payable relative to sales increases the probability of default; other activity ratios have different relationships to default.
Debt coverage	Measures a firm's ability to generate income to cover interest payments or some other measure of liabilities. → High debt coverage reduces the probability of default.
Growth	Typically includes 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.
Leverage	Examples of ratios in the leverage (or gearing) category include liabilities-to-assets and long-term debt to assets. → High leverage increases the probability of default.
Liquidity	Includes 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.
Profitability	Includes net profit and loss, ordinary profit, 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.
Size	Measured by total assets or sales deflated to a specific base year to ensure comparability. → Large firms default less often.

We then build a model with at least one variable per group. When we can increase model performance and maintain model robustness, we use several variables from each group in the model.

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

- » Is the variable readily available?
- » Is the variable meaning intuitive?
- » Does the variable help to measure default risk?
- » Are the definitions of the inputs to the variable ambiguous?
- » Is the correlation of the variable with other variables in the model not particularly high?

The RiskCalc 4.0 France model uses a similar set of ratios as the RiskCalc 3.1 France model, with some updates: Interest Expense to Sales replaces Financial Charges to Sales, Personnel Expenses to Sales replaces Change in Accounts Receivable Turnover and Operating Margin replaces EBITDA to Sales. We also include the marketable securities on the Debt Coverage and liquidity ratios, and exclude the Cash Flow to Financial Charges ratio. Table 3 lists the set of variables chosen for the RiskCalc 4.0 model.

Table 3

Financial Statement Variables in the RiskCalc 4.0 France Model

CATEGORY	RATIOS
Activity	Interest Expense/Sales Accounts Payable/Sales Personnel Expenses/Sales
Debt Coverage	Debt Coverage Ratio: (Profit for Period + Depreciation and Amortization)/ (Liabilities – Cash and Marketable Securities)
Growth	Sales Growth Change in ROA
Leverage	Equity/Assets
Liquidity	Cash and Marketable Securities/Assets
Profitability	Operating Margin
Size	Real Total Assets

VARIABLE TRANSFORMS

After we identify the variables, we transform them into a preliminary univariate EDF value. Figure 5 presents the transformations used in the model. The horizontal axis is the percentile score of the ratio, and the vertical axis is the default probability of that

ratio in isolation (univariate). The percentile score gives the percent of the database that had a ratio below the ratio of the company (for example, if Accounts Payable/Sales is in the 90th percentile, that means that 90% of the sample had Accounts Payable/Sales 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 has a larger impact on risk than if the slope is flat.

For the **Activity** group, three ratios are included. As shown in Figure 5, interest Expense/Sales, Accounts Payable/Sales and Personnel Expenses/Sales are upward-sloping, indicating that high values of these ratios are associated with higher default probabilities.

The **Debt Coverage** ratio $(\text{Profit for Period} + \text{Depreciation and Amortization}) / (\text{Liabilities} - \text{Cash and Marketable Securities})$ is downward-sloping, indicating that large values of this ratio lower the probability of default (Figure 5). The slope becomes flatter as the debt coverage ratio increases, indicating the impact of debt coverage diminishes when debt coverage ratio is large.

For the **Growth** group, Sales Growth and Change in ROA are included. The transforms are "U-shaped," indicating that large increases or decreases in sales or ROA are associated with higher default probabilities. In Figure 5 we see that large increases in Sales increase default probabilities by a larger amount than large decreases in Sales. On the other hand, we see that large decreases in ROA raise default probabilities by a larger amount than large increases in ROA.

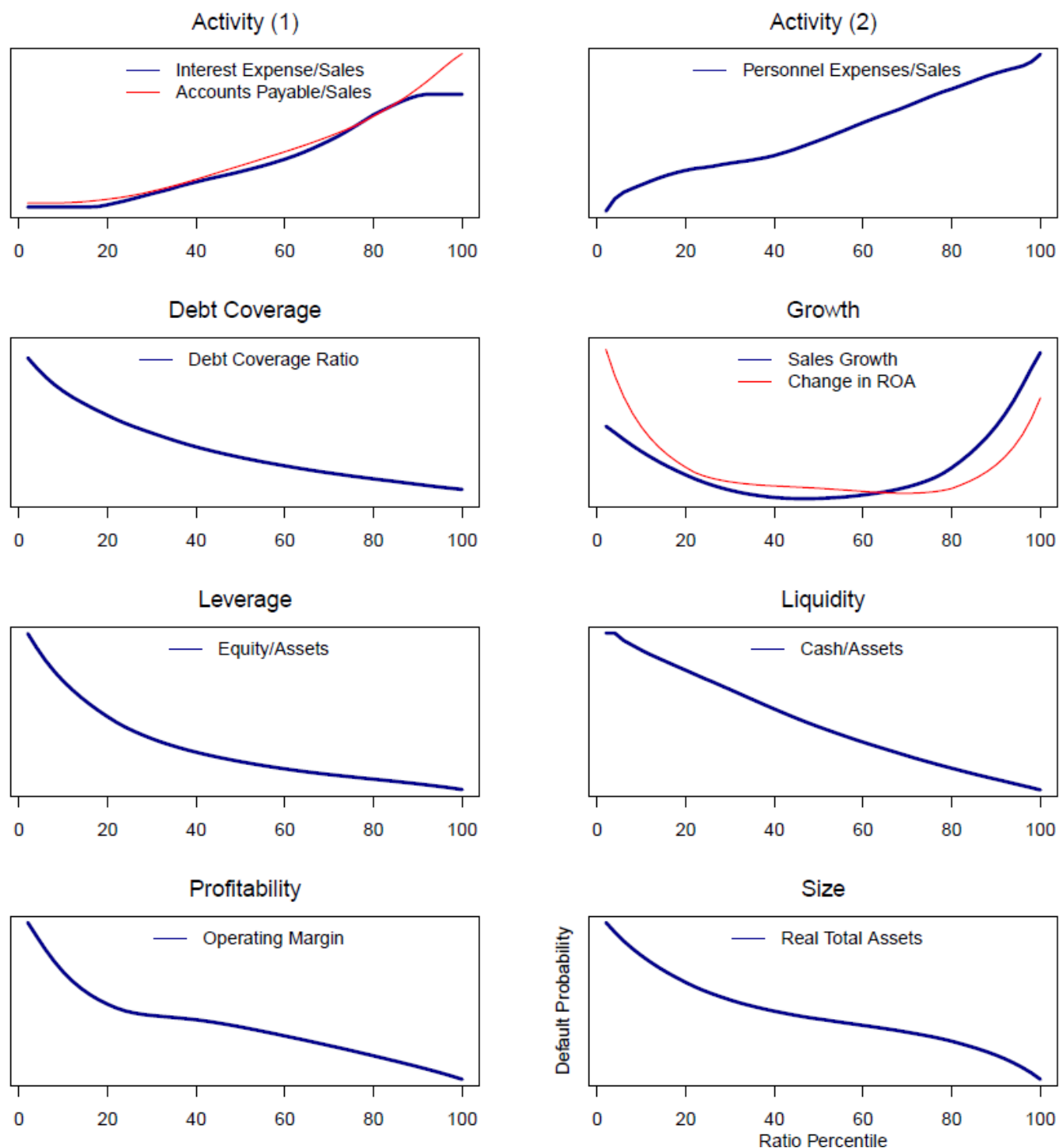
The **Leverage** ratio is Equity/Assets. Large values of this ratio decrease default probability (Figure 5). The slope becomes less negative as the ratio increases, which implies that a small increase in leverage, when leverage is high and equity is low, increases the default likelihood by a larger amount than when leverage is low and equity is high.

The **Liquidity** group variable is Cash and Marketable Securities/Assets. The transform is downward-sloping, indicating that higher values of this ratio are associated with lower default probabilities (Figure 5).

For the **Profitability** group, Operating Profit/Sales is included. As shown in Figure 5, the transform for this ratio is downward-sloping, but the slope becomes smaller as the Operating Margin becomes large. Such a transform indicates that more profitable firms have lower default probabilities, but the impact diminishes as profitability increases.

The **Size** variable is Real Total Assets. This variable's transformation is downward-sloping (Figure 5), indicating that larger firms have lower default probabilities.

Figure 5 Transformations on Financial Statement Variables in RiskCalc 4.0 France.



3.2 Model Weights

IMPORTANCE

The relative value of each variable used to calculate 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. Therefore, the model

weights are calculated based on the average EDF value for the transformation and its standard deviation. Thus, 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, we calculate the EDF value for a theoretical firm with all its variables at the average transformation. We then increase the variables one at a time by one standard deviation and calculate and add together the EDF level change for each variable (in absolute value). The relative weight of each variable is calculated as the EDF level changes for that variable as a percent of the total change in EDF level. This process gives the variable with the largest impact on the EDF level the largest weight, and the variable that has the smallest impact on the EDF level the smallest weight. Because the weights are a percentage of the total EDF value, they sum to 100%. The weight of each category is the sum of the weights of each variable in the category.

Table 4 presents the weights in the RiskCalc 4.0 France model and compares them with weights in the RiskCalc 3.1 France model. Debt Coverage is the most important category. The importance of Liquidity, Size, and Debt Coverage categories has increased, while the importance of Growth, Leverage, Profitability, and Activity has declined.

Table 4

RiskCalc 4.0 France Risk Drivers

RISKCALC 3.1 FRANCE	WEIGHT	RISKCALC 4.0 FRANCE	WEIGHT
Activity	16.3%	Activity	13.6%
Financial Charges/Sales		Interest Expense/Sales	
Accounts Payable/Sales		Accounts Payable/Sales	
Change in AR Turnover		Personnel Expenses/Sales	
Debt Coverage	16.4%	Debt Coverage	19.2%
Debt Coverage Ratio: (Profit for Period + Depreciation and Amortization)/ (Liabilities - Cash)		Debt Coverage Ratio: (Profit for Period + Depreciation and Amortization)/ (Liabilities - Cash and Marketable Securities)	
Cash Flow/Financial Charges			
Growth	16.9%	Growth	13.0%
Sales Growth		Sales Growth	
Change in ROA		Change in ROA	
Leverage	21.6%	Leverage	17.8%
Equity/Assets		Equity/Assets	
Liquidity	9.6%	Liquidity	16.0%
Cash/Assets		Cash and Marketable Securities/Assets	
Profitability	13.5%	Profitability	10.0%
EBITDA/Sales		Operating Margin	
Size	5.7%	Size	10.4%
Real Total Assets		Real Total Assets	

While the variables included in the RiskCalc model explain most of the risk factors, the relative importance of the variables can differ among industries. In the RiskCalc 4.0 France model, the EDF value is also adjusted for industry effects. Industry impact enters the model via industry indicator variables, highlighted in Section 3, Equation (1). In CCA mode, the industry further impacts the model via the industry-specific information used in the credit cycle adjustment, described in Section 3.3.

3.3 Credit Cycle Adjustment

EDF credit measures are impacted not only by a company's financials, but also by the economy's general credit cycle. To capture this effect, RiskCalc 4.0 France includes a credit cycle adjustment (CCA) factor. We design the credit cycle adjustment to incorporate the current position of the credit cycle into the private firm default risk estimate.

SELECTING AN ADJUSTMENT FACTOR

The RiskCalc 4.0 model uses the Distance-to-Default (DD) calculation from the Moody's Analytics 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.⁸ We choose this measure because it is available for a large universe of industries and has extensive validation.

If the DD factor for public firms in an industry⁹ indicates a level of risk above the historical average for that industry, the private firm EDF values in that industry adjust upward. Conversely, if the risk level falls below the historical average for that industry, then the private firm EDF values adjust 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 RiskCalc 4.0 France model, the DD factor is a weighted average of two subfactors. The first subfactor is based on an aggregation of DD for French companies in each industry and the second subfactor is based on an aggregation of European regional¹⁰ firms from each industry. The weight on the French factor is industry-specific and determined by the number of French firms in each industry. If a firm cannot be associated with a specific industry, and for firms within the Agriculture or Health Care industries, the model uses a credit cycle adjustment based on an aggregation of all public French and regional firms.

We use a Bayesian approach to assign the weight on the French DD factor and the region DD factor. If a French industry has 20 firms in a specific month, we place 50% weight on the French DD factor, with the remainder on the region DD factor. If the number of firms exceeds 50, we place more than 70% of the weight on the French industry factor. Using the Bayesian method, we place more weight on the regional factor when the number of firms in France from a particular industry is too small to impute its own credit cycle adjustment factor. We then gradually increase the weight of the French industry-specific factor as the number of firms increases.¹¹

Figure 6 provides evidence of the relationship between the DD factor and real GDP growth rate in France. The figure shows that the DD factor led (and matched well) the variation in the real GDP growth rate during the recent financial crisis. Overall, the DD factor is a strong predictor of economic conditions in each industry, and it adjusts the probabilities default to reflect the industry's position in the credit cycle.

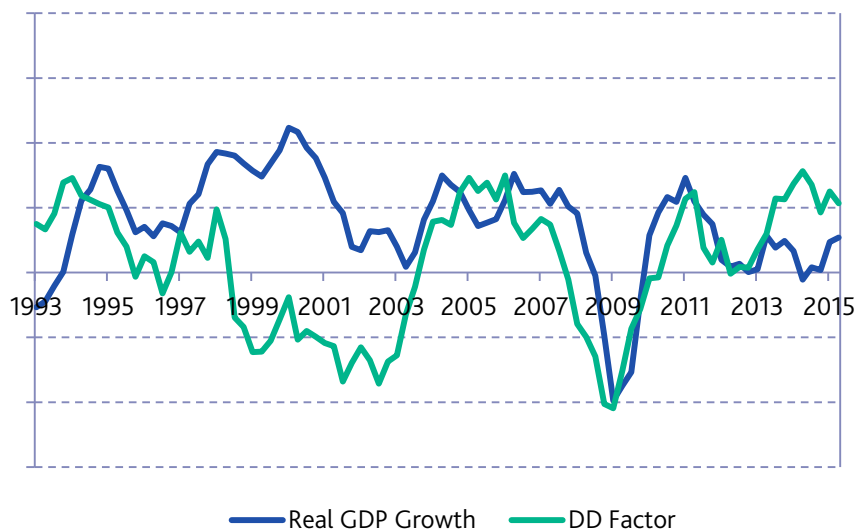
⁸ cf. Bohn and Crosbie, 2003.

⁹ The 13 industries in the RiskCalc 4.0 France model: Agriculture, Business Products, Business Services, Communication, Construction, Consumer Products, Health Care, HiTech, Mining, Services, Trade, Transportation, Utilities, and Unassigned.

¹⁰ The countries used to compute the regional component are: Austria, Belgium, Denmark, France, Germany, Greece, Italy, Luxembourg, Netherlands, Portugal, Spain, and Switzerland.

¹¹ We use the following formulas to assign weights: $\text{weight_France} = 1 / (1 + \frac{20}{N})$, and $\text{weight_Region} = \frac{20}{N} / (1 + \frac{20}{N})$, where N is number of French firms in the industry. This technique is motivated by Vasicek (1973).

Figure 6 RiskCalc 4.0 France DD Factor and Annual GDP Growth Rate.



4. Validation Results

After development, a model must prove effective in predicting defaults. In this section, we present results for the model's ranking power and the accuracy of its predicted EDF credit measure — the model's ability to estimate EDF level correctly.

Tests check the model's effectiveness, its robustness, and how well it works on data outside the development sample. To conduct out-of-sample testing, we perform walk-forward and k -fold analyses. Results show that the model is uniformly more powerful than other benchmarks across different time periods, sectors, and size classifications.

4.1 Overall Model Power and Accuracy

Table 5 presents the in-sample, overall measures of power for the RiskCalc 4.0 France model versus the RiskCalc 3.1 France model.¹² RiskCalc 4.0 France shows robust performance and outperforms the 3.1 model at both the one-year and five-year horizons.

Table 5 also contains p-values for the statistical test to display whether the difference between the accuracy ratios from the RiskCalc 4.0 model and the RiskCalc 3.1 model equals zero. A p-value of less than .05 indicates we can reject the hypothesis that the difference in the accuracy ratios (AR) equals zero, with 95% confidence.

Table 5

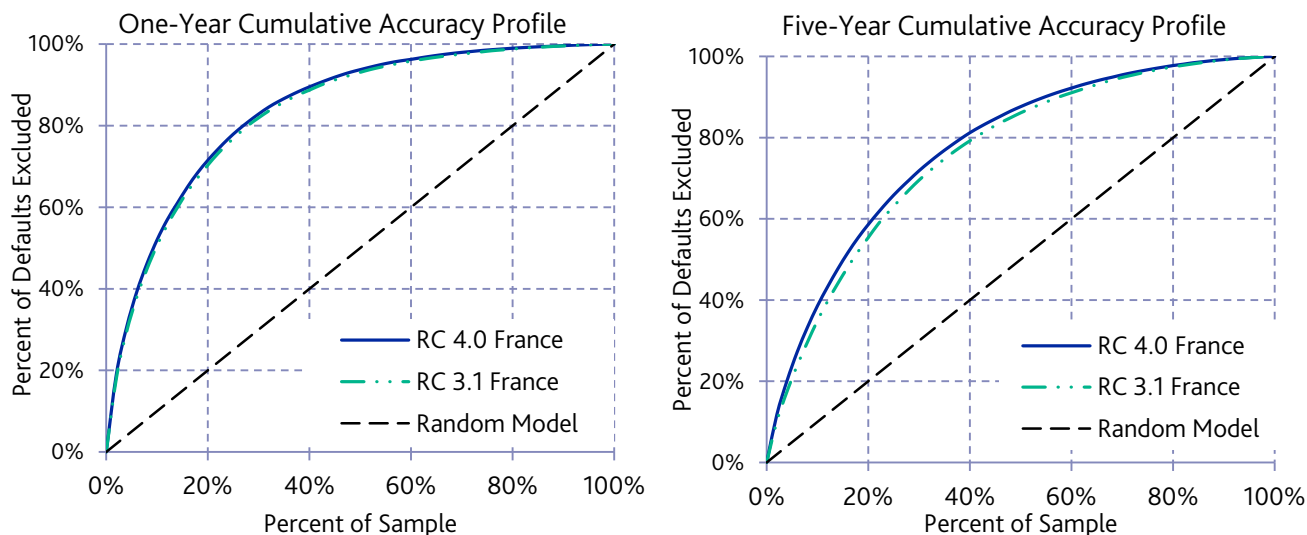
Power of RiskCalc 4.0 France: One- and Five-year Model (CCA mode)

	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE	P-VALUE OF DIFFERENCE (4.0-3.1)
One-Year model	69.1%	67.8%	<0.0001
Five-Year model	56.6%	53.4%	<0.0001

Figure 7 presents the cumulative accuracy profiles for the one-year and five-year models shown in Table 5.

¹² Reported accuracy ratios are based on CCA EDF values. In FSO mode, the one-year accuracy ratio for RiskCalc 4.0 France is 70.5%, and for RiskCalc 3.1 France the one-year accuracy ratio is 69%.

Figure 7 Power of Alternative Models One-Year and Five-Year: RiskCalc 4.0 France.



4.2 Industry Adjustments

While the variables included in the RiskCalc model explain most of the risk factors, the relative importance of these variables can differ among industries.

Table 6 presents the average EDF value, by industry, of the development sample. The table shows the combined impact of the industry adjustment. By expanding industry granularity, we can capture the default characteristics in various sectors. For instance, on average, Utility companies have lower EDF values than Transportation companies, as they tend to be more stable and default probability in this sector is lower.

Table 6

Average RiskCalc 4.0 France EDF by Sector

SECTOR	AVERAGE CCA EDF	
	ONE-YEAR	FIVE-YEAR
Agriculture	2.0%	7.8%
Business Products	2.7%	10.8%
Business Services	2.5%	9.4%
Communication	3.6%	13.0%
Construction	3.1%	11.4%
Consumer Products	2.9%	11.2%
Healthcare	1.2%	4.4%
HiTech	2.6%	9.8%
Mining	2.7%	10.0%
Services	2.2%	8.1%
Trade	2.1%	8.4%
Transportation	2.7%	10.6%
Unassigned	2.2%	9.1%
Utilities	1.4%	5.1%

4.3 Correlations and Variance Inflation Factors

To ensure model robustness, we must test the model for excessive multicollinearity, which occurs if several of the variables used in the model are highly correlated. Excessive multicollinearity can cause instability in parameter estimates. To check for this issue, we calculate the correlation coefficients for the financial statement ratios in the model, (Table 7), and the variance inflation factors (VIF) (Table 8) on the transformed variables shown in Figure 5.

The highest correlation coefficient occurs between Equity to Assets and the Debt Coverage Ratio (0.66). The next highest coefficient occurs between Operating Margin and the Debt Coverage Ratio (0.65). Such coefficients fall below what we would typically consider indications of multicollinearity. The variance inflation factor (VIF) analysis also verifies this finding.

Table 7

Correlations Among the Transformed Input Factors (Spearman Rank)

VARIABLE	1	2	3	4	5	6	7	8	9	10
1 Interest Expense to Sales	1.00									
2 Accounts Payable to Sales	0.12	1.00								
3 Personnel Expenses to Sales	0.03	-0.28	1.00							
4 Debt Coverage Ratio	0.29	0.36	-0.07	1.00						
5 Sales Growth	-0.03	0.12	-0.06	0.09	1.00					
6 Change in ROA	-0.03	-0.04	0.09	0.10	0.16	1.00				
7 Equity to Assets	0.26	0.32	-0.08	0.66	0.09	0.09	1.00			
8 Cash to Assets	0.41	0.21	-0.05	0.60	0.02	0.02	0.39	1.00		
9 Operating Margin	0.05	0.16	-0.02	0.65	0.05	0.16	0.38	0.27	1.00	
10 Real Total Assets	-0.21	-0.25	0.16	-0.05	0.02	0.19	0.10	-0.12	0.08	1.00

The variance inflation factors 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. As Table 8 shows, the estimated VIF values fall below the threshold levels of 4 to 10, commonly used in VIF analysis when testing for the presence of multicollinearity.¹³ These findings indicate that the model variables do not present any substantial multicollinearity.

Table 8

Variance Inflation Factors

VARIABLE	VIF
Debt Coverage Ratio	3.04
Operating Margin	2.05
Equity to Assets	1.73
Personnel Expenses to Sales	1.65
Cash to Assets	1.51
Accounts Payable to Sales	1.41
Interest Expense to Sales	1.32
Real Total Assets	1.28
Change in ROA	1.25
Sales Growth	1.08

4.4 Power Performance by Industry and Size Group

It is important to test model power not only overall, but also among different industry segments and firm sizes. RiskCalc 3.1 France proves to be a robust model when validated with the newly received data, as shown in the following tables. RiskCalc 4.0 France improves model performance across industry and most of the size groups when compared to the 3.1 model. Table 9 and Table 10

¹³ As Wooldridge (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 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 significant issue.

present the power comparisons by sector for the one-year and five-year models, respectively. The highest power is found in Health Care (74.6% at one-year horizon and 62.8% at five-year horizon), while the lowest is found in Communication (50% at one-year horizon and 47.1% at five-year horizon).

Table 9

Power by Industry: RiskCalc 4.0 France One-Year Model

INDUSTRY	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
Agriculture	1.3%	0.8%	70.3%	69.0%
Business Products	8.4%	10.2%	69.7%	68.5%
Business Services	13.1%	12.2%	66.8%	64.6%
Communication	0.2%	0.2%	50.0%	43.7%
Construction	17.2%	25.4%	68.6%	68.4%
Consumer Products	5.6%	7.4%	66.3%	66.1%
Health Care	1.6%	0.5%	74.6%	72.4%
HiTech	2.2%	2.3%	66.9%	65.3%
Mining	1.7%	2.0%	69.1%	68.6%
Services	10.2%	7.0%	66.6%	64.3%
Trade	32.3%	24.7%	68.5%	68.5%
Transportation	5.1%	6.2%	70.6%	69.1%
Unassigned	0.7%	0.8%	64.4%	64.4%
Utilities	0.4%	0.1%	63.0%	56.7%

Table 10

Power by Industry: RiskCalc 4.0 France Five-Year Model

INDUSTRY	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
Agriculture	1.3%	0.8%	61.4%	56.7%
Business Products	8.3%	9.8%	51.7%	49.5%
Business Services	13.1%	12.3%	56.1%	51.9%
Communication	0.2%	0.2%	47.1%	40.4%
Construction	17.0%	24.1%	57.0%	54.5%
Consumer Products	5.5%	7.3%	49.3%	47.4%
Health Care	1.6%	0.5%	62.8%	59.5%
HiTech	2.2%	2.2%	55.2%	52.9%
Mining	1.7%	1.8%	55.2%	53.4%
Services	10.3%	7.6%	56.5%	52.6%
Trade	32.5%	26.5%	56.3%	54.7%
Transportation	5.1%	6.1%	54.7%	50.7%
Unassigned	0.7%	0.7%	56.7%	56.3%
Utilities	0.4%	0.1%	53.6%	42.5%

Table 11 and Table 12 present the power comparisons by firm size (Assets in Euros) for the one-year and five-year models, respectively. The model performs well when compared to RiskCalc 3.1 France across size cuts.

Table 11

Power by Size: RiskCalc 4.0 France One-Year Model

SIZE (TA IN 2012 EUR)	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
Less than 500K	34.0%	44.9%	65.5%	64.6%
500K to 1MM	25.5%	25.8%	69.8%	68.9%
1MM to 2MM	17.6%	15.6%	69.1%	68.1%
2MM to 5MM	12.7%	9.1%	68.5%	67.8%
5MM to 10MM	4.8%	2.8%	64.7%	63.7%
Greater than 10MM	5.4%	1.9%	58.9%	59.1%

Table 12

Power by Size: RiskCalc 4.0 France Five-Year Model

SIZE (TA IN 2012 EUR)	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
Less than 500K	33.8%	42.9%	55.9%	52.8%
500K to 1MM	25.5%	27.0%	59.7%	57.5%
1MM to 2MM	17.6%	16.3%	59.2%	57.2%
2MM to 5MM	12.8%	9.2%	56.1%	54.6%
5MM to 10MM	4.9%	2.9%	54.6%	53.6%
Greater than 10MM	5.5%	1.8%	45.8%	44.7%

4.5 Power Performance Over Time

Because models are implemented at various points in a business cycle by design, we conduct power tests by year to examine whether or not model performance is excessively time-dependent.

Table 13 and Table 14 present the results from this analysis at the one- and five-year horizons, respectively. We compare the RiskCalc 4.0 France model's AR with RiskCalc 3.1 France for each year. The 4.0 model performs consistently well across the sample period.

Table 13

Power by Year: RiskCalc 4.0 France One-Year Model

YEAR	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
1993	1.4%	1.7%	62.9%	61.8%
1994	2.9%	2.2%	59.6%	58.0%
1995	3.5%	2.1%	60.2%	57.7%
1996	3.9%	2.7%	61.2%	61.1%
1997	4.2%	4.1%	67.7%	67.9%
1998	4.3%	4.4%	69.9%	70.3%
1999	5.5%	4.6%	69.6%	68.6%
2000	6.0%	5.5%	69.2%	68.3%

YEAR	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
2001	6.1%	5.9%	68.4%	67.0%
2002	5.3%	5.0%	70.1%	67.1%
2003	5.3%	4.3%	69.2%	67.8%
2004	5.7%	4.8%	68.8%	65.7%
2005	5.9%	5.4%	67.0%	64.8%
2006	5.7%	6.9%	68.5%	67.4%
2007	5.7%	7.0%	65.1%	63.5%
2008	5.6%	7.4%	69.4%	66.7%
2009	5.2%	6.2%	70.4%	69.2%
2010	6.1%	8.2%	68.8%	67.0%
2011	6.3%	8.2%	69.6%	67.7%
2012	5.4%	3.2%	74.7%	72.3%

Table 14

Power by Year: RiskCalc 4.0 France Five-Year Model

YEAR	% OF TOTAL STATEMENTS	% OF TOTAL DEFAULTS	RISKCALC 4.0 FRANCE	RISKCALC 3.1 FRANCE
1993	1.4%	1.9%	55.7%	54.2%
1994	2.9%	2.4%	52.3%	50.6%
1995	3.5%	3.1%	52.6%	51.6%
1996	3.9%	4.0%	53.6%	53.7%
1997	4.2%	4.8%	56.4%	56.1%
1998	4.3%	5.3%	57.1%	56.7%
1999	5.5%	5.7%	58.0%	56.9%
2000	6.0%	6.2%	58.1%	57.1%
2001	6.1%	6.0%	58.2%	56.9%
2002	5.3%	4.8%	58.6%	56.3%
2003	5.3%	4.9%	54.8%	53.6%
2004	5.7%	6.6%	54.2%	52.4%
2005	5.9%	7.3%	54.2%	53.4%
2006	5.7%	7.5%	58.2%	56.5%
2007	5.7%	7.3%	57.0%	54.2%
2008	5.6%	7.1%	58.5%	55.4%
2009	5.2%	5.3%	61.5%	58.9%
2010	6.1%	5.0%	64.9%	62.5%
2011	6.3%	3.5%	68.4%	66.9%
2012	5.4%	1.3%	74.4%	72.1%

4.6 Model Performance on Real Estate, Dealerships, and Not-for-Profit Companies

RiskCalc country models are generally not recommended for Real Estate, Dealerships, and Not-for-Profit companies because their business models and financial statements may differ from those of typical corporates. However, when we test the performance of RiskCalc 4.0 France on those industries, we find that the model provides reasonably good power in predicting defaults for these company types.¹⁴

Table 15 shows the default rates for these three sectors. Our validation datasets cover 1993–2014. The one-year Accuracy Ratios for these sectors follow: Real Estate is 59.3%, Dealership 70.2%, and Not-for-Profit 62.3%.

Table 15

Default Rates by Sector

	REAL ESTATE	DEALERSHIP	NOT-FOR-PROFIT
Statements	124,000+	127,000+	35,000+
Defaults	800+	1300+	400+
Default Rate	0.7%	1.1%	1.4%

4.7 Out-of-Sample Testing: *k*-fold Tests

As Table 5 shows, the model exhibits a high degree of power in distinguishing good credits from bad ones, but we must also test whether or not this power is attributable to the overall model effectiveness or the impact of a particular subsample. A standard test for evaluating this question is the *k*-fold test, which divides the defaulting and non-defaulting companies into *k* equally-sized segments. This process yields *k* equally-sized observed subsamples that exhibit the identical overall default rate and are temporally and cross-sectionally independent. We then run the model on *k*-1 subsamples, and these parameter estimates are used to score the *k*-th subsample. We repeat this procedure for all possible combinations, and the *k* scored out-of-sample subsamples are combined to calculate an accuracy ratio on this combined data set.

Table 16 summarizes *k*-fold test results (with *k*=5) for the development sample. The reported figures are the accuracy ratios by the corresponding sample and time horizons. The out-of-sample model consistently outperforms RiskCalc 3.1 EDF. Figure 8 presents the cumulative accuracy profiles associated with the overall out-of-sample results against the in-sample results of RiskCalc 4.0; model performance is maintained both in- and out-of-sample in the *k*-fold analysis.

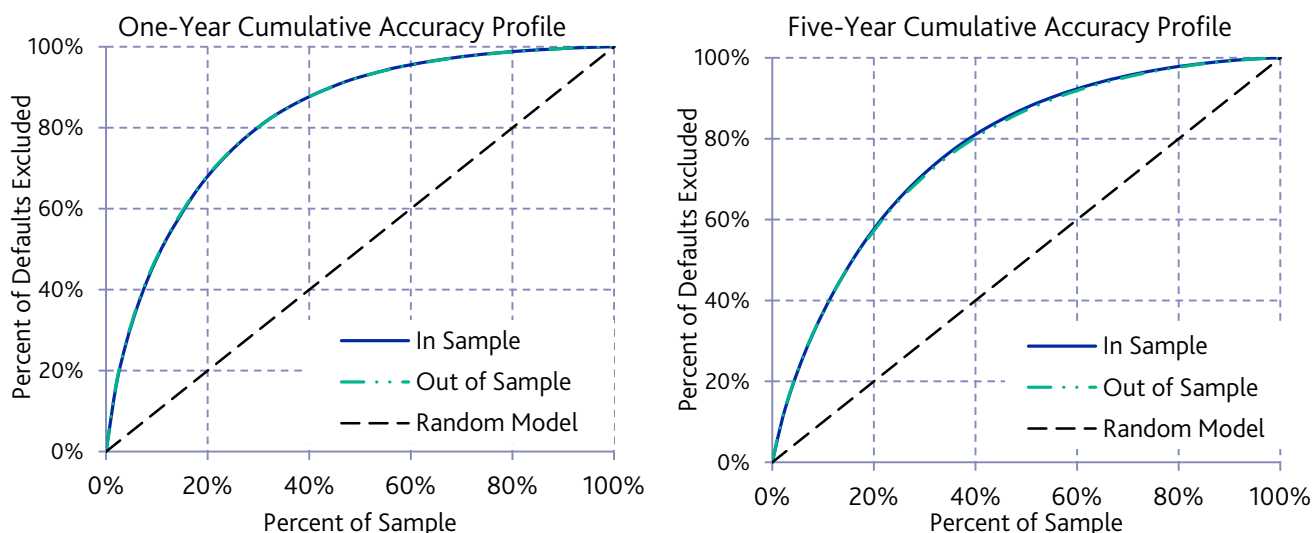
Table 16

RiskCalc 4.0 France *k*-fold Test Results

	OUT-OF-SAMPLE AR		RISKCALC 3.1 MODEL	
	ONE-YEAR AR	FIVE-YEAR AR	ONE-YEAR AR	FIVE-YEAR AR
Subsample 1	66.7%	56.8%	65.4%	55.0%
Subsample 2	66.6%	56.2%	65.1%	54.4%
Subsample 3	66.9%	56.7%	65.5%	55.0%
Subsample 4	66.8%	56.7%	65.2%	54.9%
Subsample 5	66.9%	56.7%	65.3%	55.0%
<i>k</i> -fold Overall	69.2%	57.2%	67.8%	53.4%
In-sample AR	69.1%	56.6%	---	---

¹⁴ While we observe good performance, France 4.0 model is not designed to predict defaults for these industries and should be used with caution. In case of Real Estate, RiskCalc 4.0 France model is not appropriate for certain types of real estate companies. In particular, non-income producing / single project Real Estate developers should not be scored using RiskCalc models.

Figure 8 Out-of-Sample Performance (One- and Five-Year) RiskCalc 4.0 France Model k -fold.



The in- and out-of-sample plots are virtually indistinguishable at both the one- and five-year horizons in Figure 8. The difference in AR between the overall in-sample and out-of-sample results is small for both the one-year and the five-year horizons.

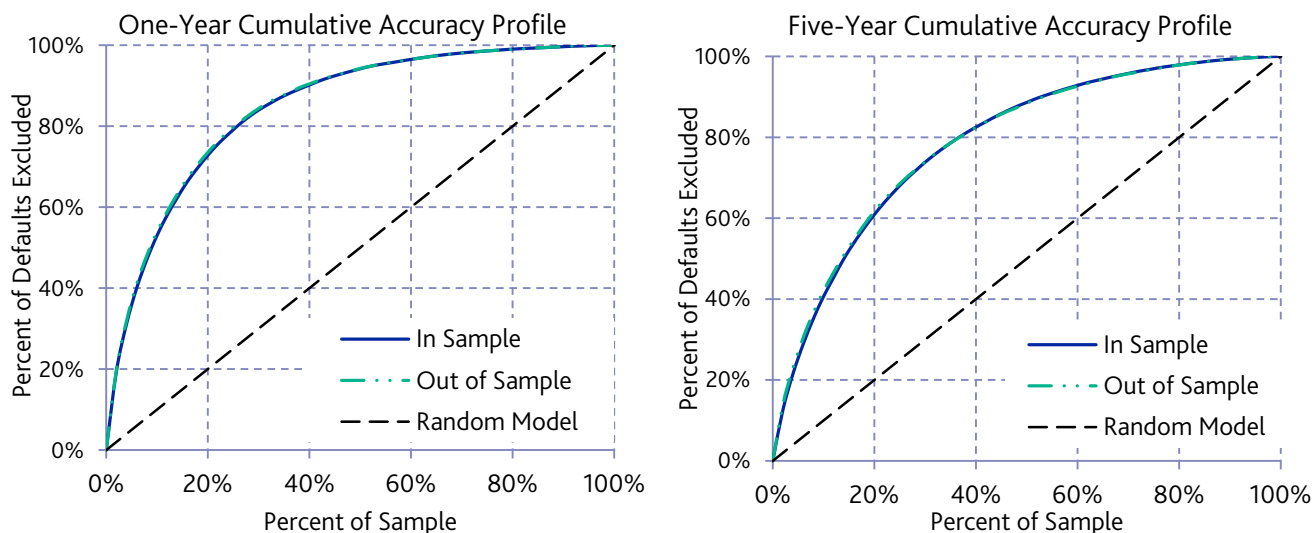
4.8 Walk-Forward Tests

An alternative out-of-sample test developed by Moody's Analytics is a walk-forward test, designed along similar lines as the k -fold test, except that it controls for time effects. We estimate the model 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. We then re-estimate the model including one more year of data. The analysis is then repeated for the next year and continued 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. We then compare the out-of-sample accuracy ratio 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. We check the parameter estimates for stability across the different samples. Figure 9 presents results from this analysis, using 2000 as the starting year for the analysis.

The difference in RiskCalc 4.0 accuracy ratio (AR) values between the in-sample and out-of-sample results is -0.5% for the one-year and -0.4% for the five-year.

Figure 9 Out-of-Sample Performance (One- and Five-Year) RiskCalc 4.0 France Model Walk-Forward.



4.9 Model Calibration and Implied Ratings

To help interpret EDF credit measures, the model maps an EDF value to an EDF-implied rating. This mapping is designed with the following considerations:

- » There is a large range of EDF-implied 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 five-year ratings is approximately the same as the distribution of one-year ratings (for consistency with rating-based analysis applications).
- » The EDF value associated with an EDF rating is approximately the same as the observed historical default rate associated with a Moody's bond rating (for consistency with rating-based analysis applications).

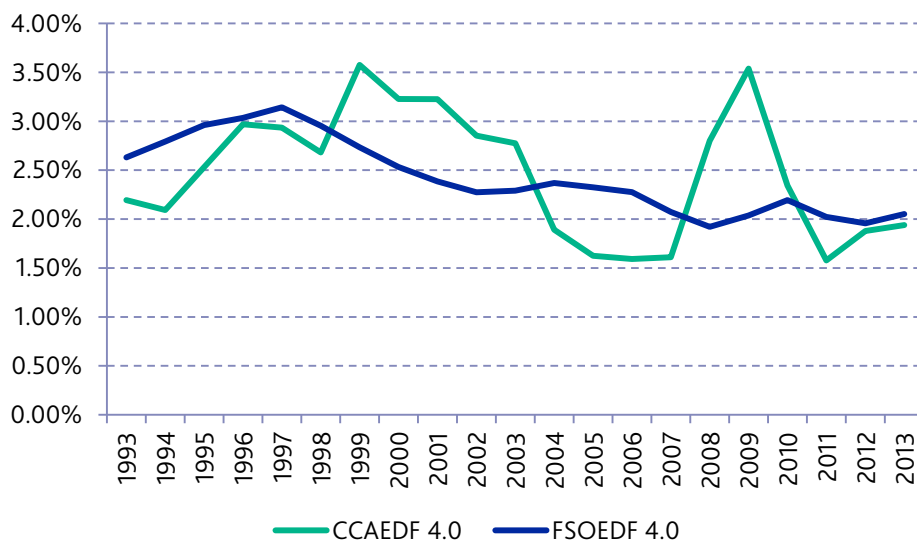
Figure 10 shows the distribution of the observations by rating category in the development sample for the FSO EDF credit measures over the full time period. Note, less than 12% of the observations fall into any one category. Distributions peak at Baa3 for both the one-year and five-year ratings. While not reported here, other research shows that the distribution of the CCA EDF-implied ratings changes over time with the credit cycle, while the distribution of the FSO EDF-implied ratings remains relatively stable over time.

Figure 10 Frequencies of EDF-Implied Ratings for the One- and Five-Year Models in the Development Sample.



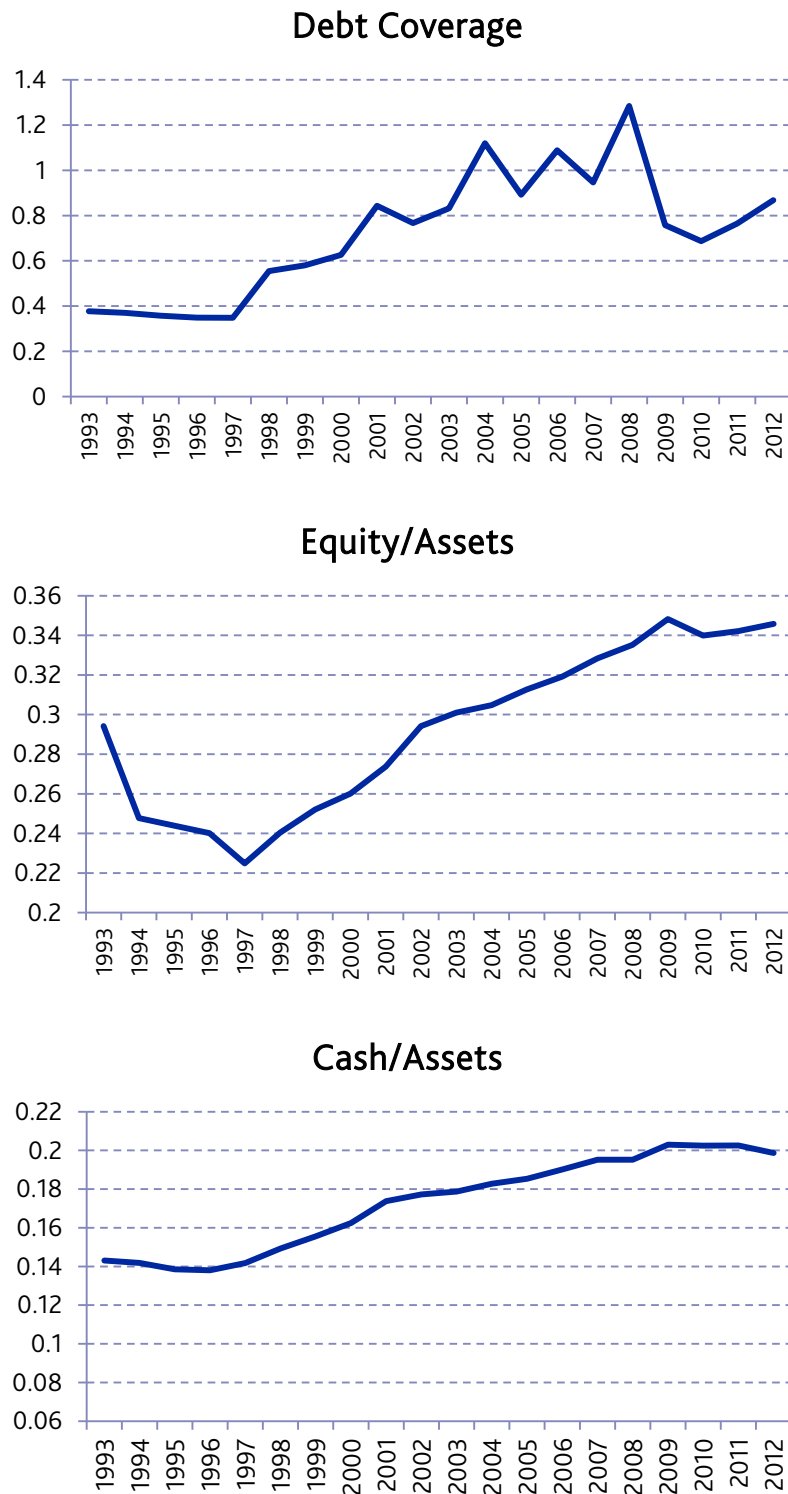
Figure 11 shows the comparison of development sample average FSO and CCA EDF levels over the years for the RiskCalc 4.0 France model. We see the average FSO EDF is relatively flat across the years, with a slight downward trend. On the other hand, the average CCA EDF reflects the fluctuations in the economic cycle.

Figure 11 Average FSO EDF and CCA EDF Levels Over Time for RiskCalc 4.0 France.



The downward trend in FSO EDF comes from the improvement of several key financial ratios. Figure 12 demonstrates trends. Firms tend to increase debt coverage and equity with respect to assets. Also, the availability of liquid assets on companies' balance sheets has been rising during the period.

Figure 12 Average Values of the Key Financial Ratios Over Time.



5. Additional Model Features

This section outlines additional RiskCalc 4.0 France model features.

5.1 Continuous Term Structure

We use the two-point estimates for the one-year and five-year estimates to fit a Weibull function and, thus, achieve a continuous term structure of EDF values for each credit; RiskCalc 4.0 France model users can obtain EDF values for any point in time between one and five years. In addition, RiskCalc 4.0 France provides EDF values for alternative definitions, such as the forward-EDF measure and the annualized-EDF measure, shown in Table 17.

CUMULATIVE EDF CREDIT MEASURES

A cumulative EDF credit measure provides the probability of default over that time period. For example, a five-year cumulative EDF credit measure of 13.44% means that that company has a 13.44% chance of defaulting during that five-year period. The second column in Table 17 provides an example of the cumulative one-year to five-year credit measures produced by the model.

FORWARD-EDF CREDIT MEASURES

The forward-EDF credit measure is the probability of default between $t-1$ and t , conditional upon survival until $t-1$. In other words, the four-year forward-EDF measure is the probability that a firm will default between years three and four, assuming the firm survived to year three.¹⁵ Table 17 displays the forward- one- to five-year EDF credit measures derived from the cumulative EDF values.

ANNUALIZED-EDF CREDIT MEASURES

The annualized-EDF credit measure is the cumulative EDF value for a given period, stated on a per-year basis. For example, a company with a cumulative five-year EDF value of 13.44% would have a five-year annualized-EDF value of 2.84%.¹⁶ Table 17 presents the annualized-EDF credit measures for years one to five. These credit measures are derived from the cumulative EDF values — the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column in Table 17 presents the annualized-EDF credit measures for years one to five. These credit measures are derived from the cumulative EDF values.

Table 17

Term Structure of EDF Credit Measures: An Example

EDF	CUMULATIVE	FORWARD	ANNUALIZED
Year 1	4.23%	4.23%	4.23%
Year 2	7.00%	2.89%	3.56%
Year 3	9.37%	2.55%	3.23%
Year 4	11.49%	2.34%	3.01%
Year 5	13.44%	2.20%	2.85%

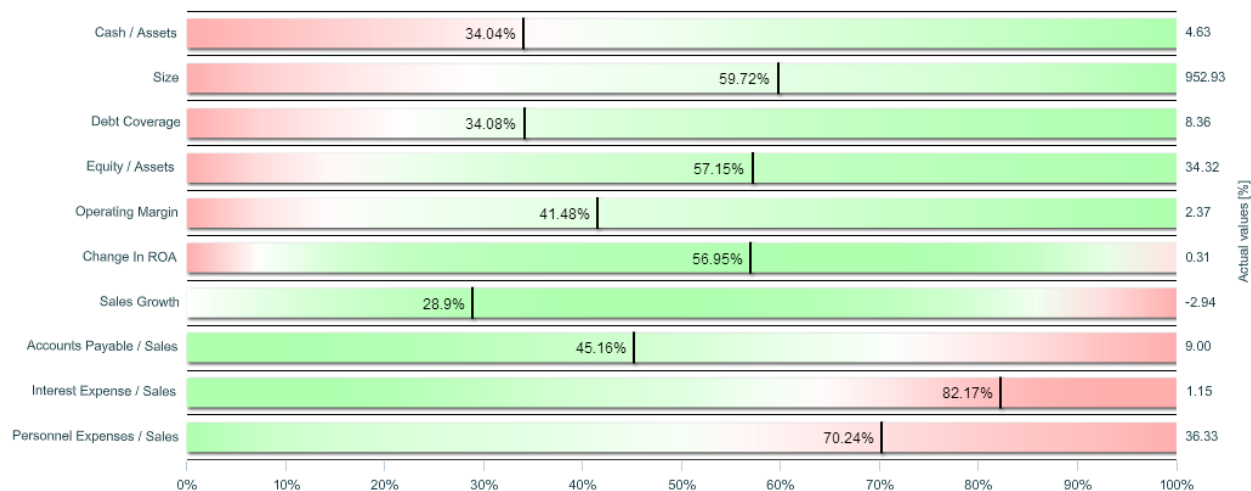
5.2 Percentile Graph

The percentile graph allows users to quickly isolate problematic ratios for a given company. As Figure 13 shows, each horizontal bar represents a ratio that is labeled on the left (for example, Operating Margin). The column on the right provides the actual value of the ratio. The percentage number within the horizontal bar graph represents what percentile the ratio was within the development sample (for example, 41.48% of the development sample had an Operating Margin of less than 2.37%). The shading represents the risk level associated with the ratio: green is low risk, red is high risk, and grey is neutral risk. The variables shaded red to green are the "good" ratios, for which higher values are associated with lower risk. Variables shaded green to red are the "bad" ratios, for which higher values are associated with higher risk. Variables shaded red to green to red have a U-shaped relationship with default risk. For these variables, both high and low values indicate high risk, while moderate values indicate low risk.

¹⁵ Specifically, $FEDF_{t-1,t} = (CEDF_t - CEDF_{t-1}) / (1 - CEDF_{t-1})$, where $FEDF_{t-1,t}$ is the forward EDF from years $t-1$ to t , and $CEDF_t$ is the cumulative EDF for year t .

¹⁶ Specifically, $AEDF_t = 1 - (1 - CEDF_t)^{1/t}$, where $AEDF_t$ is the annualized EDF for year t .

Figure 13 Percentile Map for the RiskCalc 4.0 France Model.

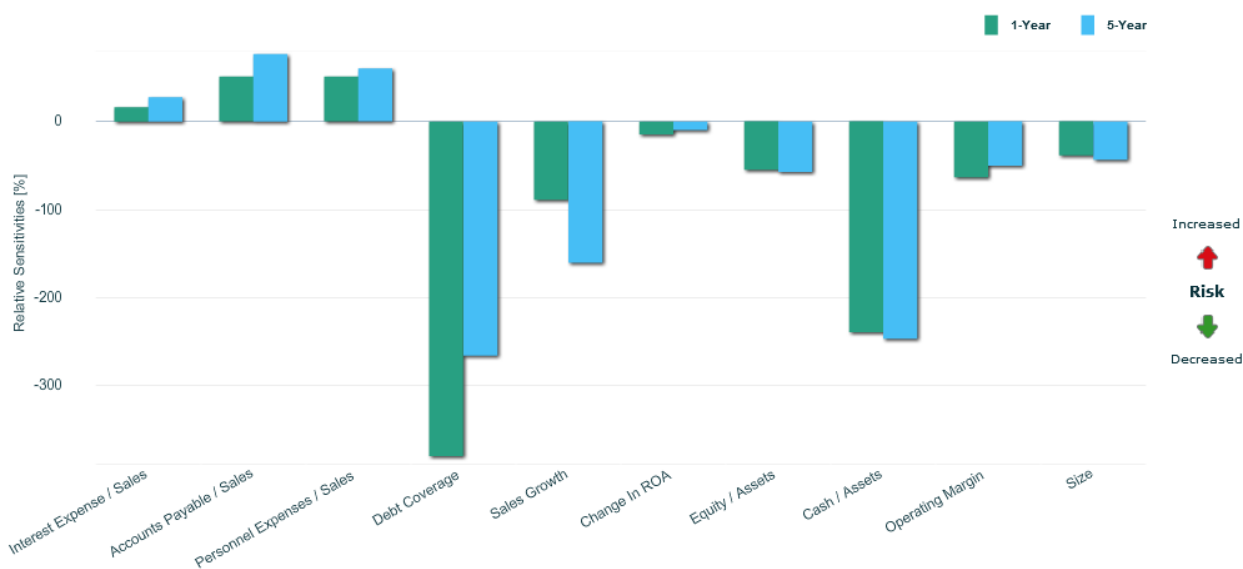


5.3 Relative Sensitivity

The RiskCalc 4.0 France application provides an analytical tool to gauge the relative impact of each variable — as a deviation from the mean of each ratio. Relative sensitivities, also known as sensitivity multiples, exhibit the EDF sensitivity to each model variable at the point of evaluation. This feature is especially useful when addressing the topic of identifying variables to improve the EDF value of a company.

The relative sensitivity provides the impact of a small change in a variable on the EDF level of the company. It indicates which variables are most sensitive to an increase / decrease. A positive number means that an increase in the variable increases risk, and a negative number decreases risk. The percentage number on the horizontal axis is the sensitivity of the variable relative to the average. For example, a small increase in the Debt Coverage changes the risk of the company. In this example, it is more than 380% as sensitive as the average variables, shown in Figure 14.

Figure 14 Relative Sensitivities for the RiskCalc 4.0 France Model.

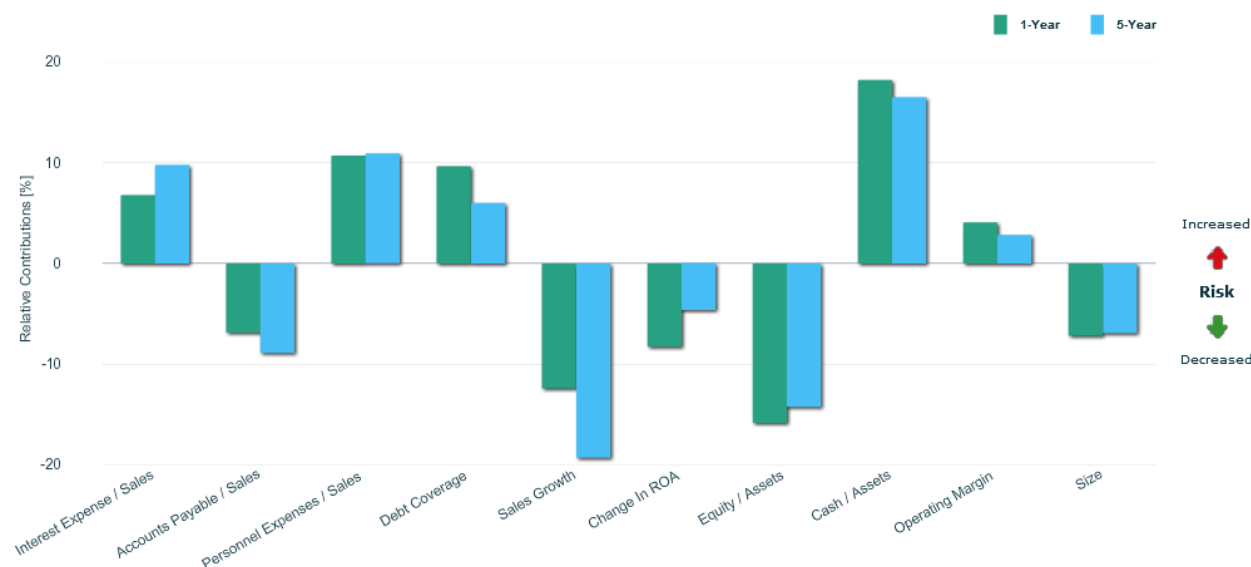


5.4 Relative Contribution

The RiskCalc 4.0 application also provides an analytical tool for gauging the relative risk contribution of each variable. The Relative Contribution graph exhibits how each model variable contributes to the EDF value. This tool is useful in identifying the strengths and weaknesses of a company in terms of default risk.

The Relative Contribution graph indicates which model variables help increase default risk, which variables help decrease default risk, and their relative magnitudes. For each ratio, if the evaluated company performs more poorly than the average firm from the development sample (the value of the ratio makes the firm riskier relative to an average firm), the relative contribution for that ratio is positive. By the same token, a ratio has a negative relative contribution if the ratio helps decrease default risk. For example, in Figure 15, Sales Growth helps decrease the default risk, whereas, Cash to Assets helps increase default risk.

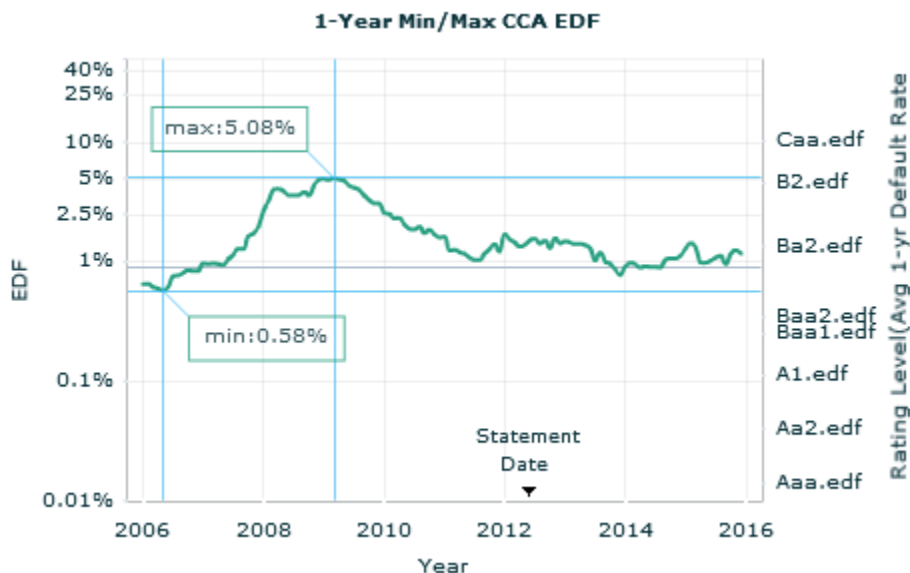
Figure 15 Relative Contributions for the RiskCalc 4.0 France Model.



5.5 Stress Testing Graph

The stress testing graph in RiskCalc 4.0 France, displayed in Figure 16, shows what the EDF value would be at a different point in time, given the same set of financial ratios and industry input. This function is available when the model's credit cycle adjustment (CCA) mode is selected. In this tool, EDF value changes across time as the credit cycle adjustment factor changes value. The credit cycle adjustment factor is based on a group of publicly listed firms with the same sector classification. If the sector has higher default risk at a time point, the evaluated firm would have a higher EDF, or vice-versa. The example firm in Figure 16 would have had an EDF value of 0.58% in May 2006, when the economy was expanding. The EDF value hit its highest point (5.08%) in March 2009, when the economy was in recession and the industry's credit risk was high. This function is not available when using financial statement only (FSO) mode.

Figure 16 Stress Testing Graph for the RiskCalc 4.0 France Model.



6. Summary

We construct the RiskCalc 4.0 France model using a large dataset of financial statements and defaults of firms in France. In addition, the RiskCalc 4.0 France model incorporates the unique characteristics of firms and market environments in France. The model outputs are conceptually comparable to those of the previous version of the RiskCalc model.

The RiskCalc 4.0 France model updates the methodology for the CCA adjustment. Using the CCA mode, the RiskCalc 4.0 France model adjusts the EDF credit measure to reflect the current stage of the credit cycle of the corresponding industry in France. If default risk is high, the EDF credit measure is adjusted upward. Likewise, when default risk is low, the EDF credit measure is adjusted downward. The CCA adjustment is based on the Moody's Analytics Public Firm Model.

The RiskCalc 4.0 France model performs well separating high risk firms from low risk firms, for the full sample as well as for the subsamples by size, sector, and statement year. The model also works well in the out-of-sample validation tests and shows increased power over the RiskCalc 3.1 France model.

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