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MOODY’S KMV RISKCALC™ V3.1 SPAIN

MODELINGMETHODOLOGY

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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, regulatory, and accounting practices of its specific region.

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

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1 INTRODUCTION

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

- Moody's KMV RiskCalc v1.0 and the Moody's KMV Private Firm Model® (PFM)
- Moody's KMV Credit Research Database™ (CRD), the world's largest and cleanest private company default database
- Industry sector information, market information, and industry-specific default rates

RiskCalc v3.1 incorporates the structural and market-based comparables approach (used in PFM), and the localized financial statement-based approach (used in RiskCalc v1.0). This allows RiskCalc v3.1 to blend market-based (systematic) information with detailed firm-specific financial statement (idiosyncratic) information to enhance the model's predictive power.

1.1 RiskCalc Modes

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

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

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

The CCA mode is specific to the firm's sector and country and is updated monthly. The CCA mode also has the ability to stress-test Moody's KMV EDF™ (Expected Default Frequency) credit measures under different credit cycle scenarios—a proposed requirement under Basel Capital Accord (BIS II).

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

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

2 DATA DESCRIPTION

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

2.1 Definition of Default

RiskCalc provides assistance to institutions and investors for determining the risk of default, missed payments, or other credit events. Proposals for 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. Accordingly, in Spain, the events which we defined as defaults include missed payments, bankruptcy, liquidation, suspension of payments, unable to pay, and dissolvent of the company. At the calibration stage, the model outputs are adjusted to ensure a consistent interpretation throughout the world. Specifically, the model outputs are converted into a term structure of actual default probabilities (1- through 5-year EDF credit measures).

2.2 Data Exclusions

Excluded Companies

The goal of the RiskCalc model is to provide an EDF credit measure for private Spanish 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 Spanish 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—Companies with Real Total Assets less than €100,000 (in 2002 Euros), as well as, Real Net Sales less than €500,000 (in 2002 Euros) are not reflective of typical middle-market companies and are excluded from the database.
- Financial Institutions—The balance sheets of financial institutions (banks, insurance companies, and investment companies) exhibit higher leverage than the typical private firm. The regulation and capital requirements of these institutions make them dissimilar to the typical middle-market company. Therefore, they are excluded from the database.
- Real Estate Development Companies—The annual accounts of real estate development and investment companies provide only a partial description of the dynamics of these firms and, therefore, their likelihood to default. This is because their financial health often hinges on a particular development.[1]
- Public Sector and Non-profit Institutions—Government run companies' default risks are influenced by the states' or municipalities' unwillingness to allow them to fail. As a result, their financial results are not comparable to other private firms. Not-for-profit financial ratios are different from for-profit firms, particularly with regard to variables relating to net income.
- Start-up Companies—Our experience has shown that the financial statements for a company during its first two years are extremely volatile and are a poor reflection of the creditworthiness of the company. The special nature of start-ups is reflected in the fact that many financial institutions have separate credit departments for dealing with these companies.

Excluded Financial Statements

The financial statements of smaller companies can be less accurate and lower quality than those of larger companies. The financial statements in the CRD are cleaned to eliminate highly suspect financial statements. Plausibility checks of financial statements are conducted, such as Assets not equal to Liabilities plus Net Worth, and financial statements covering a period of less than twelve months. If errors are detected, those statements are excluded from the analysis.

2.3 Descriptive Statistics of the Data

Overview of the Data

The extensive data on both non-defaulting and defaulting companies contained in the CRD increased since RiskCalc v1.0 was developed. Figure 1 presents the distribution of Spanish financial statements and defaults by year in the development sample only. Table 1 summarizes the total data used in the development, validation, and calibration of the RiskCalc v3.1 Spain model.

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[1] The success of many types of project finance firms depends largely on the outcome of a particular project. We recommend using separate models for such firms. At the time of writing, this characteristic is explicitly recognized within the proposals for BIS II.

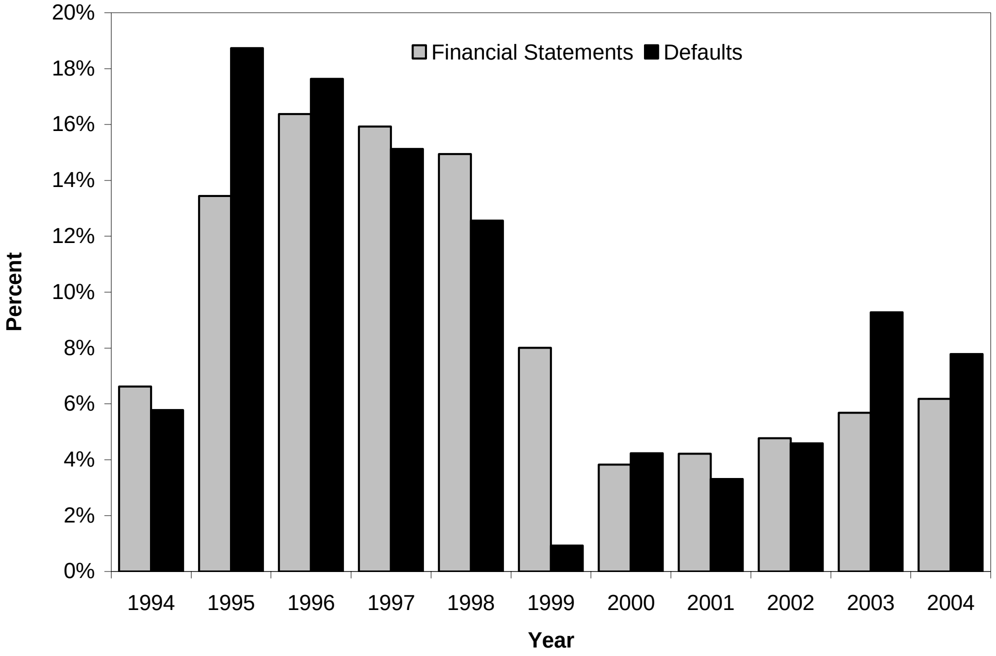

FIGURE 1 Distribution of Spanish Financial Statements and Defaults

TABLE 1 Information on Spanish Private Firm Sample Data

Spanish Private Firms	RiskCalc v1.0 Spain	RiskCalc v3.1 Spain	Change
Financial statements	569,181	1,500,000	↑ 164%
Unique number of firms	140,790	380,000	↑ 170%
Defaults	2,265	8,700	↑ 284%
Time period	1992–1999	1993–2006	+ 6 years

Robustness of the Data

In building a model, potential database weaknesses need to be examined. Not only does the database need to cover a large number of firms and defaults, but the defaults also need to be distributed among industries and company types covered. For example, if the database has significant numbers of small firms or firms in one particular industry and there are not sufficient defaults in those areas, the model may not be a good default predictor. The CRD used in developing the RiskCalc models addresses both of these issues.

Figure 2 presents the distributions of Spanish firms by industry and the proportion of defaults in each industry. Trade is the largest sector with about 30% of the sample. Figure 3 presents the distributions by the size of firms measured as Total Assets in 2002 Euros. These figures demonstrate how the proportion of defaults in any one industry group or size group is comparable to the proportion of firms in these groupings. The size distribution shows that about 50% of the firms hold assets less than 1 million Euros.

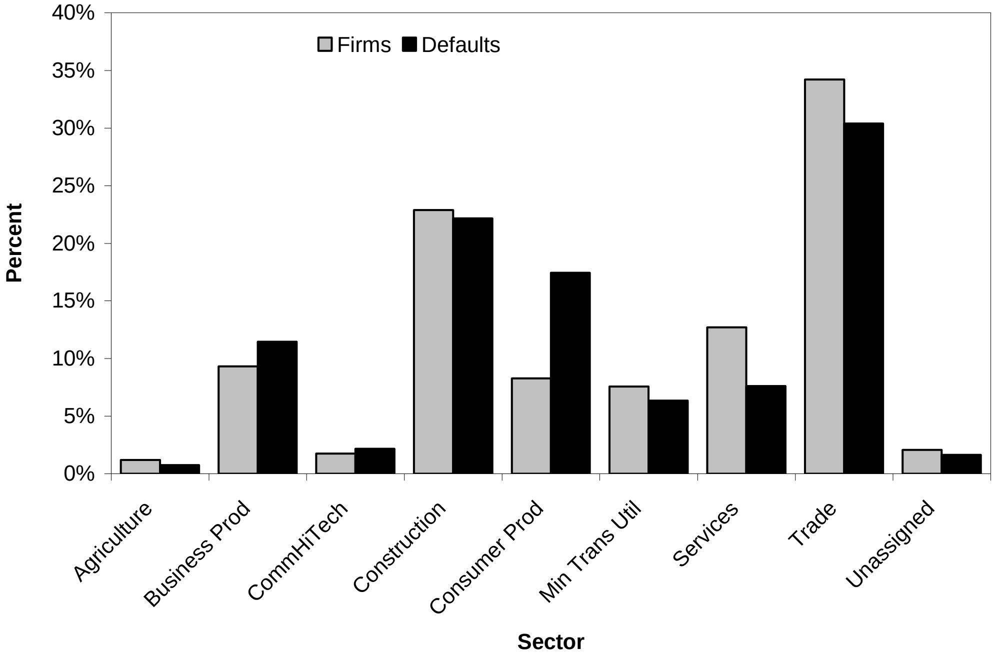

FIGURE 2 Distribution of Spanish Defaults and Firms by Industry

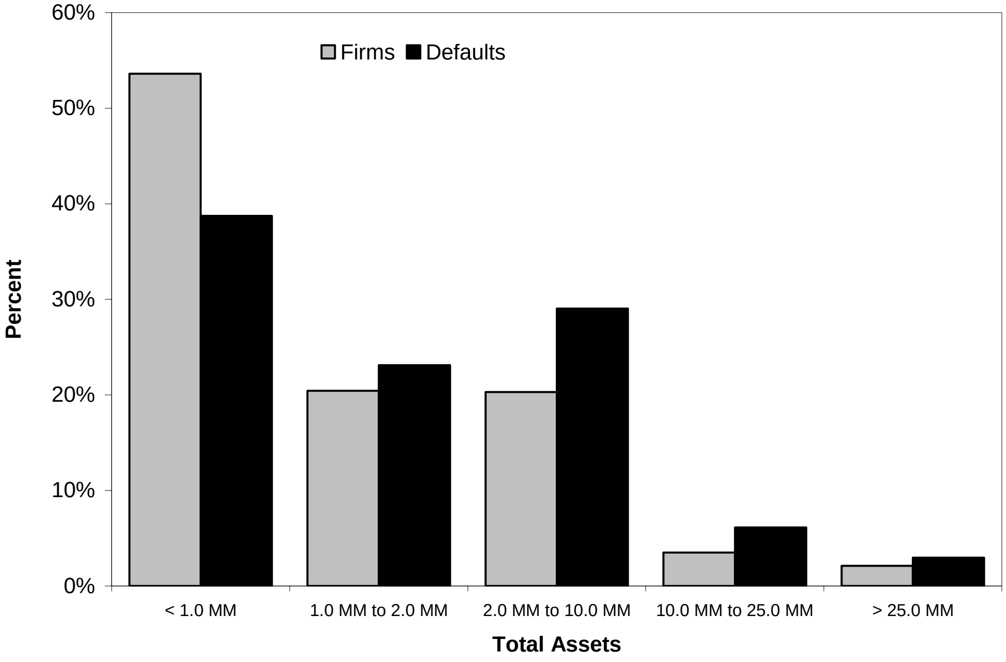

FIGURE 3 Distribution of Spanish Defaults and Firms by Size

2.4 Central Default Tendency

Because most companies do not default, companies that do default are relatively rare and thus more valuable in building a default prediction model. Much of the lack in default data comes from the data storage issues within financial institutions, such as defaulting companies being purged from the system after troubles begin, not all defaults being captured, or other sample errors. Also, if the date of default is uncertain, the financial statement associated with the firm may be excluded from model development, depending on the severity of the problem. This can result in a sample that has lower default rates than what occurs in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true central default tendency (CDT). When default definitions used in the data sample understate the defaulting population, the CDT can be used to realign the default rates.

The estimate of long-run aggregate probabilities of default (or CDT) is important as an anchor for a model. The best estimation of default probability is a ratio that reflects the number of obligors that defaulted in one year compared with the total obligors at the beginning of that year. Often these types of data are not available.

The estimate of the central default tendency for Spain is based on several sources.

- Loan loss provision data were examined from the Organization for Economic Co-operation and Development (OECD), as well as provisioning data from financial statements of large Spanish banks.
- Bankruptcy and insolvency data were examined from Spain government data sources.
- The CDT was confirmed to exceed the default rates observed in our development sample.

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

Calculating a 5-year Central Default Tendency

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

Central Default Tendency in FSO and CCA Modes

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

3 MODEL COMPONENTS

The RiskCalc v3.1 model incorporates various components to determine the EDF credit measure. The inputs to the model include a selection of the financial ratios, transforms of those ratios, the inclusion of industry information, and the credit cycle adjustment.

1. The development of a RiskCalc model involves the following steps.[2]
2. Choosing a limited number of financial statement variables for the model from a list of possible variables.
3. Transforming the variables into interim probabilities of default using non-parametric techniques.
4. Estimating the weightings of the financial statement variables using a probit model, combined with industry variables.

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

5. Creating a (non-parametric) final transform that converts the probit model score into an actual EDF credit measure.

In FSO mode, the models are based on the following functional form.

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

where $x_1,\ldots,x_N$ are the input ratios; $I_1,\ldots,I_K$ 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 $T_1,\ldots,T_N$ are non-parametric transforms; and *FSO EDF* is the financial-statement-only EDF credit measure.[3] 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 4 and discussed in detail later in the document.) *F* is the final transform (i.e., the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. 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 the final transform is adjusted to reflect our assessment of the current stage of the credit cycle, while in FSO mode it remains constant.

3.1 Financial Statement Variables

Selecting the Variables

Our variable selection process starts with a long list of possible financial statement variables. The working list of ratios is divided into groups that represent different underlying concepts regarding a firm's financial status (Table 3). A model is then built with at least one variable per group. When it is possible to increase model performance and maintain model robustness, several variables from each group will be used in the model. The following questions were asked when deciding which variables to include in the final model.

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

TABLE 2 Groupings of Financial Statement Ratios

Activity ratios include inventories to sales and accounts receivable to sales. These ratios may measure the extent to which a firm has a substantial portion of assets in accounts that may be of subjective value. For example, a firm with large inventories may not be selling its products and may have to write off these inventories. → A large stock of inventories relative to sales increases the probability of default; other activity ratios have different relationships to default.

Debt Coverage is the ratio of cash flow to interest payments or some other measure of liabilities. → High debt coverage reduces the probability of default.

Growth variables are typically the change in ROA and sales growth. These variables measure the stability of a firm's performance. → Growth variables behave like a double-edged sword: both rapid growth and rapid decline (negative growth) tend to increase a firm's default probability.

Leverage ratios include liabilities to assets and long-term debt to assets. → High leverage increases the probability of default.

Liquidity variables include pure cash or cash and marketable securities to assets, the current ratio, and the quick ratio. These variables measure the extent to which the firm has liquid assets relative to the size of its assets or liabilities. → High liquidity reduces the probability of default.

Profitability ratios include net income, net income less extraordinary items, profit before tax, and operating profit in the numerator; and total assets, tangible assets, fixed assets and sales in the denominator. → High profitability reduces the probability of default.

Size variables include sales and total assets. These variables are normally deflated to a specific base year to ensure comparability (e.g., total assets are measured in 2002 Euros). → Large firms default less often.

TABLE 3 Financial Statement Variables in RiskCalc v3.1 Spain

Category	Definition
Activity	Interest Expense to Sales
Debt Coverage	EBITDA to Interest Expense[4]
Growth	Change in AR Turnover: AR Turnover (*t*) – AR Turnover (*t*-1)[5] Sales Growth: Net Sales(t) / Net Sales(t-1) – 1
Leverage	Liabilities Less Cash & Securities to Assets
Liquidity	Current Ratio: Total Current Assets to Total Current Liabilities Cash & Securities to Current Assets
Profitability	Return On Assets

Variable Transforms

After the variables are selected, they are transformed into a preliminary EDF value. Figure 4 presents the transformations used in the model. The horizontal axis gives the percentile score of the ratio, and the vertical axis gives the default probability of that ratio in isolation (univariate). The percentile score represents the percent of the database that had a ratio below that of the company (e.g., if ROA is in the 90th percentile, then 90% of the sample had a lower ROA than that firm).

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[4] EBITDA is defined as the following: Operating Profit (or Loss) + Amortization and Depreciation.

[5] AR Turnover is defined as the following: Accounts Receivable / Net Sales.

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 **Activity** group, the transform for Interest Expense to Sales is upward sloping (Figure 4). The slope of the transform increases as activity increases. This indicates that firms with large Interest Expense relative to Sales have higher default probabilities.
- For the **Debt Coverage** group, the transform for EBITDA to Interest Expense is downward sloping (Figure 4). The slope of the transform decreases as debt coverage increases. This indicates that firms with large EBITDA relative to Interest Expense have lower default probabilities.
- For the **Growth** group, the ratios are Change In Accounts Receivable Turnover and Sales Growth (Figure 4). The transforms of these ratios are U-shaped, indicating that large increases or decreases in, for example, Sales are associated with higher default probabilities, while stable Sales year-upon-year decreases the probability of default.
- For the **Leverage** group, the transform for the Liabilities Less Cash & Securities to Assets is upward sloping (Figure 4). The slope of the transform increases as leverage increases. This indicates that firms with large Liabilities Less Cash relative to Assets have higher default probabilities.
- For the **Liquidity** group, the ratios are Current Ratio and Cash & Securities to Current Assets (Figure 4). The transforms of these ratios are downward sloping, indicating that firms with large, for example, cash holding are associated with lower default probabilities. The slope of each transform is similar across the percentile space; therefore, changes in either direction from the median imply an equal change in risk.
- For the **Profitability** group, the transform for Return On Assets is downward sloping (Figure 4). The slope of the transform decreases as profitability increases. This indicates that firms with large Return On Assets have lower default probabilities.

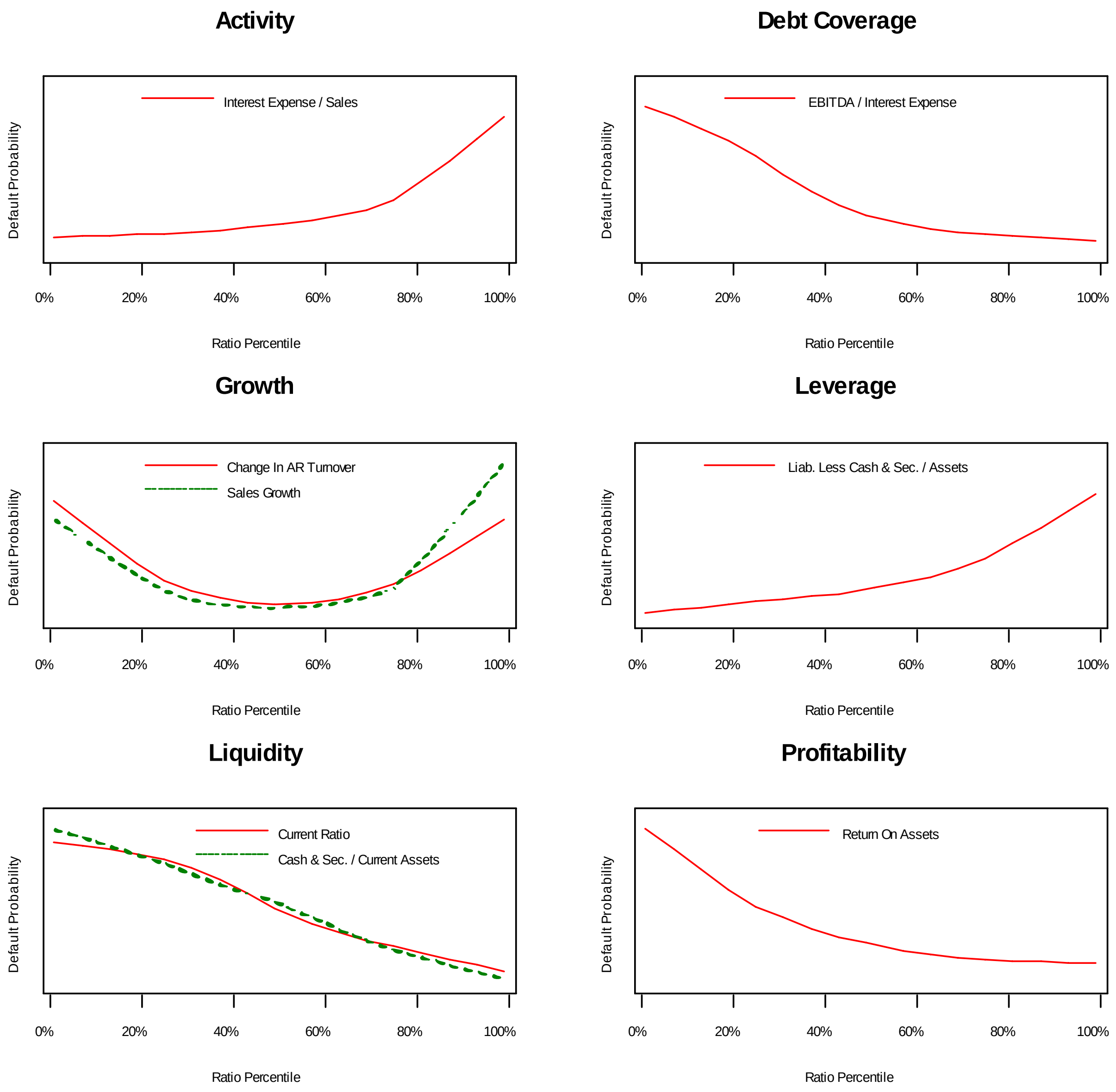

FIGURE 4 Transformations of Financial Statement Variables in RiskCalc v3.1 Spain

3.2 Model Weights

Importance

The relative value of each variable used in calculating an EDF credit measure is important in understanding a company's risk. The non-linear nature of the model makes the weight of the variables more difficult to determine, because the actual impact on the risk depends on the coefficient, the transformation shape, and the percentile ranking of the company. The model weights, therefore, are calculated based on the average EDF value for the transformation and its standard deviation. A variable with a flat transformation could have a low weight, even if the coefficient is large (Figure 4).

Calculation of Weights

To calculate the weighting of a variable, the EDF credit measure is computed for a theoretical firm with all its variables at the average transformation values. The variables are then increased one at a time by one standard deviation. The EDF change for each variable (in absolute value) is computed and added together. The relative weight of each variable is then calculated as the EDF level change for that variable as a percent of the sum of EDF level changes across all variables. This gives the variable with the largest impact on the EDF level the largest weight, and the variable with the smallest impact on the EDF level the smallest weight. Since the weights are a percentage of the total change in EDF levels, they sum to 100%. The weight of each category is the sum of the weights of each variable in that category. Table 4 presents the weights in RiskCalc v3.1 Spain. The most important category is Activity with a weight of 21%; however, the model weights are balanced among the categories.

TABLE 4 Risk Drivers in RiskCalc v3.1 Spain

Category	Weights
Activity	21%
Debt Coverage	18%
Growth	16%
Leverage	16%
Liquidity	12%
Profitability	16%

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 Spain, the EDF value is adjusted for industry effects. Table 5 presents the increase in model power and accuracy from introducing industry controls into the FSO model. Both the power and the accuracy of the EDF credit measure increase, as measured by the Accuracy Ratio (AR) and the gain in log likelihood. A large gain in likelihood indicates that the industry controls are especially important in producing an accurate EDF credit measure. Table 5 presents the average FSO EDF value by industry for the validation sample.

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

FSO Mode	1-year Model		5-year Model	
	Accuracy Ratio	p-value for the Increase in Log Likelihood	Accuracy Ratio	p-value for the Increase in Log Likelihood
Without Industry Controls	69.7%	---	59.2%	---
With Industry Controls	70.2%	0.0040	60.0%	<.0001

In this table, and hereafter, AR is the measure of the model's ability to rank order credits. Increases in log likelihood measure the extent to which the model's EDF values match observed default rates.[6] In Table 6, the values show the combined impact of the industry adjustment and the average levels of each ratio for a particular industry. The combination of the two determines the average FSO EDF credit measure for a company.

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

TABLE 6 Average FSO EDF Credit Measure by Sector

Sector	Average 1-year FSO EDF	Average 5-year FSO EDF
Agriculture	1.8%	7.1%
Business Products	1.3%	5.8%
Telecommunications and High Tech	2.3%	8.5%
Construction	2.1%	8.3%
Consumer Products	2.3%	8.4%
Mining, Transportation, Utilities and Natural Resources	3.5%	13.5%
Services	1.2%	5.4%
Trade	1.1%	4.5%

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 Spain includes a credit cycle adjustment (CCA) factor. The CCA is designed to incorporate the current credit cycle into the estimate of private firm default risk.

Selecting an Adjustment Factor

The RiskCalc v3.1 model uses the DD calculation from the Moody's KMV public firm model. This measure is specifically designed to be a forward-looking indicator of default risk. It extracts signals of default risk from the stock market performance of individual firms.[7] This measure was chosen because it is available for a large universe of industries and it has been extensively validated.

If the DD factor 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 for that industry, 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 Spanish model, the DD factor for each industry is a weighted average of two indices. The average is based on the aggregation of DD factors in each industry for all public firms in Spain together with Portugal, and public firms in a basket of fifteen continental European countries. The weight on the Spain and Portugal index is industry-specific and determined by the market value of assets of Spanish and Portuguese firms in each industry relative to all firms in the basket. In the event that a firm cannot be associated with a specific industry, the model uses a credit cycle adjustment based on an aggregation of all public firms in the associated countries.

The DD factor is meant to be a forward-looking indicator of default risk. One way to measure the markets current assessment of credit risk is to examine credit spreads on corporate bonds. When the market expects higher levels of default on public debt, the yield spread over a risk-free bond will increase to compensate for the extra risk. Figure 5 presents the evidence of the Spanish DD factor and yield spreads on Western European corporate bonds. The DD factor is inverted when graphed so that higher values on the graph indicate higher probabilities of default for Spanish public firms. One would expect a concurrent relationship between the series since both are forward-looking, which is what the figure shows.

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[7] cf. Bohn and Crosbie, 2003.

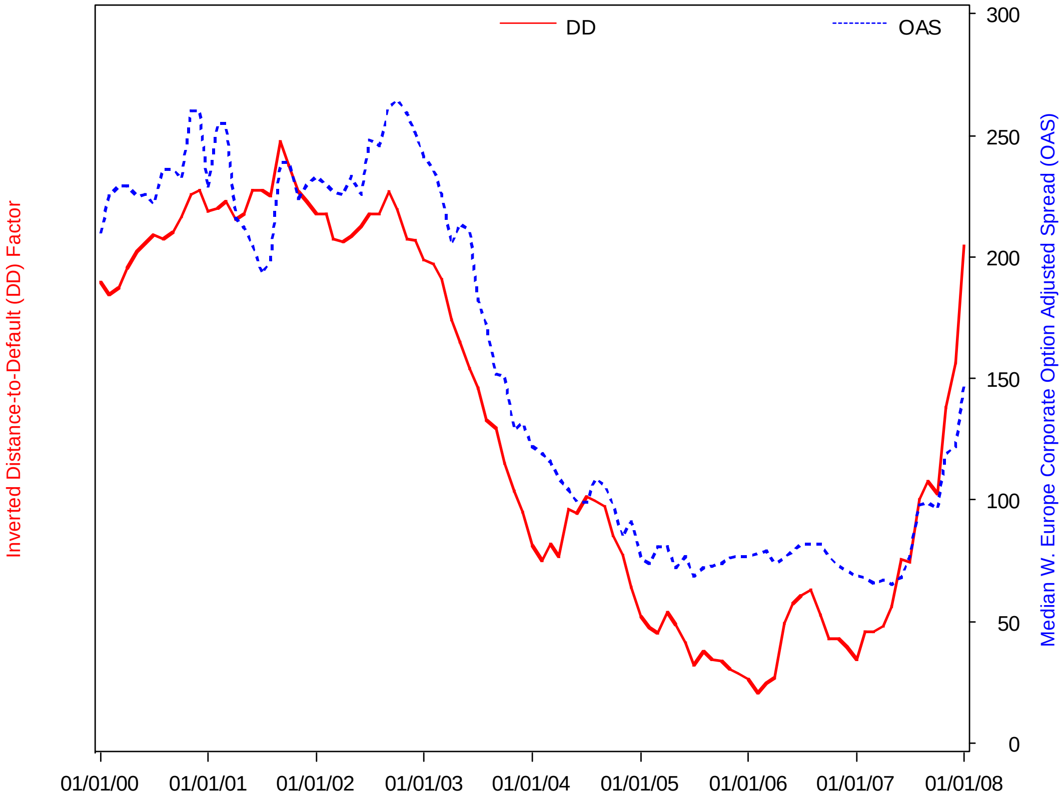

FIGURE 5 Spanish DD Factor and European Corporate Yield Spreads: 2000—2008

Figure 5 displays the Spanish DD factor (red solid line) against historical credit spread levels in Europe (blue dotted line). Bond prices and yields are from Reuters EJV, and the yield spread is over the benchmark LIBOR rate. The spread statistics are compiled using Moody's KMV CreditEdge® for the Western European Corporate Bond group.

4 VALIDATION RESULTS

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

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

In Spain, rank order validation was performed for this model in both CCA and FSO modes. As in other countries, data issues can complicate the interpretation of the differences in AR between these modes. Therefore, the focus is on determining whether the new model outperforms the old model and other benchmarks in both modes. Changes in the definition of default, legal environment, or simply the process of collecting defaults can skew the difference in AR between the two modes. We present the overall ARs for both the CCA and FSO models in this document. We also present the ARs for the FSO model relative to RiskCalc v1.0 and Z-score for the power tests across periods, sectors, and size classifications.

4.1 Increase in Overall Model Power and Accuracy

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

In FSO mode, the model's performance improves by 4.5% at the 1-year horizon, and 2.9% at the 5-year horizon compared to RiskCalc v1.0 Spain. In CCA mode, the model's performance improves by 2.6% at the 1-year horizon, and 2.7% at the 5-year horizon compared with RiskCalc v1.0 Spain.

Table 7 also contains p-values for the statistical test to display how the accuracy ratio from the RiskCalc v3.1 FSO model and the benchmark is less than or equal to zero. A p-value of less than .05 indicates we can reject the hypothesis that the difference in the accuracy ratios is less than or equal to zero with 95% confidence.[8]

Relative to other available alternatives, the results were more dramatic. The new RiskCalc v3.1 model, in FSO mode, outperformed the Z-score model (Altman, Hartzell and Peck, 1995) by 24.2% at the 1-year horizon and 26.2% at the 5-year horizon. In CCA mode, the new RiskCalc v3.1 model outperformed the Z-score model by 22.3% at the 1-year horizon and 26.0% at the 5-year horizon.

TABLE 7 Power Enhancements of the RiskCalc v3.1 Spain Model—Validation Sample

FSO Mode	**1-year Model**		**5-year Model**	
	Accuracy Ratio	**p-value**	**Accuracy Ratio**	**p-value**
RiskCalc v3.1 CCA	66.2%	---	58.7%	---
RiskCalc v3.1 FSO	68.1%	---	58.9%	---
RiskCalc v1.0	63.6%	<.0001	56.0%	<.0001
Z-score	43.9%	<.0001	32.7%	<.0001

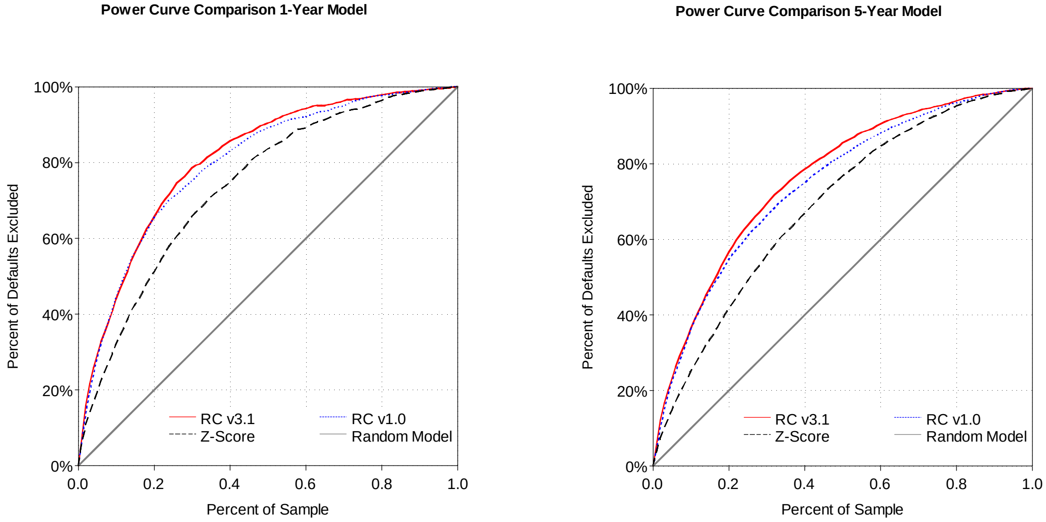

FIGURE 6 Power of Alternative Models (1- and 5-year)—Spain Validation Sample

Figure 6 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 7. The power improvements are uniformly significant across different regions of the distribution relative to RiskCalc v1.0.

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[8] See Hood (2007) for more details on the computation of the p-value.

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 (VIF) (Table 9) are computed on the transformed variables (Figure 4).[9]

Model Results

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

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

	Interest Expense to Sales	EBITDA to Interest Expense	Change in AR Turnover	Sales Growth	Liabilities Less Cash & Securities to Assets	Current Ratio	Cash & Securities to Current Assets	Return on Assets
Interest Expense to Sales	1.00							
EBITDA to Interest Expense	0.42	1.00						
Change in AR Turnover	0.16	0.08	1.00					
Sales Growth	0.05	0.10	0.35	1.00				
Liabilities Less Cash & Securities to Assets	0.28	0.43	0.12	0.16	1.00			
Current Ratio	0.19	0.24	0.04	0.11	0.59	1.00		
Cash & Securities to Current Assets	0.24	0.27	0.09	0.03	0.53	0.20	1.00	
Return on Assets	0.23	0.70	0.08	0.10	0.42	0.27	0.24	1.00

The VIF levels in Table 9 for the financial statement variables represent how much of the variation in one independent variable can be explained by all the other independent variables in the model. The correlation coefficient, however, measures only the relationships between two variables. The VIF levels are all below 3, indicating that the collinearity between the variables is low.[10] The two ratios with the highest correlation are EBITDA to Interest Expense and Return on Assets in Table 8.

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[9] For further definitions and technical discussion of the testing procedures in "Validation Results" on page16, refer to the Technical Document.

[10] As Woolridge (2000) shows, VIF is inversely related to the tolerance value (1-R2), such that a VIF of 10 corresponds to a tolerance value of 0.10. Clearly, any threshold is somewhat arbitrary and depends on the sample size. Nevertheless, if any of the R2 values are greater than 0.75 (so that VIF is greater than 4.0), we would typically suspect that multicollinearity could be a problem. If any of the R2 values are greater than 0.90 (so that VIF is greater than 10) we then conclude that multicollinearity is likely to be a serious problem.

TABLE 9 Variance Inflation Factors

Variable	VIF
Interest Expense to Sales	1.35
EBITDA to Interest Expense	2.34
Change in AR Turnover	1.21
Sales Growth	1.18
Liabilities Less Cash to Assets	2.39
Current Ratio	1.59
Cash & Securities to Current Assets	1.48
Return on Assets	2.06

4.3 Power Performance 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 Spain outperforms both RiskCalc v1.0 Spain and Z-score in all sectors. The highest power in the 1-year horizon (Table 10) is found in Business Products (69.9%), while the lowest is found in Telecommunications & High Tech (59.0%). At the 5-year horizon (Table 11), the highest power is in Construction (59.7%), and the lowest is in Services (49.0%).

TABLE 10 Power by Industry 1-year Spain Model—Validation Sample

	Percentage of Defaults	AR v3.1	AR v1.0	V3.1–v1.0 p-value	AR Z-score
Business Products	12%	69.9%	67.9%	.0915	50.4%
Telecommunications & High Tech	2%	59.0%	52.3%	.1050	44.6%
Construction	22%	68.9%	63.6%	<.0001	50.0%
Consumer Products	18%	68.7%	62.8%	<.0001	43.1%
Mining, Transportation, Utilities & Natural Resources	6%	63.2%	58.1%	.0012	43.3%
Services	8%	63.1%	58.1%	<.0001	49.7%
Trade	31%	66.6%	63.2%	<.0001	38.0%

TABLE 11 Power by Industry 5-year Spain Model—Validation Sample

	Percentage of Defaults	AR v3.1	AR v1.0	V3.1–v1.0 p-value	AR Z-score
Business Products	12%	59.5%	59.4%	.8600	33.5%
Telecommunications & High Tech	2%	55.9%	51.5%	.0997	33.3%
Construction	23%	59.7%	57.9%	.0060	39.1%
Consumer Products	18%	55.6%	51.4%	<.0001	30.2%
Mining, Transportation, Utilities & Natural Resources	7%	55.1%	52.6%	.0400	30.7%
Services	8%	49.0%	49.3%	.1425	37.1%
Trade	31%	58.7%	56.1%	<.0001	31.0%

Table 12 and Table 13 present the power comparisons by firm size (Total Assets in 2002 Euros) for the 1-year and 5-year models, respectively. RiskCalc v3.1 Spain outperforms both RiskCalc v1.0 Spain and Z-score in all size groups.

The highest powers in the 1-year and 5-year are both found in the 5 mm to 10 mm range, while the lowest powers in the 1-year and 5-year are both found in the above 25 mm range.

TABLE 12 Power by Size (Total Assets in 2002 Euros) 1-year Spain Model—Validation Sample

Range	Percentage of Defaults	AR v3.1	AR v1.0	V3.1–v1.0 p-value	AR Z-score
< € 1 MM	40%	66.4%	62.3%	<.0001	41.0%
€ 1 MM to 5 MM	42%	68.5%	63.9%	<.0001	42.5%
€ 5 MM to 10 MM	10%	68.6%	60.5%	<.0001	52.9%
€ 10 MM to 25 MM	6%	62.4%	57.1%	<.0001	50.7%
> € 25 MM	2%	46.2%	44.3%	.1071	34.1%

TABLE 13 Power by Size (Total Assets in 2002 Euros) 5-year Spain Model—Validation Sample

Range	Percentage of Defaults	AR v3.1	AR v1.0	V3.1–v1.0 p-value	AR Z-score
< € 1 MM	41%	57.8%	54.6%	<.0001	30.82%
€ 1 MM to 5 MM	41%	60.4%	57.5%	<.0001	34.27%
€ 5 MM to 10 MM	10%	63.9%	58.2%	<.0001	45.12%
€ 10 MM to 25 MM	6%	57.2%	53.5%	.0010	41.96%
> € 25 MM	2%	47.7%	46.1%	.0469	34.52%

4.4 Power Performance over Time

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

Table 14 and Table 15 present the results from this analysis at the 1- and 5-year horizons, respectively. The AR of RiskCalc v3.1 Spain is compared with RiskCalc v1.0 Spain and Z-Score for each year. RiskCalc v3.1 Spain outperforms both RiskCalc v1.0 Spain and Z-Score in all years.

TABLE 14 Power over Time: 1-year Horizon, Spain Model—Validation Sample

Year	Percentage of Defaults	AR v3.1	AR v1.0	V3.1–v1.0 p-value	AR Z-score
1994	5%	63.8%	61.9%	.2020	43.9%
1995	16%	68.0%	67.4%	.4457	42.7%
1996	17%	67.6%	65.7%	.0160	43.1%
1997	19%	64.9%	63.5%	.0798	38.6%
1998	12%	68.9%	66.5%	.0190	41.5%
1999	1%	66.1%	61.7%	.3792	18.6%
2000	3%	50.3%	48.7%	.0041	44.9%
2001	4%	60.2%	54.1%	<.0001	48.3%
2002	8%	60.0%	50.7%	<.0001	41.4%
2003	10%	64.1%	53.9%	<.0001	45.6%
2004	5%	59.9%	46.7%	<.0001	42.1%

TABLE 15 Power over Time: 5-year Horizon, Spain Model—Validation Sample

Year	Percentage of Defaults	AR v3.1	AR v1.0	V3.1–v1.0 p-value	AR Z-score
1994	11%	54.6%	52.3%	.0098	30.4%
1995	22%	60.6%	59.3%	.0161	36.7%
1996	18%	62.5%	59.4%	<.0001	38.7%
1997	12%	64.7%	62.8%	.0128	38.7%
1998	7%	69.2%	66.4%	.0062	41.5%
1999	<1%	65.7%	61.6%	.0185	29.0%
2000	8%	39.2%	34.2%	<.0001	28.7%
2001	7%	51.3%	44.3%	<.0001	35.3%
2002	6%	56.9%	49.1%	<.0001	36.1%
2003	6%	61.9%	53.1%	<.0001	44.4%
2004	3%	58.7%	46.7%	<.0001	42.1%

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

The model exhibits a high degree of power in distinguishing good credits from bad ones (Table 7), but whether this power is attributable to the overall model effectiveness or the impact of a particular sub-sample also needs to be tested. A standard test for evaluating this is the *k*-Fold test, which divides the defaulting and non-defaulting companies into *k* equally-sized segments. This yields *k* equally-sized observed 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. This procedure is repeated for all possible combinations, and the *k* scored out-of-sample sub-samples are put together to calculate an accuracy ratio on this combined data set.

Table 16 summarizes the *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 v1.0 Spain. Figure 7 presents the cumulative accuracy profiles associated with the overall out-of-sample results against the in-sample results. The model performance is maintained both in- and out-of-sample in the *k*-Fold analysis.

TABLE 16 RiskCalc v3.1 Spain *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	64.8%	60.1%	59.5%	55.6%
Subsample 2	64.3%	60.2%	60.5%	56.2%
Subsample 3	67.5%	62.4%	64.5%	59.1%
Subsample 4	64.8%	59.9%	60.6%	56.8%
Subsample 5	62.0%	58.1%	59.0%	54.6%
k-fold Overall	67.4%	59.7%	---	---
In-Sample AR	67.6%	59.9%	63.2%	55.7%

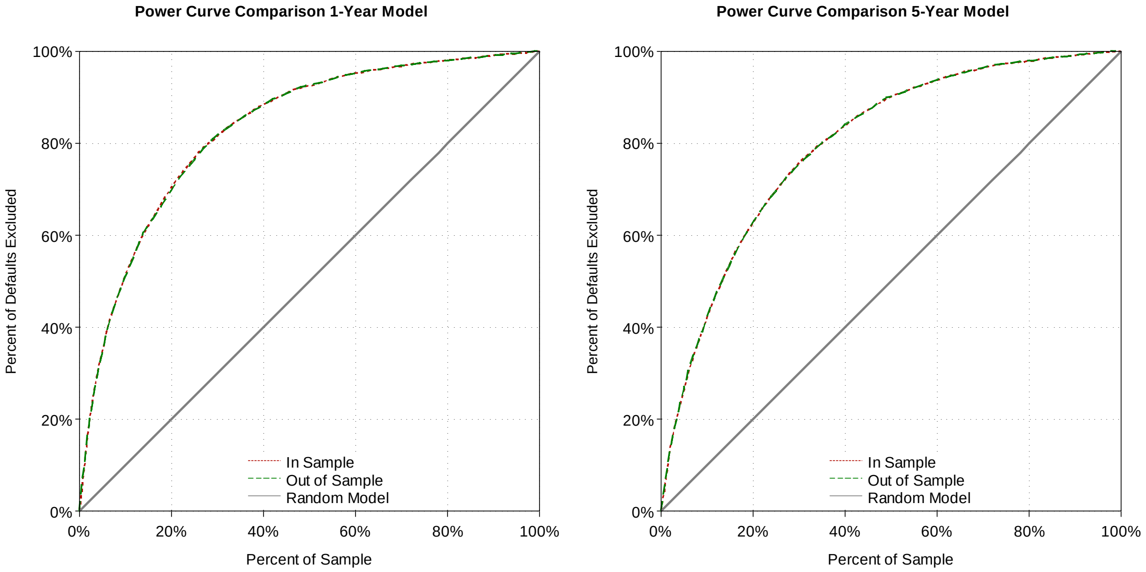

FIGURE 7 Out-of-sample Performance (1- and 5-year) Spain *k*-Fold

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 how the model would have performed during those volatile periods because the model is estimated with full information on those time periods.

Results

The in- and out-of-sample plots are virtually indistinguishable at both the 1- and 5-year horizons in Figure 7. The difference in AR between the overall in-sample and out-of-sample results is not larger than 20 basis points in both cases. Furthermore, RiskCalc v3.1 Spain outperforms RiskCalc v1.0 Spain in an out-of-sample context at both the 1- and 5-year horizons (Table 16).

4.6 Walk-forward Tests

An alternative out-of-sample test developed by Moody's KMV is a walk-forward test, 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. 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. 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 data from only future periods is used for testing it. The parameter estimates are checked for stability across the different samples. In Spain, given the structure of the data, it is not possible to conduct a meaningful 5-year walk forward test. The data structure is such that our development sample is composed of multiple data sources with different time-series lengths. Figure 8 presents the results from this analysis.

Similar to the *k*-Fold results, the in- and out-of-sample plots for the walk-forward results are close in power at 1-year horizon in Figure 8. The difference in ARs between the in-sample and out-of-sample results is 0.7%.[11]

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[11] The out-of-sample AR is 66.2% for the 1-year model. The out-of-sample AR is 6.1% higher than RiskCalc v1.0 Spain for the 1-year model.

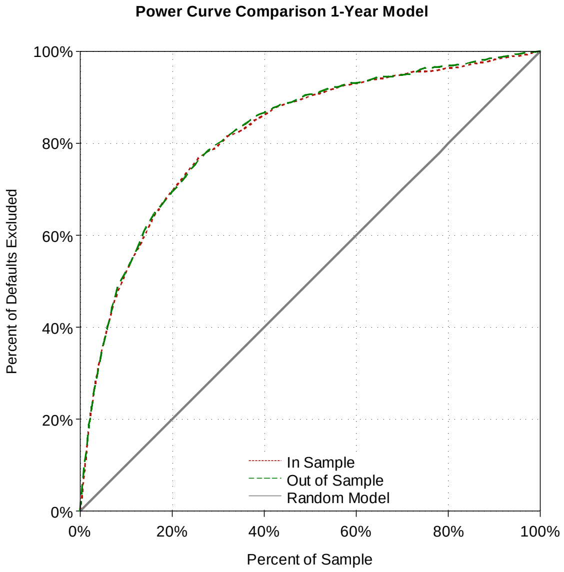

FIGURE 8 Out-of-sample Performance (1-year) Spain Walk-forward

4.7 Model Calibration and Implied Ratings

To aid in the interpretation of an EDF credit measure, an EDF value is mapped to an EDF-implied rating. All RiskCalc v3.1 models to date have used the same mapping. This mapping is designed with the following considerations:

- There is a large range of EDF-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 5-year ratings is approximately the same as the distribution of 1-year ratings (for consistency with rating-based analysis applications).
- The EDF value associated with an EDF rating is approximately the same as the observed historical default rate associated with a Moody's bond rating (for consistency with rating-based analysis applications).

Figure 9 shows the distribution of CRD observations by rating category in the development sample (for the CCA EDF credit measures over the full time period). Note that 14 categories between Aa3 and Caa/C are utilized and that less than 20% of the observations are in any one category. The distributions peak at Ba1 for the 1-year rating and Baa3 for the 5-year rating. While not reported here, other research has shown that the distribution of the CCA EDF-implied ratings changes over time with the credit cycle, while the distribution of the FSO EDF implied ratings remains relatively stable over time.

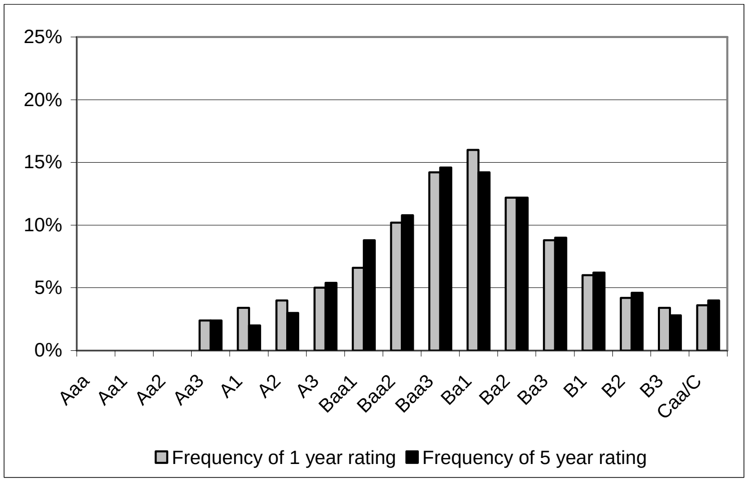

FIGURE 9 EDF-implied Ratings for the 1- and 5-year Models in the Development

5 FURTHER MODEL IMPROVEMENTS

This section outlines some other improvements to the model.[12]

5.1 Continuous Term Structure

The previous version of the RiskCalc model provided two discrete default probability estimates: a 1-year and a 5-year EDF credit measure. In this version, utilizing the two-point estimates for 1- and 5-year estimates fits a Weibull function, and thus achieves a continuous term structure of EDF values for each credit. In other words, users of RiskCalc v3.1 Spain can now obtain EDF values for any point between one and five years. In addition, RiskCalc v3.1 provides EDF values for alternative definitions, such as the forward EDF and the annualized EDF (Table 17).

Cumulative EDF Credit Measures

A cumulative EDF credit measure gives 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 over that five year period. The second column of Table 17 provides an example of the cumulative 1- to 5-year credit measures produced by the model.

Forward EDF Credit Measures

The forward EDF credit measure is the probability of default between t-1 and t conditional upon survival until t-1. In other words, the 4-year forward EDF measure is the probability that a firm will default between years three and four assuming the firm survived to year three.[13] The third column of Table 17 displays the forward 1- to 5-year EDF credit measures that are derived from the cumulative EDF values.

Annualized EDF Credit Measures

The annualized EDF credit measure is the cumulative EDF value for a given period, stated on a per-year basis. For example, a company with a cumulative 5-year EDF value of 13.44% would have a 5-year annualized EDF value of

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

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

2.84%.[14] This means that the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column of Table 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	2.90	3.57
Year 3	9.37	2.55	3.23
Year 4	11.49	2.34	3.01
Year 5	13.44	2.20	2.84

5.2 New Analytical Tools: Relative Sensitivity

The RiskCalc v1.0 application provides 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 of the model variables at the point of evaluation. This feature is especially useful when addressing the topic of identifying variables to improve the EDF value of a company.

The relative sensitivity gives the impact of a small change in a variable on the EDF level of the company. It indicates which variables are most sensitive to an increase. A positive number means an increase in the variable will increase risk, and a negative number will decrease risk. The percentile is the sensitivity of the variable relative to the average.

For example, a small increase in Liabilities - Cash & Securities / Assets ratio will change the risk of the company. It is about 150% (5-year) as sensitive as the average variables (Figure 10).

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

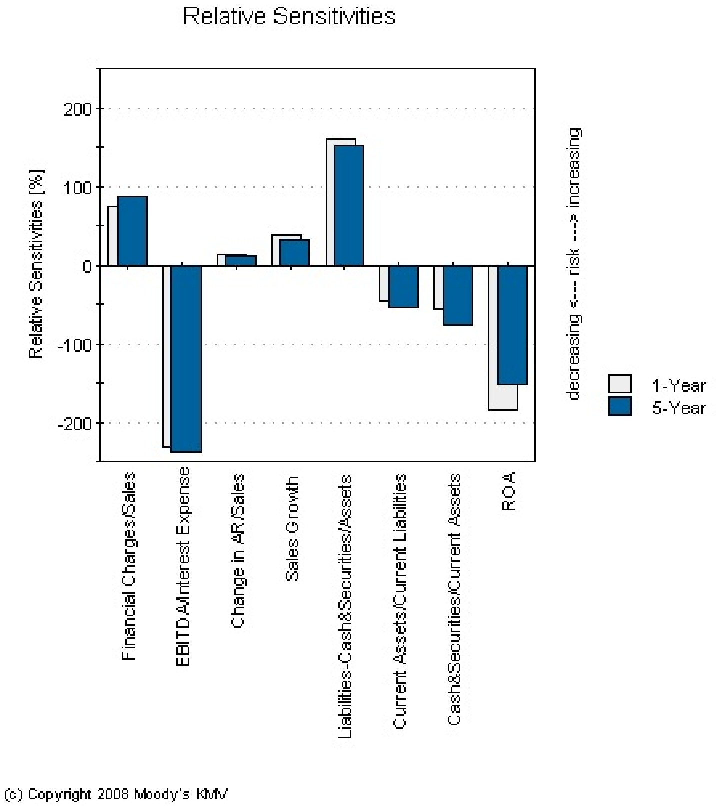

FIGURE 10 Relative Sensitivities for the RiskCalc v3.1 Spain Model

5.3 Asset Value and Volatility Calculation

One of the features of the RiskCalc v3.1 model is that it provides an implied asset volatility. Clients of Credit Monitor® and CreditEdge can use this volatility to analyze a private firm that is to go public through an IPO. After the firm is public, the public firm model should be used. However, this model requires an asset volatility derived from the public share price. In the RiskCalc v3.1 model, the asset volatility of the firm is estimated using its industry and size, as well as, a methodology that is similar to the Private Firm Model. A structural model framework is then used to solve for the implied asset value from the estimated EDF credit measure, the estimated volatility, and the firm's liability structure.

6 CONCLUSION

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

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

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

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

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