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MOODY'S KMV™ RISKCALC™ V3.1 UNITED STATES

MODELING**METHODOLOGY**

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ABSTRACT

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

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

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

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1 INTRODUCTION

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

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

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

RiskCalc Modes

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

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

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

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

RiskCalc v3.1 U.S. versus RiskCalc v1.0 North America

Since the release of RiskCalc v1.0 North America, Moody's KMV has significantly increased the size of the North America database and substantially improved its data cleansing technologies. As a result of these improvements, MKMV has been able to separate the North American model into a U.S. model and a Canadian model. The new model includes additional financial statement variables as well industry adjustments. Moreover, the EDF output can be adjusted for the credit cycle. We have also made substantial advances in our model development and testing techniques. As a result, the new model is more powerful and precise than its predecessor. Finally, the new model includes additional analytic tools that increase model usability and transparency.

2 DATA DESCRIPTION

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

2.1 Definition of Default

Moody's KMV RiskCalc™ provides assistance to institutions and investors in determining the risk of default, missed payment, or other credit events. The proposals for the new Basel Capital Accord (BIS II) have stimulated debates about what constitutes an appropriate definition of default. RiskCalc applies the criteria used by most of the advanced economies in the world.

Default is defined as any of the following events:

- 90 days past due
- Bankruptcy
- Placement on internal non-accrual list
- Write-down

2.2 Data Exclusions

Excluded Companies

The goal of the RiskCalc model is to provide an Expected Default Frequency™ (EDF) for private U.S. 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 U.S. middle-market companies, companies that did not reflect the typical company in this market were eliminated. The following types of companies are not included in the data:

- **Small companies** – For companies with assets of less than $100,000 (2001 U.S. dollars), future success is often linked to the finances of the key individuals. For this reason, they are not reflective of typical middle-market companies and are excluded from the database.
- **Financial institutions** – The balance sheets of financial institutions (banks, insurance companies, and investment companies) exhibit higher leverage than the typical private firm. The regulation and capital requirements of these institutions make them dissimilar to the typical middle-market company. Therefore, they are excluded from the database.
- **Real estate development companies** –The annual accounts of real estate development and investment companies provide only a partial description of the dynamics of these firms and, therefore, their likelihood of default. This is because their financial health often hinges on a particular development.[1]
- **Public sector and non-profit institutions** – Government run companies' default risk are influenced by the states' or municipalities' unwillingness to allow them to fail. As a result their financial results are not comparable to other private firms. Not-for-profit financial ratios are very different from for-profit firms, particularly with regard to variables relating to net income.

[1] There are many types of "project finance" firms whose success depends largely on the outcome of a particular project. We would recommend use of separate models for such firms. At the time of writing, this characteristic is explicitly recognized within the proposals for the new Basel capital accord.

Excluded Financial Statements

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

2.3 Descriptive Statistics of the Data

Overview of the Data

The extensive data on both non-defaulting and defaulting companies contained in Moody's CRD has increased substantially since RiskCalc v1.0. In addition to the increase in time-series data, there has been an increase in the number of participants in the CRD.

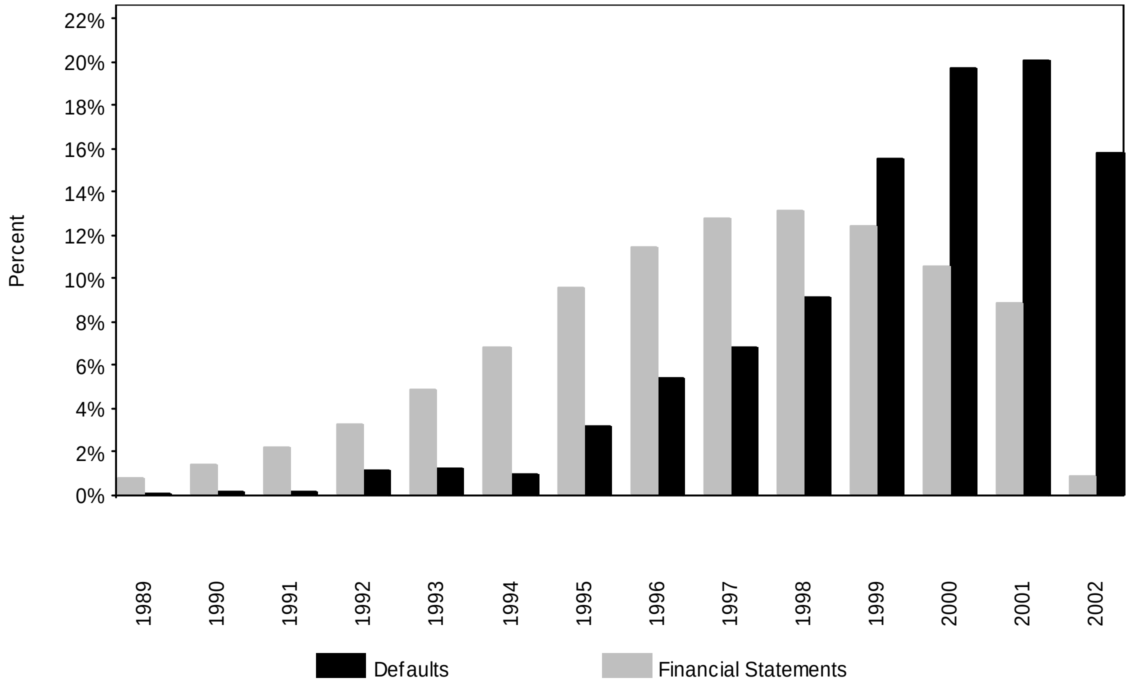
Figure 1 presents the distribution of financial statements and defaults by year. The years 2000, 2001, and 2002 represent a period of intense default activity adding to the credit cycle information of the 1.0 model.

Table 1 summarizes the data used in the development, validation, and calibration of the RiskCalc v3.1 U.S. model. The number of financial statements, firms, and defaults is considerably larger even though the original model was based on both U.S. and Canadian firms. This sample does not include the data that was used for the post-production testing described in Section 4.7.

TABLE 1 Information on Private Firm Sample Data

U.S. and Canadian Private Firms	RiskCalc v1.0 North America	RiskCalc v3.1 U.S.	RiskCalc v3.1 Canada	Credit Research Database Growth
Financial statements	115,000+	183,000+	44,000+	↑95%
Unique number of firms	24,000+	40,000+	11,000+	↑112%
Defaults	1,621	3,157	607	↑132%
Time period	1989-1999	1989-2002	1989-2002	↑ 3 additional years

FIGURE 1 Date Distribution of Financial Statements and Default Data



Robustness of the Data

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

Figure 2 and Figure 3 present the distributions of defaults and firms by industry and size classification, respectively, as well as the proportion of defaults in one industry or size group. The largest industry groups are trade and services. Firm size as measured by assets range from $100,000 to $500,000 to over $50 million in assets. Figure 2 and Figure 3 show that the proportion of defaults in one size group or industry is comparable to the number of firms in these groupings.

FIGURE 2 Distribution of Defaults and Firms by Industry

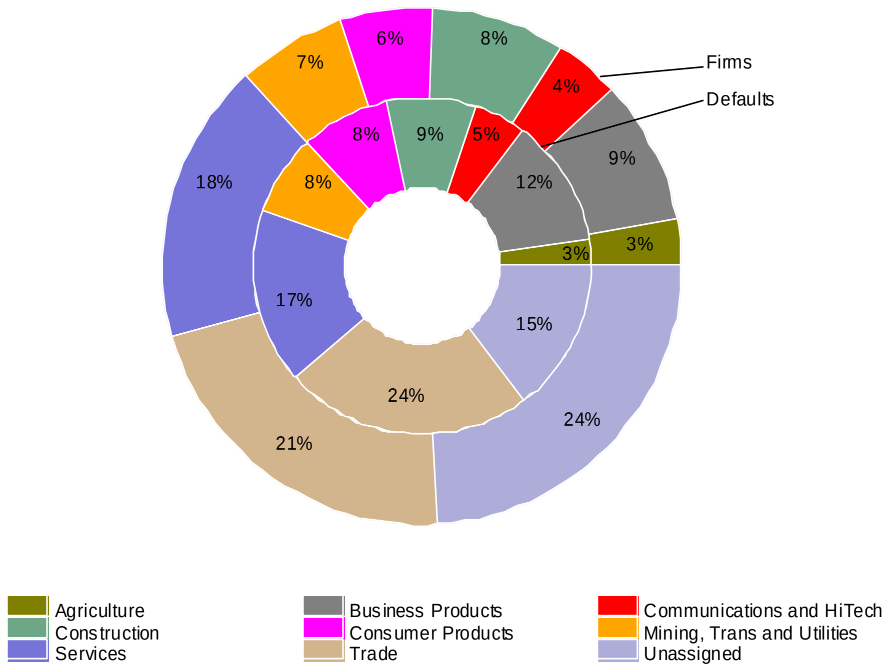
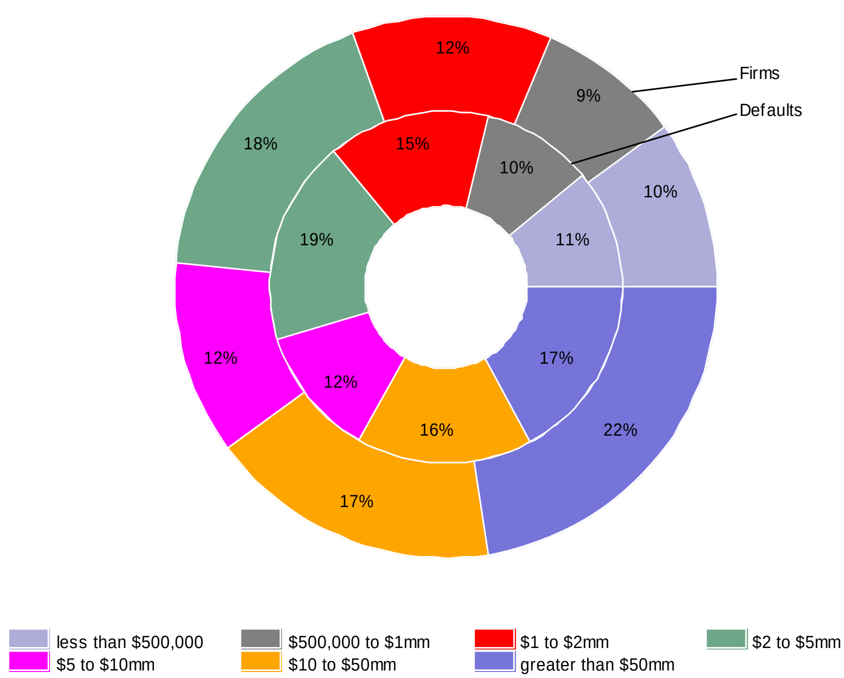


FIGURE 3 Size Distribution of Defaults and Firms



2.4 Cleaning the Data

In the development of a RiskCalc model, the first step is the collection of a large and appropriate database. In addition, data needs to be "cleaned" so that it is representative of the actual risk of the firms covered. MKMV has developed techniques for cleaning the database to improve the model results.

2.5 Central Default Tendency

Since most companies do not default, defaulting companies are relatively rare and thus more valuable in building default prediction models. Much of the lack in default data is due to the data storage issues within financial institutions, such as defaulting companies being purged from the system after troubles begin, not all defaults being captured, or other sample errors. Also, if the date of default is uncertain[2] the financial statement associated with the firm may be excluded from model development, depending on the severity of the problem. These issues can result in a sample that has lower defaults rates than occur in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true central default tendency.[3]

In order to calculate the overall population default rate, the RiskCalc model uses a triangulation approach that integrates information from both private and public records. The central default tendency 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 a variety of sources, a more accurate central tendency estimate is achieved than that inferred directly from the development sample.

Reliable Third-Party Data Sources

In order to determine the central tendency used in RiskCalc, we first examine reliable data sources representative of the underlying population and in which the default information is relatively complete. From these sources an average default rate is computed. In developing RiskCalc v1.0 NA, we had consulted a variety of sources and derived 1.7% as the central default tendency (Falkenstein, 2000).

Bank Charge-offs and Provisions

An alternative approach one can implement to infer a central tendency is from provisioning or write-off data from banks. Banks make provisions for bad loans that are estimates of their expected write-offs. From the volume of losses and the volume of loans, an average default rate can be inferred given the loss given default (LGD):

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

therefore

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

[2] This results from imperfections in the loan accounting systems of financial institutions. For example, following a merger of two institutions, the loan accounting systems may be integrated and the date of defaults may be lost in the integration.

[3] A famous example of a sampling issue leading to an incorrect forecast was in 1948 when the Chicago Daily Tribune printed papers that read "Dewey Defeats Truman" the day after the election. The forecast was based on telephone surveys that created a biased sample because it turned out that at the time of the survey, telephones were relatively rare and having a telephone was systematically related to household income, which, in turn, was systematically related to supporting Dewey.

The foundation approach to capital allocation as described in Basel II uses a loss given default rate of 50%, so this assumption can be used to calculate the implied default rates. We applied this technique to U.S. commercial banks as reported by the OECD (2002). For these institutions the average implied probability of default hovered around 1.7%. We also applied this technique to charge-off rates for Commercial and Industrial Loans 1990-2003 as reported by the Federal Reserve Board. Using a loss given default of 50%, the implied probability of default ranges from less than 1% during the trough of the credit cycle to over 4% at the peak of the credit cycle. The average over this time period turns out to be 1.7% thus confirming the selected central default tendency for RiskCalc v1.0.

Calculating a 5-year Central Default Tendency

There is a lack of publicly available data for direct calculation of the central tendency rate of a cumulative 5-year default probability. Based on extensive MKMV research, a 5-year cumulative default tendency is derived from the 1-year estimate. This research, combined with the information provided by the CRD, shows that the 5-year cumulative default rate is, on average, 4 times the level of the 1-year default rate. Therefore, 6.8% is used as the central default tendency for the 5-year model.

Central Default Tendency in FSO and CCA Modes

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

3 MODEL COMPONENTS

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

The development of a RiskCalc model involves the following steps:

1. Choosing a limited number of financial statement variables for the model from a list of possible variables.[4]
2. Transforming the variables into interim probabilities of default using non-parametric techniques.
3. Estimating the weightings of the financial statement variables, using a probit model, combined with industry variables.
4. Creating a (non-parametric) final transform that converts the probit model score into an actual EDF credit measure.

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

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

where $x_1,\ldots,x_N$ are the input ratios; $I_1,\ldots,I_K$ are indicator variables for each of the industry classifications; β and γ are estimated coefficients; Φ is the cumulative normal distribution; F and $T_1,\ldots,T_N$ are non-parametric

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

transforms; and FSO EDF is the financial-statement-only EDF credit measure.[5] 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. We describe the final transform as calibrating the model score to an actual EDF credit measure. The difference between the FSO EDF and the credit cycle adjusted EDF is that in CCA mode the final transform is adjusted to reflect our assessment of the current stage of the credit cycle, while in FSO mode it remains constant.

3.1 Financial Statement Variables

Selecting the Variables

Our variable selection process starts with a long list of possible financial statement variables. The working list of ratios is divided into groups that represent different underlying concepts regarding a firm's financial status (see Table 2). A model is then built with at least one variable per group. When it is possible to increase model performance while maintaining model robustness, several variables from each group will be used in the model. Criteria that must be met for variables to be included in the final model are:

- Is the variable readily available?
- Are the definitions of the inputs to the variable unambiguous?
- Is the meaning of the variable intuitive?
- Does the variable predict default activity?
- Is the variable generally uncorrelated with other variables in the model?

RiskCalc v1.0 versus RiskCalc v3.1 Variables

Since RiskCalc v1.0 NA was completed, MKMV has been able to collect more data and better (cleaner) data in the CRD. The impact of this is that the variables originally used in v1.0 can be improved. This is because more data and cleaner data provide a clearer picture of the predictive power of alternative ratios. Table 3 presents the variables used in RiskCalc U.S. v3.1. They differ from the variables chosen for RiskCalc NA v1.0 in several important ways. The following are some of the major changes:

- Operating cash flow is used in the numerator of the debt coverage ratio instead of EBIT.[6] Cash flow is used because a company that has profits but no cash flow is at risk. Also, since cash flow is a more difficult number to manipulate, the impact of accounting irregularities is reduced. Using cash flow in the model penalizes a firm that has negative cash flow even if both its net income and EBIT are positive.
- LTD to the sum of LTD and NW is used as the primary leverage variable instead of Total Liabilities to Total Assets. This change reduced the degree of multicollinearity in the model.[7] Including total liabilities to total assets would have increased multicollinearity due to the relatively high correlation between [Total Liabilities to Total Assets] and [Net Income to Total Assets].

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

[6] We implement operating cash flow as EBITDA plus changes in accounts payable less changes in accounts receivable less changes in inventories. This implementation requires seven inputs including three from the previous year's financial statement.

[7] Excessive multicollinearity may reduce the stability of parameter estimates.

- Long-term debt used in this analysis is the non-current portion of long-term debt and typically includes capitalized leases. If capitalized leases are not explicitly included under LTD, users should include them.
- ROA is Net Income to Assets whereas in v1.0 ROA was Net Income less Extraordinary Items to Assets. Not allowing for the subtraction of extraordinary items makes the model more objective. The user no longer needs to decide whether an item is truly extraordinary or an accounting ploy.
- A new variable, the Change in Accounts Receivable Turnover (accounts receivable to sales) is included. This variable indicates potential collection problems within the firm. A dramatic increase in accounts receivable without an accompanying increase in sales may indicate a collection problem, and a dramatic decline without a reduction in sales may mean excessive write-offs.
- Inventories are divided by net sales rather than cost of goods sold (COGS). This was done since COGS is often not reported in our database and the definition of COGS is inconsistent across industries.

TABLE 2 Groupings of Financial Statement Ratios

Examples of ratios in the **profitability** group include: net income, net income less extraordinary items, EBITDA, EBIT and operating profit in the numerator; and total assets, tangible assets, fixed assets and sales in the denominator. → *High profitability reduces the probability of default.*
Examples of ratios in the **leverage** group include liabilities to assets and long-term debt to assets. → *High leverage increases the probability of default.*
Debt coverage is the ratio of cash flow to interest payments or some other measure of liabilities. → *High debt coverage reduces the probability of default.*
Growth variables are typically the change in ROA and sales growth. These variables measure the stability of a firm's performance. → *Growth variables behave like a double-edged sword: both rapid growth and rapid decline (negative growth) will tend to increase a firm's default probability.*
Liquidity variables include cash and marketable securities to assets, the current ratio and the quick ratio. These variables measure the extent to which the firm has liquid assets relative to the size of its liabilities. → *High liquidity reduces the probability of default.*
Activity ratios include inventories to sales and accounts receivable to sales. These ratios may measure the extent to which a firm has a substantial portion of assets in accounts that may be of subjective value. For example, a firm with a lot of inventories may not be selling its products and may have to write off these inventories. → *A large stock of inventories relative to sales increases the probability of default; other activity ratios have different relationships to default.*
Size variables include sales and total assets. These variables are converted into a common currency as necessary and then are deflated to a specific base year to ensure comparability (e.g., total assets are measured in 2001 U.S. dollars). → *Large firms default less often.*

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

Category	Variable
Leverage	LTD to (LTD plus Net worth)
	Retained Earnings to Current Liabilities
Profitability	ROA
	Change in ROA
Debt Coverage	Cash Flow to Interest Expense
Liquidity	Cash and Marketable Securities to Total Assets
Activity	Inventories to Sales
	Change in AR Turnover
	Current Liabilities to Sales
Growth	Sales Growth
Size	Total Assets

*LTD is long-term debt, ROA is net income to total assets and AR Turnover is the ratio of accounts receivable to sales.

Variable Transforms

Once the variables are selected, they are transformed into a preliminary EDF value. Figure 4 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 that of the company (e.g., if ROA is in the 90th percentile that means that 90% of the sample had an ROA lower than that firm).

The shape of the transformation indicates how significantly a change in level impacts the EDF value. If the slope of the transform is steep, a small change will have a larger impact on risk than if the slope were flat.

- For the **Profitability** group, ROA and Change in ROA are included. ROA's transform is downward sloping, but the slope becomes almost zero as ROA becomes large (Figure 4). Such a transform indicates that more profitable firms have lower default probabilities, but the impact diminishes as ROA increases. Change in ROA is “U-shaped” indicating that large increases or decreases in ROA increase the default likelihood. The actual transform shape indicates that large reductions in ROA increase the likelihood of default by a larger amount than large increases in ROA.

- For the **Leverage** group, retained earnings to current liabilities and LTD to the sum of LTD plus Net Worth are used. Large values of retained earnings to current liabilities lower default probabilities while large values of LTD to the sum of LTD plus net worth increase default probabilities (Figure 4).

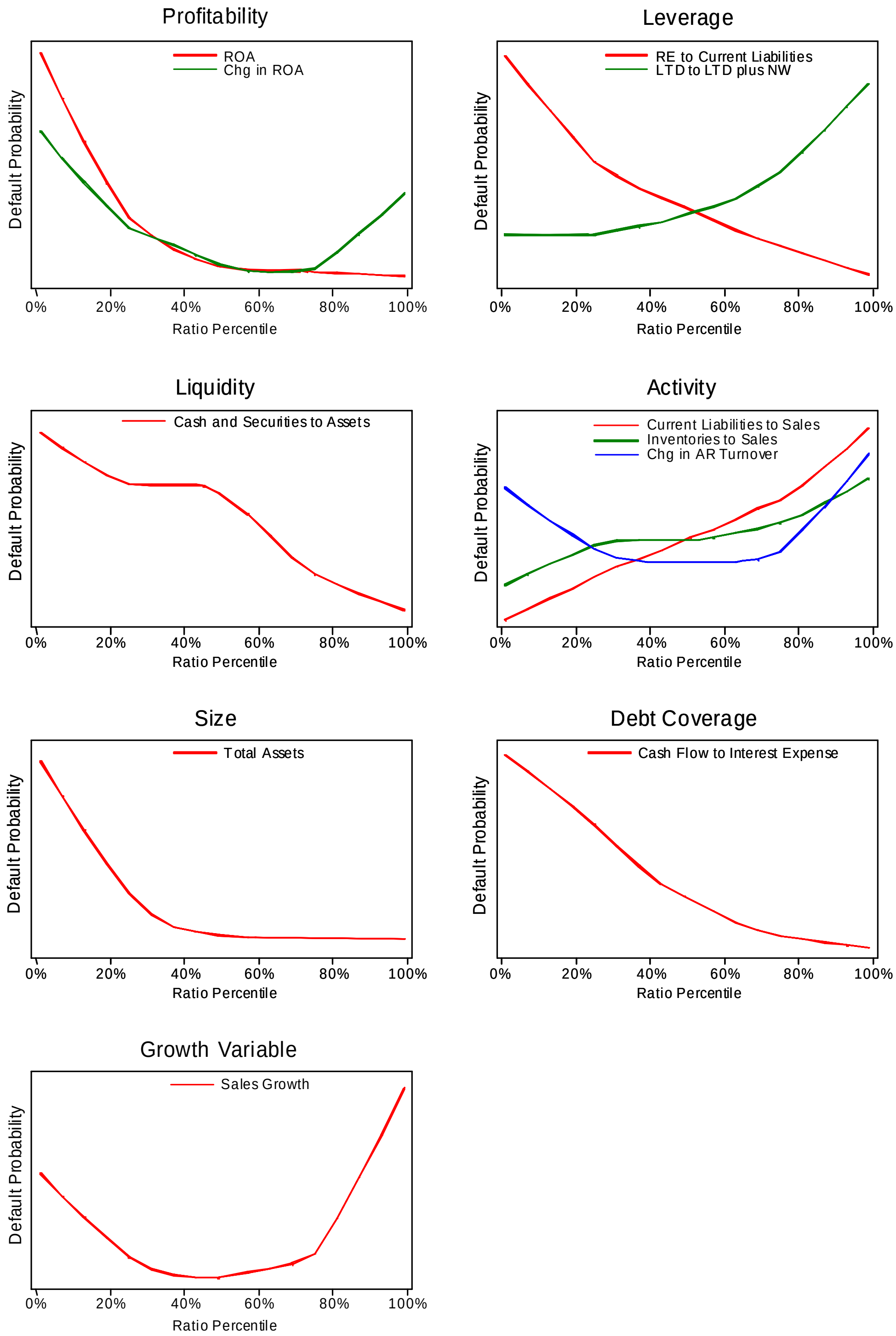
- For the **Liquidity** group, Cash and Securities to Total Assets is downward sloping, indicating that higher values of this ratio are associated with lower default probabilities (Figure 4).

- For the **Activity** group, three ratios are included. Inventories to Sales and Current Liabilities to Sales are both upward sloping indicating that high values of these ratios are associated with higher default probabilities (Figure 4). Change in Accounts Receivable Turnover is “U shaped,” indicating that large positive values or large negative values are associated with higher default probabilities, while stable accounts receivable turnover is associated with lower default probabilities.

- The **Size** variable is Total Assets. This variable's transformation is downward sloping, but the slope becomes almost zero as size become large (Figure 4). This indicates that larger firms have lower default probabilities, but the impact of size on default probabilities is diminishing as firm size increases.

- The **Debt Coverage** variable is Cash Flow to Interest Expense. This variable is downward sloping, indicating that large values of cash flow relative to interest expense lower the probability of default (Figure 4).
- The **Growth** variable is Sales Growth. It is “U shaped,” indicating that large increases or decreases in sales are associated with higher default probabilities (Figure 4). The actual shape indicates that large increases in sales increase default probabilities by a larger amount than large decreases in sales.

FIGURE 4 Transformations of Financial Statement Variables Used in the Model



3.2 Model Weights

Importance

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

Calculation of Weights

To calculate the weighting of a variable, the EDF credit measure for a theoretical firm with all its variables at the average transformation values is computed. The variables are then increased one at a time by one standard deviation. The EDF change for each variable (in absolute value) is computed and added together. 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 gives the variable with the biggest impact on the EDF level the biggest weight, and the variable that has the smallest impact on the EDF level the smallest weight. Since the weights are a percentage of the total EDF value, they sum to 100%. The weight of each category is the sum of the weights of each variable in the category. Table 4 presents the weights in RiskCalc v1.0 NA and RiskCalc v3.1 U.S. Leverage and profitability continue to be the most important categories while size has lessened. As more variables are included in the model, size becomes less important in determining default risk. Table 4 shows the risk drivers and their weights in RiskCalc v1.0 NA and RiskCalc v3.1.

TABLE 4 Risk Drivers in RiskCalc v1.0 NA versus RiskCalc v3.1 U.S.*

RiskCalc v1.0 North America		RiskCalc v3.1 U.S.	
Risk Drivers	**Weight**	**Risk Drivers**	**Weight**
Profitability Net Income/Assets Net Income Growth Interest Coverage	23%	Profitability Cash Flow/Interest Expense ROA (Net Income/Assets) Change in ROA	27%
Capital Structure Retained Earnings/Assets Liabilities to Assets	21%	Capital Structure LTD/LTD plus Net Worth Retained Earnings/Current Liabilities	22%
Liquidity Cash/Assets Quick Ratio	19%	Liquidity Cash/Assets	15%
Size Assets	14%	Size Assets	7%
Growth Sales Growth	12%	Growth Sales Growth	10%
Activity Inventories/COGS	12%	Activity Inventories/Sales Current Liabilities/Sales Change in Accounts Receivable Turnover	19%

*Note that the model weights for RiskCalc v1.0 sum to 101% due to rounding errors. LTD stands for long-term debt, and accounts receivable turnover is accounts receivable divided by sales. For a description of the variable selection process see Section 3.1. For a discussion of the procedure used to compute model weights see Section 3.2.

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. One important difference is inventories. For an industry that does not keep inventories, the inventory to sales ratio is zero. This occurs over 40% of the time in several of the industries in the U.S. development sample (Table 5). Also, for the same set of financials, industries may have different default probabilities.

TABLE 5 Percent of Observations with Zero Inventories by Sector

Sector	Percent Zero
Agriculture	28.1%
Business Products	9.8%
Communications and Hi Tech	19.2%
Construction	42.6%
Consumer Products	9.5%
Mining, Transportation, Utilities and Natural Resources	45.0%
Services	49.9%
Trade	15.1%
Unassigned	35.9%

In the FSO mode of RiskCalc v3.1 U.S., the EDF value is adjusted for industry effects. Table 6 presents the increase in model power and accuracy from introducing industry controls into the FSO model. Both the power and the accuracy of the EDF credit measure increase as measured by the accuracy ratio and the gain in log likelihood. Table 7 presents the average EDF value by industry for the development sample. The highest EDF values are in Consumer Products while the lowest are in Construction.

TABLE 6 Increase in Model Power and Accuracy from Introducing Industry Controls

	One-year Model		Five-year Model	
	Accuracy Ratio	Relative increase in Log Likelihood	Accuracy Ratio	Relative increase in Log Likelihood
FSO mode without industry controls	54.4%		38.1	
FSO mode with industry controls	55.1%	58.16***	38.8	99.8***

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

In this table, and hereafter, Accuracy Ratio (or AR) is the measure of the model's ability to rank order credits. Increases in log likelihood measure the extent to which the model's EDF values match observed default rates. For further details, see Dwyer and Stein (2004), *Technical Document on RiskCalc v3.1 Methodology* (Technical Document).

TABLE 7 Average EDF Credit Measure in Development Sample by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Agriculture	1.9%	6.4%
Business Products	2.5%	9.3%
Communications and Hi Tech	2.8%	9.0%
Construction	1.4%	5.2%
Consumer Products	2.9%	10.0%
Mining, Transportation, Utilities and Natural Resources	2.2%	7.5%
Services	2.4%	8.2%
Trade	1.8%	6.6%
Unassigned	2.4%	7.9%

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 U.S. includes a credit cycle adjustment factor. The credit cycle adjustment is designed to incorporate the current credit cycle into the estimate of private firm default risk.

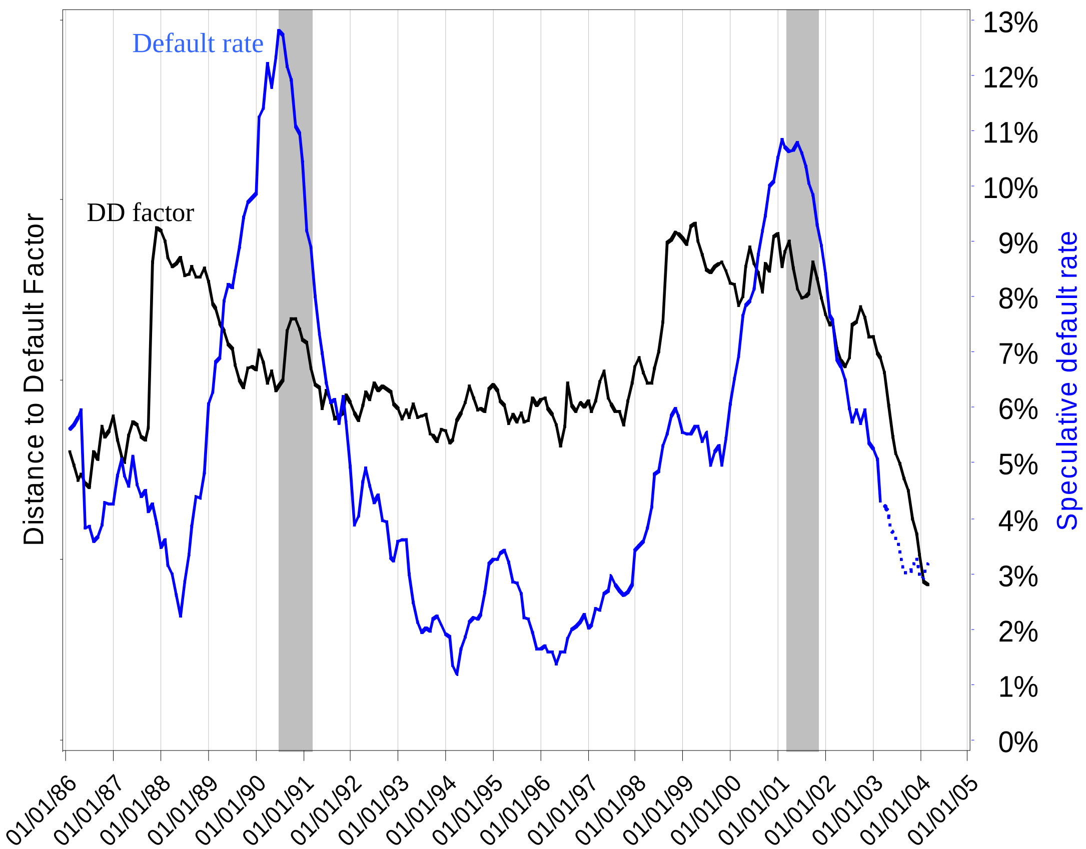
Selecting an Adjustment Factor

The RiskCalc v3.1 model uses the distance-to-default calculation from the Moody's KMV public firm model. This measure is specifically designed to be a forward-looking indicator of default risk. It extracts signals of default risk from the stock market performance of individual firms (cf., Bohn and Crosbie, 2003). This measure was chosen because it is available for a large universe of industries and it has been extensively validated.

If the distance-to-default for public firms in an industry indicates a level of risk above the historical average for that industry, then the private firms' EDF values in that industry are adjusted upward by some factor. Conversely, if the level of risk is below the historical average, then the private firms' EDF values are adjusted downward. When the credit cycle adjustment factor is neutral, the CCA EDF coincides with the FSO EDF. For the Canadian and the U.S. model, the distance-to-default factor is based on an aggregation of all public North American firms in the industry. In the event that a firm cannot be associated with a specific industry, the model uses a credit cycle adjustment that is based on an aggregation of all public North American firms.

Figure 5 presents the distance-to-default factor based on all public North American firms and contrasts that to the speculative-grade default rate as measured by Moody's Investors Service default studies (see, Hamilton and Varma, 2003). For both recessions, the speculative default rate increases in advance of the recession so that a risk indicator that is *coincident* with the business cycle will not predict increases in risk. The distance-to-default factor anticipates both the recession and the increase in defaults measured by the speculative default rate. Therefore, it is a *forward-looking* measure of default risk in an industry. Table 8 shows that including the credit cycle adjustment factor increases both the power and the accuracy of the model.

FIGURE 5 North American DD Factor and the Speculative Default Rate 1986-2004



Presents the DD factor (black line) against the historical Speculative Bond Default Index (blue line; the dotted blue line indicates forecasted values). Gray vertical bars indicate periods of recession as defined by the NBER. Large values of the DD factor provided early warnings of increased default rates for both recessions.

4 VALIDATION RESULTS

Once a model is developed, it must be shown to be effective in predicting defaults. There are a variety of tests of model power: those that test rank ordering (grouping credits from worst to best) and those that test the calibration of the model (level of EDF credit measure is correct).

The tests need to check not only the model effectiveness, but also its robustness and how well it works on data outside the sample. To do such out-of-sample testing, we performed walk-forward and k-fold analyses. In addition to the typical out-of-sample testing, we tested using data that became available after the model was finalized and in production.

The results of the testing show that the model is uniformly more powerful than other models across different time periods, sectors, and size classifications.

4.1 Increase in Overall Model Power and Accuracy

Table 8 presents the in-sample overall measures of power and likelihood for RiskCalc v3.1 versus alternative models. With the credit cycle adjustment, the model's performance improves by almost eight points of accuracy ratio at the 1-year horizon compared with RiskCalc v1.0. Relative to other available alternatives, the results were more dramatic. The new RiskCalc v3.1 U.S. model outperformed the Z-score model (Altman, Hartzell and Peck, 1995) by more than ten points at both the 1-year and 5-year horizons. The Financial Statement Only (FSO) mode outperforms the old model by five points at both horizons.[8] RiskCalc v3.1 is also more accurate than alternative models as measure by the log-likelihood differences.[9]

TABLE 8 Power Enhancements of the new RiskCalc v3.1 U.S. Model

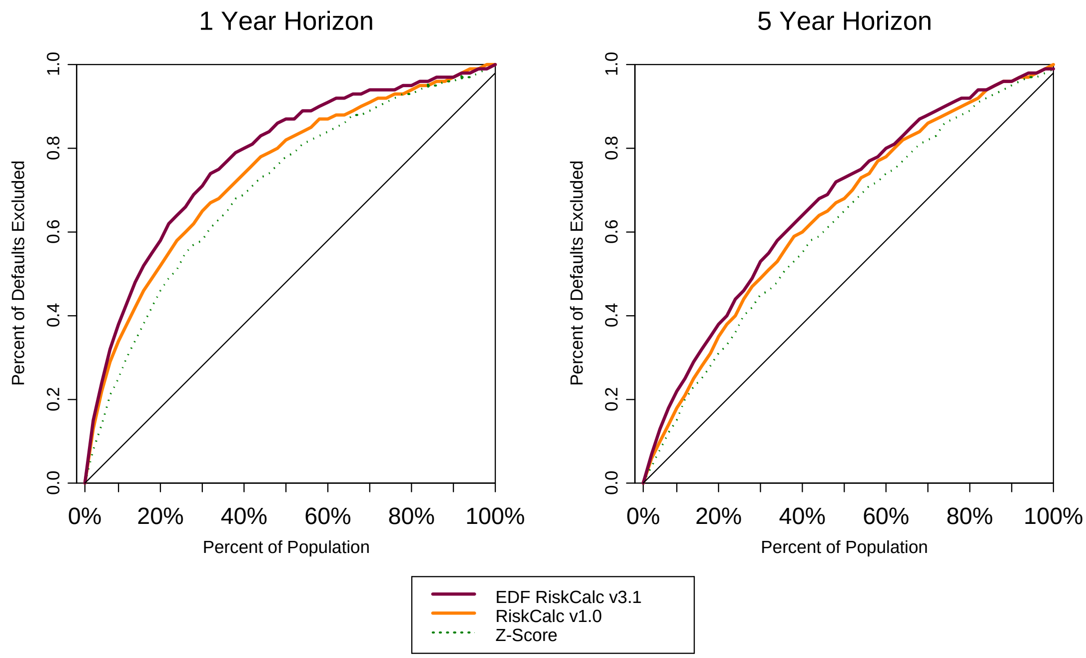
	One-year Model		Five-year Model	
	Accuracy Ratio	Lead in Log Likelihood*	Accuracy Ratio	Lead in Log Likelihood*
RiskCalc v3.1 Model	57.0%		35.7%	
RiskCalc v1.0	49.5%	403.6	30.7%	196.7
Z-score	42.3%	1356.5	24.7%	803.3

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

Figure 6 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 8. The power improvements are largely in the middle of the distribution relative to RiskCalc v1.0 (particularly for the 1-year model). This result implies that both very good and very poor credits are correctly identified by both RiskCalc v1.0 and RiskCalc v3.1. The added discriminatory power is assessing the credit quality of credits that fall in the middle range.

[8] The corresponding accuracy ratios are 54.3% (FSO) vs. 49.5% (RiskCalc v1.0) for the 1-year horizon and 35.7% (FSO) vs. 30.7% (RiskCalc v1.0) for the 5-year horizon.
[9] The log likelihood can be thought of as a measure of closeness of the predicted EDF values to the actual default rates.

FIGURE 6 Power of Alternative Models (1- and 5-year) — U.S.



4.2 Correlations and Variance Inflation Factors

In order to ensure model robustness, the model must be tested for excessive multicollinearity. This occurs if a number of the variables used in the model are highly correlated. Excessive multicollinearity can cause instability in parameter estimates. In order to check for this issue, the correlation coefficients (Table 9) for the financial statement ratios in the model and the variance inflation factors (Table 10) are computed on the transformed variables (see Figure 4).[10] The highest correlation coefficient is between [Cash Flow to Interest Expense] and [Net Income to Total Assets] (0.44). The next highest coefficient is between [Retained Earnings to Current Liabilities] and [Current Liabilities to Net Sales] (0.43). Such coefficients are well below what we would typically consider indications of multicollinearity, and this finding is also verified by the VIF analysis.

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

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

	LTD to LTD plus NW	Net Income to Total Assets	Net Sales Growth	Cash & Securities to Total Assets	Chg in AR turnover	Chg in ROA	Inventories to Net Sales	Cash Flow to Int. Exp.	RE to CL	CL to Net Sales	Total Assets
LTD to LTD plus NW	1.0										
NI to Assets	0.173	1.0									
Sales Growth	-0.054	0.029	1.0								
Cash to Assets	0.212	0.190	-0.011	1.0							
Chg in AR turnover	-0.099	0.033	0.223	0.017	1.0						
Chg in ROA	-0.070	0.045	0.183	-0.054	0.107	1.0					
Inventory to Net Sales	-0.063	0.061	-0.031	0.223	-0.015	-0.073	1.0				
Cash Flow to Int. Exp.	0.166	0.443	0.077	0.252	0.082	0.009	0.131	1.0			
Ret. Earnings to Current Liab.	0.210	0.308	0.118	0.220	0.045	0.048	0.027	0.322	1.0		
Curr. Liab. to Sales	0.117	0.284	0.113	0.254	0.217	-0.031	0.150	0.266	0.434	1.0	
Total Assets	-0.125	-0.041	0.104	-0.087	0.019	0.194	-0.131	0.024	0.038	-0.197	1.0

The Variance Inflation Factors (Table 10) for the financial statement variables represent how much of the variation in one independent variable can be explained by all the other independent variables in the model. The correlation coefficient measured only the relationships between two variables. The estimated VIF values are notably below the threshold levels of 4 to 10 that are commonly used in VIF analysis when testing for presence of multicollinearity.[11] Therefore, the findings indicate that the model variables do not present any substantial multicollinearity.

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

TABLE 10 Variance Inflation Factors

Variable	VIF
Retained Earnings to Current Liabilities	1.53
Current Liabilities to Net Sales	1.48
Net Income to Total Assets	1.42
Cash Flow to Total Interest Expense	1.33
Inventories to Net Sales	1.29
LTD to LTD plus NW	1.26
Change in ROA	1.24
Change in Accounts Receivable Turnover	1.20
Cash and Marketable Securities to Total Assets	1.20
Net Sales Growth	1.13
Total Assets	1.14

4.3 Model Power by Industry and Size Groups

It is important to test the power of a model not only overall, but also among different industry segments and firm sizes.

Table 11 and Table 12 present the power comparisons by sector for the 1-year and 5-year models, respectively. RiskCalc v3.1 outperforms both RiskCalc v1.0 and Z-score in all sectors. The highest power in the 1-year model is found in Construction (66.5%) while the lowest is found in Agriculture (52.3%). At the 5-year horizon (Table 11) the highest power is in Agriculture (46.5%) and the lowest is in Business Products (27.6%).

TABLE 11 Model Power by Industry 1-year Model

	Percentage of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Agriculture	3.6%	52.3%	46.5%	46.4%
Business Products	15.1%	58.3%	50.6%	47.1%
Communications and Hi Tech	5.9%	58.7%	52.1%	49.7%
Construction	9.2%	66.5%	56.9%	51.1%
Consumer Products	10.5%	61.7%	56.4%	47.2%
Mining, Transportation, Utilities and Natural Resources	9.1%	55.9%	50.6%	44.9%
Services	20.2%	56.1%	46.9%	34.9%
Trade	26.4%	55.2%	46.5%	36.8%

TABLE 12 Model Power by Industry 5-year Model

	Percentage of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Agriculture	4.3%	46.5%	39.4%	35.4%
Business Products	14.7%	27.6%	25.3%	24.1%
Communications and Hi Tech	5.2%	41.8%	35.0%	24.9%
Construction	8.9%	38.8%	34.2%	21.2%
Consumer Products	11.1%	37.2%	28.8%	25.4%
Mining, Transportation, Utilities and Natural Resources	9.4%	40.2%	37.9%	28.5%
Services	19.5%	30.8%	23.0%	16.7%
Trade	26.9%	33.2%	31.9%	28.6%

Table 13 and Table 14 present the power comparisons by firm size for the 1-year and 5-year models, respectively. RiskCalc v3.1 out performs both RiskCalc v1.0 and Z-score in all size groups. The highest power in the 1-year model is found in the largest firms—over $50 million in assets, and the lowest is in the smallest firms—under $500,000 in assets. This is because the quality of financial statements generally increases with firm size. For example, larger firms are more likely to have audited statements.

TABLE 13 Model Power by Size 1-year model

	Percentage of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
<$500,000	4.8%	49.7%	43.1%	43.6%
$500,000 to $1mm	9.1%	47.6%	43.3%	41.1%
$1mm to $2mm	15.3%	57.0%	52.4%	44.1%
$2mm to $5mm	20.8%	59.2%	53.2%	47.0%
$5mm to $10mm	15.2%	53.7%	43.9%	41.9%
$10mm to $50mm	20.0%	55.1%	49.6%	34.9%
over $50mm	14.7%	62.9%	54.8%	42.3%

TABLE 14 Model Power by Size 5-year model

	Percentage of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
<$500,000	6.8%	36.7%	29.0%	28.5%
$500,000 to $1mm	11.2%	42.0%	39.3%	33.4%
$1mm to $2mm	17.1%	32.3%	30.1%	22.8%
$2mm to $5mm	21.9%	34.9%	28.4%	20.1%
$5mm to $10mm	14.7%	42.6%	35.9%	33.0%
$10mm to $50mm	17.7%	41.1%	37.0%	26.8%
over $50mm	10.8%	33.8%	27.9%	16.4%

4.4 Power Performance Over Time

Since models are designed to be implemented at various points in a business cycle, power tests were conducted by year (Table 15 and Table 16). These tests examine whether or not the model performance is excessively time dependent.

Table 15 and Table 16 present the results from this analysis at the one and five year horizons, respectively. The AR of RiskCalc v3.1 is compared with RiskCalc v1.0 and Z-score for each year. RiskCalc v3.1 consistently outperforms both RiskCalc v1.0 and Z-score by a considerable margin. The RiskCalc v1.0 consistently outperforms the Z-score model in 1999, 2000, and 2001. These years should be regarded as out-of-sample since RiskCalc v1.0 was released in early 2000 and the majority of the observations in 1999 are based on year-end financial statements and would not have been in the RiskCalc v1.0 development sample. This out-of-sample robustness demonstrates that RiskCalc v1.0 was not "over fit."

TABLE 15 Model Power over Time: 1-year Horizon

	Percent of Defaults	AR* RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
1993	1.2%	68.2%	64.5%	59.4%
1994	3.3%	57.4%	55.4%	52.5%
1995	5.6%	56.6%	53.0%	44.6%
1996	7.1%	60.5%	60.1%	53.0%
1997	11.3%	47.7%	44.2%	36.3%
1998	20.8%	38.9%	35.0%	28.3%
1999	23.6%	44.6%	39.6%	33.5%
2000	19.8%	49.0%	43.6%	36.0%
2001	7.2%	71.9%	66.5%	55.1%

*AR = accuracy ratio

TABLE 16 Model Power over Time: 5-year Horizon

	Percent of Defaults	AR* RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
1993	3.2%	45.1%	43.5%	33.6%
1994	6.7%	44.7%	43.2%	34.9%
1995	11.6%	38.3%	35.7%	26.2%
1996	16.2%	36.1%	31.5%	22.0%
1997	19.8%	33.6%	28.2%	22.2%
1998	19.0%	37.4%	31.1%	26.2%
1999	14.6%	42.3%	35.9%	31.7%
2000	8.8%	48.5%	40.9%	34.8%

*AR = accuracy ratio

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

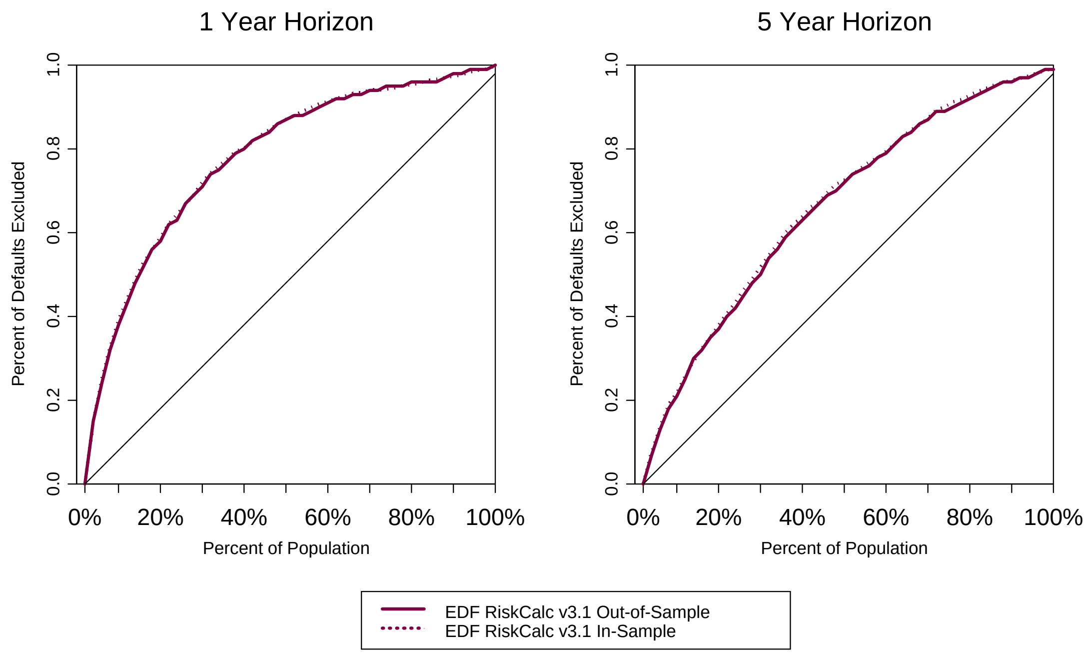
The model exhibits a high degree of power in distinguishing good credits from bad ones (in Table 8), but whether this power is attributable to the overall model effectiveness or the impact of a particular sub-sample also needs to be tested. A standard test for evaluating this is the "*k*-fold test," which divides the defaulting and non-defaulting companies into *k* equally sized segments. This yields *k* equally sized observation sub-samples that exhibit the identical overall default rate and are temporally and cross-sectionally independent. The model is then run on *k-1* sub-samples and these parameter estimates are used to score the *k-th* sub-sample. We repeat this procedure for all possible combinations, and put the *k* scored "out-of-sample" sub-samples together and calculate an accuracy ratio on this combined data set.

Table 17 summarizes the *k*-fold test results (with *k*=5). The reported figures are the accuracy ratios by the corresponding sample and time horizons. The out-of-sample model consistently out-performs RiskCalc v1.0. 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. The difference in AR between the overall in-sample and out-of-sample results is not larger than one point in all cases. Further, RiskCalc v3.1 outperforms RiskCalc v1.0 in an out-of-sample context at both the 1- and 5-year horizons (Table 17).

TABLE 17 RiskCalc v3.1 *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	51.5%	38.3%	45.7%	36.1%
Subsample 2	56.3%	35.2%	48.5%	33.6%
Subsample 3	54.8%	36.0%	46.5%	31.1%
Subsample 4	50.4%	34.9%	45.3%	31.0%
Subsample 5	54.7%	35.9%	47.3%	34.0%
K-fold Overall	56.8%	34.7%	50.3%	31.1%
In-sample AR	57.5%	35.7%		

FIGURE 7 RiskCalc v3.1 U.S. K-fold



The K-fold testing does not control for time dependence. Each of the *k* sub-samples contains data from all periods. As a result, if there were a particularly high period of default rates, this would be included in each of the *k* samples. Such testing does not give a true sense of the how the model would have performed during those volatile periods because the model is estimated with full information on those time periods.

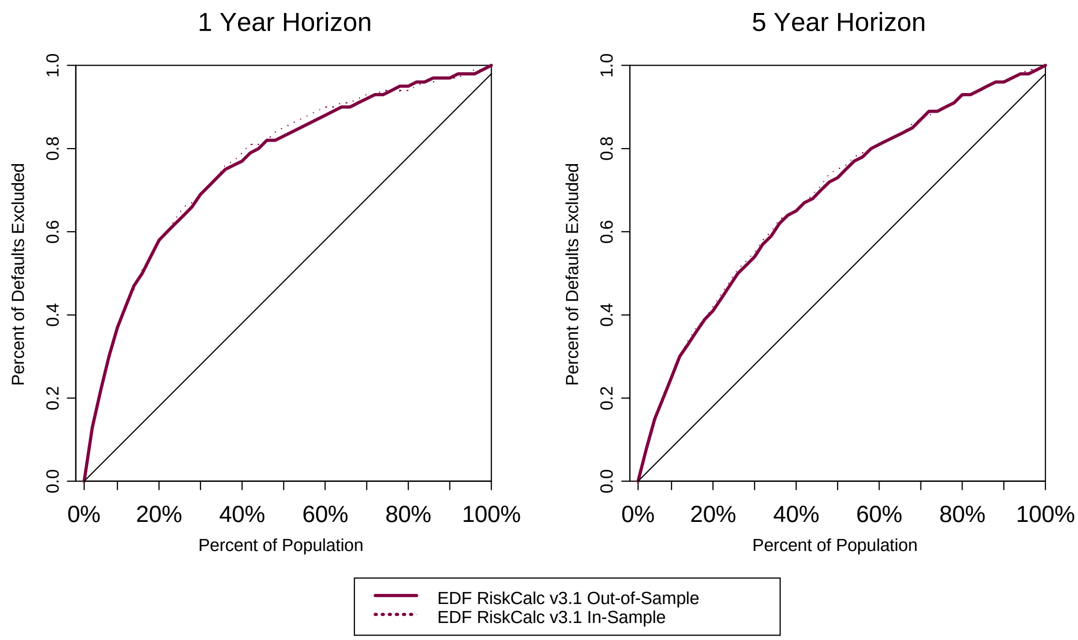
4.6 Walk-Forward Tests

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

No data from a future period is used in fitting the model and only data from future periods is used for testing it. The parameter estimates are checked for stability across the different samples. Figure 8 presents the results from this analysis. The difference in AR between the in-sample and out-sample results is no more than one point in all cases. Further, RiskCalc v3.1 outperforms RiskCalc v1.0 in an out-of-time context at both the 1- and 5-year horizons.[12]

[12] The out-of-sample ARs are 53.6% and 37.7% for the 1-year and 5-year models, respectively. These out-of-sample ARs are 1.0 and 0.6 points lower than the in-sample ARs and 5.9 and 6.0 points higher than RiskCalc v1.0, for the one and five year models respectively.

FIGURE 8 Out-of-sample Performance (1- and 5-year) U.S. Walk-forward



4.7 Out-of-Sample Test on Newly Received Data

In addition to the other testing done on the model, the model was also tested on a dataset that only became available once the model was completed (i.e., a dataset that was not used for either developing or calibration of the model or for any of the other validation tests). This data set included the most recent submissions from contributors to the CRD.

This holdout sample includes only firms that were never in the development or validation sample and includes more than 20,000 usable new observations and 500 usable new defaults. The holdout sample provides an ideal test of the variable selection process and the model's functional form, because it is not subject to a data snooping issue.[13]

[13] For a discussion of the issues surrounding exploratory analysis contaminating the holdout sample (also known as data-snooping), see Campbell et al. (1997, pages 523-524).

TABLE 18 Out-of-Sample Performance of the new RiskCalc v3.1 Model

	One-year		Five-year	
	Accuracy Ratio	Log Likelihood Margin*	Accuracy Ratio	Log Likelihood Margin*
RiskCalc v3.1	60.8%	0	36.4%	0
RiskCalc v1.0	54.8%	193	28.4%	330
Z-score	43.3%	691	21.5%	862

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

Table 18 reports the results of the analysis. RiskCalc v3.1 outperforms RiskCalc v1.0 by 6.0 and 8.0 points in the 1-year and 5-year horizons, respectively. While not directly comparable because they are based on different samples, the gains in power are very consistent with those observed in Table 8.[14] RiskCalc v1.0 continues to outperform the Z-score by a considerable margin. Finally, the likelihood gains of RiskCalc v3.1 over every other model remain substantial as well. This provides the strongest evidence of the robustness and accuracy of RiskCalc v3.1. While not always possible, such "holdout" testing is one of the best possible validation techniques for determining the robustness of a model.

4.8 Model Calibration and Implied Ratings

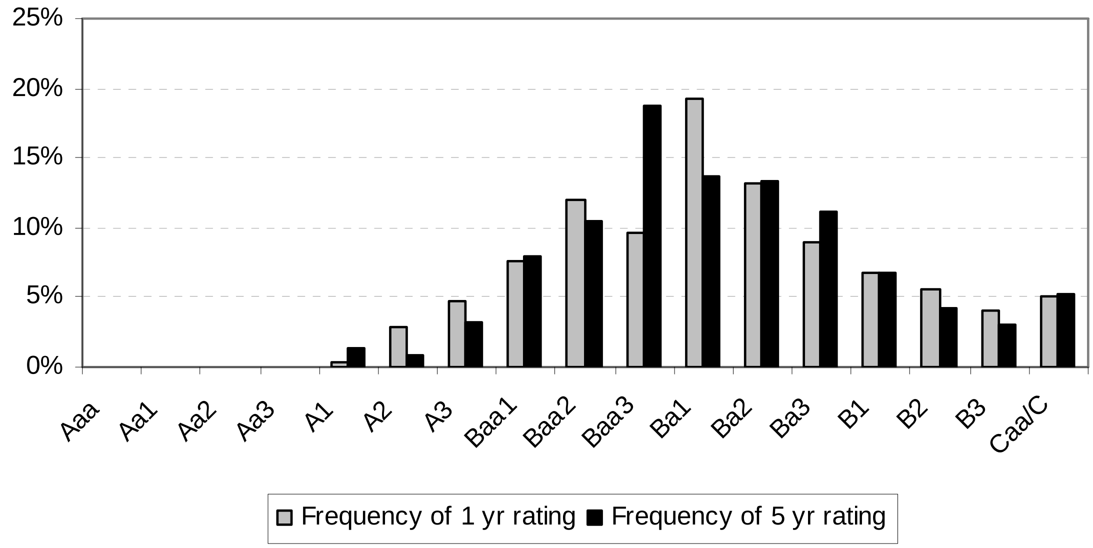
To aid in the interpretation of an EDF credit measure, an EDF value is mapped to an .edf rating (an EDF-implied rating). All RiskCalc v3.1 models to date have used the same mapping. The mapping is designed so that:

- There is a large range of .edf ratings (as required for economic and regulatory applications);
- No one rating contains too many credits (as required for economic and regulatory applications);
- The distribution of the 5-year ratings is approximately the same as the distribution of 1-year ratings (for consistency with rating-based analysis applications);
- The EDF value associated with 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 Credit Cycle Adjusted EDF credit measures over the full time period). Note that 13 categories between A1 and Caa/C are utilized and that less than 20% of the observations are in any one category. A trace number of Aa3.edf ratings are observed in the sample, but are not visible in the histogram. The 1-year distribution peaks at Ba1 and the 5-year distribution peaks at Baa3. While not reported here, other research has shown that the distribution of the credit cycle adjusted .edf ratings changes over time with the credit cycle while the distribution of the FSO .edf ratings remains relatively stable over time.

[14] The in-sample power gains are not directly comparable to the pure out-of-sample gains since they are based on different samples. See Stein (2002) for a discussion of issues in comparing validation results from tests on different samples.

FIGURE 9 EDF-implied Ratings for the 1- and 5-year models in the development sample



5 FURTHER MODEL IMPROVEMENTS

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

5.1 Continuous Term Structure

The previous version of the RiskCalc model provided the user with two discrete default probability estimates: a 1-year and a 5-year EDF. In this version, utilizing the two point estimates for 1- and 5-year estimates we fit a Weibull function, and thus achieve a continuous term structure of EDF values for each credit. In other words, users of RiskCalc v3.1 U.S. now can obtain EDF estimates for any point between 1 and 5 years. In addition, RiskCalc v3.1 provides EDF estimates for alternative definitions, such as the Forward EDF and the Annualized EDF (Table 19):

- **Cumulative EDF**

  A cumulative EDF credit measure gives the probability of default over that time period. For example, a five year cumulative EDF of 13.44% means that that company has a 13.44% chance of defaulting over that five year period. The second column of Table 19 provides an example of the cumulative 1- to 5-year credit measures produced by the model.

- **Forward EDF**

  The forward EDF is the probability of default between t-1 and t conditional upon survival until t-1. In other words, the 4-year Forward EDF is the probability that a firm will default between years three and four assuming the firm survived to year 3.[15] The third column of Table 19 displays the forward 1- to 5-year EDF credit measures that are derived from the cumulative EDF values.

- **Annualized EDF**

The annualized EDF credit measure is the cumulative EDF value for a given period, stated on a per year basis. For Example, a company with a cumulative 5-year EDF of 13.44% would have a 5-year annualized EDF of 2.84%.[16] This means that the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column of Table 19 presents the annualized EDF credit measures for years 1 to 5 that are derived from the cumulative EDF values.

TABLE 19 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 interface provides users with an analytical tool to gauge the relative impact of each variable – as a deviation from the mean of each ratio. In order to equip the users of the model with further tools, we developed relative sensitivities (also known as sensitivity multiples), which exhibit the EDF sensitivity to each of the model variables at the point of evaluation. This feature is especially useful when addressing the question of identifying variables to improve the EDF value of a company.

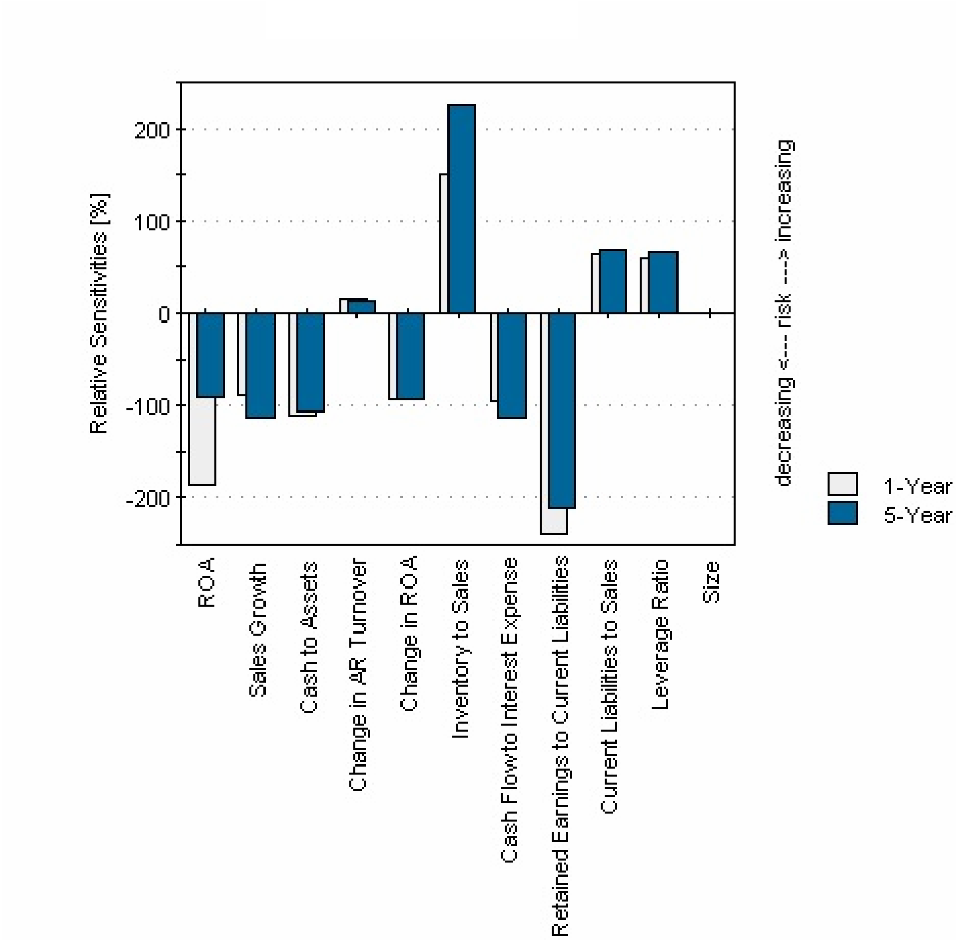
The relative sensitivity gives the impact of a small change in a variable on the EDF level of the company. It indicates which variables are most sensitive to an increase. A positive number means an increase in the variable will increase risk and a negative number indicates a decrease in risk. The percentile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

Example: A small increase in ROA will reduce the riskiness of the company. It is about 185% (1 year) as sensitive as the average variable (Figure 10).

[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 10 Relative Sensitivities



5.3 Asset Value and Volatility Calculation

One of the features of the 3.1 version of the model is that it provides an implied asset volatility. Clients of Credit Monitor and Credit Edge can use this volatility to analyze a private firm that is to go public through an IPO. Once the firm is public, the public firm model should be used, however, this model requires an asset volatility that is derived from the public share price. In the 3.1 version of the model, the asset volatility of the firm is estimated using its industry and size and a methodology that is very similar to PFM. 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 U.S. model is based on a substantially larger database than RiskCalc v1.0 North America. Further, we have an additional three years of data. Improved data coverage has allowed us to refine our financial statement model and achieve a very robust prediction model of private firm default behavior.

The new model includes several new variables that make it more responsive to accounting irregularities. The debt coverage ratio is based on operating cash flow rather than EBIT. Return on assets is calculated using net income rather than net income before extraordinary items. Finally, there is a variable that accounts for strong trends in accounts receivable turnover.

The model is more powerful than any publicly available alternatives that we have tested. We have demonstrated that the increase in power is consistent across industry secctors and size classifications as well as for different time periods. The power advantage is maintained in both an in-sample and out-of-sample context. RiskCalc v3.1 is the first model of its kind to incorporate both market (systematic) and company specific (idiosyncratic) risk factors. We have shown that the power advantage holds in a pure out-of-sample context—using data that became available after the model was finalized.

The RiskCalc v3.1 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 dramatically and allows users to monitor their portfolios on a monthly basis.

In addition, the RiskCalc v3.1 framework offers some further enhancements, such as a continuous term structure (providing EDF estimates for any point between 1 and 5 years), newer analytics, and the ability to calculate asset value and volatilities using a structural model framework.

This model will be very useful for financial institutions seeking to implement quantitative tools for originating loans, managing portfolio risk, and meeting regulatory requirements. Further, it provides an objective external benchmark of the risk associated with a private firm, which will be useful in securitizing middle-market debt. Finally, as an established benchmark, RiskCalc will enable institutions to communicate between each other on their exposures.

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