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MOODY'S KMV RISKCALC™ V3.1
NORTH AMERICA LARGE FIRM MODEL

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 Large Firm model.

The RiskCalc v3.1 Large Firm model is designed to provide a measure of default risk for firms that are large enough to have publicly-traded equity, but do not have it. The RiskCalc Large Firm model is developed, calibrated, and validated using both public and private firms from throughout North America.

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1 INTRODUCTION

The Moody's KMV RiskCalc™ v3.1 North America (NA) Large Firm 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).
- A combination of public firms and private firms. For public firms, we obtain financial statements for SEC filings and default information from our own public firm default database. For private firms, we use 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 financial statements only, 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 mode reflects the market's current assessment of the credit cycle and is a forward-looking indicator of default.

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

1.2 Differences between RiskCalc v3.1 NA Large Firm Model, RiskCalc v3.1 U.S., and RiskCalc v3.1 Canada

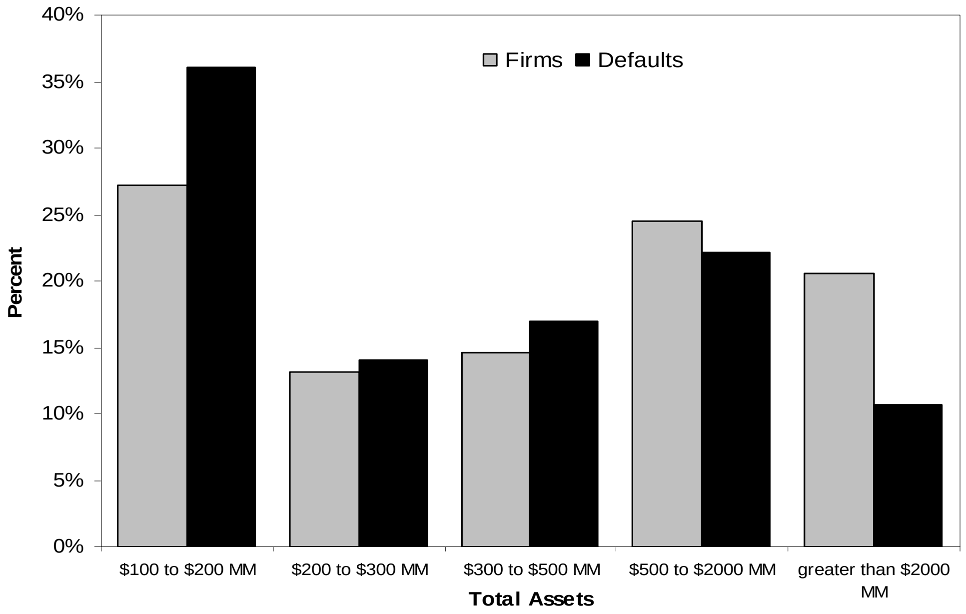
The NA Large Firm model focuses on North American firms with at least 100 million in assets in 2007 U.S. Dollars. The development sample includes firms incorporated in the U.S., Canada, Bahamas, Bermuda, British Virgin Islands, Cayman Islands, and Panama. Table 1 shows the sample distribution across countries. The RiskCalc v3.1 U.S. and Canada models cater more to smaller firms.

TABLE 1 Information on Sample Data across Countries

Country	Period	No. of Firms	No. of Defaults	No. of Statements
U.S.	1986–2008	12,963	1,241	72,132
Canada	1986–2008	1,086	87	8,817
Other*	1986–2008	135	6	799

* Includes Bahamas, Bermuda, British Virgin Islands, Cayman Islands, and Panama.

Figure 1 and Figure 2 compare the size distribution of defaults and firms between the Large Firm model and the v3.1 U.S. model. Almost 80% of the development sample for RiskCalc v3.1 U.S. has assets less than 50 mm.



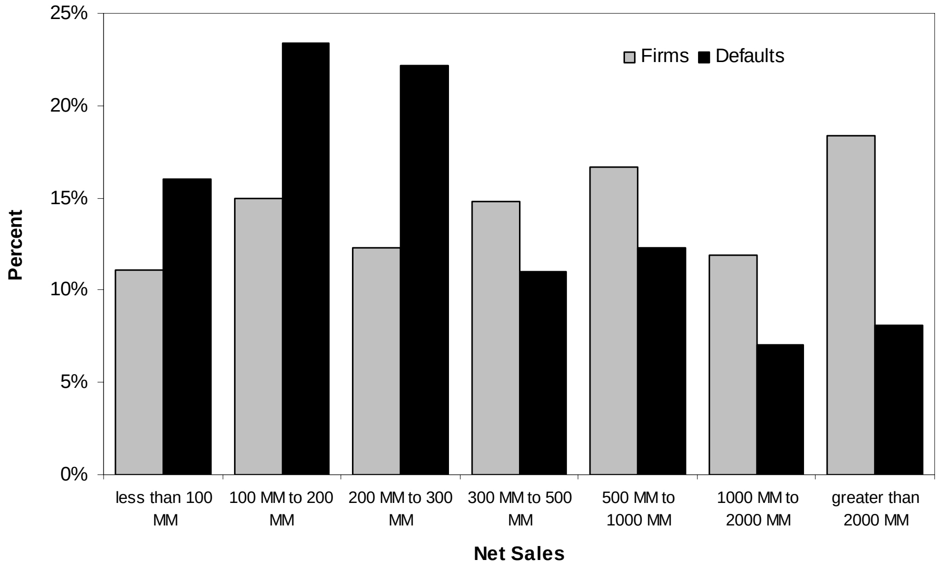


FIGURE 1 Size Distribution of Defaults and Firms: NA Large Firm Model

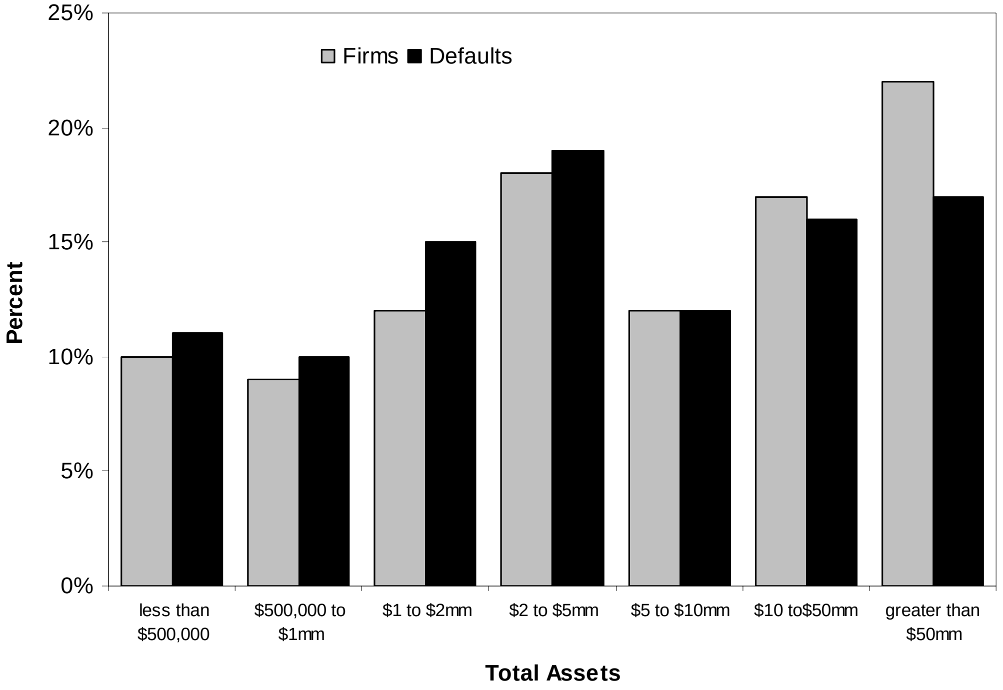


FIGURE 2 Size Distribution of Defaults and Firms: v3.1 U.S. Model

2 DATA DESCRIPTION

The data sources for the RiskCalc v3.1 NA Large Firm model are the Moody's KMV CRD and Compustat. The CRD collects default data and financial statements from participating institutions, the majority of which are not publicly-available.[1] Compustat contains publicly-available financial statements. The public firm defaults are taken from the Moody's KMV default database.

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 the NA Large Firm model, the events we define as defaults include 90-days-past-due, substandard/doubtful, non-accruals, charge-off, default on payment, distressed exchanges, and bankruptcy of the company[2]. 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).

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[1] We compared the Compustat data with CRD data. If a firm appears in both databases, we delete the duplicate financial statements.

[2] Our research indicates that "90-days-past-due" defaults with a "PASS" grade are likely to be technical defaults; those firms tend to have characteristics similar to healthy firms rather than to distressed firms. We exclude these defaults in our development sample.

2.2 Data Exclusions

Excluded Companies

The goal of the NA Large Firm model is to provide an EDF credit measure for large firms that are not covered by the Moody's KMV public firm model. The firms and industries covered in the model must have similar default characteristics. To create the most powerful model, 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 assets less than \$100 mm (in 2007 U.S. dollars) 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 firm. The regulation and capital requirements of these institutions make them different from other firms. 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.[3]
- Public Sector and Not-for-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.

Excluded Financial Statements

The financial statements in CRD come from participating financial institutions and may or may not be audited. 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. Financial statements retrieved from Compustat are mostly audited and are publicly-available, therefore they are relatively clean.

2.3 Descriptive Statistics of the Data

Overview of the Data

Figure 3 presents the distribution of financial statements and defaults by year in the development sample. The sample covers financial statements ranging from 1986–2006. Table 2 decomposes the sample by data source.

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[3] 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. This characteristic is explicitly recognized as part of the Basel Capital Accord.

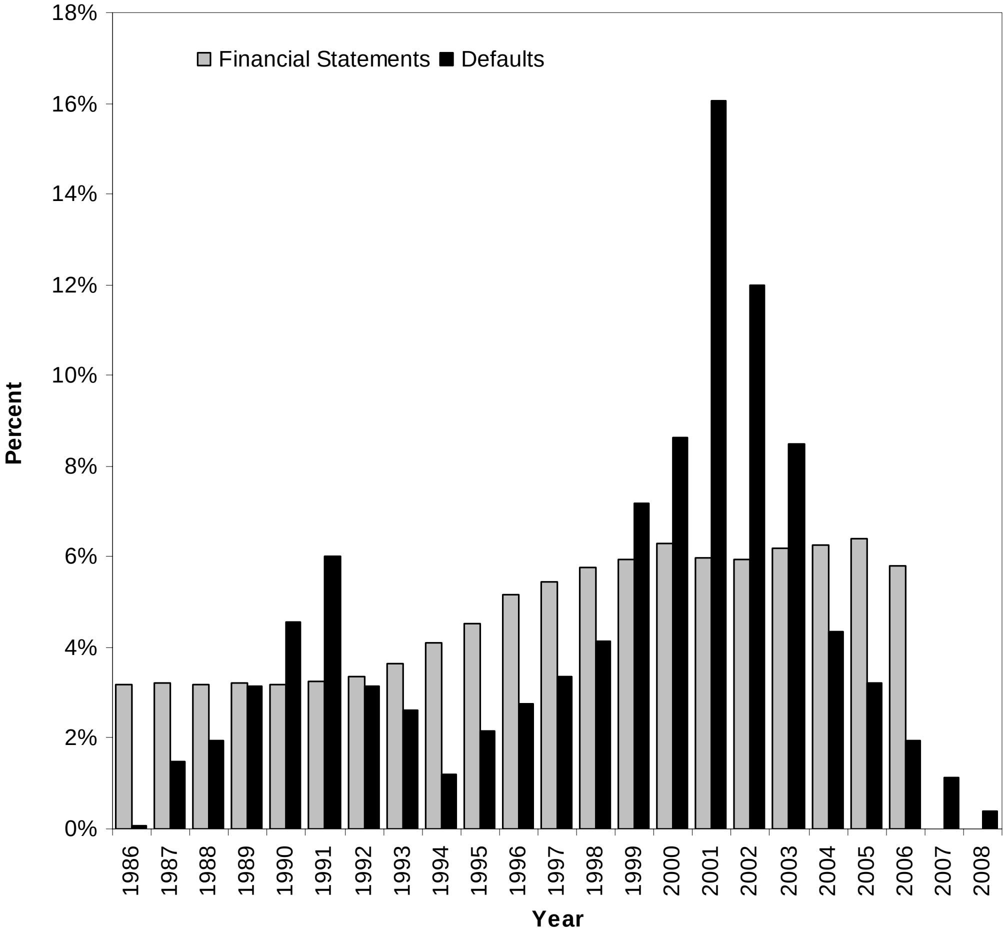

FIGURE 3 Distribution of Financial Statements and Defaults

TABLE 2 Information on Sample Data across Data Sources

Data Source	Period	No. of Firms	No. of Defaults	No. of Statements
CRD Sample	1991–2008	5,659	153	17,535
Compustat Sample	1986–2008	8,525	1,181	63,583

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 size. For example, if the database has few firms in one particular industry or in a particular size range without sufficient defaults in those groups, the model may not be a good default predictor. The Large Firm model assigns firms to 13 sectors by their Standard Industrial Classification (SIC) code or North American Industry Classification System (NAICS) code. Firms without industry information are grouped into an "Unassigned" category. Compared with the sector classification used in other v3.1 models, we separate CommHiTech into Communication and High Tech. We split MiningTransUtility into three sectors: Mining, Transportation, and Utilities. We also add two new sectors: Automobile and Health. We believe the new sector classification is more appropriate to the large firm target population. The flip side of having finer sector classification is that we have fewer defaults in each sector. The final set of sectors is a trade-off between economic intuition and reasonable number of defaults in each sector.

Figure 4 presents the distributions of the sample firms by industry and the proportion of defaults in each industry. Business Products is the largest sector with about 15% of the sample, and the Trade sector has more defaults than other sectors. Figure 5 presents the distributions by firm size measured as Assets. 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 smaller firms default more. Firms with assets between $100–$200 mm account for 27% of the sample and 36% of the defaults.

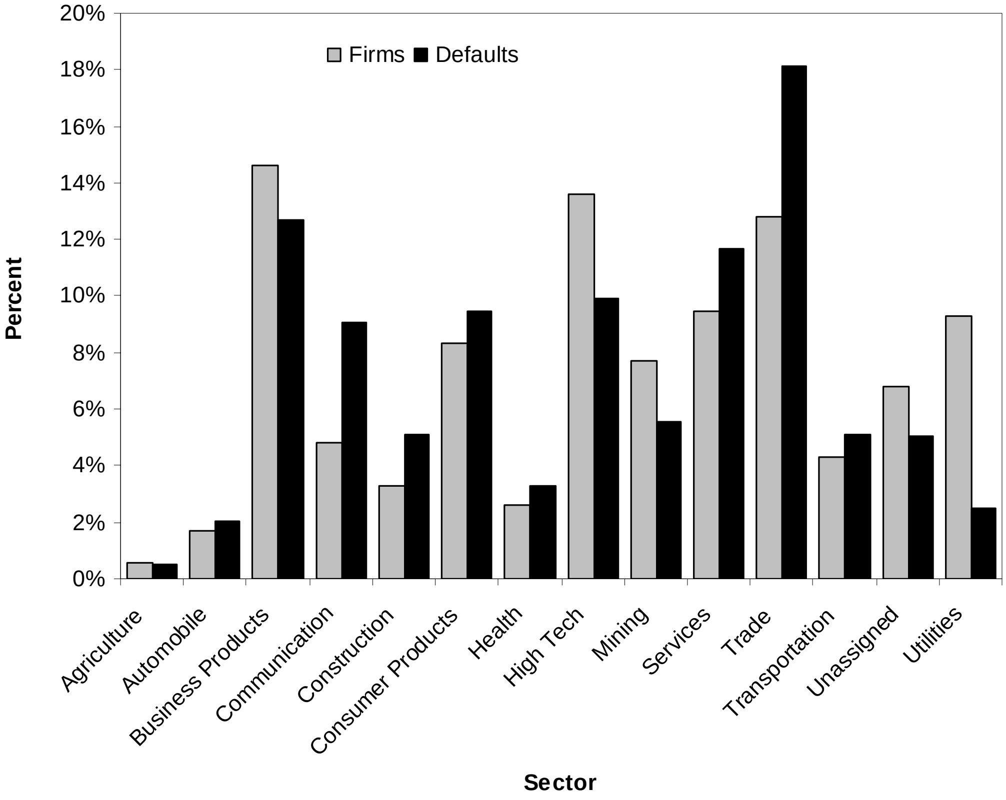

FIGURE 4 Distribution of Defaults and Firms by Industry

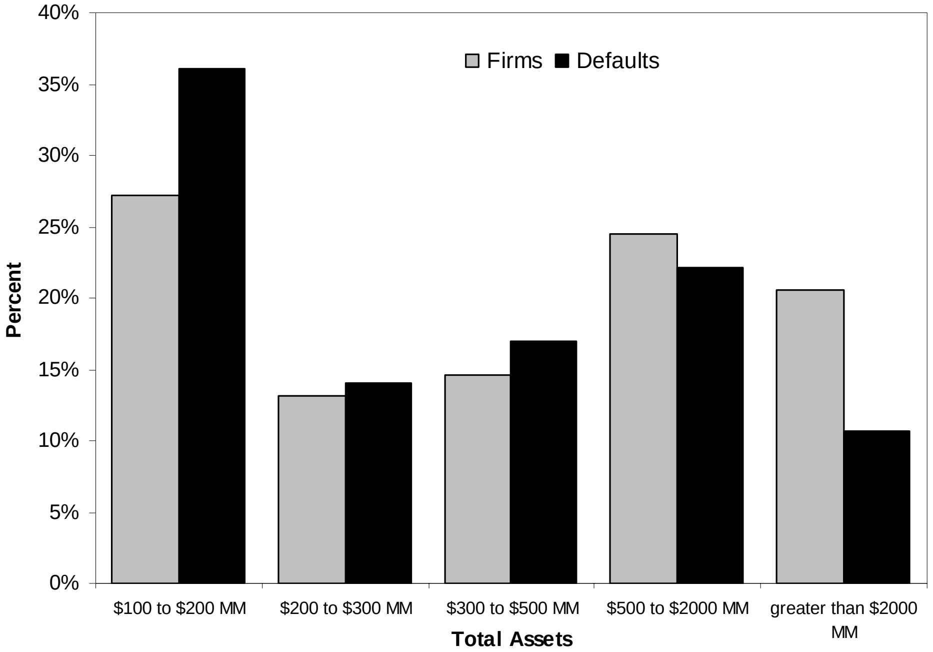

FIGURE 5 Distribution of Defaults and Firms by Size

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. The lack in default data may come from the data storage issues within financial institutions (e.g., defaulting companies being purged from the system after troubles begin), data collection issues (e.g., 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 (i.e., 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 is based on several sources.

- Loan loss provision data from the Organization for Economic Co-operation and Development (OECD).
- Bank charge-offs and delinquency rates data from Federal Reserve.
- Confirmation of the CDT exceeding the default rates observed in our development sample.

The multiple sources of external data led us to an estimate of 1.9% 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. We pick a 5-year CDT so that forward EDF values on average line up with realized EDF values. 6.8% 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 decrease in 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.

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.

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

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,

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, as is shown in Figure 6 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.

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[4] These variables are often ratios but not always. For example, one measures 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] By non-parametric, we mean that the $T(x_i)$ is a continuous function of x not requiring a specification of a closed (i.e., parametric) functional form. We estimate these transforms using a variety of local regression and density estimation techniques.

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.

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

- Is the variable readily available?
- Are the definitions of the inputs to the variable ambiguous?
- Is the meaning of the variable intuitive?
- Does the variable predict default activity?
- Is the variable generally not correlated with other variables in the model?

TABLE 3 Groupings of Financial Statement Ratios

Activity ratios measure a firm's operating efficiency. These ratios typically involve working capital items such as inventory, accounts receivable, or accounts payable. → 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 typically include 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 or debt to assets. → High leverage increases the probability of default.

Liquidity variables include cash and marketable securities to assets or liabilities, 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 is measured by total assets or sales deflated to a specific base year to ensure comparability. → Large firms default less often.

TABLE 4 Financial Statement Variables in RiskCalc v3.1 NA Large Firm Model

Category	Definition
Activity	Change in Working Capital Accruals
Debt Coverage	EBITDA to Interest Expense[6]
Growth	Sales Growth Change in Leverage
Leverage	Total Debt/Total Assets
Liquidity	Cash & Marketable Securities to Current Liabilities
Profitability	Return on Assets (ROA) Change in ROA
Size	Total Assets (in 2007 U.S. dollars)

Variable Transforms

After the variables are selected, they are transformed into a preliminary EDF value. Figure 6 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).

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 Change in Working Capital Accruals is U-shaped (Figure 6). Both rapid increase and decrease in working capital accruals indicate higher default probabilities. Working capital accruals is the difference between non-cash current assets and non-debt current liabilities, scaled by sales. Non-cash current assets typically include inventory, accounts receivable, and prepaid expense. Non-debt current liabilities typically include accounts payable and unearned revenue. A rapid increase in working capital accruals may come from a pile-up in inventories or accounts receivables. A rapid decrease may result from write-offs of inventories and accounts receivable, or increase in accounts payable. Healthy firms tend to see stable change in working capitals relative to sales. Similar measures have long been used in accounting literature to measure accounting quality.[7]
- For the **Debt Coverage** group, the transform for EBITDA to Interest Expense is downward-sloping (Figure 6). 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 Sales Growth and Change in Leverage (Figure 6). The transforms of Sales Growth is U-shaped, indicating that large increases or decreases in sales are associated with higher default probabilities, while stable sales year-upon-year decrease the probability of default. The transform of Change in Leverage is upward-sloping. A large increase in leverage is associated with higher default probabilities.
- For the **Leverage** group, the transform for the Total Debt to Total Assets ratio is upward-sloping (Figure 6). The slope of the transform increases as leverage increases. This indicates that firms with more leverage have higher default probabilities.
- For the **Liquidity** group, the transform of Cash & Marketable Securities to Current Liabilities is downward-sloping (Figure 6), indicating that firms with more cash holdings to cover their current liabilities are associated with lower default probabilities.
- For the **Profitability** group, the transform of Return on Assets is downward-sloping (Figure 6). The slope of the transform decreases as profitability increases. This indicates that firms with large Return on Assets have lower default

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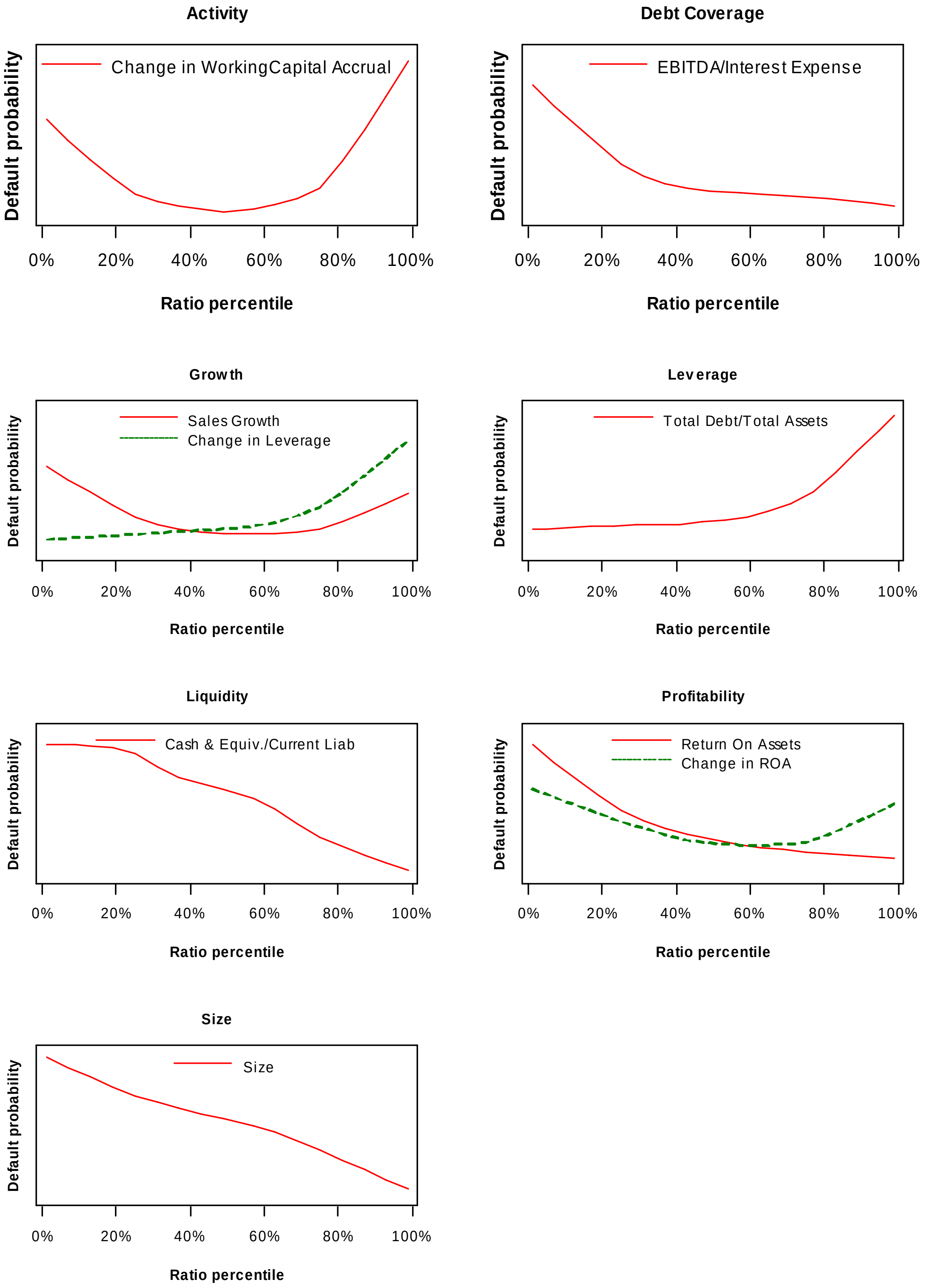
[6] EBITDA is defined as the following: Operating Profit (or Loss) + Amortization and Depreciation.

[7] For further details, see Sloan (1996), Do Stock Prices Fully Reflect Information in Cash Flows and Accruals About Future Earnings? The Accounting Review, Volume 71, Issue 3.

probabilities. The transform of Change in ROA is U-shaped. Very large increase or decrease in ROA indicates high default probability.

- For the **Size** group, the transform of Size is downward-sloping (Figure 6), indicating that larger firms have lower default probabilities.


Activity

Debt Coverage

Growth

Leverage

Liquidity

Profitability

Size

FIGURE 6 Transformations of Financial Statement Variables in RiskCalc v3.1 NA Large Firm Model

3.2 Model Weights

Importance

The relative value of each variable used in calculating an EDF credit measure is important in understanding a company's risk. The non-linear nature of the model makes the weight of the variables more difficult to determine, because the actual impact on the risk depends on the coefficient, the transformation shape, and the percentile ranking of the company. The model weights, therefore, are calculated based on the average EDF value for the transformation and its standard deviation. A variable with a flat transformation could have a low weight, even if the coefficient is large (Figure 6).

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 5 presents the weights in the RiskCalc v3.1 Large Firm model. The most important category is Profitability, with a weight of 30.94% at the 1-year horizon. Size is the most important category at the 5-year horizon.

TABLE 5 Risk Drivers in RiskCalc v3.1 Large Firm Model

Category	Weights: 1–Year	Weights: 5–year
Activity	2.29%	12.50%
Debt Coverage	17.04%	18.79%
Growth	10.34%	14.66%
Leverage	14.14%	17.73%
Liquidity	14.60%	4.56%
Profitability	30.94%	9.11%
Size	10.65%	22.66%

3.3 Industry Adjustments

For the same set of financials, different industries may have different default probabilities. The EDF value is adjusted for industry effects. Table 6 presents the increase in model power and accuracy from introducing industry controls. 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 important in producing an accurate EDF credit measure.

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

	1-year Model		5-year Model	
	Accuracy Ratio	Increase in Log Likelihood	Accuracy Ratio	Increase in Log Likelihood
Without Industry Controls	77.8%	---	53.6%	---
With Industry Controls	78.4%	50.13***	56.2%	89.93***

*** Indicates significance at the 1% level.

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.[8] Table 7 presents the average EDF value by industry for the development sample.

TABLE 7 Average EDF Credit Measured by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Agriculture	2.7%	8.1%
Automobile	2.3%	7.4%
Business Products	1.6%	4.7%
Communication	3.9%	12.8%
Construction	2.8%	9.7%
Consumer Products	2.1%	7.0%
Health	2.4%	7.5%
High Tech	1.5%	4.5%
Mining	1.4%	3.8%
Services	2.5%	8.4%
Trade	2.6%	8.8%
Transportation	1.9%	6.3%
Unassigned	1.8%	6.7%
Utilities	0.5%	1.1%

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, the RiskCalc v3.1 Large Firm model 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.[9] 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 Large Firm 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 based on the mean DD factor across industries.

Figure 7 presents the DD factor based on all public North American firms and contrasts that to the speculative grade default rate extracted from Moody's Investors Service default studies.[10] For all three recessions, the speculative default

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

[9] cf. Bohn and Crosbie, 2003.

[10] cf. Hamilton and Varma, 2003.

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 DD factor anticipates both the recession and the increase in defaults measured by the speculative grade default rate. Therefore, it is a forward-looking measure of default risk in an industry.

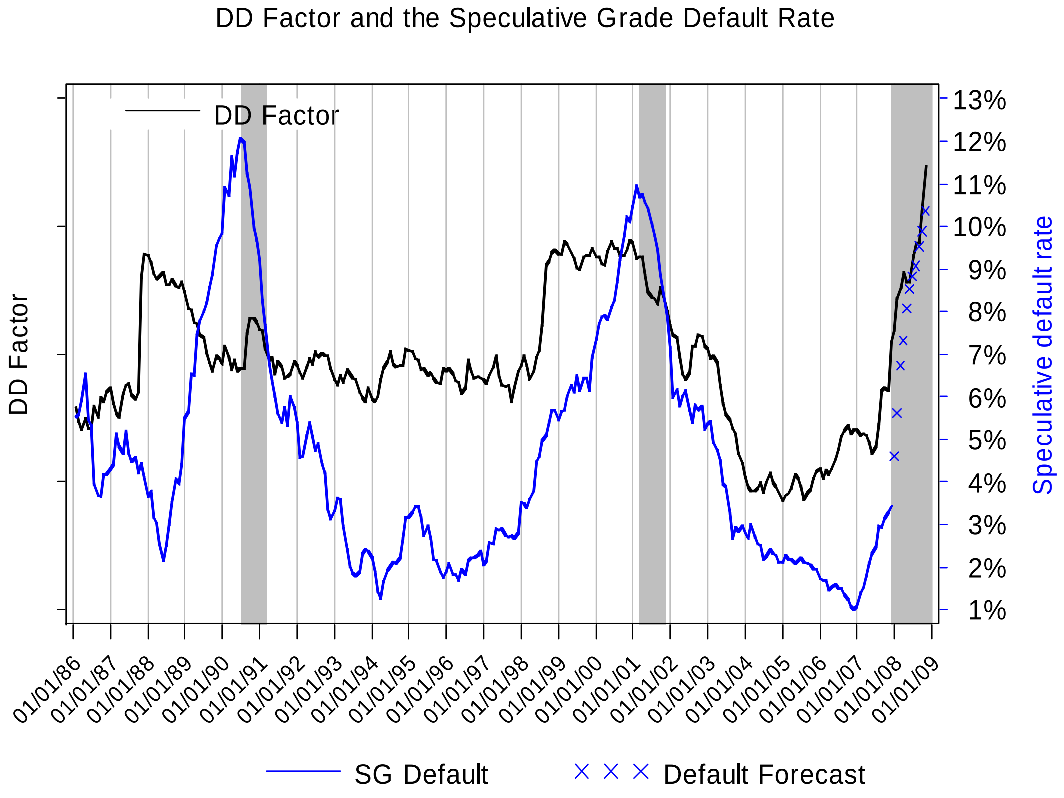

FIGURE 7 DD Factor and Speculative Grade Default Rate: 1986–2009

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 (i.e., 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 in general 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 for the RiskCalc v3.1 Large Firm model versus alternative models. The Large Firm model's performance improves by 4.2% at the 1-year horizon, and 5.2% at the 5-year horizon compared to RiskCalc v3.1 U.S./Canada.

Table 8 also contains p-values for the statistical test to display how the difference between the accuracy ratios from the Large Firm model and the benchmark is equal to zero. A p-value of less than .05 indicates we can reject the hypothesis that the difference in the accuracy ratios is equal to zero with 95% confidence.

Relative to other available alternatives, the results were more dramatic. The Large Firm model outperformed the Z-score model by 32.9% at the 1-year horizon and 35.2% at the 5-year horizon.

TABLE 8 Power Enhancements of the RiskCalc v3.1 Large Firm Model[11]

Model	**1-year Model**		**5-year Model**	
	Accuracy Ratio	**p-value**	**Accuracy Ratio**	**p-value**
RiskCalc Large Firm	79.7%	---	58.6%	---
RiskCalc U.S./CAN	75.5%	<.0001	53.4%	<.0001
Z-score	46.8%	<.0001	23.4%	<.0001

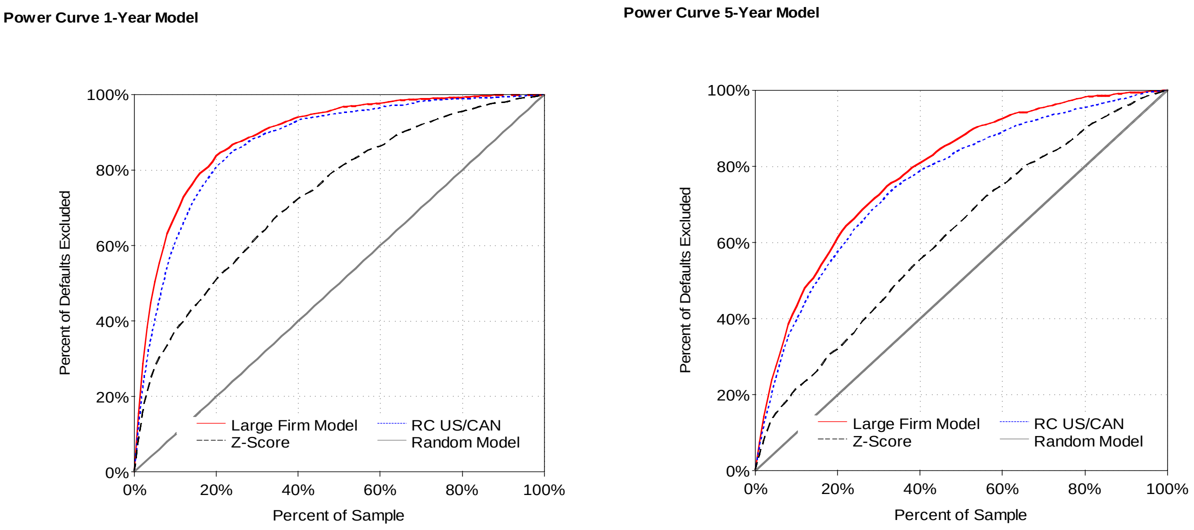

FIGURE 8 Power of Alternative Models (1- and 5-year)—Large Firm Model

Figure 8 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 8. The power improvements are uniformly significant across different regions of the distribution relative to RiskCalc v3.1 U.S./Canada and Z-score.

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 in Table 9 for the financial statement ratios in the model and the variance inflation factors (VIF) in Table 10 are computed on the transformed variables in Figure 6.

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[11] The reported accuracy ratios are based on CCA EDF values. When FSO EDF values are used, NA Large Firm model has an accuracy ratio of 78.6% (56.4%) at 1-year horizon (5-year horizon); U.S./CAN has an accuracy ratio of 74.6% (50.6%) at 1-year horizon (5-year horizon).

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

	Change in Working Capital Accruals	EBITDA/Interest Expense	Sales Growth	Change in ROA	Change in Leverage	Total Debt /Total Assets	Cash & Marketable Securities/Current Liabilities	Return on Assets	Real Total Assets
Change in Working Capital Accruals	1.00								
EBITDA/Interest Expense	0.14	1.00							
Sales Growth	0.21	0.20	1.00						
Change in ROA	0.18	0.16	0.26	1.00					
Change in Leverage	0.08	0.08	0.05	0.16	1.00				
Total Debt/Total Assets	0.03	0.63	0.03	-0.01	0.20	1.00			
Cash & Marketable Securities/Current Liabilities	-0.10	0.18	-0.06	-0.12	0.06	0.33	1.00		
Return On Assets	0.16	0.69	0.25	0.29	0.20	0.34	0.08	1.00	
Real Total Assets	0.09	-0.01	0.05	0.15	-0.01	-0.13	-0.10	0.01	1.00

The VIF levels in 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, however, measures only the relationships between two variables. The highest VIF level is 2.44, indicating that the collinearity between the variables is low.[12] The two ratios with the highest correlation are EBITDA to Interest Expense and Return on Assets in Table 9.

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

TABLE 10 Variance Inflation Factors

Variable	VIF
EBITDA/Interest Expense	2.44
Return on Assets	2.42
Total Debt/Total Assets	1.48
Change in ROA	1.46
Sales Growth	1.22
Cash & Marketable Securities/Current Liabilities	1.22
Change in Leverage	1.18
Change in Working Capital Accruals	1.17
Real Total Assets	1.16

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 11 and Table 12 present the power comparisons by sector for the 1-year and 5-year models, respectively. The highest power in the 1-year horizon (Table 11) is found in Communication (83.6%), while the lowest is found in Agriculture (47.2%). At the 5-year horizon (Table 12), the highest power is in Communication (74.1%), and the lowest is in Unassigned (38.2%).

TABLE 11 Power by Industry 1-year: Large Firm Model

	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
Agriculture	0.5%	47.2%	59.3%	0.2518	75.9%
Automobile	2.1%	76.5%	75.2%	0.7663	65.8%
Business Products	12.8%	80.6%	77.8%	0.0231	62.4%
Communication	9.1%	83.6%	81.8%	0.1119	74.7%
Construction	5.1%	77.9%	80.1%	0.3446	62.7%
Consumer Products	9.3%	82.0%	80.2%	0.159	67.7%
Health	3.3%	78.0%	80.3%	0.2047	65.6%
High Tech	9.9%	79.3%	73.5%	<.0001	62.7%
Mining	5.6%	80.0%	75.1%	0.0018	66.5%
Services	11.8%	76.5%	73.6%	0.0218	53.5%
Trade	18.1%	78.3%	75.8%	0.0314	48.1%
Transportation	5.0%	80.0%	79.0%	0.5193	50.3%
Unassigned	5.1%	59.1%	63.6%	0.1054	45.8%
Utilities	2.5%	81.6%	79.5%	0.5552	58.8%

TABLE 12 Power by Industry 5-year: Large Firm Model

	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
Agriculture	0.5%	48.9%	55.3%	0.6837	73.0%
Automobile	2.0%	58.0%	58.3%	0.9633	41.6%
Business Products	12.2%	60.3%	56.2%	0.0936	38.1%
Communication	8.6%	74.1%	70.8%	0.08	49.5%
Construction	5.0%	51.1%	60.2%	0.0247	44.6%
Consumer Products	9.3%	59.3%	59.6%	0.915	42.8%
Health	3.3%	52.3%	62.6%	0.0249	40.8%
High Tech	10.4%	54.6%	50.9%	0.0958	29.9%
Mining	5.3%	55.2%	47.9%	0.0431	39.2%
Services	12.8%	56.3%	54.7%	0.4387	30.7%
Trade	17.9%	48.0%	48.2%	0.8965	31.3%
Transportation	4.6%	42.5%	49.2%	0.1778	20.9%
Unassigned	5.8%	38.2%	46.4%	0.0752	30.5%
Utilities	2.4%	64.1%	52.9%	0.0671	13.0%

Table 13 and Table 14 present the power comparisons by firm size (Assets in 2007 U.S. dollars) for the 1-year and 5-year models, respectively. For firms between 100mm and 200mm, Large Firm model has about the same power as v3.1 U.S./Canada at 1-year horizon and even under-performs v3.1 U.S./Canada model at the 5-year horizon. For larger firms, Large Firm model performs significantly better. The highest powers in the 1-year and 5-year are both found for firms greater than 2 billion, while the lowest powers in the 1-year and 5-year are both found in the 100 mm to 200 mm range.

TABLE 13 Power by Size (Total Assets in 2007 U.S. dollars): 1-year Large Firm Model

Range	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
$100 MM to 200 MM	32.6%	71.6%	70.9%	0.4523	50.8%
$200 MM to 300 MM	16.2%	76.9%	74.4%	0.0503	49.2%
$300 MM to 500 MM	18.0%	77.7%	73.5%	<.0001	50.0%
$500 MM to 2 billion	23.0%	79.6%	75.5%	<.0001	47.9%
> $2 billion	10.2%	86.0%	81.3%	0.0003	53.2%

TABLE 14 Power by Size (Total Assets in 2007 U.S. dollars) 5-year Large Firm Model

Range	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
$100 MM to 200 MM	33.0%	55.9%	58.9%	0.0193	37.6%
$200 MM to 300 MM	18.9%	57.0%	55.3%	0.312	32.9%
$300 MM to 500 MM	19.2%	56.6%	53.9%	0.0848	32.0%
$500 MM to 2 billion	20.9%	63.8%	57.7%	<.0001	34.9%
> $2 billion	8.0%	67.3%	56.6%	0.0001	29.6%

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 15 and Table 16 present the results from this analysis at the 1- and 5-year horizons, respectively. The AR of the RiskCalc v3.1 Large Firm model is compared with RiskCalc v3.1 U.S./Canada for each year.

TABLE 15 Power over Time: 1-year Horizon, Large Firm Model

Year	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm– U.S./CAN p-value	AR Z-Score
1986	2.3%	68.8%	70.8%	0.4569	54.3%
1987	2.4%	67.0%	66.1%	0.8206	39.3%
1988	4.9%	70.2%	63.9%	0.0011	39.2%
1989	5.7%	78.4%	75.0%	0.0861	43.0%
1990	4.1%	78.0%	74.4%	0.1032	42.7%
1991	2.8%	77.0%	72.9%	0.0884	34.4%
1992	1.9%	73.9%	62.3%	0.025	27.7%
1993	2.1%	69.2%	56.1%	<.0001	16.7%
1994	2.7%	64.5%	57.7%	0.009	24.3%
1995	3.0%	76.2%	71.6%	0.0757	24.5%
1996	3.9%	74.3%	72.2%	0.3264	38.5%
1997	6.2%	69.6%	67.9%	0.361	44.4%
1998	8.5%	69.1%	67.5%	0.4072	40.2%
1999	12.9%	66.9%	63.8%	0.0353	41.6%
2000	13.6%	70.5%	68.0%	0.0672	54.4%
2001	9.9%	72.7%	67.0%	0.0001	49.9%
2002	5.3%	69.8%	61.6%	0.0001	43.4%
2003	3.6%	66.2%	59.4%	0.0016	34.5%
2004	2.4%	74.4%	66.9%	0.0049	39.9%
2005	1.4%	84.2%	75.3%	0.0009	30.8%
2006	0.6%	79.0%	78.8%	0.967	41.0%

TABLE 16 Power over Time: 5-year Horizon, Large Firm Model

Year	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm– U.S./CAN p-value	AR Z-Score
1986	4.3%	57.1%	45.4%	<.0001	20.9%
1987	4.5%	62.7%	55.9%	0.0145	31.1%
1988	4.8%	66.5%	56.3%	<.0001	32.2%
1989	4.5%	71.5%	63.9%	0.0011	33.9%
1990	3.2%	64.7%	56.3%	0.0046	26.8%
1991	2.5%	63.3%	58.4%	0.1003	18.5%
1992	2.4%	58.6%	45.4%	0.0003	8.3%
1993	2.7%	60.4%	45.4%	<.0001	8.1%
1994	3.5%	59.3%	49.3%	0.0002	10.3%
1995	4.7%	53.1%	52.9%	0.9374	20.0%
1996	7.2%	55.2%	54.1%	0.564	26.8%
1997	8.9%	52.7%	52.8%	0.9468	33.1%
1998	10.2%	55.1%	55.3%	0.9101	36.2%
1999	11.1%	56.6%	55.6%	0.5272	36.2%
2000	9.7%	56.2%	57.5%	0.4802	44.4%
2001	6.8%	62.5%	57.8%	0.0116	42.0%
2002	4.0%	57.7%	52.5%	0.0355	32.8%
2003	2.5%	61.5%	55.3%	0.0542	30.1%
2004	1.6%	62.9%	61.3%	0.6767	32.3%
2005	0.7%	74.8%	73.3%	0.7858	35.1%
2006	0.3%	66.6%	77.4%	0.1623	41.0%

4.5 Power Performance by Data Source and Country

Table 17 and Table 18 present the power comparison results by data source. We collect the sample data from two sources: the Moody's KMV CRD for private firm data, and Compustat for public firm data. For public firm data, the Large Firm model is more powerful than the U.S./Canada models (AR 82.2% versus 76.7% at the 1-year horizon; 62.2% versus 52.2% at the 5-year horizon). However, for the private firm data, the Large Firm model underperforms against the U.S./Canada models (AR 59.1% versus 63.1% at the 1-year horizon; 49.2% versus 56.9% at the 5-year horizon). A closer look into the data reveals that firms from the CRD sample are smaller than those from the Compustat sample, with mean total assets of 367 million versus 2,899 million, and median total assets of 196 million versus 588 million.

As shown in Table 13 and Table 14, the Large Firm model has better power for relatively larger firms. Size difference can explain the inconsistency in the power comparison observed across data sources. In addition, Compustat data are of higher quality than CRD data. All financial statements compiled by Compustat are publicly-available and mostly audited by large accounting firms. Financial statements in CRD are submitted by private firms to the lending banks and may or may not be audited. Compared with public firm statements, private firm statements do not benefit from the supervision of the SEC or the stock exchanges, or from the scrutiny of public investors.

The private firm data also have a lower default rate than the public firm data, indicating that missing defaults may be a more severe issue for the private firm data. The difference in data quality may explain the differences in power across the models on the two populations. Data quality may also be the reason that the ARs for the private firm sample (CRD) are lower than those for the public firm sample (Compustat).

TABLE 17 Power by Data Source: 1-year Horizon, Large Firm Model

Data Source	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
CRD (Private)	10.8%	59.1%	63.1%	0.0298	38.5%
Compustat (Public)	89.2%	82.2%	76.7%	<.0001	47.0%

TABLE 18 Power by Data Source: 5-year Horizon, Large Firm Model

Data Source	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
CRD (Private)	12.8%	49.2%	56.9%	0.0031	32.9%
Compustat (Public)	87.2%	62.2%	52.5%	<.0001	20.4%

We also look at power comparison by country. The numbers of firms and defaults from Bahamas, Bermuda, British Virgin Islands, Cayman Islands, and Panama are too small to produce a meaningful accuracy ratio. In Table 19 and Table 20, we present the results only for Canada and the U.S. For both countries, the Large Firm model outperforms the U.S./Canada model and the Z-score significantly, at both the 1-year and 5-year horizons.

TABLE 19 Power by Country: 1-year Horizon, Large Firm Model

Data Source	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
Canada	10.8%	77.5%	68.2%	0.0007	49.7%
U.S.	89.2%	79.7%	76.4%	<.0001	47.4%

TABLE 20 Power by Country: 5-year Horizon, Large Firm Model

Data Source	Percentage of Defaults	AR Large Firm	AR U.S./CAN	Large Firm: U.S./CAN p-value	AR Z-Score
Canada	6.2%	55.7%	48.9%	0.094	32.9%
U.S.	93.8%	58.6%	54.4%	<.0001	24.1%

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

The model exhibits a high degree of power in distinguishing good credits from bad ones (Table 8), but whether this power is attributable to the overall model effectiveness or the impact of a particular subsample 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 subsamples that exhibit the identical overall default rate and are temporally and cross-sectionally independent. The model is then run on *k*-1 subsamples and these parameter estimates are used to score the *k*-th subsample. This procedure is repeated for all possible combinations, and the *k* scored out-of-sample subsamples are put together to calculate an accuracy ratio on this combined data set.

Table 21 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 v3.1 U.S./Canada. Figure 9 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 21 RiskCalc v3.1 Large Firm Model *k*-Fold Test Results

	Out-of-sample AR		**RiskCalc U.S./CAN**	
	1-year AR	**5-year AR**	**1-year AR**	**5-year AR**
Subsample 1	76.5%	62.4%	68.6%	53.5%
Subsample 2	73.6%	59.6%	66.7%	53.1%
Subsample 3	73.8%	61.3%	70.2%	55.6%
Subsample 4	74.9%	61.1%	66.9%	53.2%
Subsample 5	74.5%	62.1%	67.6%	55.5%
k-fold Overall	79.1%	55.1%	74.5%	49.6%
In-sample AR	79.3%	55.4%	---	---

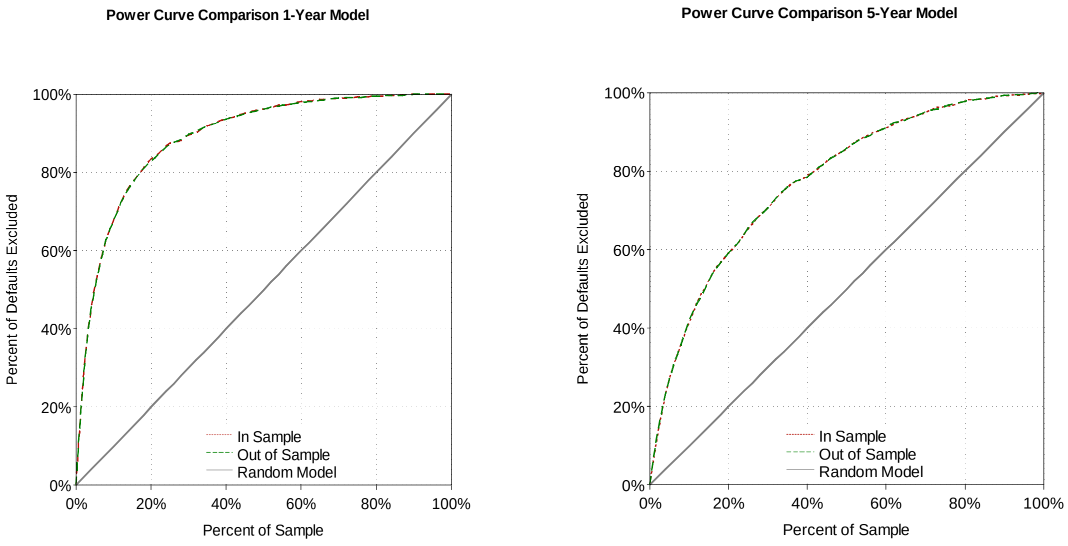

FIGURE 9 Out-of-sample Performance (1- and 5-year) Large Firm Model *k*-Fold

The *k*-Fold testing does not control for time dependence. Each of the *k* subsamples 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 9. The difference in AR between the overall in-sample and out-of-sample results is not larger than 30 basis points for the 1-year and the 5-year. Furthermore, the RiskCalc v3.1 Large Firm model outperforms RiskCalc v3.1 U.S./Canada in an out-of-sample context at both the 1- and 5-year horizons (Table 21).

4.7 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. Figure 10 presents the results from this analysis.

In the walk-forward test, the out-of-sample accuracy ratios are smaller than the in-sample accuracy ratios (Figure 10). However, the difference is small (1.2% at the 1-year horizon; 1.8% at the 5-year horizon).[13]

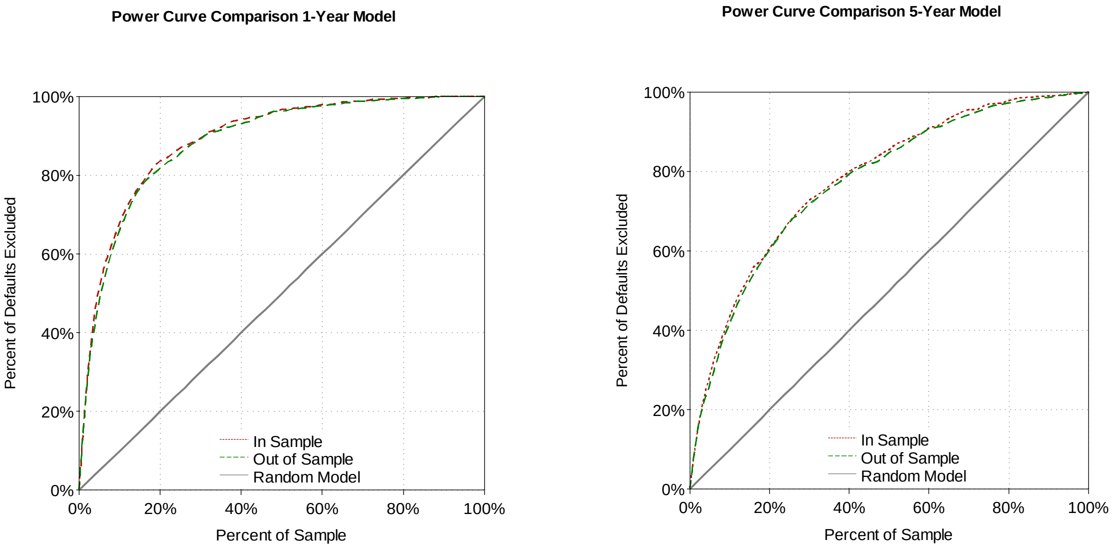

FIGURE 10 Out-of-sample Performance (1-year) Large Firm Model Walk-forward

4.8 Power Comparison: Large Firm Model and Public Firm Model

Figure 11 and Figure 12 compare the power curve between the RiskCalc v3.1 Large Firm model and the Moody's KMV Public Firm model (i.e., CreditEdge and CreditMonitor). Figure 11 uses a sample of firms with public listed equity and assets greater than $100 mm. At the 1-year horizon, the public firm model outperforms the Large Firm model (AR 84.2% vs. 79.1%), At the 5-year horizon the public firm model also has higher power (76.0% vs. 74.3%); however, the power curves cross in the middle, indicating that the public firm model does not strictly dominate the Large Firm model at this horizon. Figure 12 presents a sample of public firms with assets greater than $300 mm. For this sample, the public firm model outperforms the Large Firm model at both the 1- and 5-year horizons. In general, the Moody's KMV public firm model is more powerful than the RiskCalc v3.1 Large Firm model. For firms with equity price, we recommend using the Public Firm model.

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[13] The out-of-sample AR is 78% for the 1-year model, 3.4% higher than RiskCalc v3.1 US for the 1-year model.

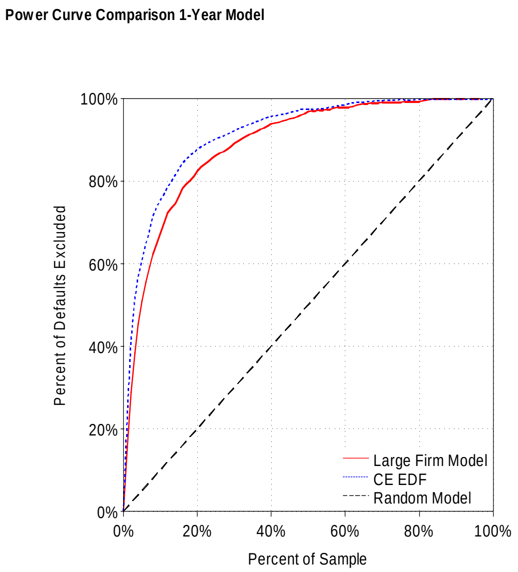


FIGURE 11 Power Curve Comparison: Large Firm Model vs. CreditEdge (Public Firm Model), for Publicly Listed Firms with Assets Greater than $100 MM

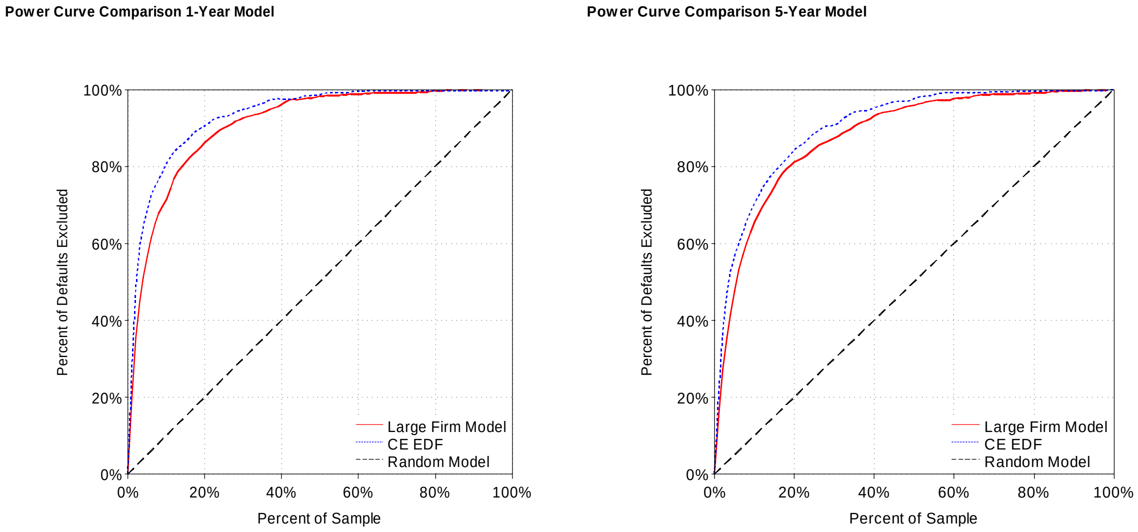


FIGURE 12 Power Curve Comparison: Large Firm Model vs. CreditEdge (Public Firm Model), for Publicly Listed Firms with Assets Greater than $300 MM

4.9 Model Calibration and Implied Ratings

To help interpret EDF credit measures, the model maps an EDF value 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 13 shows the distribution of the observations by rating category in the development sample for the FSO EDF credit measures over the full time period. Note that all categories between Aaa and Caa/C are utilized, and that less than 10% of the observations are in any one category. The distributions peak at Baa1 for the 1-year rating and Baa2 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.

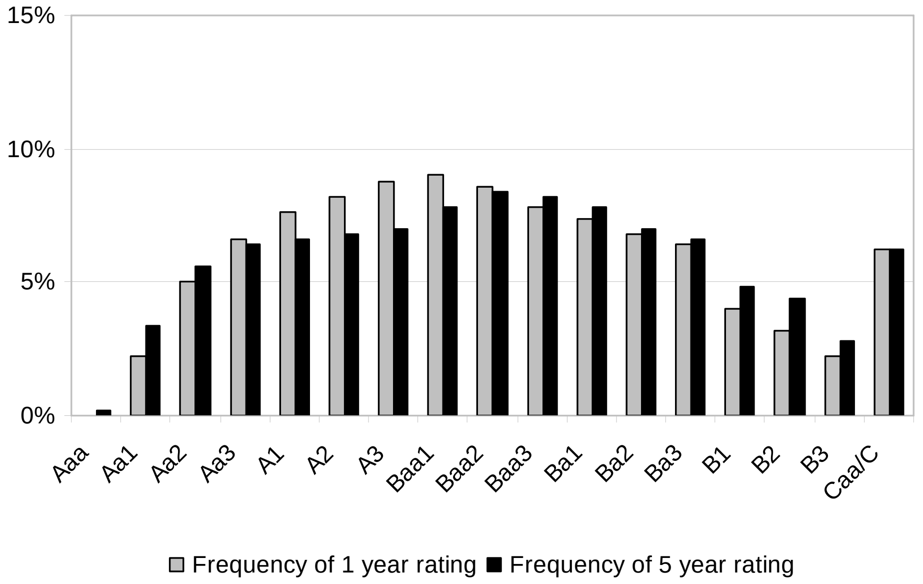


FIGURE 13 EDF-implied Ratings for the 1- and 5-year Models in the Development

4.10 Compare EDF Levels: Large Firm Model vs. v3.1 U.S. Model and Public Firm Model

This section compares the EDF levels from the RiskCalc v3.1 Large Firm model to those from the RiskCalc v3.1 U.S. model and the Moody's KMV Public Firm model (i.e., CreditEdge and CreditMonitor) on the same datasets. CCA EDF-implied ratings are used in the comparisons.

Figure 14 shows the median EDF values from v3.1 U.S. model and the Large Firm model each year between 1985 and 2006. We extend the sample to include firms with assets greater than $50mm for this exercise. For firms with asset great then $50mm, median EDF values from v3.1 U.S. model are 2–4 times those of the median EDF values from the Large Firm model.

To better understand the difference, we divide the sample into four categories, representing firms with the following ranges:

- $50mm–$150mm
- $150mm–$500mm
- $500mm–$2 billion
- Greater than $2 billion

We then compare the median EDF values for each subsample.

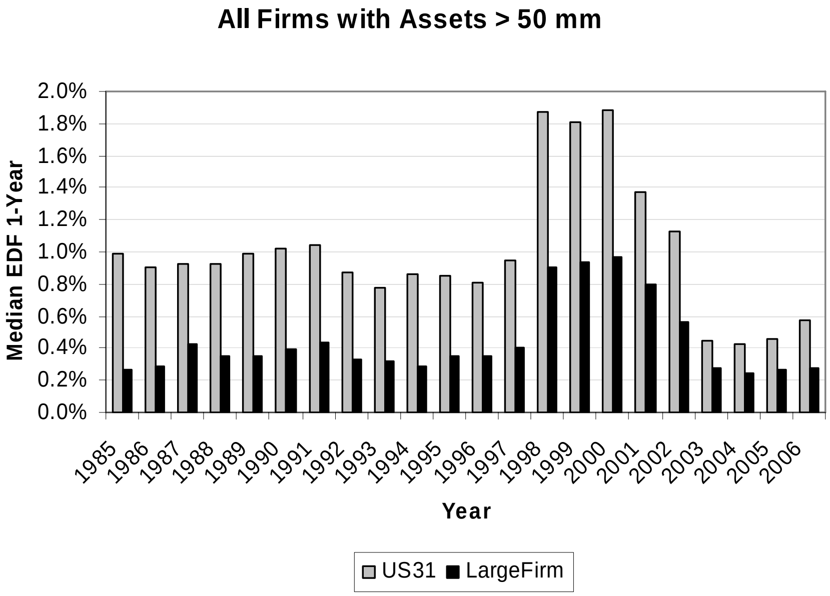
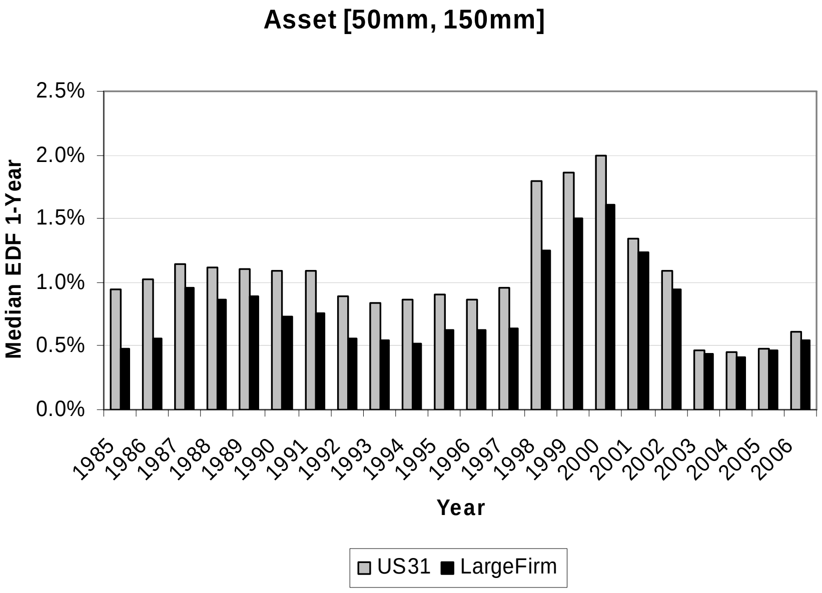


FIGURE 14 Median EDF Values across Years: Large Firm Model vs. U.S. v3.1, 1-year Horizon, All Firms with Assets [>$50 mm]

Figure 15 shows the results for firms between $50mm and $150mm, and the results for firms greater than $2 billion. For the smaller firms (between $50mm and $150mm), the difference between the median EDF values from these two models narrows significantly. While for larger firms with assets greater than $2 billion, the difference is elevated. Unreported analysis confirms that the difference between U.S. v3.1 and the Large Firm model EDF values increase with firm size. Similar observation can be made for the 5-year EDF values.



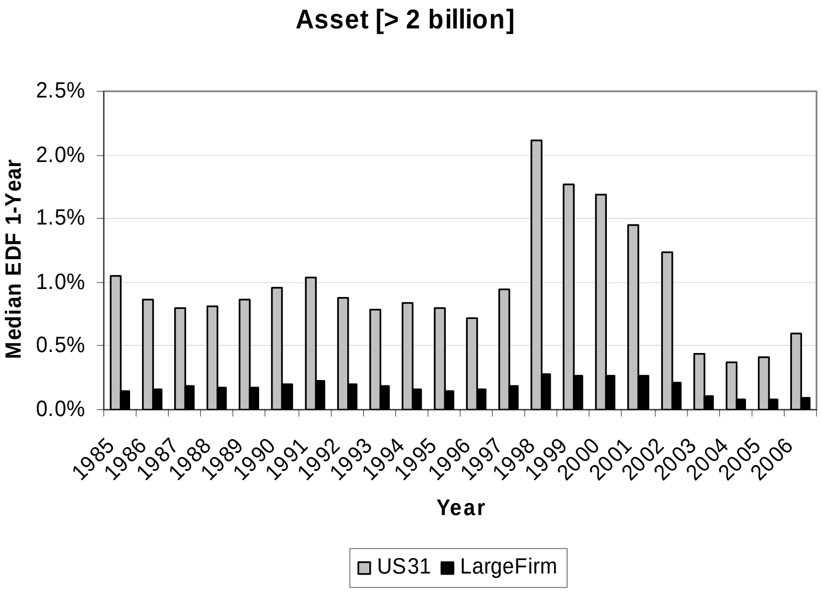


FIGURE 15 Median EDF Values across Years: Large Firm Model vs. U.S. v3.1, 1-year Horizon, Firms with Assets [$50mm to $150mm] and Firms with Assets [>$2 billion]

Figure 16 compares the EDF values from the Large Firm model with those from the Moody's KMV public firm model. The sample used in this exercise includes public firms with assets greater than $50 mm. EDF values from the two models are mostly comparable.

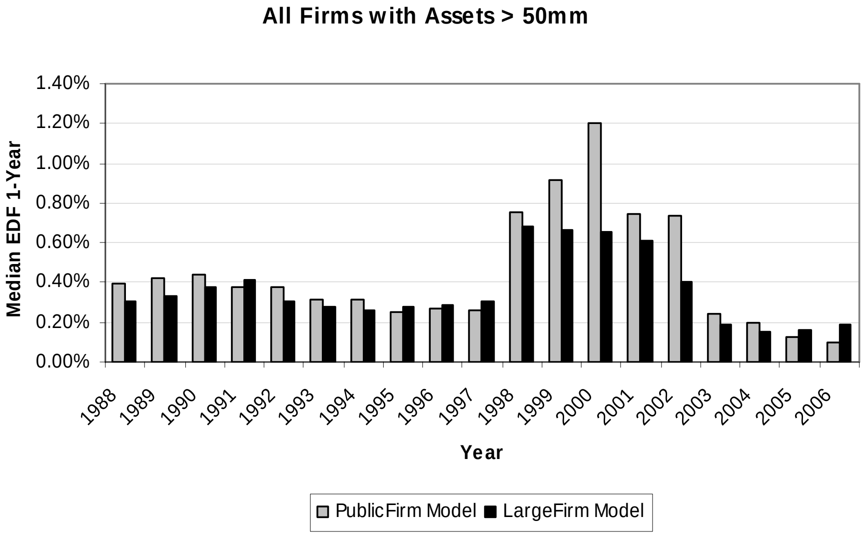
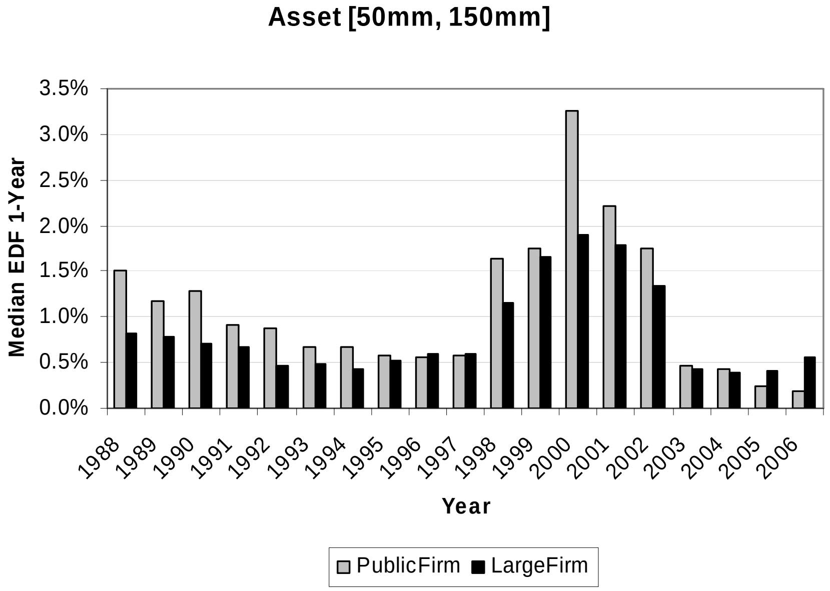


FIGURE 16 Median EDF values across Years: Large Firm Model vs. Public Firm Model, 1-Year Horizon, Firms with Assets [>$50 mm]

Figure 17 compares these two models for two groups: relatively small firms (assets between $50 mm and $150 mm), and relatively large firms (assets greater than $2 billion). For small firms, the EDF values from the two models are comparable. For large firms, they are comparable during the second half of the sample period (1999–2006); during the first half of the sample period (1988–1998), median EDF values from the Large Firm model are larger than those from the public firm model. The largest difference is in 1997 (median EDF 18 bps versus 8 bps).



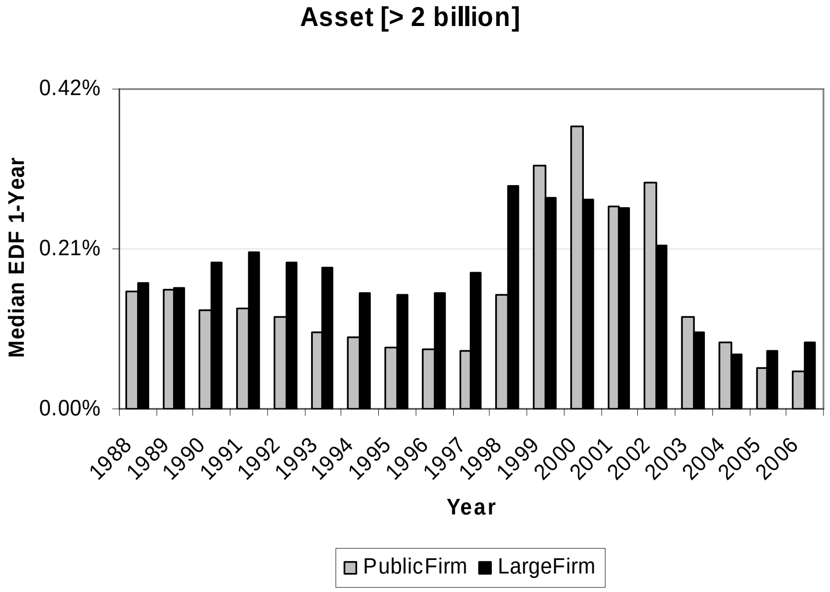


FIGURE 17 Median EDF Values across Years: Large Firm Model vs. Public Firm Model, 1-year Horizon, Firms with Assets [$50 mm to $150 mm] and Firms with Assets [>$2 billion]

5 FURTHER MODEL IMPROVEMENTS

This section outlines some other improvements to the model.[14]

5.1 Continuous Term Structure

We utilize the two-point estimates for 1- and 5-year estimates to fit a Weibull function, and thus achieve a continuous term structure of EDF values for each credit. In other words, users of the RiskCalc v3.1 Large Firm model 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 22).

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 22 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.[15] The third column of Table 22 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 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 22 presents the annualized EDF credit measures for years one to five. These credit measures are derived from the cumulative EDF values.

TABLE 22 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 v3.1 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

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

[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.

model variable at the point of evaluation. This feature is especially useful when addressing the topic of identifying variables to improve the EDF value of a company.

The relative sensitivity 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 EBITDA/Interest Expense ratio will change the risk of the company. It is about 280% (5-year) as sensitive as the average variables (Figure 18).

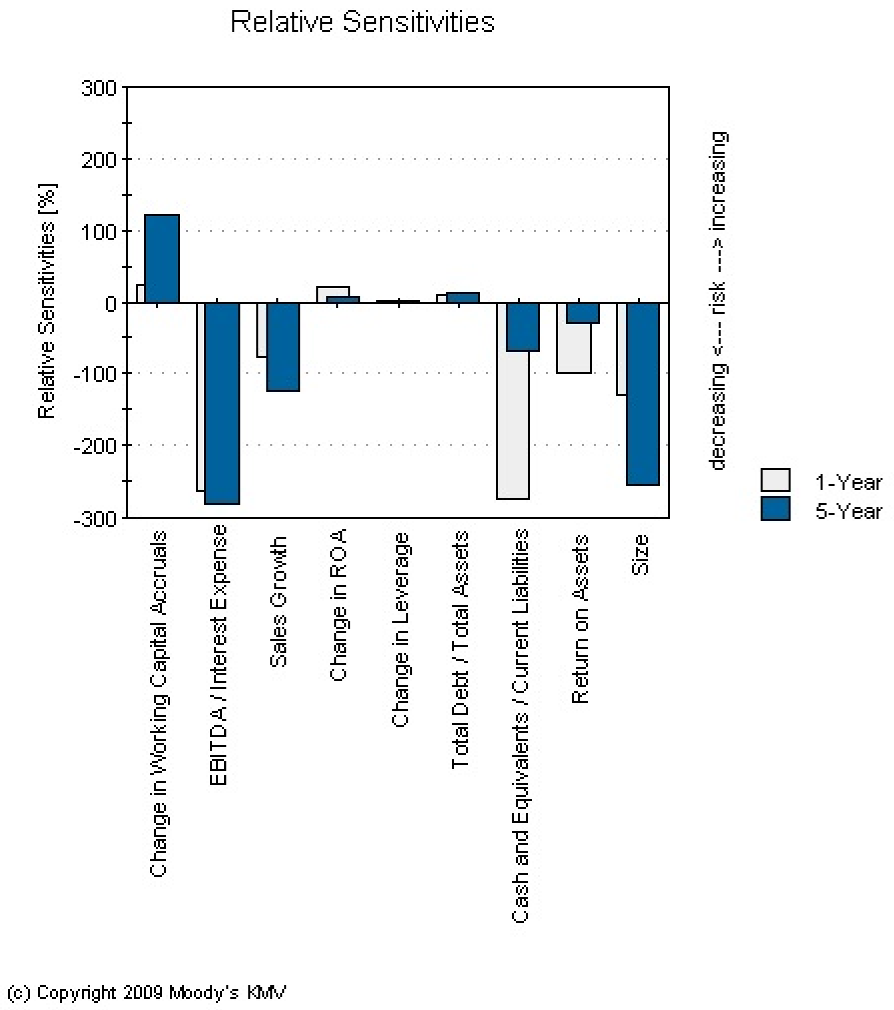

FIGURE 18 Relative Sensitivities for the RiskCalc v3.1 Model

5.3 New Analytical Tools: Percentile Map

The percentile map feature allows users to quickly isolate the problematic ratios for a given company. As shown in Figure 19, each horizontal bar represents a ratio that is labeled on the left (e.g., Sales Growth). The column on the right gives the actual value of the ratio. The percentage number within the horizontal bar graph represents what percentile the ratio was within the development sample (e.g., 30.7% of the development sample had Sales Growth less than 2.09%). The shading represents the risk level associated with the ratio: green is low risk, red is high risk, and grey is neutral risk. The variables shaded red to green are the "good" ratios for which higher values are associated with lower risk. The variables shaded green to red are the "bad" ratios for which higher values are associated with higher risk. Variables shaded red to green to red have a U-shaped relationship with default risk. For these variables, both high and low values indicate high risk while moderate values indicate low risk.

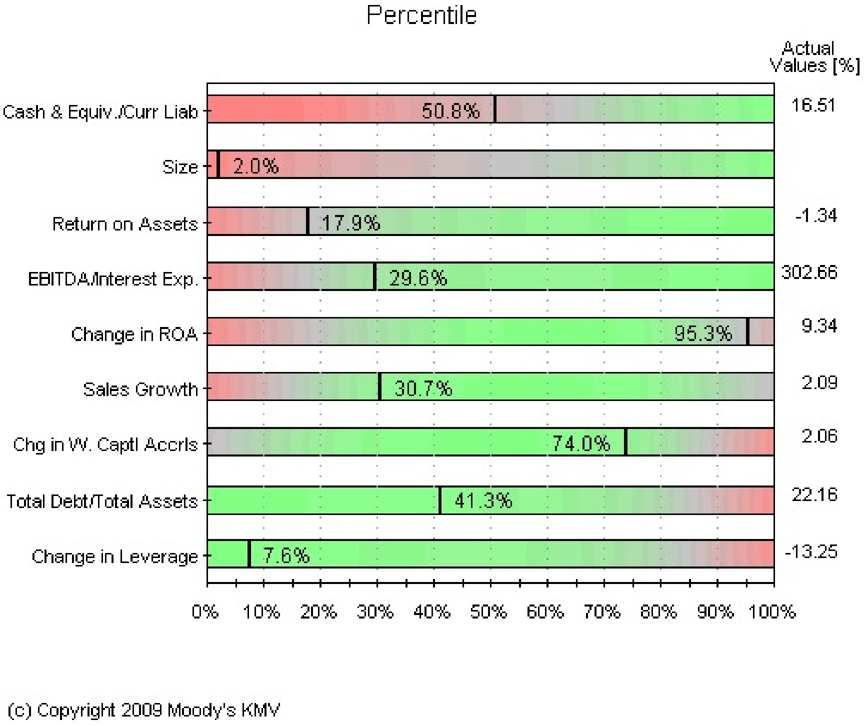

FIGURE 19 Percentile Map for the RiskCalc v3.1 Model

6 CONCLUSION

The RiskCalc v3.1 North America Large Firm model is based on a sample of firms larger than $100 mm in assets. Therefore, we selected a set of ratios and transforms more suitable to this population. Not surprisingly, the new model has a higher AR on a sample of large firms than the RiskCalc v3.1 U.S. and Canada models, which are calibrated on a sample of primarily small firms. Consistent with its better ability to rank order credit risk, the Large Firm model produces more spread-out EDF credit measures as well as implied ratings.

We demonstrate that the model exhibits strong performance both across industry sectors and size classifications as well as for different time periods. We also demonstrate how the power advantage is maintained both in- and out-of-sample. Nevertheless, the Moody's KMV Public Firm model (i.e., CreditEdge and CreditMonitor) exhibits higher power on the population with publicly traded common stock.

The RiskCalc v3.1 NA Large Firm model controls for differences in the default risk across industries. 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 model power and precision and allows users to monitor their portfolios on a monthly basis.

The EDF credit measures produced by the model align well with CreditEdge and CreditMonitor. The EDF credit measures are considerably lower than the EDF values produced by RiskCalc v3.1 U.S. or RiskCalc v3.1 Canada when used to evaluate large firms. The RiskCalc v3.1 NA Large Firm model is very useful for risk managers who want to evaluate the risk of large firms without listed equity equally with comparable firms that have listed equity.

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