

MOODY'S KMV RISKCALC™ V3.1 MEXICO

MODELING METHODOLOGY

ABSTRACT

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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 Mexico model.

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1 INTRODUCTION

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

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

RiskCalc v3.1 incorporates the structural and market-based comparables approach (used in the Moody's KMV 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.

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

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

The CCA adjustment 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 II.

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

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

2 DATA DESCRIPTION

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

2.1 Definition of Default

RiskCalc provides assistance to institutions and investors for determining the risk of default, missed payments, or other credit events. The proposals for the new Basel Capital Accord (BIS II) 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 Mexico, the events which we defined as defaults include 90-days past due and bankruptcy. At the calibration stage, the model outputs are adjusted to ensure a

consistent interpretation throughout the world. Specifically, the model outputs are converted into a term structure of actual default probabilities (1- through 5-year EDF credit measures).

2.2 Data Exclusions

Excluded Companies

The goal of the RiskCalc model is to provide an EDF credit measure for private Mexican 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 Mexican 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 Total Assets less than 50,000 pesos (in 2002 pesos), 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 to default. This is because their financial health often hinges on a particular development.¹
- Public sector and non-profit institutions – Government run companies' default risks are influenced by the states' or municipalities' unwillingness to allow them to fail. As a result, their financial results are not comparable to other private firms. Not-for-profit financial ratios are different from for-profit firms, particularly with regard to variables relating to net income.
- Start-up companies – Our experience has shown that the financial statements for a company during its first two years are extremely volatile and are a poor reflection of the creditworthiness of the company. The special nature of start-ups is reflected in the fact that many financial institutions have separate credit departments for dealing with these companies.

Excluded Financial Statements

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

2.3 Descriptive Statistics of the Data

Overview of the Data

The extensive data on both non-defaulting and defaulting companies contained in the Moody's KMV CRD increased since RiskCalc v1.0 was developed. Figure 1 presents the distribution of Mexican financial statements and defaults by year in the CRD. Table 1 summarizes the data used in the development, validation, and calibration of the RiskCalc v3.1 Mexico model.

¹ The success of many types of *project finance* firms depends largely on the outcome of a particular project. We recommend using separate models for such firms. At the time of writing, this characteristic is explicitly recognized within the proposals for the new Basel Capital Accord.

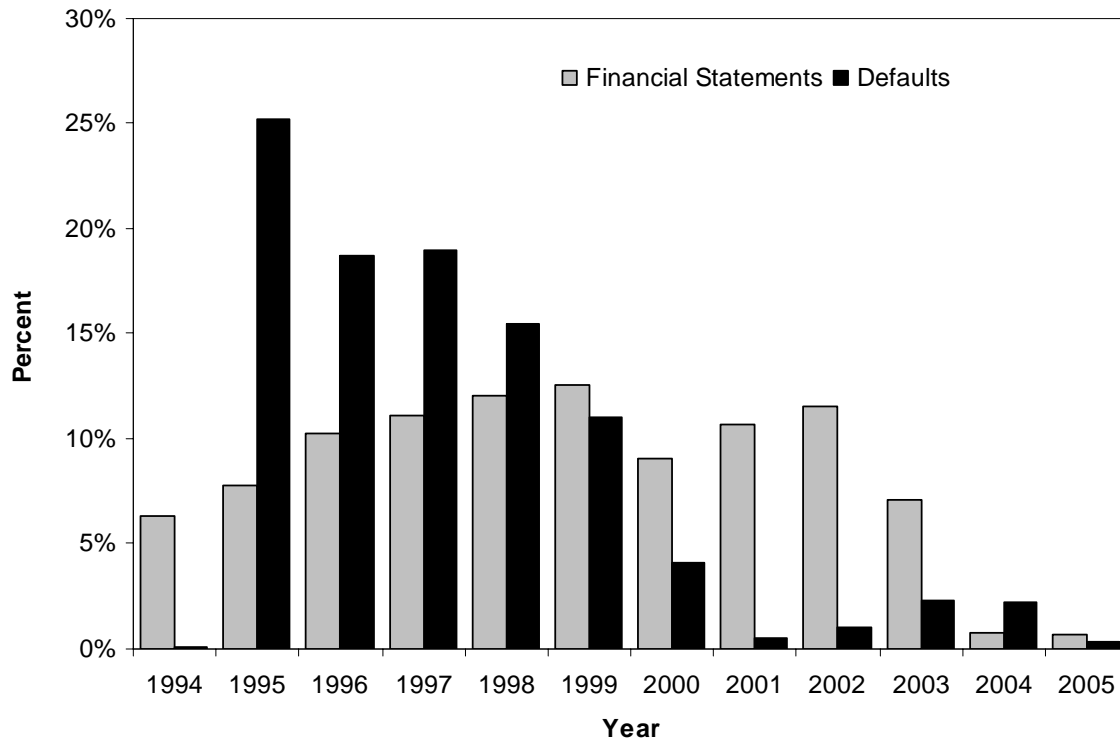


FIGURE 1 Date Distribution of Mexican Financial Statements and Defaults

TABLE 1 Information on Mexican Private Firm Sample Data

Mexican Private Firms	RiskCalc v1.0 Mexico	RiskCalc v3.1 Mexico	Change
Financial statements	9,151	15,795	↑ 73%
Unique number of firms	3,797	5,349	↑ 41%
Defaults	1,762	1,780	↑ 1%
Time period	1990–1999	1994–2005	+ 2 years

Robustness of the Data

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

Figure 2 presents the distributions of Mexican firms by industry and the proportion of defaults in each industry. Figure 3 presents the distributions by the size of firms measured as Total Assets in 2002 pesos. These figures demonstrate how the proportion of defaults in any one industry group or size group is comparable to the proportion of firms in these groupings. The size distribution shows that about 50% of the firms hold assets less than 5 million pesos.

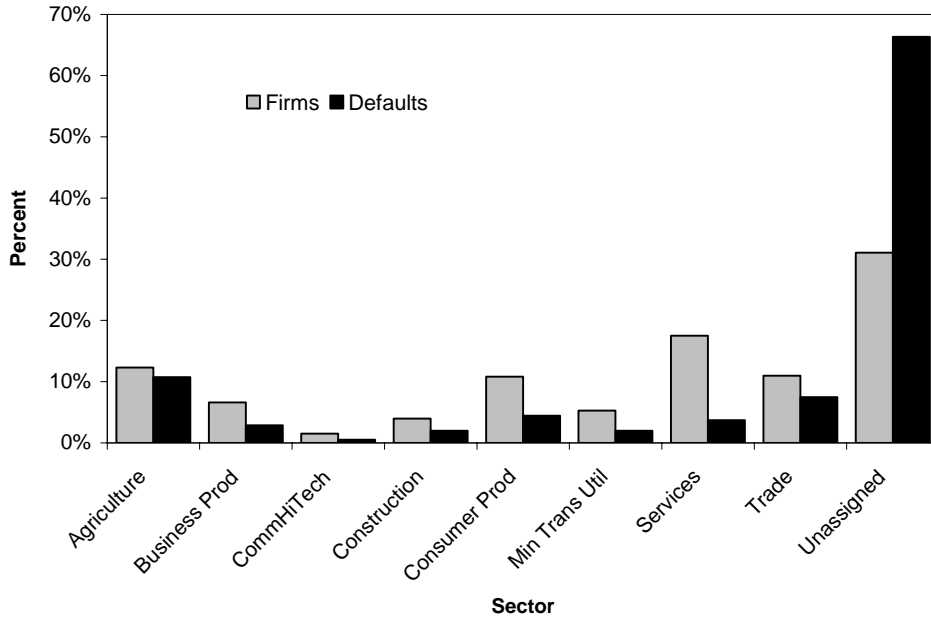


FIGURE 2 Distribution of Mexican Defaults and Firms by Industry

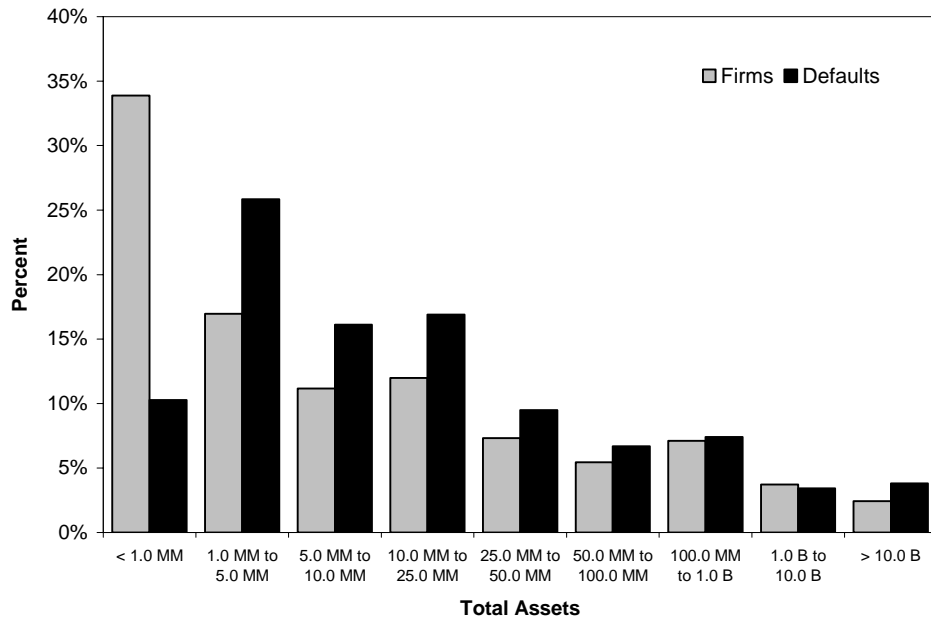


FIGURE 3 Size (as Total Assets in pesos) Distribution of Defaults and Firms

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. Moody's KMV developed techniques for cleaning the database to improve the model results.

2.5 Central Default Tendency

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

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

The estimate of the central default tendency for Mexico is based on the following sources.

- We examined loan loss provision data from the Organization for Economic Co-operation and Development (OECD) and provisioning data from financial statements of large Mexican banks.
- We examined bankruptcy data from Mexico.

For the Mexico model calibration, we must carefully consider the time period of the underlying sample. The sample data distribution is concentrated in a period of economic stress in Mexico. Therefore, when we calculate the average 1-year EDF credit measure in the development sample, we expect it to be higher than the long-run EDF credit measure moving forward in Mexico assuming this type of economic stress does not return.

The multiple sources of external data lead us to an estimate of 4.0% as the average sample EDF credit measure for the 1-year model. This estimate is below the average probability of default from the RiskCalc v1.0 Mexico model on the development sample. In addition, the average EDF credit measure based on the recent data is below the economic stress period. In the absence of another financial crisis, going forward the central default tendency of the model is anticipated to be lower than 4.0%. The average 1-year EDF credit measure for the 1-year model is 4.2% for statements between 1993 and 1999, and 3.1% between 2000 and 2003.

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 Moody's KMV research, a 5-year cumulative default tendency is derived from the 1-year estimate. This research, combined with the information provided by the CRD, shows that the 5-year cumulative default rate is, on average, four times the level of the 1-year default rate. Therefore, we calibrate the average 5-year EDF credit measure in the sample to 16.0%.

Central Default Tendency in FSO and CCA Modes

In FSO mode, the central default tendency remains constant over time. In CCA mode, the central default tendency is equal to the central default tendency of the FSO mode when the effects of the credit cycle are neutral. When the forward-looking prediction of the credit cycle indicates increasing default risk, the central default tendency of the CCA mode will be larger, and when the effects of the credit cycle indicate reducing default risk, the central default tendency will be smaller. In Mexico, the CCA mode causes the average CCA EDF credit measure to be higher than 4.2% during the 1993–1999 period of economic stress.

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, and the credit cycle adjustment. There is no industry information available for inclusion to the model.

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.²
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.
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:

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

where x_1, \dots, x_N are the input ratios; I_1, \dots, I_K are indicator variables for each of the industry classifications (if applicable); β and γ are estimated coefficients; Φ is the cumulative normal distribution; F and T_1, \dots, T_N are non-parametric transforms; and FSO EDF is the financial-statement-only EDF credit measure.³ The T s are the transforms of each financial statement variable, which capture the non-linear impacts of financial ratios on the default likelihood. (This is shown in Figure 4 and discussed in detail later in the document.) F is the final transform (i.e., the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. We describe the final transform 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. For Mexico, detailed industry classifications were not available for the defaulting population, so there is no indicator variable for the industries in the function.

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 2). A model is then built with at least one variable per group. When it is possible to increase model performance and maintaining 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 unambiguous?
- Is the meaning of the variable intuitive?
- Does the variable predict default activity?
- Is the variable not highly correlated with other variables in the model?

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

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

TABLE 2 Groupings of Financial Statement Ratios

Examples of ratios in the profitability group include net income, net income less extraordinary items, 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.

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) tend to increase a firm's default probability.

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

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

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

TABLE 3 Financial Statement Variables Used in RiskCalc v3.1 Mexico

Category	Definition ⁴
Activity	Inventory to Sales Interest Expense to Sales
Debt Coverage	EBITDA ⁵ to Interest Expense
Growth	Sales Growth: Net Sales(t) / Net Sales(t-1) - 1
Leverage	Liabilities to Adjusted Assets ⁶
Liquidity	Cash and Marketable Securities to Total Assets
Profitability	Gross Profit to Total Assets
Size	Total Assets ⁷

⁴ The following are CPI Adjusted variables: Inventory to Sales, EBITDA to Interest Expense, Sales Growth, and Gross Profit to Total Assets.

⁵ EBITDA is defined as the following: Total Operating Profit + Amortization and Depreciation.

⁶ Adjusted Assets is defined as the following: Total Assets - Tangible Fixed Assets - Intangible Fixed Assets.

⁷ Total Assets is in 2002 pesos.

Variable Transforms

After the variables are selected, they are transformed into a preliminary EDF value. Figure 4 presents the transformations used in the model. The horizontal axis gives the percentile score of the ratio and the vertical axis gives the default probability of that ratio in isolation (univariate). The percentile score represents the percent of the database that had a ratio below that of the company (e.g., if ROA is in the 90th percentile 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, the transform for Gross Profit to Total Assets is downward sloping. For this ratio the slope decreases as profitability becomes large (Figure 4). The slope of the transform is similar across the percentile space; therefore, changes in either direction from the median imply an equal change in risk (Figure 4).
- For the **Leverage** group, the transform for the Liabilities to Adjusted Assets is upward sloping (Figure 4). The transform is flat until the 35th percentile and then becomes upward sloping. The slope of the transform in this upward region is fairly constant.
- For the **Liquidity** group, the transform for Cash and Securities to Total Assets is downward sloping. It measures the portion of Total Assets that are immediately available for use. The slope of the transform is similar across the percentile space.
- For the **Activity** group, the transforms for both the Inventory to Sales and Interest Expense to Sales are upward sloping. The slope of both transforms is flat and then becomes steeper (Figure 4). These shapes indicate that risk levels are fairly insensitive to movements in the ratios below the 50th and 30th percentile, respectively.
- For the **Size** group, the variable is inflation adjusted Total Assets (in 2002 pesos). This transform is flat until the 45th percentile and then becomes downward sloping (Figure 4). This indicates that once the size variable reaches a level near the median, the marginal impact of risk is zero.
- For the **Debt Coverage** group, the transform for EBITDA to Interest Expense is downward sloping. For this ratio the slope is fairly constant across the percentile space. This indicates that firms with large EBITDA relative to financing costs have lower default probabilities (Figure 4).
- For the **Growth** group, the variable is Sales Growth. This variable's transformation is U-shaped, indicating that large increases or decreases in Sales are associated with higher default probabilities, while stable Sales year-upon-year decreases the probability of default (Figure 4).

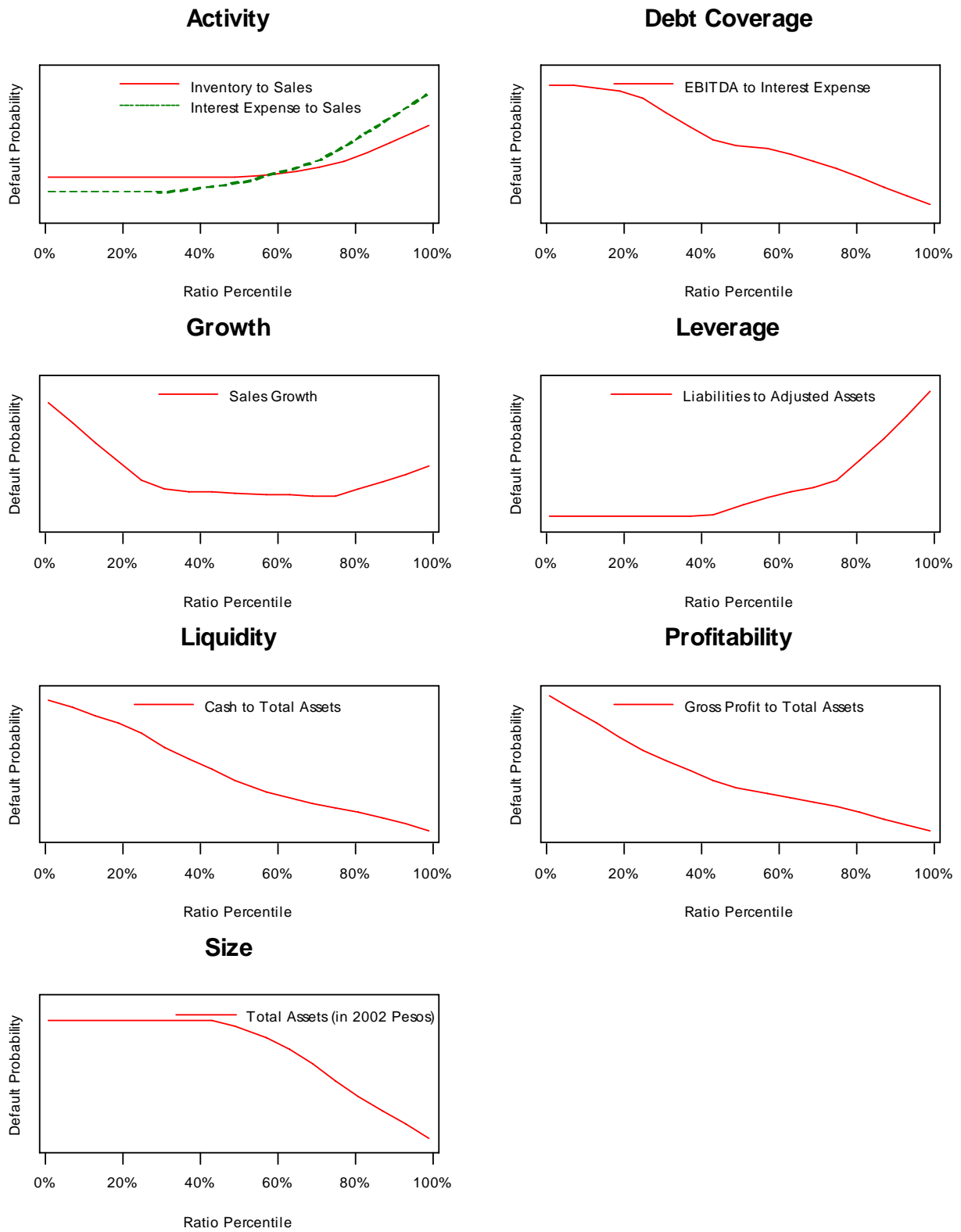


FIGURE 4 Transformations of Financial Statement Variables Used in the Model

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, because the actual impact on the risk depends on the coefficient, the transformation shape, and the percentile ranking of the company. The model weights, therefore, are calculated based on the average EDF value for the transformation and its standard deviation. A variable with a flat transformation could have a low weight, even if the coefficient is large (Figure 4).

Calculation of Weights

To calculate the weighting of a variable, the EDF credit measure 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 level 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 that has the smallest impact on the EDF level the smallest weight. Because the weights are a percentage of the total change in EDF levels, they sum to 100%. The weight of each category is the sum of the weights of each variable in that category. Table 4 presents the weights in RiskCalc v3.1 Mexico. The most important categories are Activity, Leverage, and Liquidity.

TABLE 4 Risk Drivers in RiskCalc v3.1 Mexico

Category	Weights
Activity	26%
Leverage	17%
Liquidity	17%
Growth	15%
Profitability	9%
Debt Coverage	9%
Size	7%

3.3 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 Mexico 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 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.⁸ This measure was chosen because it is available for a large universe of firms and it has been extensively validated.

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

⁸ cf., Bohn and Crosbie, 2003.

Adjustment Factor Used in the Model

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

Figure 6 provides evidence of the relationship between the DD factor and changes in Gross Domestic Product (GDP) and Industrial Production (IP) in Mexico. For these graphs, the DD factor is not inverted so that it aligns with GDP and IP growth. Similar to credit spread evidence, the factor is a forward-looking measure of state of the economic cycle. Overall, the evidence shows that the DD factor is a strong predictor of economic conditions in Mexico and will adjust the probabilities of default to reflect the position in the credit cycle.

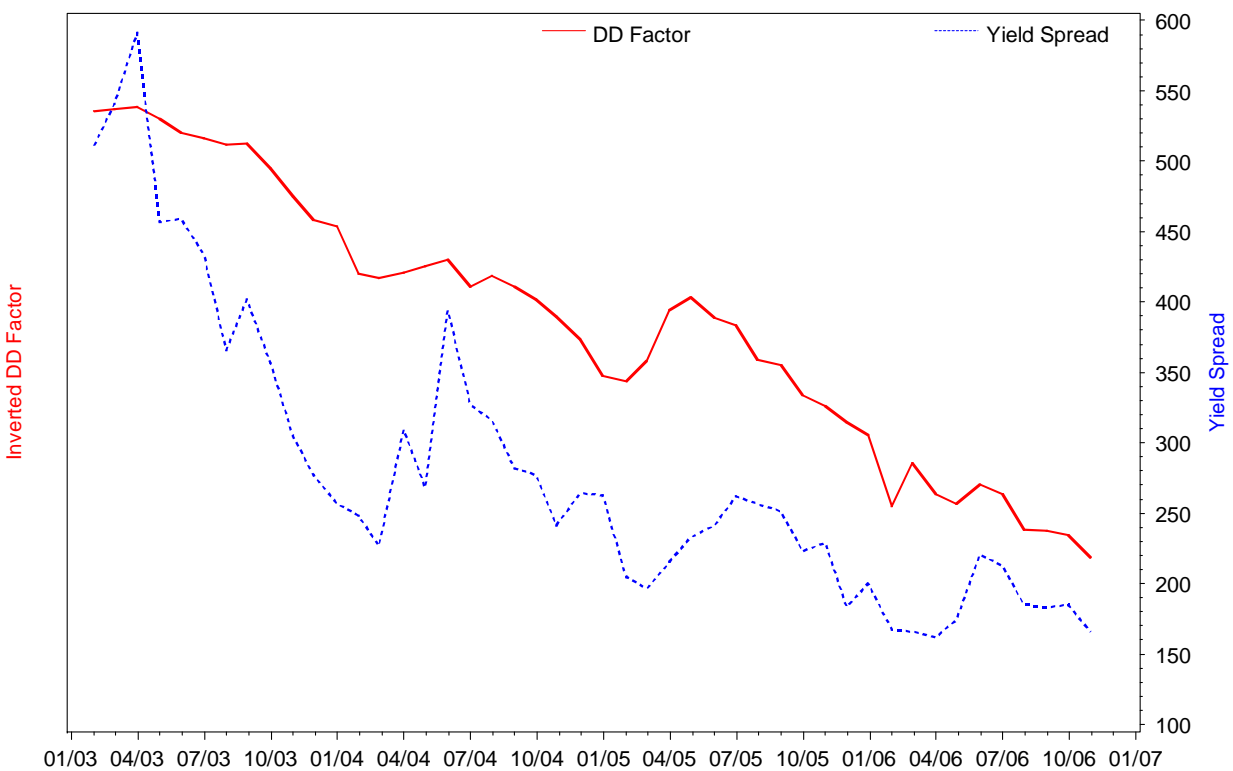


FIGURE 5 Mexican DD Factor and Corporate Bond Yield Spreads: Jan. 2003—Jan. 2007

Figure 5 displays the Mexican DD factor (red solid line) against Mexican Corporate Bond Yield Spreads (blue dotted line). The spread statistics are compiled using Moody's KMV CreditEdge[®] for the Mexican Corporate Bond Group.

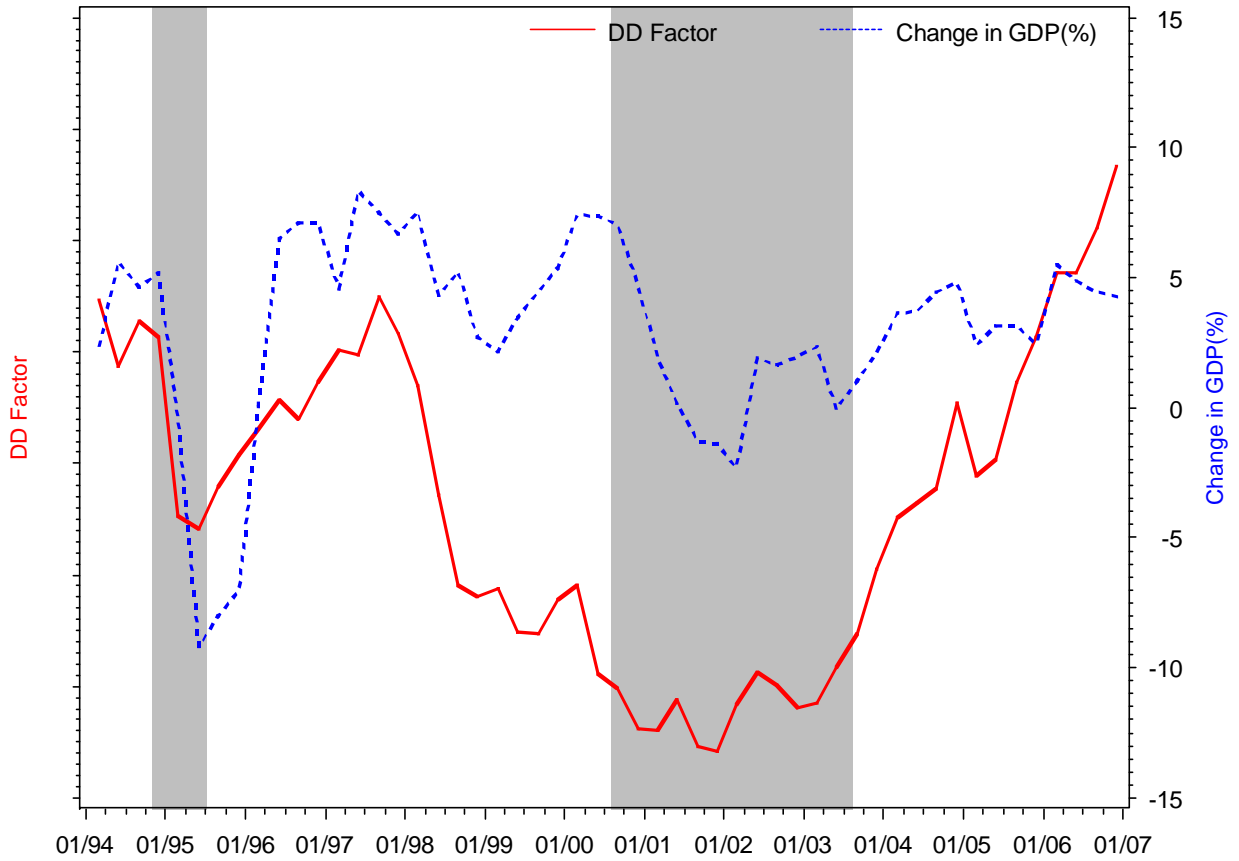


FIGURE 6 Mexican DD Factor and Gross Domestic Product Growth: 1994—2006

Figure 6 displays the Mexican DD factor (red solid line) against GDP Growth (blue dotted line). The DD factor decreased risk in periods of economic growth. The grey shaded area denotes a recession as defined by the Economic Cycle Research Institute (ECRI). GDP data is from the International Monetary Fund (IMF).

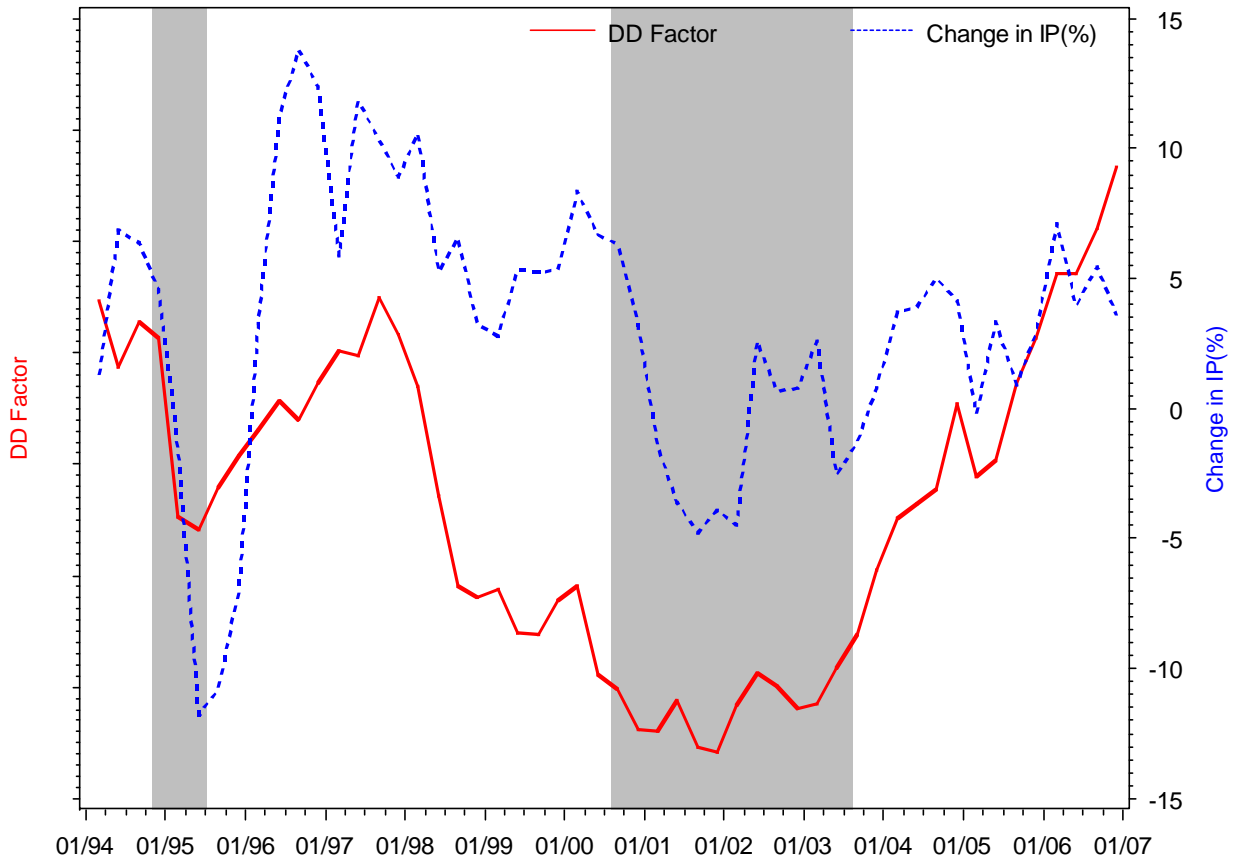


FIGURE 7 Mexican DD Factor and Industrial Production Growth: 1994—2006

Figure 8 displays the Mexican DD factor (red solid line) against Industrial Production Growth (blue dotted line). The DD factor decreased risk in periods of economic growth. The grey shaded area denotes a recession as defined by the Economic Cycle Research Institute. Industrial Production data is from the IMF.

4 VALIDATION RESULTS

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

The tests need to check not only the model effectiveness, but also its robustness and how well it works on data outside the sample. For out-of-sample testing, we performed a *k*-fold analysis. The results of the testing show that the model is uniformly more powerful than other models across size classifications. In Mexico, we have limited information on the sector of the defaulters and clustering of the default events in time. Therefore, we present the power across size classification in FSO mode. Time clustering of defaulters biases the interpretation of the comparison of accuracy ratio (AR) in FSO versus CCA mode, in addition to walk-forward type of out-of-sample tests.

4.1 Increase in Overall Model Power and Accuracy

Table 5 presents the in-sample overall measures of power for RiskCalc v3.1 Mexico versus alternative models. In FSO mode, the model's performance improves by almost 9 percentage points of accuracy ratio at the 1-year horizon, and over 9 percentage points at the 5-year horizon compared with RiskCalc v1.0 Mexico. Table 7 also contains p-values for the statistical test, which shows the difference between the accuracy ratio from v3.1 and the benchmark is less than or equal

to zero. A p-value of less than .05 indicates how we can reject the hypothesis that the difference in the accuracy ratios is less than or equal to zero with 95% confidence.⁹

Relative to other available alternatives, the results were more dramatic. The new RiskCalc v3.1 model outperformed the Z-score model (Altman, Hartzell, and Peck, 1995) by more than 25 percentage points at the 1-year horizon and 30 percentage points at the 5-year.

TABLE 5 Power Enhancements of the New RiskCalc v3.1 Mexican Model

	1-year Model		5-year Model	
	Accuracy Ratio	p-value	Accuracy Ratio	p-value
RiskCalc v3.1	47.7%	<.0001	47.7%	<.0001
RiskCalc v1.0	39.0%	<.0001	38.6%	<.0001
Z-score	22.6%	<.0001	17.2%	<.0001

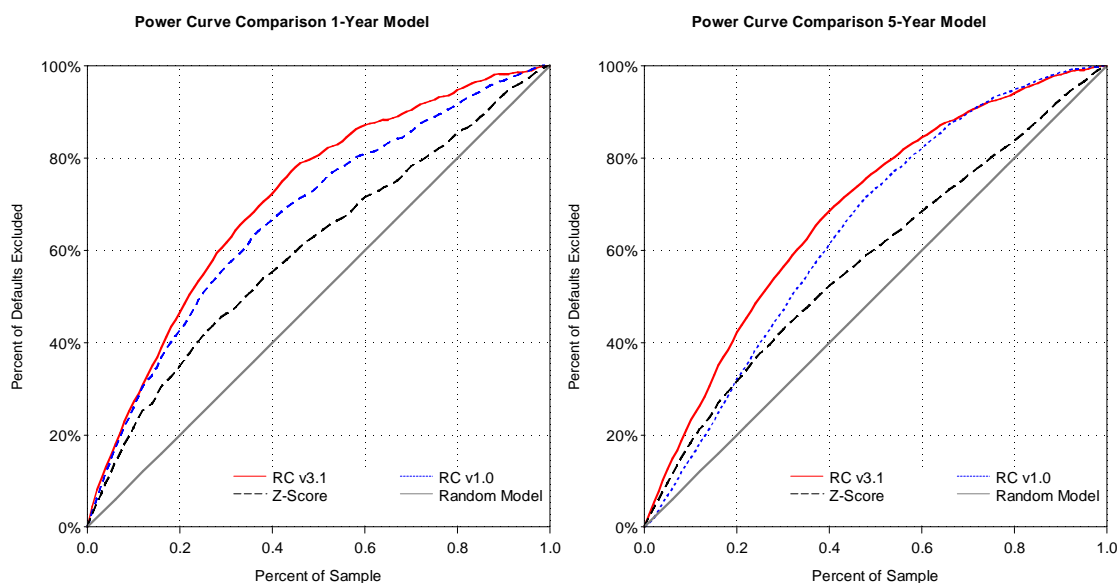


FIGURE 8 Power of Alternative Models (1- and 5-year)—Mexico

Figure 8 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 5. The power improvements are uniformly significant across different regions of the distribution relative to RiskCalc v1.0.

4.2 Correlations and Variance Inflation Factors

To ensure model robustness, the model must be tested for excessive multicollinearity, which occurs if a number of the variables used in the model are highly correlated. Excessive multicollinearity can cause instability in parameter estimates. To check for this issue, the correlation coefficients (Table 6) for the financial statement ratios in the model and the variance inflation factors (VIF) (Table 7) are computed on the transformed variables (Figure 4).¹⁰

⁹ See Hood (2007) for more details on the computation of the p-value.

¹⁰ For further definitions and technical discussions of the testing procedures in Section 4, see *Technical Document on RiskCalc v3.1 Methodology*, Moody's KMV, 2004.

Model Results

This section shows the results of the model, after being tested for excessive multicollinearity. Table 6 displays the correlations among the transformed input factors. Table 7 displays the variance of inflation factors.

TABLE 6 Correlations Among the Transformed Input Factors (Spearman Rank)

	Inventory to Sales	Interest Expense to Sales	EBITDA to Interest Expense	Sales Growth	Liabilities to Adjusted Assets	Cash to Total Assets	Gross Profit to Total Assets	Total Assets
Inventory to Sales	1.00	0.11	0.00	0.15	-0.19	0.14	0.32	0.09
Interest Expense to Sales	0.11	1.00	0.65	0.15	0.36	0.18	0.29	-0.14
EBITDA to Interest Expense	0.00	0.65	1.00	0.10	0.21	0.10	0.15	-0.11
Sales Growth	0.15	0.15	0.10	1.00	0.07	0.14	0.23	0.09
Liabilities to Adjusted Assets	-0.19	0.36	0.21	0.07	1.00	0.22	0.27	-0.07
Cash to Total Assets	0.14	0.18	0.10	0.14	0.22	1.00	0.35	0.12
Gross Profit to Total Assets	0.32	0.29	0.15	0.23	0.27	0.35	1.00	-0.04
Total Assets	0.09	-0.14	-0.11	0.09	-0.07	0.12	-0.04	1.00

The variance inflation factors (Table 7) for the financial statement variables represent how much of the variation in one independent variable can be explained by all the other independent variables in the model. The correlation coefficient, however, measures only the relationships between two variables. The VIF levels are low, indicating that the collinearity between the variables is low.¹¹ The two ratios with the highest correlation are EBITDA to Interest Expense and Interest Expense to Sales in Table 6.

TABLE 7 Variance Inflation Factors

Variable	VIF
Interest Expense to Sales	1.76
EBITDA to Interest Expense	1.58
Gross Profit to Total Assets	1.44
Liabilities to Adjusted Assets	1.33
Inventory to Sales	1.26
Cash to Total Assets	1.20
Sales Growth	1.13
Total Assets	1.07

¹¹ As Wooldridge (2000) shows, VIF is inversely related to the tolerance value ($1-R^2$), such that a VIF of 10 corresponds to a tolerance value of 0.10. Clearly, any threshold is somewhat arbitrary and depends on the sample size. Nevertheless, if any of the R^2 values are greater than 0.75 (so that VIF is greater than 4.0), we typically suspect that multicollinearity could be a problem. If any of the R^2 values are greater than 0.90 (so that VIF is greater than 10), we then conclude that multicollinearity is likely to be a serious problem.

4.3 Model Power by Size Group

It is important to test the power of a model not only overall, but also with firm sizes as well.

Table 8 and Table 9 present the power comparisons by firm size (Total Assets in 2002 pesos) for the 1-year and 5-year models, respectively. RiskCalc v3.1 Mexico outperforms both RiskCalc v1.0 Mexico and Z-score in all size groups but one, the 10 MM to 100 MM range at the 5-year model. The highest power in the 1-year and 5-year is found in the greater than 100 MM range, while the lowest power is in the 50K to 2 MM range.

TABLE 8 Model Power by Size (Total Assets in 2002 pesos) 1-year model

	Percentage of Defaults	AR* v3.1	AR v1.0	v3.1-v1.0 p-value	AR Z-score**
50 K to 2 MM	5.79%	42.47%	29.42%	<.0001	21.46%
2 MM to 10 MM	17.33%	34.62%	31.91%	0.0562	23.24%
10 MM to 100 MM	13.99%	48.97%	44.57%	0.0006	33.94%
> 100 MM	8.25%	60.11%	57.07%	0.0657	35.37%

*AR = accuracy ratio; **Z-score = Z-score 5

TABLE 9 Model Power by Size (Total Assets in 2002 pesos) 5-year model

	Percentage of Defaults	AR* v3.1	AR v1.0	v3.1-v1.0 p-value	AR Z-score**
50 K to 2 MM	7.73%	39.48%	19.92%	<.0001	17.80%
2 MM to 10 MM	25.82%	41.67%	42.64%	0.4813	23.48%
10 MM to 100 MM	19.02%	51.07%	55.60%	<.0001	28.96%
> 100 MM	10.29%	55.76%	58.98%	0.0966	28.39%

*AR = accuracy ratio; **Z-score = Z-score 5

4.4 Out-of-sample Testing: k -fold Tests

The model exhibits a high degree of power in distinguishing good credits from bad ones (Table 5), but whether this power is attributable to the overall model effectiveness or the impact of a particular sub-sample also needs to be tested. A standard test for evaluating this is the k -fold test, which divides the defaulting and non-defaulting companies into k equally-sized segments. This yields k equally-sized observed sub-samples that exhibit the identical overall default rate and are temporally and cross-sectionally independent. The model is then run on $k-1$ sub-samples, and these parameter estimates are used to score the k -th sub-sample. We repeat this procedure for all possible combinations, and put the k -scored out-of-sample sub-samples together to calculate an accuracy ratio on this combined data set.

Table 10 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 Mexico. 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 10 RiskCalc v3.1 Mexico *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	44.5%	46.6%	41.5%	37.5%
Subsample 2	44.4%	43.4%	35.8%	36.3%
Subsample 3	39.6%	50.4%	34.8%	37.3%
Subsample 4	41.4%	47.3%	37.7%	36.7%
Subsample 5	41.5%	47.4%	37.2%	35.8%
<i>k</i> -fold Overall	46.5%	47.2%	---	---
In-sample AR	47.7%	47.7%	39.0%	38.6%

*AR = accuracy ratio

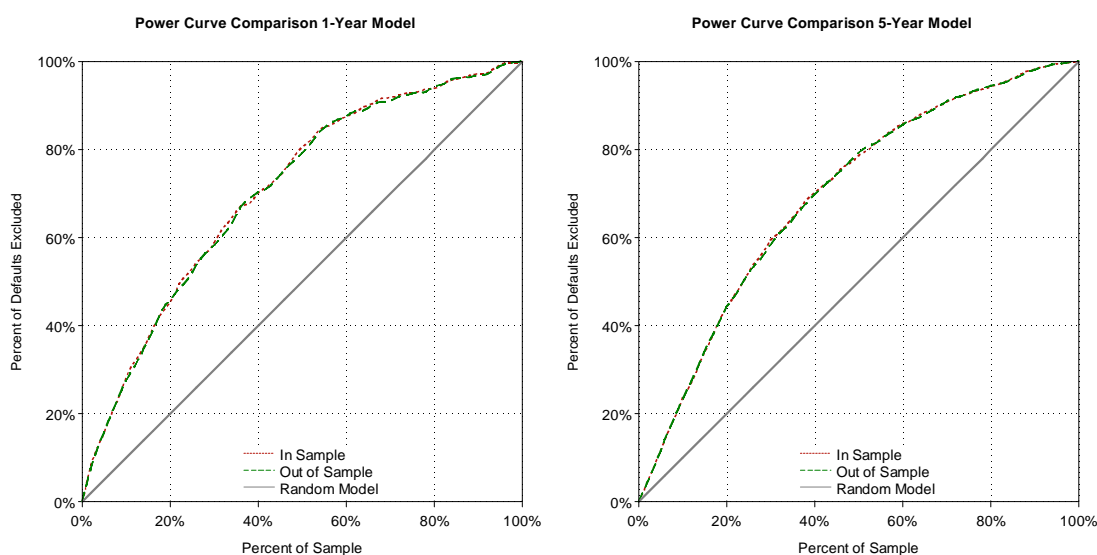


FIGURE 9 Out-of-sample Performance (1- and 5-year) Mexico *k*-fold

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

Results

The in- and out-of-sample plots are virtually indistinguishable at both the 1- and 5-year horizons in Figure 9. The difference in AR between the overall in-sample and out-of-sample results is not larger than 120 basis points in both cases. Furthermore, RiskCalc v3.1 Mexico outperforms RiskCalc v1.0 Mexico in an out-of-sample context at both the 1- and 5-year horizons (Table 10).

4.5 Model Calibration and Implied Ratings

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

- There is a large range of EDF 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 10 shows the distribution of CRD observations by rating category in the development sample (for the CCA EDF credit measures over the full time period). Note that 11 categories between A3 and Caa/C are utilized, and that less than 15% of the observations are in any one category, except for Caa/C at the 5-year rating. Disregarding Caa/C, the distributions peak both at Ba1 for the 1-year and Ba3 for the 5-year. 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.

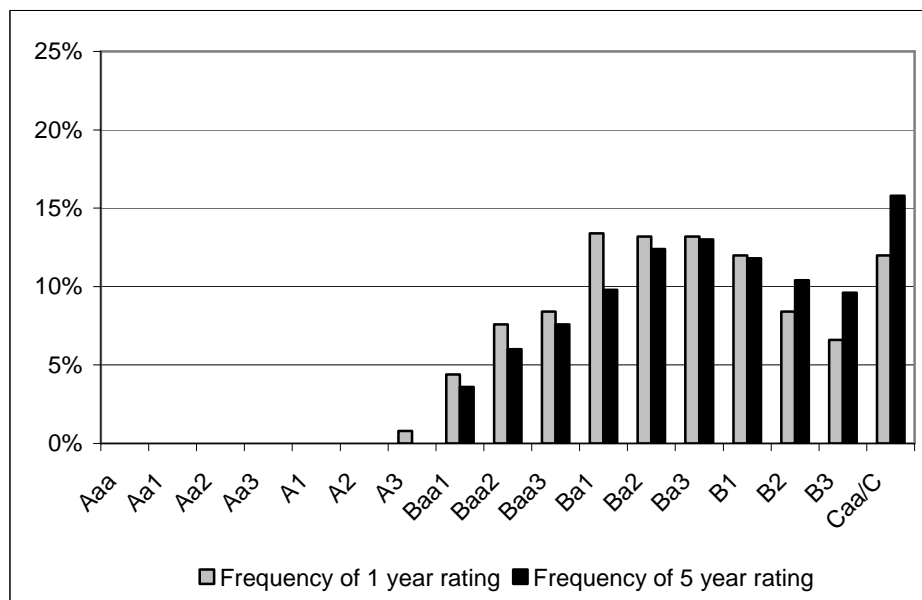


FIGURE 10 EDF-implied Ratings for the 1- and 5-year Models in the Development

5 FURTHER MODEL IMPROVEMENTS

In this section, we briefly outline some other improvements to the model.¹²

5.1 Continuous Term Structure

The previous version of the RiskCalc model provided the user two discrete default probability estimates: a 1-year and a 5-year EDF estimate. 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 Mexico 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 11).

Cumulative EDF

A cumulative EDF credit measure gives the probability of default over that time period. For example, a 5-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 11 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 survives to year three.¹³ The third column of Table 11 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 credit measure of 2.84%.¹⁴ This means that the average default rate per year for a 13.44% cumulative default rate is 2.84%. The last column of Table 11 presents the annualized EDF credit measures for years 1 to 5 that are derived from the cumulative EDF values.

TABLE 11 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

RiskCalc v3.1 provides users an analytical tool to gauge the relative impact of each variable—as a deviation from the mean of each ratio. To equip users of the model with further tools, we developed relative sensitivities (also known as

¹² For a detailed discussion of these improvements, refer to *Technical Document on RiskCalc v3.1 Methodology*, Moody's KMV, 2004.

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

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

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 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 indicates a decrease in risk. The percentile is the sensitivity of the variable relative to the average.

For example, a small increase in Interest Expense/Sales will change the risk of the company. It is about 200% (5-year) as sensitive as the average variables (Figure 11).

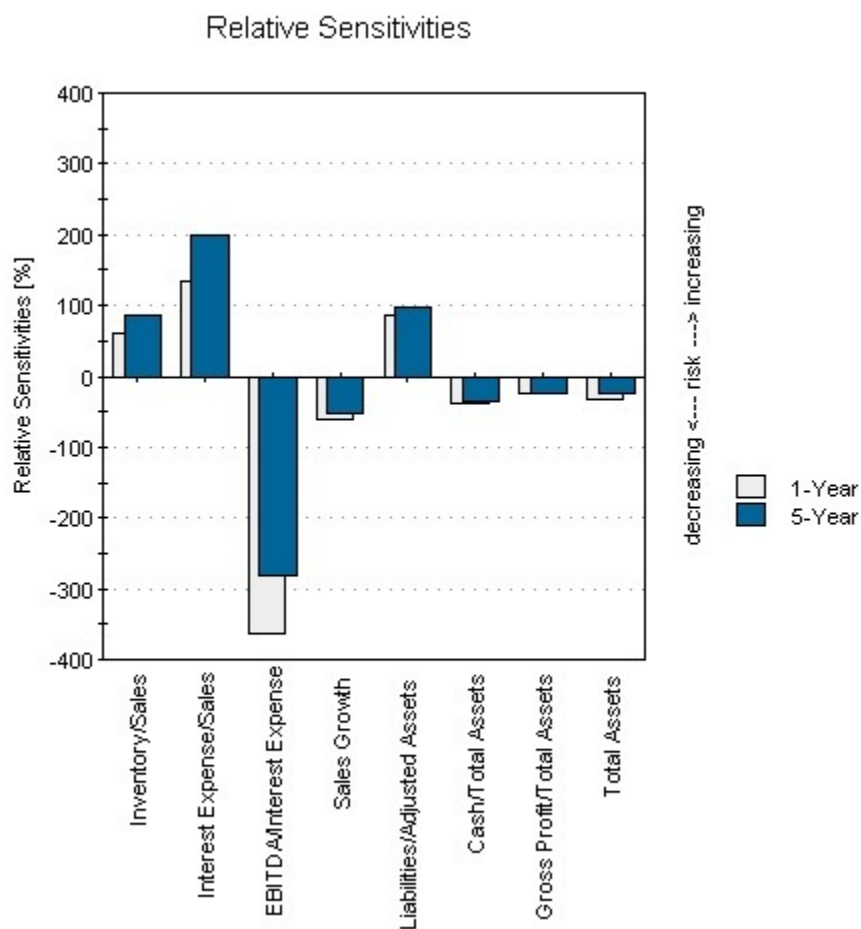


FIGURE 11 Relative Sensitivities

5.3 Asset Value and Volatility Calculation

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

6 CONCLUSION

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

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

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

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

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