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MOODY'S KMV RISKCALC™ V3.1 UNITED KINGDOM

MODELING**METHODOLOGY**

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ABSTRACT

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 over 200 institutions worldwide. While using the same underlying framework, each model reflects the domestic lending, regulator, and accounting practices of its specific region.

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

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

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1 INTRODUCTION

The Moody's KMV RiskCalc™ v3.1 U.K. 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®
- Moody's KMV Credit Research Database™ (CRD, the world's largest and cleanest private company default database)
- Industry sector information, market information and industry-specific default rates.

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

RiskCalc Modes

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

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

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

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

RiskCalc v3.1 U.K. versus RiskCalc v1.0 U.K.

Since the release of RiskCalc v1.0 U.K. in early 2002, Moody's KMV has significantly increased the size of the database and substantially improved its data cleansing technologies. The new model includes additional financial statement variables as well industry adjustments within the model. Moreover, the EDF output can be adjusted for the credit cycle. We have also made substantial advances in our model development and testing techniques. As a result, the new model is more powerful and precise than its predecessor. Finally, the new model includes additional analytic tools that increase model usability and transparency.

2 DATA DESCRIPTION

The source of the data for RiskCalc v3.1 U.K. is Moody's KMV Credit Research Database™ (CRD). The CRD collects data from participating institutions, obtained by working closely with them to understand the strengths and weaknesses of the data. In countries like the U.K., where financial statement data is publicly available, the CRD collects this information as well. As of May 2004, the CRD contained 6.5 million financial statements, over 1.5 million unique private firms, and more than 97,000 default events worldwide. Moody's KMV uses this data for model development and testing purposes.

2.1 Data Exclusions

Excluded Companies

The goal of the RiskCalc model is to provide an Expected Default Frequency™ (EDF) for private U.K. companies in the middle market. The firms and industries covered in the model must have similar default characteristics. To create the most powerful model for U.K. middle-market companies, companies that did not reflect the typical company in this market were eliminated. The following types of companies are not included in the data:

- **Small companies** – For companies with assets of less than £350,000 (in 2001 Pounds Sterling) 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 gearing than the typical private firm. The regulation and capital requirements of these institutions make them dissimilar to the typical middle-market company and, therefore, they are excluded from the database.
- **Real estate development companies** – The annual accounts of real estate development and investment companies provide only a partial description of the dynamics of these firms and, therefore, their likelihood of default. This is because their financial health often hinges on a particular development.[1]
- **Public sector and non-profit institutions** – The default risk of government run companies is influenced by the states' or municipalities' unwillingness to allow them to fail. As a result, their financial results are not comparable to other private firms. Financial ratios of not for profits are very different from those of 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.
- **Subsidiaries –** These firms have been excluded from the final data set used to build the model, because their success is largely dependent on the success of the parent.

Excluded Financial Statements

The financial statements of smaller companies can be less accurate and of lower quality than those of larger companies. The financial statements in the CRD are cleaned to eliminate any suspect financial statements.

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

Plausibility checks of financial statements are conducted (e.g., 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.

2.2 Definition of Default

RiskCalc provides assistance to institutions and investors in determining the risk of default, missed payment, or other credit events. The proposals for the new Basel Capital Accord (BIS II) have stimulated debates about what constitutes an appropriate definition of default. In model development, RiskCalc uses the local criteria for default. Accordingly, in the U.K., we defined default as the following insolvency-related events: Administration, Receiverships, Winding Up Petitions, Moratoriums and Liquidations. 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).

2.3 Descriptive Statistics of the Data

Overview of the Data

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

Figure 1 presents the distribution of financial statements and defaults by year.[2]

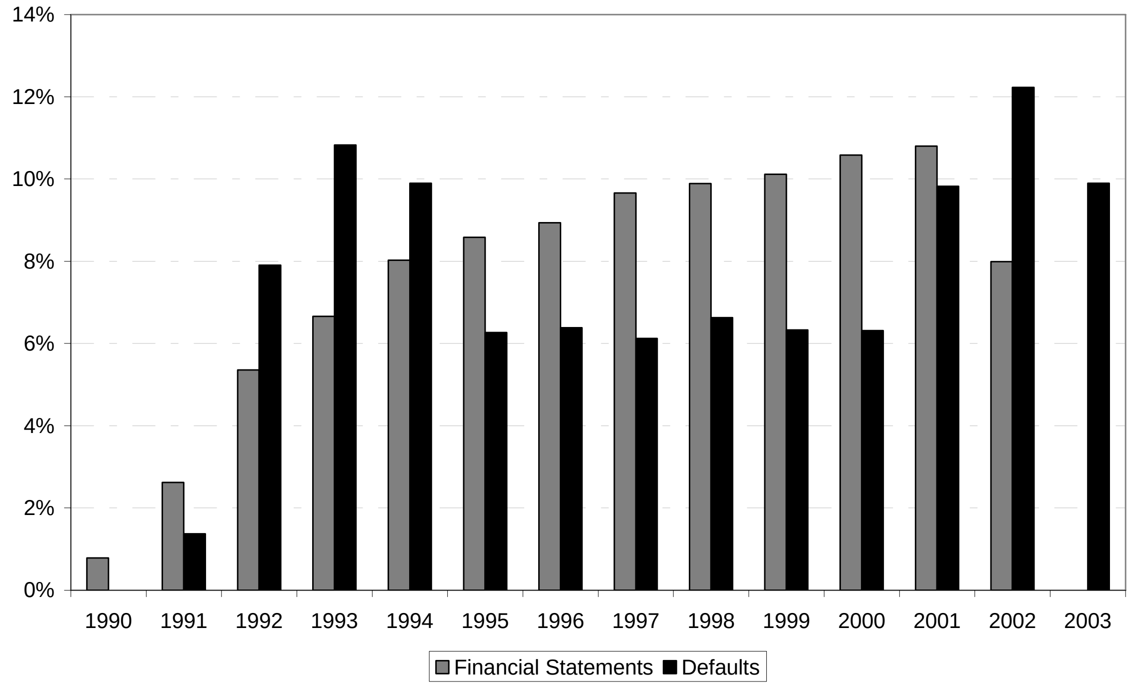
Table 1 summarises the data used in the development, validation, and calibration of the RiskCalc v3.1 U.K. model. The number of financial statements, firms, and defaults is considerably larger than was the case for RiskCalc v1.0 U.K.

TABLE 1 Information on Private Firm Sample Data

Private Firms	RiskCalc v1.0 U.K.	RiskCalc v3.1 U.K.	Credit Research Database Growth
Financial statements	283,511	445,000+	↑57%
Unique number of firms	64,531	125,000+	↑94%
Defaults	4,723	9,900+	↑110%
Time period	1989-2000	1989-2003	↑ 3 additional years

[2] In Figure 1, we have excluded 1989 and 2003 financial statements, because there were very few financial statements in these years.

FIGURE 1 Date Distribution of Financial Statements and Default Data



Robustness of the Data

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

Figure 2 and Figure 3 present the distributions of defaults and firms by industry and size classification, respectively. The largest industry groups are trade and services. Firm size (as measured by assets) ranges from £350,000 to over £50 million. Figure 2 and Figure 3 show that the proportion of defaults in any one size group or industry is comparable to the proportion of firms in these groupings. This size distribution (Figure 3) shows that the majority of companies hold between £500,000 and £5mm in assets.

FIGURE 2 Distribution of Defaults and Firms by Industry

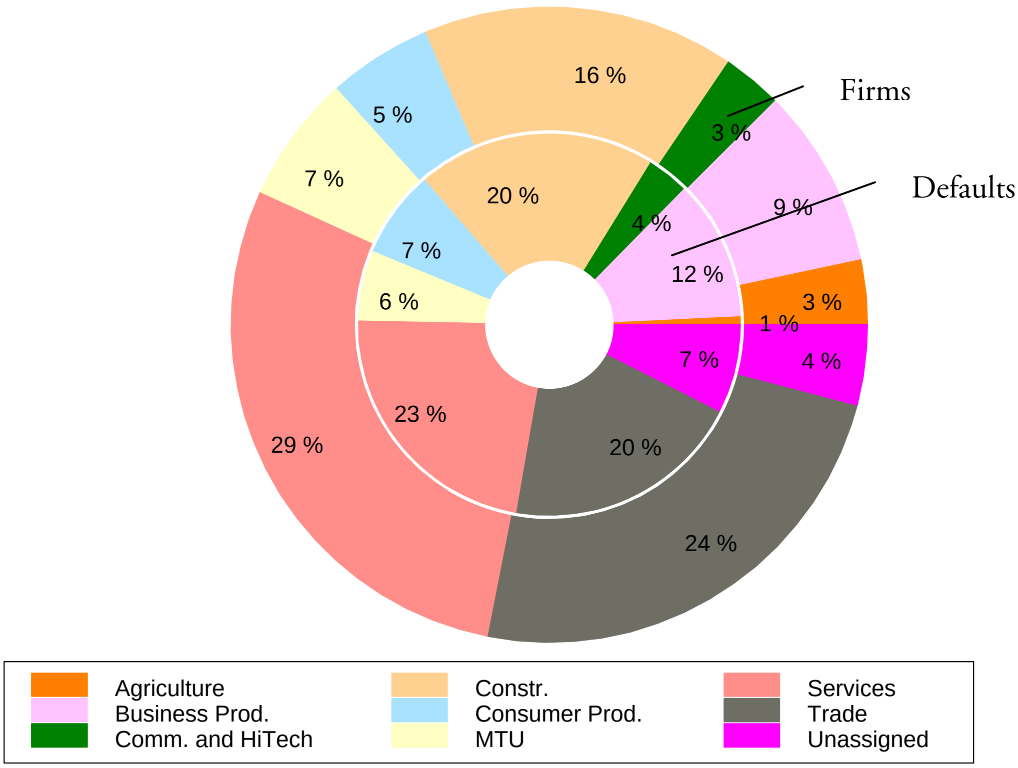
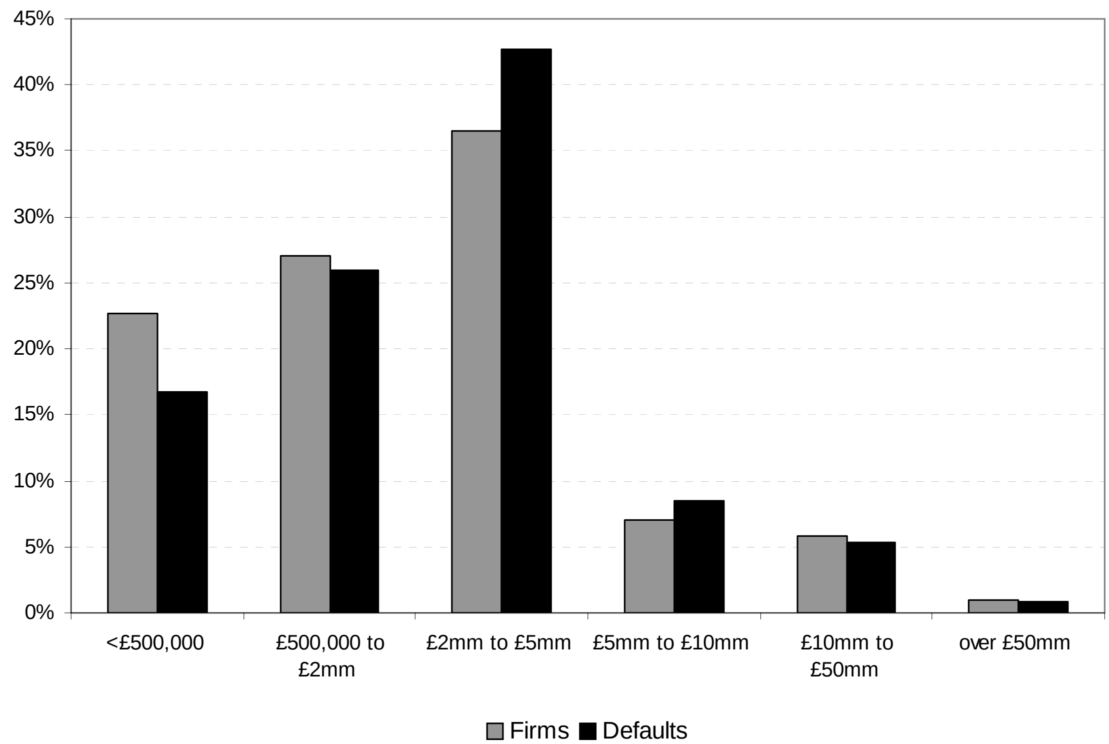


FIGURE 3 Size Distribution of Defaults and Firms (Assets)



2.4 Cleaning the Data

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

2.5 Central Default Tendency

Since most companies do not default, defaulting companies are relatively rare and thus more valuable in building a default prediction model. Much of the lack in default data is due to the data storage issues within financial institutions, such as defaulting companies being purged from the system after troubles begin, not all defaults being captured, or other sample errors. Publicly available sources of default data generally only reflect bankruptcy related events and therefore do not capture all default events. These issues can result in a sample that has a lower default rates than occurs in the general population. If the underlying sample is not representative, then it needs to be adjusted for the true central default tendency.

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

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

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

Reliable Third-Party Data Sources

In order to determine the central tendency used in RiskCalc, MKMV consulted several prominent U.K. financial institutions as well as Moody's analysts. The analysts and experts recommended a mean annual default rate of about 2% for the U.K.

Bank Charge-Offs

An alternative approach we implement in determining the mean default rate is based on provisioning or write-off data from banks. Banks make provisions for bad loans that are estimates of their expected write-offs. From the volume of losses and the volume of loans, an average default rate can be inferred given the loss given default (LGD):

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

therefore

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

The foundation approach to capital allocation as described in Basel II uses a loss given default rate of 50%, so this assumption can be used to calculate the implied default rates. For the period 1980-2000, an article published by the Bank of England reports that the average of the new provisions charge ratio for major U.K. commercial banks centres around 1.1 through the credit cycle (Hoggarth and Pain, 2002, Chart 7). Using the above formula and a LGD of 50% yields 2.2% as an estimate of the central tendency. Similarly, we have found in an analysis of the provisions for all U.K. Commercial banks from 1984-2001 as reported by the OECD (2002) that the implied probability of default was approximately 2.0%. These additional analyses confirm the reasonableness of the chosen central default tendency.

Accordingly, in calibrating RiskCalc v3.1 for U.K. private companies, a central tendency of 2% was used for the 1-year models, which coincides with the calibration of RiskCalc v1.0 U.K. (Kocagil et al, 2002).

Calculating a 5-year Tendency

There is a lack of publicly available data for direct calculation of the central tendency rate of a cumulative 5-year default probability. Based on extensive MKMV research, a 5-year cumulative default tendency is derived from the 1-year estimate. This research, combined with the information provided by the CRD, shows that the 5-year cumulative default rate is, on average, 4 times the level of the 1-year default rate. Therefore, 8.0% is used as the central default tendency for the 5-year model.

Central Default Tendency in FSO and CCA Modes

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

3 MODEL COMPONENTS

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

The development of a RiskCalc model involves the following steps:

1. Choosing a limited number of financial statement variables for the model from a list of possible variables.[3]

2. Transforming the variables into interim probabilities of default using non-parametric techniques.

3. Estimating the weightings of the financial statement variables, using a probit model, combined with industry variables.

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

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

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

where $x_1,\ldots,x_N$ are the input ratios; $I_1,\ldots,I_K$ are indicator variables for each of the industry classifications; β and γ are estimated coefficients; Φ is the cumulative normal distribution; F and $T_1,\ldots,T_N$ are non-parametric transforms; and FSO EDF is the financial statement-only EDF credit measure.[4] The *Ts* 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 (the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. We describe the final transform as calibrating the model score to an actual EDF credit measure. The difference between the FSO EDF and the credit cycle adjusted EDF is that the final transform is adjusted to reflect our assessment of the current stage of the credit cycle in CCA mode while in FSO mode it remains constant.

3.1 Financial Statement Variables

Selecting the Variables

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

- Is the variable readily available?

- Is the meaning of the variable intuitive?

- Does the variable predict default activity?

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

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

- Is the variable generally uncorrelated with other variables in the model?
- Are the definitions of the inputs to the variable unambiguous?

RiskCalc v1.0 versus RiskCalc v3.1 Variables

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

- Operating cash flow is used in the numerator of the debt coverage ratio instead of ordinary profit plus depreciation and amortisation.[5] Cash flow is used because a company that has profits but no cash flow is at risk. Using cash flow in the model penalises a firm that has negative cash flow even if both its ordinary profit and net P&L are positive.
- There are several new dynamic variables. In RiskCalc U.K.v1.0, the only dynamic variable was Sales Growth (or Turnover Growth). We now have changes in ROA, which captures the stability of profits. Further, the change in accounts receivable turnover (the ratio of accounts receivable to sales)[6] is included as a new variable. If accounts receivable increase dramatically without an accompanying increase in turnover, this may indicate a collection problem, and a dramatic decline without a reduction in turnover may mean excessive write-offs.
- The new model contains one debt coverage variable (instead of two) and the measure of profitability has been changed from [Net P&L to Assets] to [Net P&L to Turnover]. These changes reduced the degree of multicollinearity in the model.[7] Including both [Net P&L to Assets] and [Total Liabilities to Total Assets] would yield substantial multicollinearity due to the relatively high correlation between these two variables. Using two debt coverage variables would have created a similar issue.

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[5] We implement operating cash flow as EBITDA plus changes in trade creditors (accounts payable) less changes in trade debtors (accounts receivable) less changes in stocks and provisions (inventories).

[6] Or alternatively, trade debtors to turnover.

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

TABLE 2 Groupings of Financial Statement Ratios

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

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

Category	Variable
Gearing	Liabilities to Total Assets
Profitability	Net P&L to Turnover (ROA)
	Change in ROA
Debt Coverage	Cash Flow to Interest Expense
Liquidity	Current Assets to Current Liabilities
Activity	Trade Creditors to Turnover
	Change in Accounts Receivable to Turnover
Growth	Sales Growth
Size	Total Assets

Variable Transforms

Once the variables are identified, they are transformed into a preliminary univariate EDF value. Figure 4 presents the transformations used in the model. The horizontal axis is the percentile score of the ratio and the vertical axis is the default probability of that ratio in isolation (univariate). The percentile score gives the percent of the database that had a ratio below that of the company (e.g., if Net P&L to Turnover 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, Net P&L to Turnover and Changes in ROA (Net P&L to Total Assets) are included. As shown in Figure 4, the transform for Net P&L to Turnover is downward sloping but the slope becomes smaller as Net P&L to Turnover becomes large. Such a transform indicates that more profitable firms have lower default probabilities, but the impact diminishes as Net P&L to Turnover increases. Change in ROA has a "U-shaped" transform indicating that large increases or decreases in ROA to Total Assets increase the default likelihood. The actual transform shape indicates that large reductions in ROA increase the likelihood of default by a larger amount than large increases in ROA.

- For the **Gearing** group, the ratio is Total Liabilities to Total Assets. Large values of this ratio increase default probabilities (Figure 4).

- The **Liquidity** group variable is Current Assets to Current Liabilities. The transform is downward sloping indicating that higher values of this ratio are associated with lower default probabilities (Figure 4).

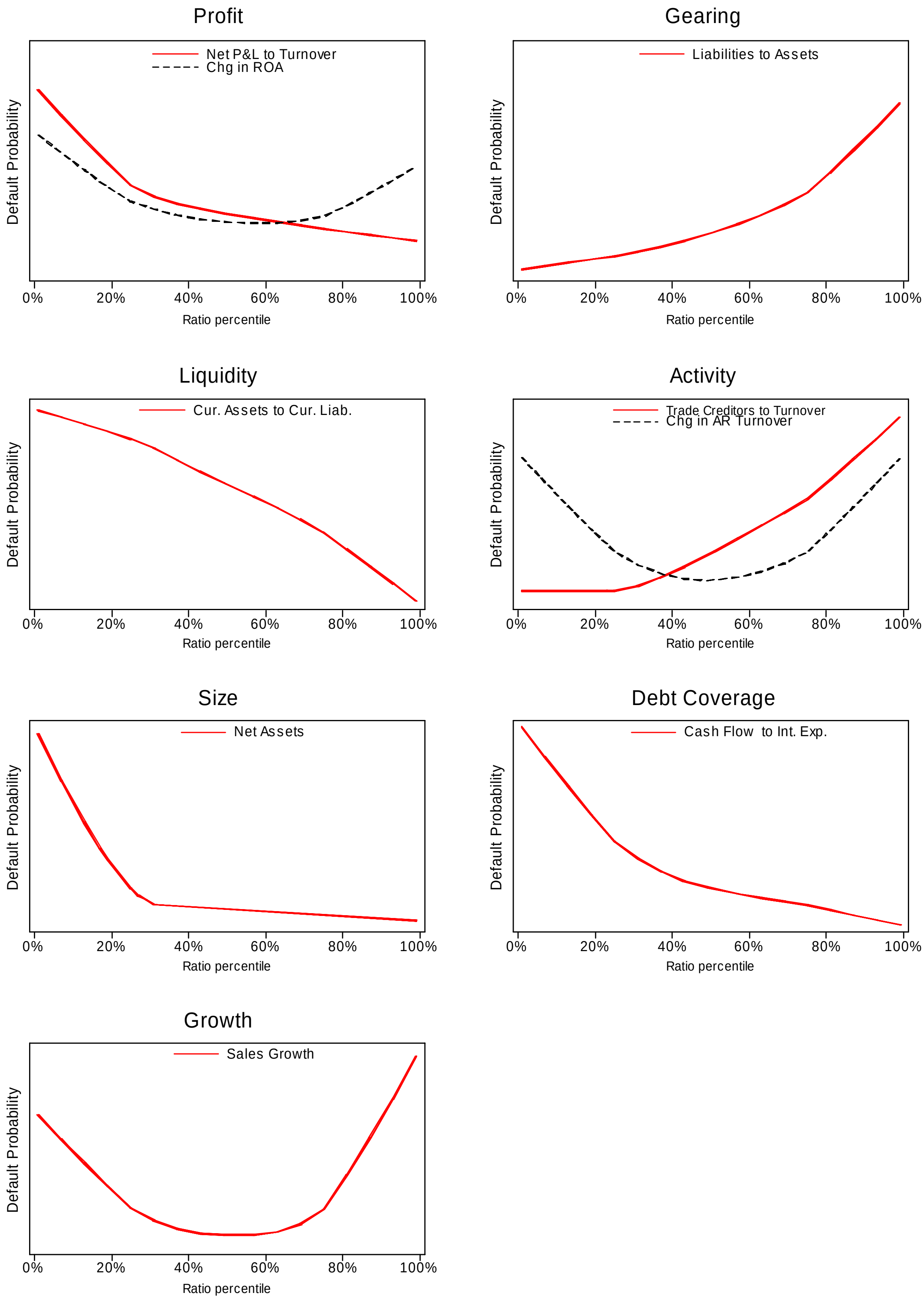
- For the **Activity** group, two ratios are included. As shown in Figure 4, Trade Creditors to Turnover (Accounts Payable to Sales) is upward sloping indicating that high values of this ratio are associated with higher default probabilities. Change in Accounts Receivable to Sales (Trade Debtors to Turnover) has a "U shaped" transform indicating that large positive values or large negative values are associated with higher default probabilities, while stable values are associated with lower default probabilities.

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

- The **Debt Coverage** variable is Cash Flow to Interest Expense. This variable is downward sloping indicating that large values of cash flow relative to interest expense lower the probability of default (Figure 4).

- The **Growth** variable is Sales Growth (Turnover Growth). The transform is "U shaped," indicating that large increases or decreases in sales are associated with higher default probabilities (Figure 4). The actual shape indicates that large increases in sales increase default probabilities by a larger amount than large decreases in sales.

FIGURE 4 Transformations of Financial Statement Variables Used in the Model



3.2 Model Weights

Importance

The relative value of each variable used in calculating an EDF credit measure is important in understanding a company's risk. The non-linear nature of the model makes the weight of the variables more difficult to determine 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. Thus, 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 value for a theoretical firm with all its variables at the average transformation values is computed. The variables are then increased one at a time by one standard deviation. The EDF change for each variable (in absolute value) is computed and added together. The relative weight of each variable is calculated as the EDF level changes for that variable as a percent of the total change in EDF level. This gives the variable with the biggest impact on the EDF level the biggest weight, and the variable that has the smallest impact on the EDF level the smallest weight. Since the weights are a percentage of the total EDF value, they sum to 100%. The weight of each category is the sum of the weights of each variable in the category.

Table 4 presents the weights in RiskCalc v1.0 and RiskCalc v3.1 for the U.K. model. Gearing continues to be the most important category. The introduction of Change in ROA has increased the importance of the profitability group, whereas the importance of debt coverage has declined as a result.

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

RiskCalc v1.0 U.K.		RiskCalc v3.1 U.K.	
Risk Drivers	**Weight**	**Risk Drivers**	**Weight**
Gearing Liabilities/Assets (Current Liabilities -Cash)/Assets	29%	Gearing Liabilities/Assets	30%
Profitability Net P&L/Assets	18%	Profitability Net P&L/Turnover Chg in ROA	28%
Activity Trade Creditors/Turnover	9%	Activity Trade Creditors/Turnover Chg in AR/Sales	13%
Debt Coverage Ordinary Profit/Liabilities (Ordinary Profit + Depreciation & Amortisation)/Interest Charges	25%	Debt Coverage Operating Cash Flow/Interest Expense	11%
Liquidity Cash/Assets	14%	Liquidity Current Assets/Current Liabilities	8%
Growth Sales Growth	5%	Growth Sales Growth	7%
		Size Total Assets	3%

* Operating cash flow is defined as EBITDA less change in inventories less change in accounts receivable (trade debtors) plus change in accounts payable (trade creditors). For a description of the variable selection process see Section 3.1. For a discussion of the procedure used to compute model weights see Section 3.2.

3.3 Industry Adjustments

While the variables included in the RiskCalc model explain most of the risk factors, the relative importance of an individual variable can be different among industries. Also, for the same set of financial statements, industries may have different default probabilities.

Accordingly, in the FSO mode of RiskCalc v3.1 U.K., the EDF level is adjusted for industry effects. Table 5 presents the increase in model power and accuracy from introducing industry controls into the FSO model. Both the power and the accuracy of the EDF credit measure increase as measured by the Accuracy Ratio and the gain in log-likelihood. Table 6 presents the average EDF credit measure by industry for the development sample. The highest average EDF credit measures are in Communications and Hi Tech while the lowest are in Agriculture.

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

	One-year Model		Five-year Model	
	Accuracy Ratio	Relative increase in Log Likelihood	Accuracy Ratio	Relative increase in Log Likelihood
FSO mode without industry controls	56.7%		50.9%	
FSO mode with industry controls	58.5%	754.4***	52.6%	2426.4***

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

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

TABLE 6 Average EDF Credit Measure in Development Sample by Sector

Sector	Average 1-year EDF	Average 5-year EDF
Agriculture	1.20%	4.58%
Business Products	2.63%	10.50%
Communications and Hi Tech	3.31%	11.40%
Construction	2.60%	9.35%
Consumer Products	2.86%	11.40%
Mining, Transportation, Utilities and Natural Resources	1.80%	7.27%
Services	2.26%	7.98%
Trade	1.44%	5.94%
Unassigned	2.34%	8.43%

3.4 Credit Cycle Adjustment

EDF credit measures are influenced not only by the financials of a company, but also by the general credit cycle in the economy. To capture this effect, RiskCalc v3.1 U.K. includes a credit cycle adjustment factor. The credit cycle adjustment is designed to incorporate the current credit cycle into the estimate of private firm default risk.

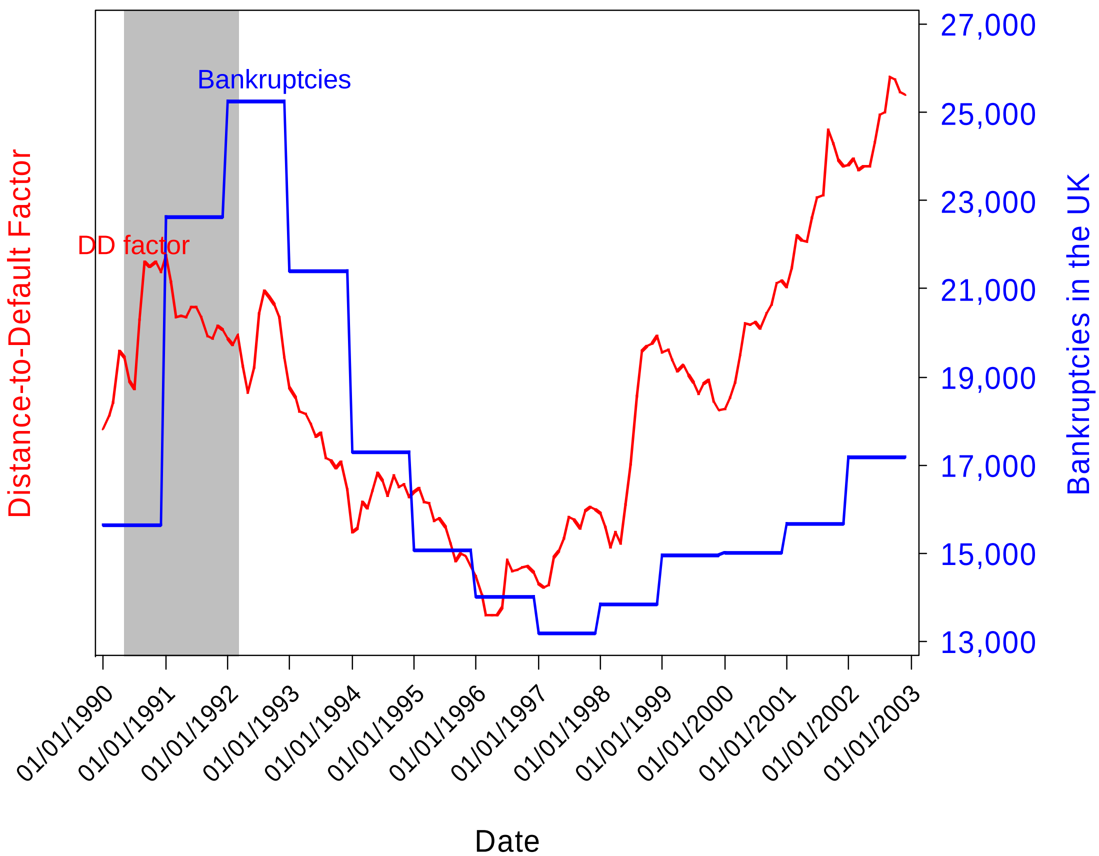
Selecting an Adjustment Factor

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

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

When the credit cycle adjustment factor is neutral, the CCA EDF coincides with the FSO EDF. This relationship does not necessarily imply that the average of the CCA EDF on any particular sample will equal the average of the FSO EDF, as the sample may not cover a sufficient historical window to contain a complete credit cycle.[8] Figure 5 presents the distance-to-default factor based on all public firms in the U.K. along with the number of bankruptcies in the U.K. During the early 1990s there was a severe recession with substantial default activity, which was captured by a high DD factor. During 2001 and 2002, there was an economic slowdown in the U.K. and a rise in bankruptcies, which was also captured by a high DD factor. Table 7 shows that including the credit cycle adjustment factor increases both the power and the accuracy of the model.

FIGURE 5 U.K. DD Factor and Bankruptcies



Presents the DD factor (red line) against the historical counts of bankruptcies ("Compulsory liquidations" and "Creditor's voluntary liquidations" Annual Abstract of Statistics 2003). Grey vertical bars indicate periods of recession as defined by the Economic Cycle Research Institute. Increases in the DD factor correspond with increases in the number of bankruptcies in the U.K.

[8] Additionally, the distribution of firms and industries within the sample may not be the same as that of the overall population, and the relationship between the CCA EDF and the FSO EDF is nonlinear.

4 VALIDATION RESULTS

In this section, we present testing results on the RiskCalc v3.1 U.K. model's ranking power (the model's ability to sort credits from worst to best) and the accuracy of its predicted EDF credit measures (the model's ability to estimate correctly the level of EDF). We also present the results of Moody's KMV tests of model robustness and stability. These include examining the correlation matrices and variance inflation factors of the independent variables to ensure that the model does not contain excessive multicollinearity.

Our results show that the model is uniformly more powerful than other models across regions, time periods, sectors, and size classifications. We also measure the out-of-sample power of the model using our walk-forward and k-fold analyses. These analyses demonstrate that the model is robust out-of-sample and out-of-time. More detail on how to interpret these analyses is provided in the Technical Document and in Stein (2002).

4.1 Increase in Overall Model Power and Accuracy

Table 7 presents the in-sample overall measures of power and likelihood for RiskCalc v3.1 versus alternative models. In this table, we see that with the credit cycle adjustment the model's performance improves by almost five points of accuracy ratio at the 1-year horizon and over six points at the 5-year horizon when compared with RiskCalc v1.0. 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 10 points at both the 1-year and 5-year horizons. The Financial Statement Only (FSO) Mode outperforms the old model by 3.6 points and 5.2 points at the 1- and 5-year horizons, respectively.[9] RiskCalc v3.1 is also more accurate than alternative models as measured by the log-likelihood differences.

TABLE 7 Power Enhancements of the new RiskCalc v3.1 U.K. Model

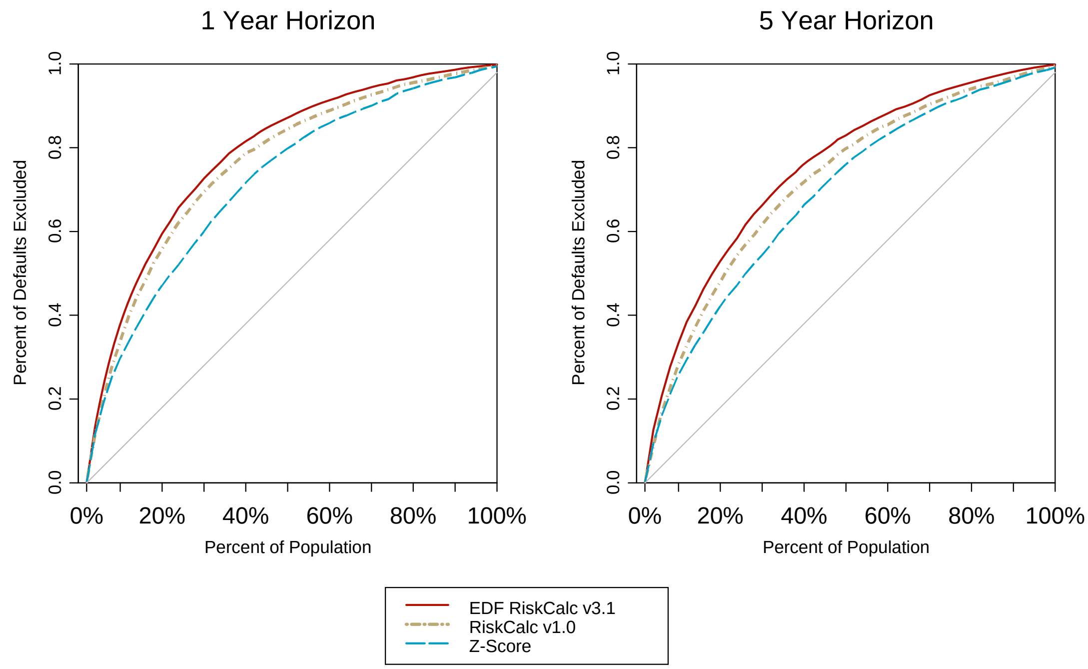
	One Year		Five Year	
	Accuracy Ratio	Log Likelihood Margin*	Accuracy Ratio	Log Likelihood Margin*
RiskCalc v3.1 Model	59.7%		53.7%	
RiskCalc v1.0	54.8%	1354.6	47.4%	1983.4
Z-score	46.3%	7690.0	40.9%	9980.6

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

Figure 6 presents the cumulative accuracy profiles for the 1- and 5-year models corresponding to Table 7.

[9] The corresponding accuracy ratios are 58.4% (FSO) vs. 54.8% (RiskCalc v1.0) for the 1-year horizon and 52.6% (FSO) vs. 47.4% (RiskCalc v1.0) for the 5-year horizon.

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



4.2 Correlations and Variance Inflation Factors

In this section, we present the correlation coefficients (Table 8) for the model ratios and the variance inflation factors (Table 9). These analyses represent checks for whether or not there is excessive multicollinearity in the model, which can cause instability in parameter estimates. For further details on the definitions and how to interpret these analyses, please see the Technical Document.

In Table 8, we present the Spearman rank correlation coefficients that are computed on the transformed variables as they enter into the probit regression (see Figure 4). The highest correlation coefficient is between [Total Assets to Total Liabilities] and [Current Assets to Current Liabilities] (0.44). The next highest coefficient is between [Cash Flow to Interest Expense] and [Net Profit and Loss to Turnover] (0.40). Such coefficients are well below what we would consider indications of multicollinearity, and this is verified by the VIF analysis below.

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

	Liabilities to Assets	Net P&L to Turnover	Cash Flow to Interest Expense	Change in ROA	Sales Growth	Change in AR to Sales	Trade Creditors to Turnover	Current Assets to Current Liabilities	Total Assets
Liabilities to Assets	1.0								
Net P&L to Turnover	0.338	1.0							
Cash Flow to Interest Expense	0.273	0.404	1.0						
Change in ROA	0.067	0.106	0.043	1.0					
Sales Growth	0.101	0.013	0.052	0.214	1.0				
Change in AR to Sales	0.063	-0.049	0.038	0.131	0.246	1.0			
Trade Creditors to Turnover	0.293	0.142	0.068	-0.005	0.072	0.176	1.0		
Current Assets to Current Liabilities	0.440	0.208	0.183	-0.019	-0.024	-0.038	0.124	1.0	
Total Assets	0.061	-0.074	-0.030	0.211	0.099	0.144	-0.045	-0.010	1.0

Table 9 presents the Variance Inflation Factors (VIFs) for the financial statement variables in the model. The VIFs represent how much of the variation in one independent variable can be explained by all the other independent variables in the model, which is in contrast to the pair-wise correlation coefficients in Table 8 that show how closely two variables move together. As Table 9 indicates, the estimated VIF values are notably below the threshold level of four that is commonly used in VIF analysis when testing for presence of multicollinearity.[10] The highest VIF factor is for Liabilities to Assets, which is 1.45. Thus, the findings indicate that the model variables do not present any substantial multicollinearity.

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

TABLE 9 Variance Inflation Factors

Variable	VIF
Liabilities to Assets	1.45
Net Profit and Loss to Turnover	1.41
Cash Flow to Interest Expense	1.29
Current Assets to Current Liabilities	1.23
Change in Accounts Receivable Turnover	1.20
Change in ROA	1.19
Trade Creditors to Turnover	1.17
Sales Growth	1.15
Size	1.05

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

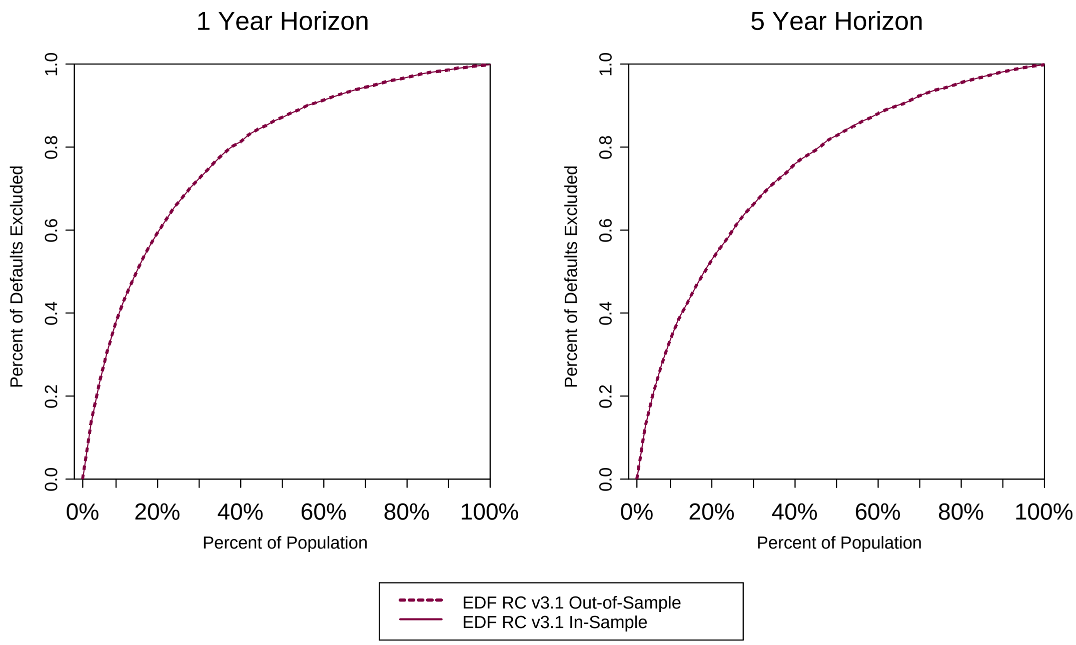
The model exhibits a high degree of power in distinguishing good credits from bad ones (in Table 7), but whether this power is attributable to the overall model effectiveness or the impact of a particular sub-sample also needs to be tested. A standard test for evaluating this is called the "*k*-fold test," which divides the defaulting and non-defaulting companies into *k* equally sized segments. This yields *k* equally sized observation sub-samples that exhibit the identical overall default rate and are temporally and cross-sectionally independent. The model is then run on *k-1* sub-samples and these parameter estimates are used to score the *k-th* sub-sample. We repeat this procedure for all possible combinations, and put the *k* scored "out-of-sample" sub-samples together and calculate an accuracy ratio (AR) on this combined data set.

Table 10 summarises the *k*-fold test results (with *k*=5). The reported figures are the accuracy ratios by the corresponding sample and time horizons. The out-of-sample model consistently out-performs RiskCalc v1.0. Figure 7 presents the cumulative accuracy profiles associated with the overall "out-of-sample" results against the in-sample results and the original model. The model performance is maintained both in- and out-of-sample in the *k*-fold analysis. The difference in AR between the in-sample and out-of-sample results is minimal at both horizons. Further, RiskCalc v3.1 outperforms RiskCalc v1.0 in an out-of-sample context at both the 1- and 5-year horizons (Table 10).

TABLE 10 RiskCalc v3.1 *k*-fold Test Results

	Out of Sample AR		RiskCalc v1.0	
	1-year AR	5-year AR	1-year AR	5-year AR
Subsample 1	55.9%	48.9%	51.5%	43.9%
Subsample 2	55.0%	50.2%	50.9%	45.4%
Subsample 3	57.8%	52.1%	53.5%	47.7%
Subsample 4	58.0%	51.5%	53.7%	47.3%
Subsample 5	56.8%	51.9%	52.8%	47.5%
K-fold Overall	59.6%	53.8%	54.8%	47.3%
In-sample AR	59.6%	53.8%		

FIGURE 7 RiskCalc v3.1 U.K. *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 period of particularly high default rates, this would be included in each of the *k* samples. Such testing does not give a true sense of the how the model would have performed during those volatile periods because the model is estimated with full information on those time periods.

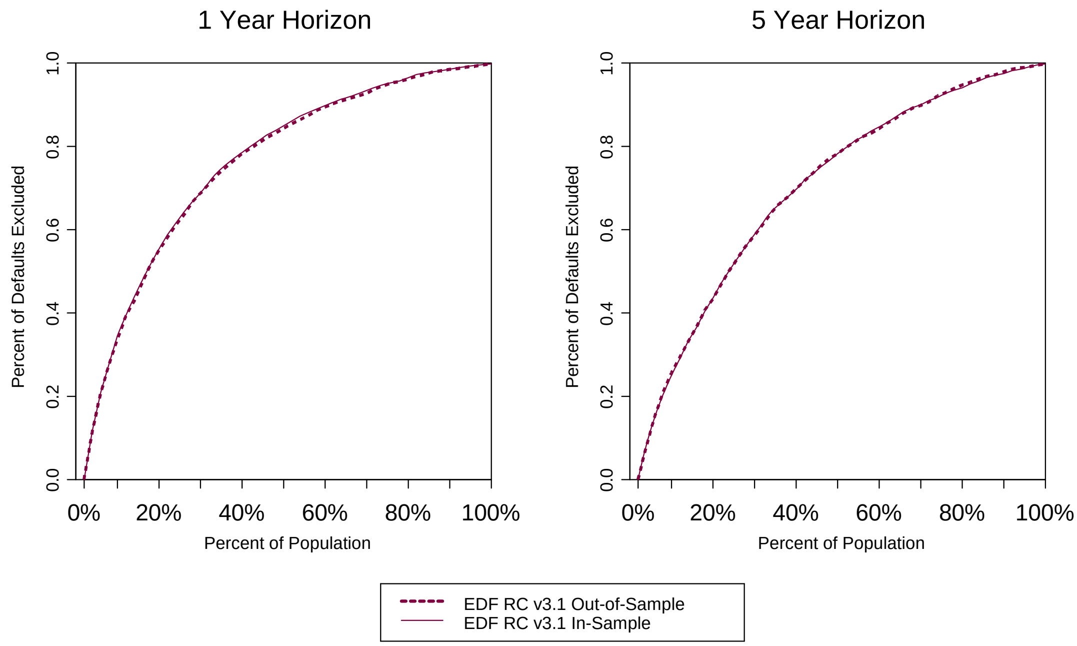
4.4 Walk-Forward Tests

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

No data from a future period is used in fitting the model and only data from future periods is used for testing it. The parameter estimates are checked for stability across the different samples. Figure 8 presents the results from this analysis. The difference in AR between the overall in-sample and out-sample results is less than one point for both horizons. Further, RiskCalc v3.1 outperforms RiskCalc v1.0 in an out-of-time context at both the 1- and 5-year horizons.[11]

[11] The out-of-sample ARs are 54.4% and 44.8% for the 1-year and 5-year models, respectively. These out-of-sample ARs are 0.8 and -0.1 points lower than the in-sample ARs and 3.5 and 2.9 points higher than RiskCalc v1.0, for the one and five year models respectively.

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



4.5 Model Power by Industry and Size Groups

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

Table 11 and Table 12 present the power comparisons by sector for the 1-year and 5-year models, respectively. RiskCalc v3.1 outperforms both RiskCalc v1.0 and Z-score in all sectors. The highest power in the 1-year model is found in Consumer Products (64.3%) while the lowest is found in Services (50.9%). At the 5-year horizon (Table 11) the highest power is in the Unassigned group (55.9%) and the lowest is in Communications and Hi Tech (47.9%). RiskCalc v3.1 outperforms RiskCalc v1.0 and the Z-score across all segments at both horizons.

TABLE 11 Model Power by Industry 1-Year Model

	Percent of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Business Products	12.4%	59.2%	55.2%	47.8%
Communications and Hi Tech	3.6%	51.5%	50.4%	44.8%
Construction	21.6%	61.3%	59.0%	52.5%
Consumer Products	8.4%	64.3%	62.2%	49.1%
Mining, Transportation, Utilities and Natural Resources	6.0%	56.1%	52.4%	44.2%
Services	21.8%	50.9%	46.6%	38.5%
Trade	20.5%	60.1%	54.0%	46.7%
Unassigned	5.7%	54.8%	52.0%	45.5%

TABLE 12 Model Power by Industry 5-Year Model

	Percent of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Business Products	12.2%	49.3%	46.5%	39.5%
Communications and Hi Tech	3.4%	47.9%	44.8%	35.9%
Construction	21.3%	54.8%	49.7%	45.8%
Consumer Products	8.2%	54.7%	54.1%	47.2%
Mining, Transportation, Utilities and Natural Resources	6.2%	48.7%	45.6%	37.4%
Services	21.9%	48.7%	42.5%	35.5%
Trade	20.8%	51.8%	43.6%	39.6%
Unassigned	6.0%	55.9%	48.1%	44.0%

Table 13 and Table 14 present the power comparisons by firm size for the 1-year and 5-year models, respectively. RiskCalc v3.1 outperforms both RiskCalc v1.0 and Z-score in all size groups. At the 1-year horizon, the power of the model is largely uniform across size groups ranging from a low of 57.3% (£5mm to £10mm) to a high of 61.9% (£10mm to £50mm). At the 5-year horizon, the least powerful category is the smallest firms (52%) and the most powerful category is the largest firms (63.4%).

TABLE 13 Model Power by Size 1-Year Model

	Percent of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
< £500,000	15.0%	59.2%	52.8%	45.2%
£500,000 to £2mm	25.9%	60.4%	53.5%	46.9%
£2mm to £5mm	42.8%	58.7%	55.0%	45.6%
£5mm to £10mm	9.8%	57.3%	55.7%	42.8%
£10mm to £50mm	5.7%	61.9%	55.5%	44.9%
Over £50mm	0.9%	59.5%	46.2%	42.0%

TABLE 14 Model Power by Size 5-Year Model

	Percent of Defaults	AR RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
< £500,000	16.5%	52.0%	44.7%	37.8%
£500,000 to £2mm	26.5%	55.1%	47.3%	41.7%
£2mm to £5mm	41.1%	53.8%	48.1%	39.7%
£5mm to £10mm	9.8%	53.4%	49.4%	38.8%
£10mm to £50mm	5.5%	57.0%	51.1%	43.2%
Over £50mm	0.7%	63.4%	52.8%	45.8%

4.6 Power Performance Over Time

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

Table 15 and Table 16 present the results from this analysis at the one and five year horizons, respectively. The AR of RiskCalc v3.1 is compared with RiskCalc v1.0 and Z-score for three different time periods. RiskCalc v3.1 consistently outperforms both RiskCalc v1.0 and Z-score by a considerable margin.

TABLE 15 Model Power over Time: 1-year Model

	Percent of Defaults	AR* RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Before 1993	31.6%	55.7%	52.6%	41.6%
1993-1997	34.1%	57.3%	55.9%	42.9%
After 1997	34.3%	54.4%	48.9%	43.4%

*AR = accuracy ratio

TABLE 16 Model Power over Time: 5-year Model (AR = accuracy ratio)

	Percent of Defaults	AR* RiskCalc v3.1	AR RiskCalc v1.0	AR Z-score
Before 1993	30.8%	54.9%	51.5%	38.9%
1993-1997	36.2%	49.7%	45.1%	37.4%
After 1997	33.0%	44.4%	41.6%	38.8%

*AR = accuracy ratio

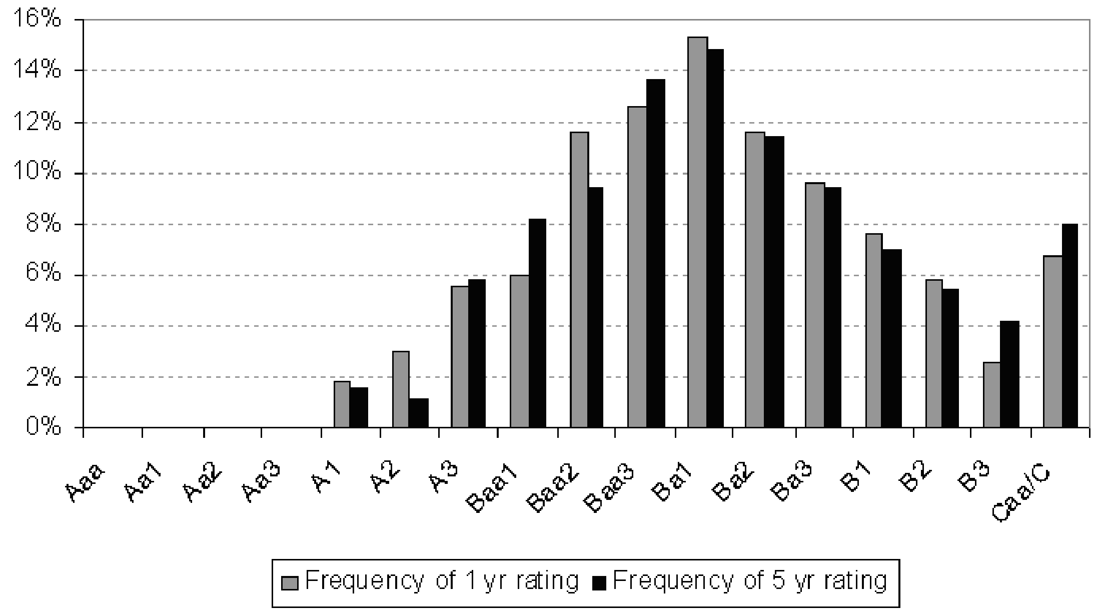
4.7 Model Calibration and Implied Ratings

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

- There are a large range of .edf ratings (as required for economic and regulatory applications);
- No one rating contains too many credits (as required for economic and regulatory applications);
- The distribution of the 5-year ratings is approximately the same as the distribution of 1-year ratings (for consistency with rating-based analysis applications);
- The EDF value associated with an .edf rating is approximately the same as the observed historical default rate associated with a Moody's Bond Rating (for consistency with rating-based analysis applications).

Figure 9 shows the distribution of CRD observations by rating category in the development sample (for the Credit Cycle Adjusted EDF credit measures over the full time period). Note that 13 categories between A1 and Caa/C are utilised and that less than 16% of the observations are in any one category. There are actually traces of Aa3s produced by the model that are not visible in the histogram. Both the 1-year and the 5-year distribution peaks at Ba1. While not reported here, other research has shown that the distribution of the credit cycle adjusted .edf ratings changes over time with the credit cycle while the distribution of the FSO .edf ratings remains relatively stable over time.

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



5 FURTHER MODEL IMPROVEMENTS

In this section, we will briefly outline some additional enhancements to the model.[12]

5.1 Continuous Term Structure

The previous version of the RiskCalc model provided the user with two discrete default probability estimates: a 1-year and a 5-year EDF value. In this version, utilizing the two point estimates for 1- and 5-year estimates we fit a Weibull function, and thus achieve a continuous term structure of EDF values for each credit. In other words, users of RiskCalc v3.1 U.K. 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 Annualised EDF (Table 17):

- **Cumulative EDF**

  A cumulative EDF credit measure gives the probability of default over that time period. For example, a 5-year cumulative EDF value of 13.44% means that that company has a 13.44% chance of defaulting over that 5-year period. The second column of Table 17 provides an example of the cumulative 1- to 5-year EDF credit measures produced by they model.

- **Forward EDF**

  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 value is the probability that a firm will default between years three and four assuming the firm survived to year three.[13] The third column of Table 17 displays the forward 1- to 5-year EDF values that are derived from the cumulative EDF credit measures.

- **Annualised EDF**

  The annualised 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 annualised EDF value 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 17 presents the annualised EDF credit measures for years 1 to 5 that are derived from the cumulative EDF values.

TABLE 17 Term Structure of EDF Credit Measures: An Example

EDF	Cumulative	Forward	Annualised
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

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

[13] 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*.

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

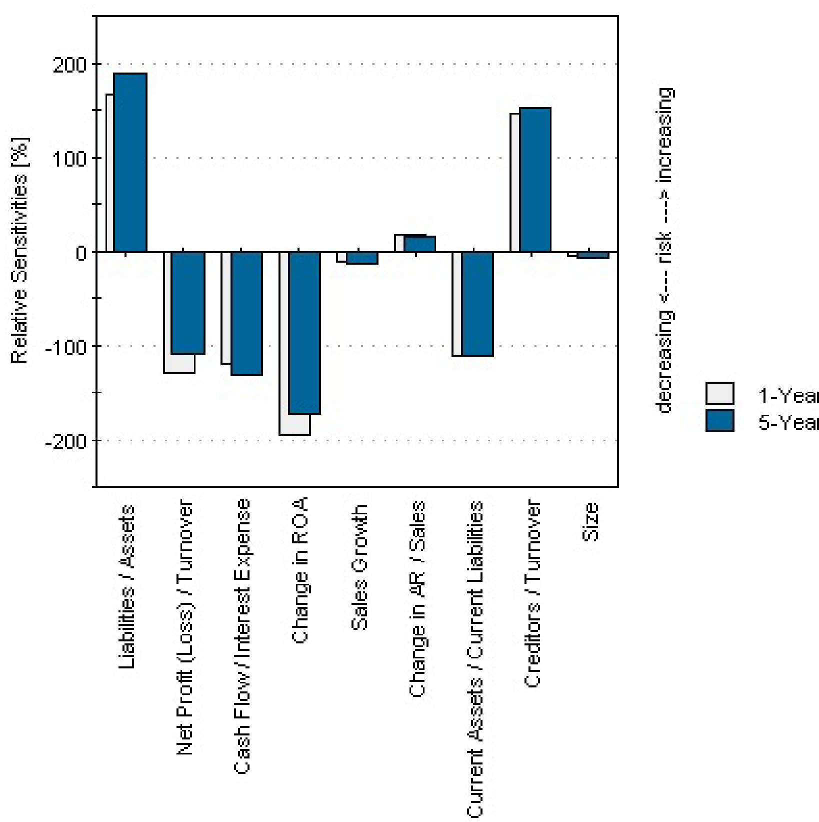
5.2 New Analytical Tools: Relative Sensitivity

The RiskCalc v1.0 interface provides users with an analytical tool to gauge the relative impact of each variable – as a deviation from the mean of each ratio. In order to equip the users of the model with further tools we developed relative sensitivities (also known as sensitivity multiples), which exhibit the EDF sensitivity to each of the model variables at the point of evaluation. This feature is especially useful when addressing the question of identifying variables to improve the EDF value of a company.

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

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

FIGURE 10 Relative Sensitivities



5.3 Asset Value and Volatility Calculation

One of the features of the 3.1 version of the model is that it provides implied asset volatility. Clients of Credit Monitor and Credit Edge can use these measures to analyse a private firm that is to go public through an IPO. Once the firm is public, the Public Firm models should be used, however, these models require an asset volatility that is derived from the public share price. In the 3.1 version of the model, the asset volatility of the firm is estimated using its industry and size and a methodology that is very similar to PFM. A structural model framework is then used to solve for the implied asset value from the estimated EDF value, the estimated volatility, and the firm's liability structure.

6 CONCLUSION

The RiskCalc v3.1 U.K. model is based on a substantially larger database than its predecessor, RiskCalc v1.0 U.K. The larger database includes three additional years of data. Improved data coverage has allowed us to further refine our financial statement model and achieve a very robust prediction model of private firm default behaviour.

The new model includes several new variables that make it more responsive to accounting irregularities and the stability of the firms' operations. The debt coverage ratio is based on operating cash flow rather than ordinary profit. The inclusion of such a variable penalises a firm with negative cash flow even if ordinanry profit and net P&L are both positive. In order to account for the stability of profits, we include Changes in Net P&L to Assets. Finally, there is a variable that accounts for strong trends in trade debtors (accounts receivable) to turnover (sales).

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

The RiskCalc v3.1 model controls for differences in the default risk across industries in the FSO mode. In addition, it also 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, then the EDF level is adjusted upward. Likewise, when default risk is low, then the EDF level is adjusted downward. This additional feature of the model increases both model power and precision dramatically, and also allows users to monitor their portfolios on a monthly basis.

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

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

7 REFERENCES

1. Altman, E., J Hartzell, and M. Peck. "Future of Emerging Market Flows." New York: Salomon Brothers, Inc, 1995.
2. Crosbie, Peter J. and Jeff R. Bohn. “Modeling Default Risk.” San Francisco: KMV, 2003.
3. Dwyer, Douglas, Ahmet Kocagil and Roger Stein. "The Moody's KMV RiskCalc v3.1 Model: Next-Generation Technology for Predicting Private Firm Credit Risk." Moody's KMV, 2004.
4. Dwyer, Douglas and Roger Stein. "Technical Document on RiskCalc v3.1 Methodology." Moody's KMV, 2004.
5. Falkenstein, Eric. "RiskCalc Private Model: Moody's Default Model for Private Firms." New York: Moody's Investors Service, 2000.
6. Hoggarth, Glenn and Darren Pain. "Bank Provisioning: The UK Experience." *Financial Stability Review*, no. 12 (2002): 116-27.
7. Kocagil, Ahmet E., Phil Escott, Frank Glormann, Wolfgang Malzkom, and Alison Scott. "Moody's RiskCalc for Private Companies: UK." Moody's Investors Service, 2002.
8. OECD. *Bank Profitability: Financial Statements of Banks*. 2002.
9. Penny, David, ed., *Annual Abstract of Statistics: United Kingdom*, Office for National Statistics, 2004.
10. Stein, Roger M., "Benchmarking Default Prediction Models: Pitfalls and Remedies in Model Validation." Moody’s KMV, New York, 2002.
11. Woolridge, *J.M. Introductory Econometrics*: A Modern Approach, South Western, 2000.