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# MOODY'S KMV RISKCALC™ V3.1 AUSTRIA

MODELING**METHODOLOGY**

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## ABSTRACT

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

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

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

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# 1 INTRODUCTION

The Moody's KMV RiskCalc v3.1 Austria 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 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. The CCA model reflects the market's current assessment of the credit cycle and is a forward-looking indicator of default.

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

## 1.2 Differences Between RiskCalc v3.1 Austria and RiskCalc v1.0 Austria

Since the release of RiskCalc v1.0 Austria, Moody's KMV significantly increased the size of the database for Austria and improved its data cleansing technologies. Due to improved data coverage, RiskCalc Austria 3.1 includes new ratios to expand the coverage on dynamic factors of private firms' credit risk. Furthermore, the new model allows for more granular industry adjustments, credit cycle adjustment, and a complete term structure of EDF credit measures. RiskCalc Austria 3.1 also provides new analytic tools that increase model usability and transparency. Given the advances in modeling, RiskCalc Austria 3.1 is a more powerful predictor of default than its predecessor.

# 2 DATA DESCRIPTION

The source of the data for RiskCalc v3.1 Austria 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

Moody's KMV 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) have stimulated debates about what constitutes an appropriate definition of default. RiskCalc applies the criteria used by most of the advanced economies in the world. In model development, RiskCalc uses the local criteria for default. Accordingly, in Austria, the events which we defined as defaults include 90-days past due, initiation of proceedings, bankruptcy, insolvency, and liquidation. 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 Expected Default Frequency™ (EDF) for private Austrian 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 Austrian 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 Net Sales less than € 500,000 (2002 Euros), 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 Moody's CRD increased since RiskCalc v1.0 was developed. Figure 1 presents the distribution of Austrian 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 Austria 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 Austrian Financial Statements and Defaults

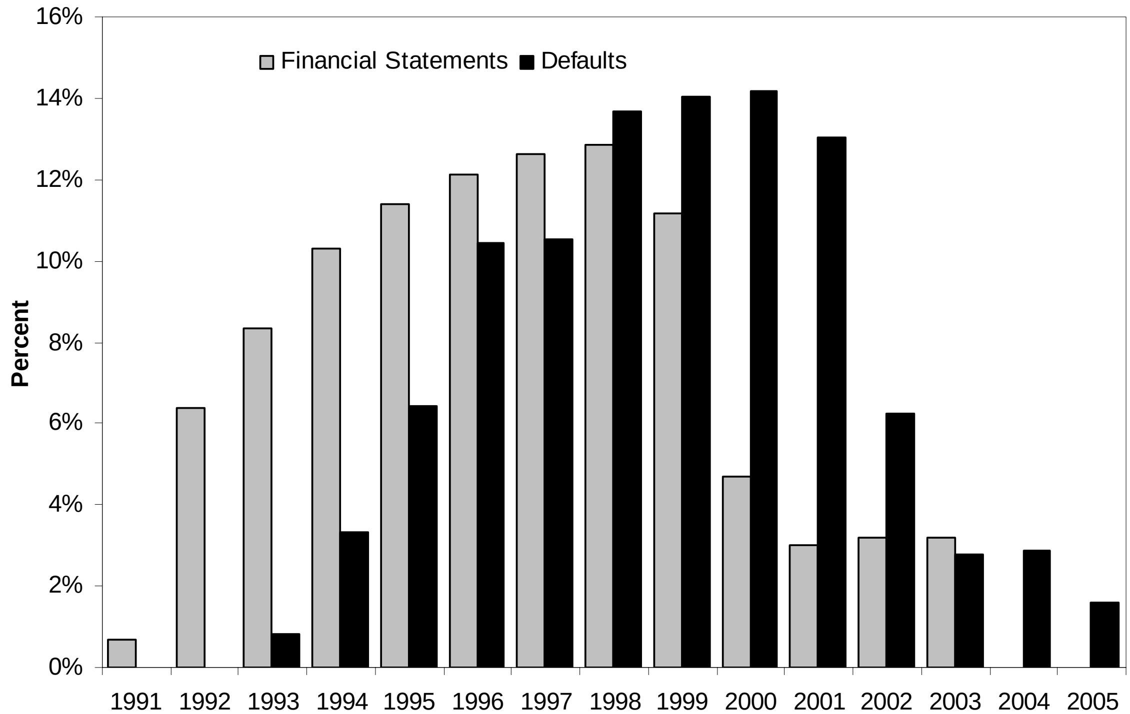



TABLE 1 Information on Austrian Private Firm Sample Data

| Austrian Private Firms | RiskCalc v1.0 Austria | RiskCalc v3.1 Austria | Change |
|---|---|---|---|
| Financial statements | 83,613 | 100,000+ | ↑ 20% |
| Unique number of firms | 19,524 | 25,000+ | ↑ 28% |
| Defaults | 2,156 | 3,000+ | ↑ 39% |
| Time period | 1991–2000 | 1991–2005 | +5 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 Austrian 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 Euros. These figures demonstrate that 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 45% of the firms hold assets less than 1 million Euros.

FIGURE 2 Distribution of Austrian Defaults and Firms by Industry

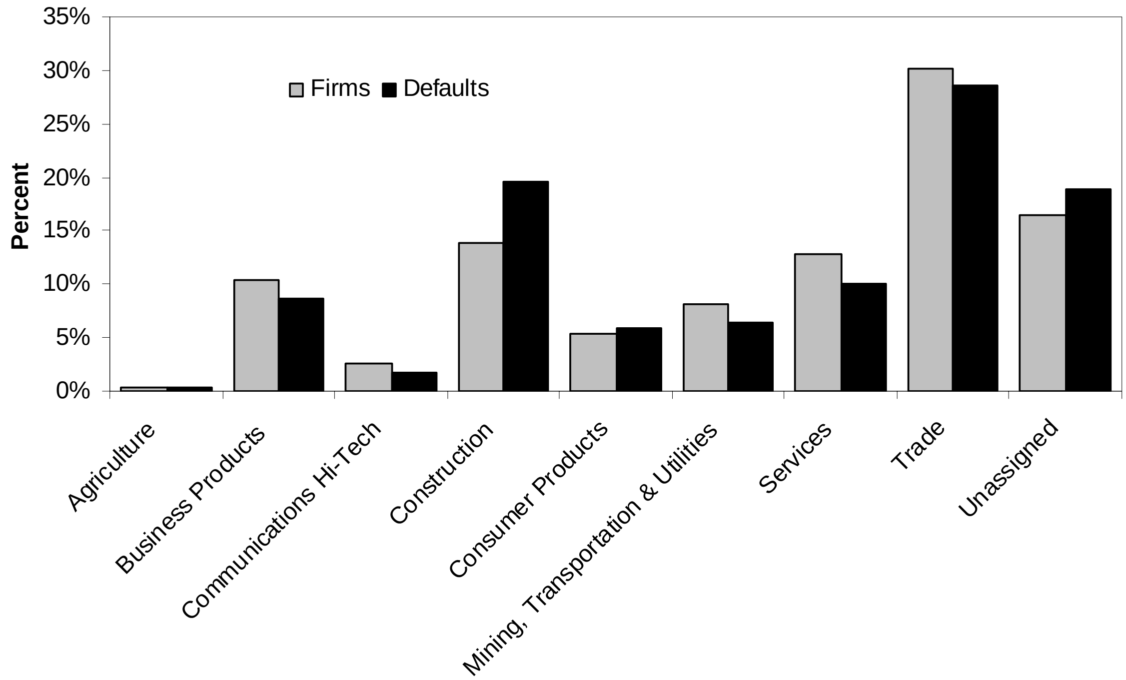
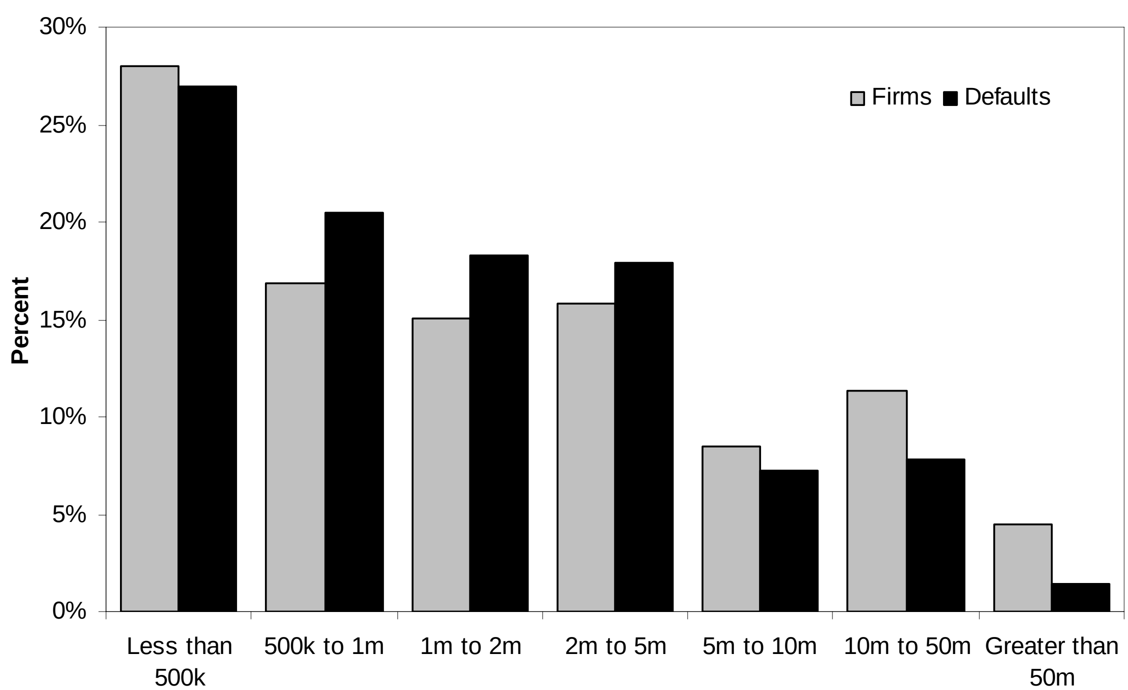



FIGURE 3 Size (as Total Assets in Euros) Distribution of Defaults and Firms



## 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 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, as is the case with Austria, 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 Austria is based on several 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 Austrian banks.
- We examined bankruptcy data from Austria.
- We ensured that the central default tendency exceeded the default rates observed in our development sample.

The multiple sources of external data lead us to an estimate of 2.0% as the central tendency figure for the 1-year model. This estimate is consistent with the average probability of default from the RiskCalc v1.0 Austria model on the development sample.

### 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, 8.0% is used as the central default tendency for the 5-year model.

### Central Default Tendency in FSO and CCA Modes

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

# 3 MODEL COMPONENTS

The RiskCalc v3.1 model incorporates various components to determine the EDF credit measure. The inputs to the model include a selection of the financial ratios 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.[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, 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:

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

where x1,...,xN are the input ratios; I1,...,IK are indicator variables for each of the industry classifications; β and γ are estimated coefficients; Φ is the cumulative normal distribution; F and T1,...,TN are non-parametric transforms; and FSO EDF is the financial-statement-only EDF credit measure.[3] 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 (i.e. the final mapping). The final transform captures the empirical relationship between the probit model score and actual default probabilities. We describe the final transform as calibrating the model score to an actual EDF credit measure. The difference between the FSO EDF and the credit cycle adjusted EDF is that in CCA mode the final transform is adjusted to reflect our assessment of the current stage of the credit cycle, while in FSO mode it remains constant.

## 3.1 Financial Statement Variables

### Selecting the Variables

Our variable selection process starts with a long list of possible financial statement variables. The working list of ratios is divided into groups that represent different underlying concepts regarding a firm's financial status (see Table 2). A model is then built with at least one variable per group. When it is possible to increase model performance while maintaining model robustness, several variables from each group will be used in the model. 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 $T(x_i)$ 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.

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 (or gearing) 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 Euros). → Large firms default less often. |

TABLE 3 Financial Statement Variables used in RiskCalc v3.1 Austria

| Category | Definition |
|---|---|
| Activity | Creditors Ratio: (Accounts Payable from Trade + Notes Payable) / Net Sales<br><br>Staff Expenses to Sales: Staff Expenses / Net Sales |
| Debt Coverage | Debt Coverage Ratio: Cash Flow / (Interest Expense + Debt Due) |
| Growth | Sales Growth: Net Sales(t) / Net Sales(t-1) – 1<br><br>Change in ROA: Net Income(t) / Assets(t) – Net Income(t-1) / Total Assets(t-1) |
| Leverage/Gearing | Equity Ratio: Equity / Accounts Payable<br><br>Liabilities Structure: (Accounts Payable from Trade + Accounts Payable to Credit Institutions + Notes Payable) / (Accounts Payable + Provisions) |
| Liquidity | Current Assets Structure: Cash at Bank and in Hand / Current Assets |
| Profitability | Profit on Sales: (Ordinary Profit + Depreciation) / Net Sales |
| Size | Size: Total Real Assets in 2002 Euros |