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MODELING METHODOLOGY

RiskCalc Banks v4.0 Model

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Abstract

There has been a significant increase in the demand for quantitative tools that assess the default risk of banks across different geographies. Pooling data from more than 90 countries, we see commonalities in linking default risk to a specific set of financial ratios. This finding suggests that a prescribed set of financial ratios, properly transformed, works well in estimating banks' default risk in a robust fashion.

With this insight, we constructed the RiskCalc™ Banks v4.0 Model, intended for assessing the probability of default (PD) for banks across different geographies and regulatory environments. The model provides a unified framework to assess bank risk across different countries and regions, as well as different economic cycles. The one-year model is based upon a set of well-defined and ready-to-calculate financial ratios that effectively measure bank profitability, leverage, liquidity, growth, and asset quality. The five-year model combines these ratios with a measure derived from an economic capital framework based upon portfolio theory. Specifically, this measure captures the unexpected loss of a bank's loan portfolio relative to its loss-absorbing capital. Validation results show that the model delivers strong and robust power in rank ordering high risk banks from low risk banks, and that the results are robust across geographies and bank sizes.

This note is an abbreviated overview of our full-length methodology paper. To learn more about this comprehensive version, please contact MA_support@moodys.com.

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1. Introduction

A forward-looking and accurate measure of bank default risk is of great interest and significance to many, including the bank's regulators, creditors, and depositors. For banks with market information such as equity and CDS spreads, equity-based EDF™ (Expected Default Frequency) credit measures and CDS-Implied EDF can provide forward-looking and accurate measures. It is particularly challenging to develop similarly effective measures from a fundamental-based approach, given heterogeneity in domestic legal, operating, financial reporting, and banking regulatory differences. We address this challenge when developing the RiskCalc Banks v4.0 Model.

The RiskCalc Banks v4.0 Model utilizes a set of readily-defined financial ratios, which capture bank profitability, leverage, liquidity, growth, and asset quality, and a country- (region) specific credit-cycle adjustment based upon the Moody's Analytics Public Firm model to effectively measure the default risk of banks across different countries. We combine a capital adequacy ratio derived from an economic capital framework based upon portfolio theory with the other ratios in evaluating bank default risk in the long horizon, when information on a bank's loan portfolio composition is available.

The model shows strong and robust performance across geographies in the development sample, which includes more than 90 countries, covering the period 1988–2012. Furthermore, the model demonstrates robust performance across different data sources with different data formats, out-of-sample.

The RiskCalc Banks v4.0 Model allows users to assess the stand-alone risk of banks in two ways: Financial Statement Only (FSO) mode and Credit Cycle Adjusted (CCA) mode. FSO delivers a bank's default risk based only upon its financial statement information. For example, Bank A from Country X would have the same risk assessment as Bank B from Country Y if the two banks provide exactly the same financial ratio values for ratios utilized within the model.

CCA mode adjusts bank default risk by taking into account the credit cycle of a particular country or region on a given analysis date. The CCA adjustment for a country (region) is derived directly from the Moody's Analytics Distance-to-Default (DD) measure at the aggregate level for a specific country's (region) banking industry. The CCA mode reflects the market's current assessment of the credit cycle and is a forward-looking indicator of default risk. As a result, Bank A from Country X and Bank B from Country Y with the same FSO assessments are likely to have different CCA assessments. The CCA adjustment is specific to a country (region) and is updated monthly.

The RiskCalc Banks v4.0 Model is applicable to banks outside U.S. To assess the default risk of banks in the U.S., including FDIC insured banks, bank holding companies, and credit unions, please refer to the RiskCalc U.S. Banks 4.0 Model.

The remainder of this paper is organized as follows: Section 2 describes the data used to estimate the model and to populate inputs. Section 3 describes the components of the model, including a description of model factors. Section 4 reports validation results. Section 5 outlines additional model features. Section 5 provides concluding remarks.

2. Data Description

2.1 Financial Data

We construct the v4.0 model using annual financial statement information collected from a data vendor, referred to as Vendor1. The two-digit SIC code 60 (deposit-taking credit institutions) is used to identify banks from Vendor1. Because we aim to create a unified framework that evaluates banks across geographies, we include both U.S. and non-U.S. banks in the sample. The sample period range is 1988–2012. We use a total of 30,000+ financial statements in the development sample, with 16,000+ statements from non-U.S. banks and 16,000+ statements from U.S. banks. The development sample covers 90+ countries.

2.2 Descriptive Statistics

Our sample includes 16,000+ annual statements and 70+ defaults for non-U.S. banks, and 16,000+ U.S. bank statements with 80+ U.S. bank defaults. Table 1 presents the distribution of non-U.S. bank statements by region.

Table 1 DISTRIBUTION OF NON-U.S. SAMPLE BY REGION

REGION	NUMBER OF STATEMENTS	NUMBER OF UNIQUE BANKS
Western Europe	5,000+	400+
Asia (ex. Japan)	3,000+	300+
Japan	2,500+	100+
Central and Eastern Europe	1,000+	100+
Central and Southern America	1,000+	90+
Africa	1,000+	100+
Middle East	500+	75+
North America (ex. U.S.)	300+	20+
Australia and New Zealand	200+	20+

Figure 1 and Figure 2 present the distribution of financial statements and defaults by year for the non-U.S. sample and the U.S. sample, respectively. We classify financial statements based upon fiscal year and defaults based upon calendar year. For the non-U.S. sample, financial statements are relatively evenly distributed across years after 1999. Year 2008 shows the highest number of defaults, and year 2001 ranks second. Recent defaults are due primarily to the financial crisis as well as the European sovereign crisis. We also see elevated defaults at the end of the 1990s, reflecting the impact of the Asian crisis during that period.

Figure 1 Distribution of Statements and Defaults by Year: Non-U.S.

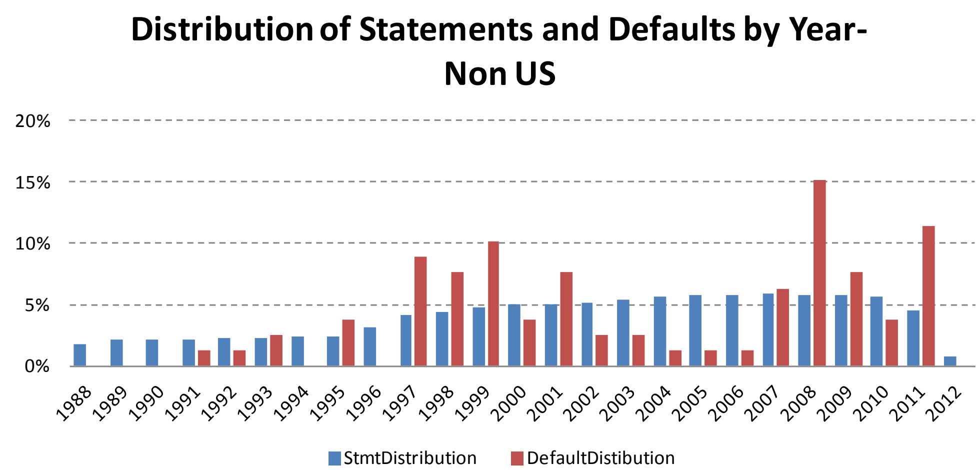
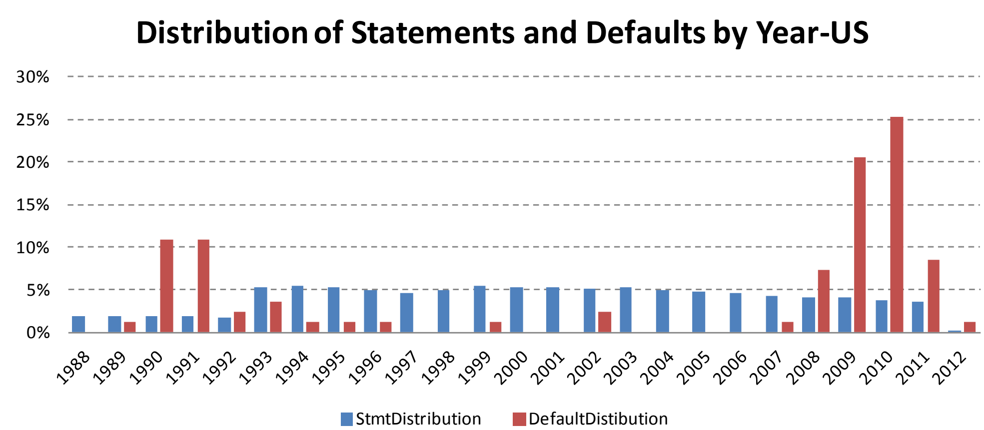


Figure 2 Distribution of Statements and Defaults by Year: U.S.



3. Model Components

The RiskCalc Banks v4.0 Model incorporates various components to determine the EDF™ (Expected Default Frequency) credit measure. Model inputs include a selection of financial ratios, transforms of these ratios, and the credit cycle adjustment based upon country (region).

The development of the RiskCalc Banks v4.0 Model involves the following steps:

» Choose a limited number of financial statement variables for the model from categories of the variables shown in Table 2. The selected variables are compatible with IFRS accounting standard.
» Transform the variables into interim probabilities of default using non-parametric techniques.
» Estimate the weights of the financial statement variables, using a probit model.
» Create a (non-parametric) final transform that converts the probit model score into an actual EDF credit measure.
» Add Credit Cycle Adjustments based upon country or regional information.

Table 2 GROUPINGS OF FINANCIAL STATEMENT VARIABLES USED IN BANKS V4.0 MODEL

CATEGORY	DESCRIPTION
Portfolio Composition	Variables in this category capture the impact that composition of the portfolio have upon the bank's likelihood of default.
Profitability	Metrics used to asses company's ability to generate earnings relative to its costs. Ratios in this category often include net income, profit before tax, operating profit in the numerator and total assets, tangible assets, fixed assets, or sales in the denominator. High profitability reduces the probability of default.
Asset Quality	These variables evaluate the credit risk associated with assets in the bank's portfolio. Low asset quality increases the probability of default.
Leverage	For the corporate model, this ratio category often includes liabilities to assets or debt to assets. For the banks model, we also consider equity - intangibles. High leverage increases the probability of default.
Liquidity	These variables measure the extent to which the bank has liquid assets relative to the size of its assets or liabilities. Ratios in this category include such inputs as net loans, short term investments, brokered deposits, total deposits, and total assets. High liquidity reduces the probability of default.

3.1 Variable Transforms

After selecting variables, we transform them into a preliminary EDF value. The shape of the transformation indicates how significantly a level change impacts the EDF credit measure. If the slope of the transform is steep, a small change has a larger impact on risk than if the slope is flat.

3.2 CCA Mode

The EDF credit measure is impacted not only by a company's financials, but also by an economy's general credit cycle. To capture this effect, the RiskCalc Bank v4.0 Model includes a credit cycle adjustment factor for supported countries and regions. The credit cycle adjustment is designed to incorporate the current credit cycle into the assessment of bank default risk.

COUNTRY AND REGIONAL ADJUSTMENT FACTOR

For the RiskCalc Banks v4.0 Model, the distance-to-default (DD) factor is based upon an aggregation of all publicly listed banks within a specific country/region. Each month, we calculate the DD factor for each of the supported countries and the nine regions.[1] We then use a combination of the country-specific DD factor and the DD factor based upon all publicly traded banks in the corresponding region. For countries with fewer publicly traded banks, we place more weight on the regional DD factor. As the number of publicly traded banks in the country increases, so does the weight we place on the country-specific DD factor.

4. Validation

In this section, we present validation results for the model's ranking power (the model's ability to rank order credits from worst to best), as well as the overall levels of predicted EDF credit measure. Since the model is intended to be robust across geographies, we also present model performance results on different data population. Results show that the RiskCalc Banks v4.0 Model effectively captures the default risk of banks across geographies and size classifications.

4.1 Overall Model Power and Accuracy

Table 3 presents the in-sample, overall measures of power for the RiskCalc Banks v4.0 Model versus a benchmark ratio of Equity/Assets. We use this ratio as a benchmark because it is a relatively well-defined capital (leverage) ratio. The RiskCalc Banks v4.0 Model outperforms the Equity/Assets ratio at both the one-year and five-year horizons. Table 4 presents the performance for non-U.S. banks only.

[1] As listed in the previous section, the nine regions include Western Europe, Asia (excluding Japan), Japan, Central and Eastern Europe, Central and South America, Africa, Middle East, North America, and Australia/New Zealand. The DD factor for Canada always has a 100% weight on the Canadian DD factor, regardless of the number of banks in Canada.

Table 3 POWER PERFORMANCE OF THE RISKCALC BANKS V4.0 MODEL ON FULL SAMPLE

MODEL	ONE-YEAR MODEL	FIVE-YEAR MODEL
RiskCalc Banks v4.0	79.0%	35.3%
Equity/Assets	50.4% (p value<.0001)	21.0% (p value=.0017)

Table 4 POWER PERFORMANCE OF THE RISKCALC BANKS V4.0 MODEL ON NON-U.S. SAMPLE

MODEL	ONE-YEAR MODEL	FIVE-YEAR MODEL
RiskCalc Banks v4.0	62.3%	33.4%
Equity/Assets	35.1% (p value<.0001)	17.4% (p value=.0086)

5. Conclusion

The RiskCalc Banks v4.0 Model provides a unified framework to assess bank risk, across different countries and regions, as well as different economic cycles. The one-year model is based upon a set of financial ratios that we believe are the best predictors of risk. The five-year model can also take into account a bank's portfolio composition. Validation studies show that the model performs well across geographies and size cuts.

Operating in CCA mode, the model adjusts the EDF credit measure to reflect the current stage of the credit cycle in the banking industry for a specific country/region. If default risk in the banking industry for a particular country/region is high, the EDF credit measure is adjusted upward. Likewise, when default risk is low, the EDF credit measure is adjusted downward. The CCA adjustment in the v4.0 Model is based upon the Moody's Analytics Public Firm Model.

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