Moody's Analytics

RiskCalc: New Research and Model Validation Results

Douglas Dwyer, Managing Director

May 2011

RiskCalc Models

Seek to maximize predictive power, provided the model is:

» Transparent

» Intuitive

» Reasonable

Extract a risk assessment from the financial statements:

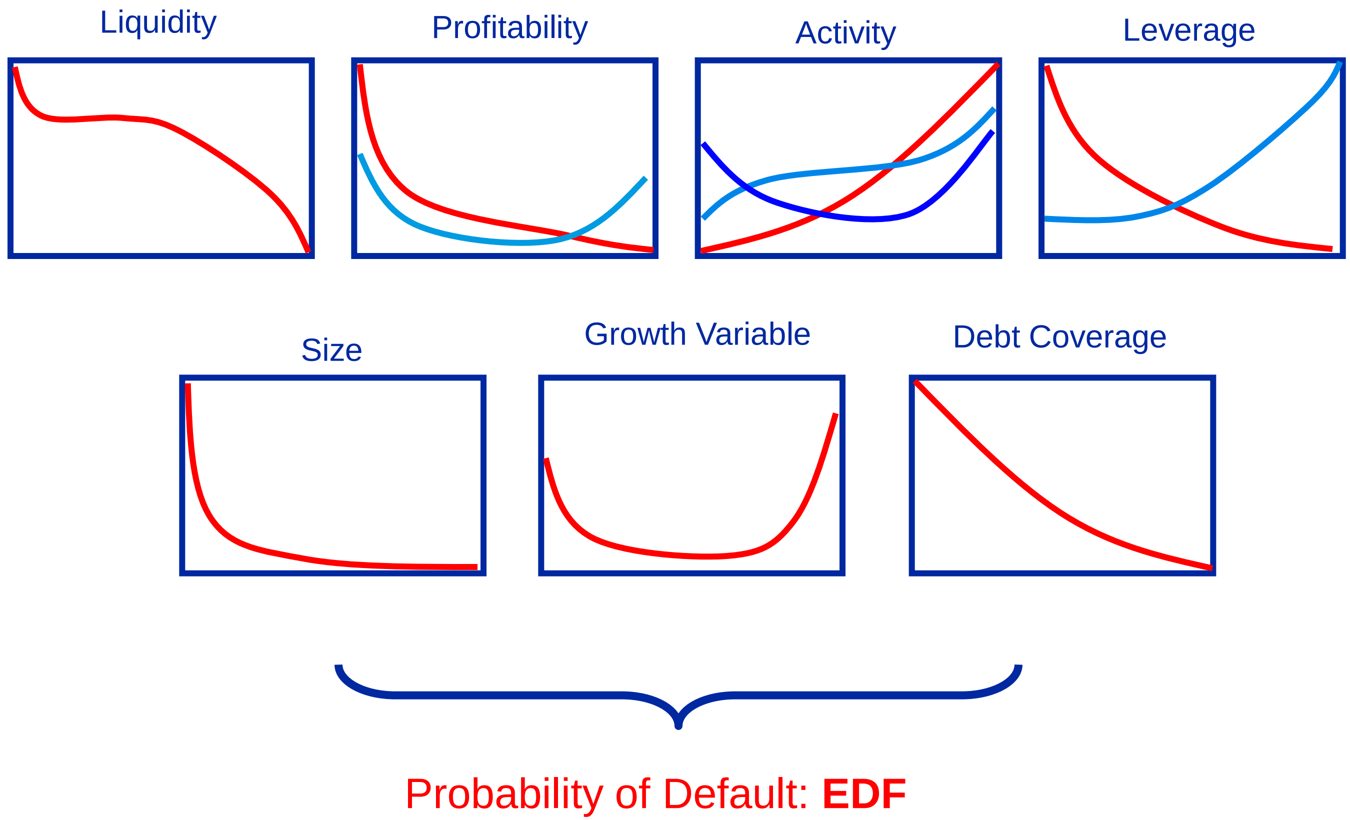
» Localized to the specific accounting practices of the country

» Makes an adjustment for industry differences

» Assesses the current state of the credit cycle

RiskCalc Statistically Combines the Risk Assessment of Different Ratios into a Single EDF

RiskCalc combines several relationships between ratios and default frequencies in a consistent and objective credit risk measure.



The RiskCalc Credit Cycle Adjustment

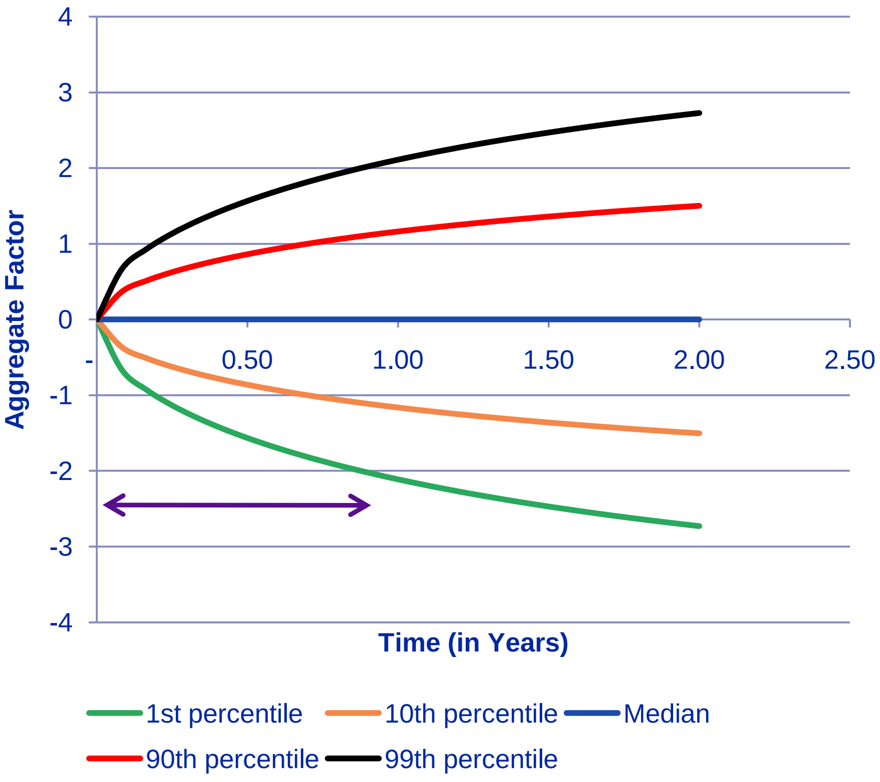
The RiskCalc v3.1 model suite incorporates a forward-looking assessment of the credit cycle by drawing from Moody's KMV Public Firm Model (e.g., CreditEdge/CreditMonitor).

Since default risk varies with the credit cycle, we adjust private firm EDF credit measures by implementing a cycle adjustment factor:

- Based on a transformation of MKMV's DD (Distance to Default) measure
- Based on industry aggregates
- Based on the public sector data, and
- Is dynamic within the year (its value changes every month)

Conditional Versus Unconditional PD

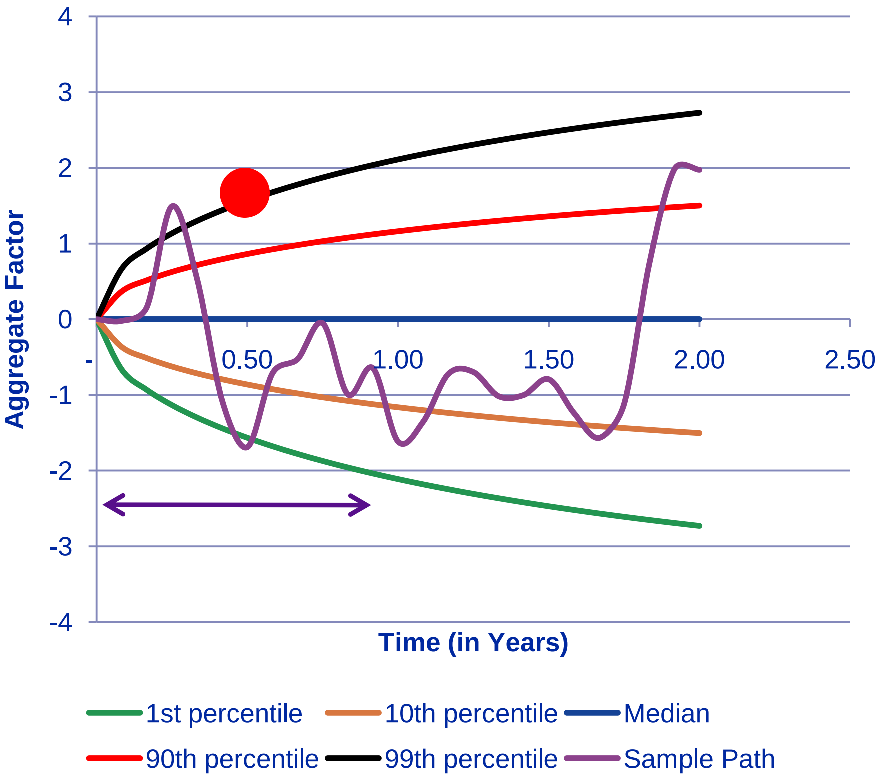
Most credit risk models incorporate systematic risk through an aggregate factor(s). For a specific firm, the PD over a short time interval depends on both the value of the aggregate factor and the characteristics of the firm.



Conditional vs. Unconditional PD

One could use the red dot to compute a Stressed PD. This red dot would have the interpretation that there is a 1 in a 100 chance that your *unconditional PD* could be at this value six months from now.

Over a fixed interval for a fixed path, one could compute the PD given this path. This is a PD conditional on a specific scenario. The interpretation of this PD is that it represents the idiosyncratic risk of the exposure given the aggregate factor.



Moody's Economy.com: Seven Macroeconomic Scenarios (US)

» **Baseline Scenario:** Middle of the distribution of possible economic

» **Stronger Near-Term Recovery ("S1") Scenario**: This above-baseline scenario is designed so that there is a 10% probability that the economy will perform better than in this scenario and a 90% probability that it will perform worse.

» **Mild Second Recession ("S2") Scenario**: there is a 75% probability that economic conditions will be better, broadly speaking, and a 25% probability that conditions will be worse.

» **Deeper Second Recession ("S3") Scenario**: there is a 90% probability that the economy will perform better, broadly speaking, and a 10% probability that it will perform worse.

» **Complete Collapse, Depression ("S4") Scenario:** there is a 96% probability that the economy will perform better, broadly speaking, and a 4% probability that it will perform worse.

» **Aborted Recovery, Below-Trend Long-Term Growth ("S5") Scenario:** With this low-performance long-term scenario, there is a 96% probability that the economy will perform better, broadly speaking, and a 4% probability that it will perform worse.

» **Fiscal Crisis, Dollar Crashes, Inflation ("S6") Scenario:** With this stagflation scenario, there is a 90% probability that the economy will perform better, broadly speaking, and a 10% probability that it will perform worse.

Moody's Economy.com: three UK Macroeconomic Scenarios

» **Baseline Scenario:** Middle of the distribution of possible economic

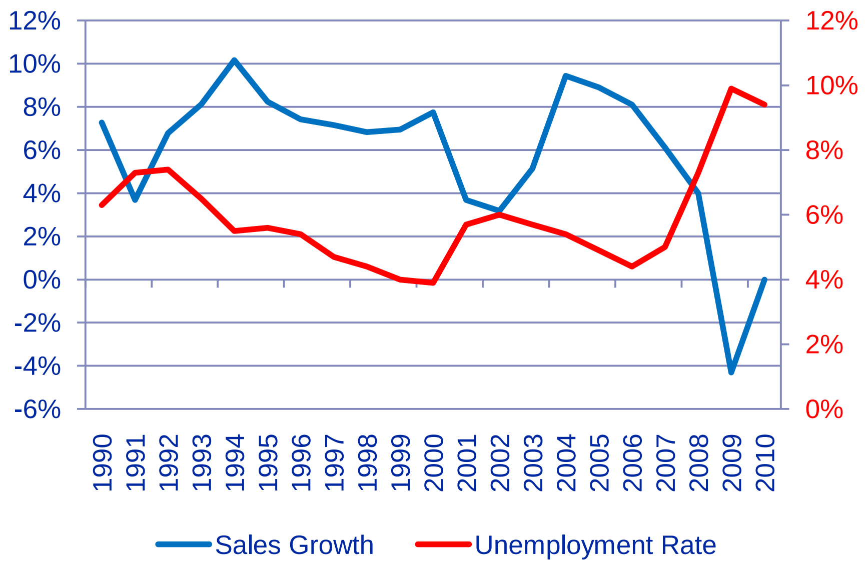
» **Mild Second Recession ("S2") Scenario:** there is a 75% probability that economic conditions will be better, broadly speaking, and a 25% probability that conditions will be worse.

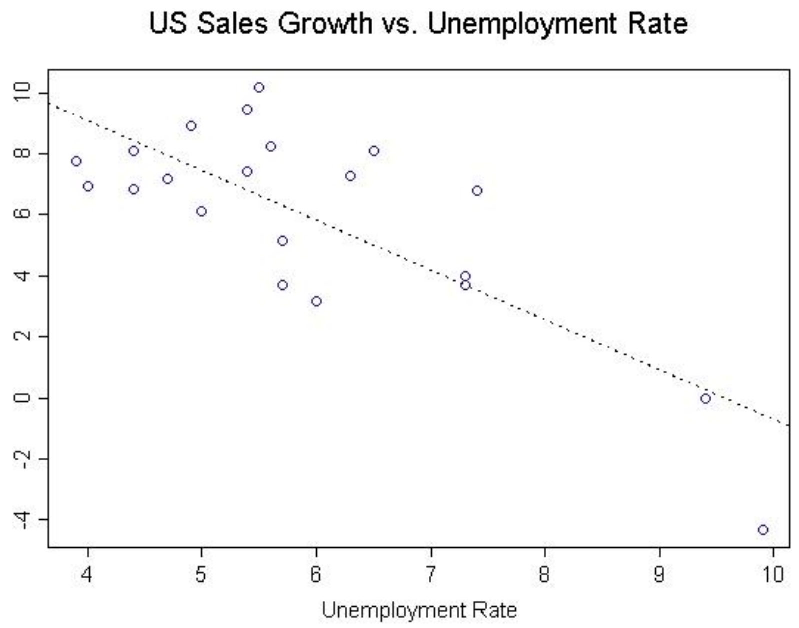
» **Deeper Second Recession ("S3") Scenario**: there is a 90% probability that the economy will perform better, and a 10% probability that it will perform worse.

» **Severe Second Recession ("S4") Scenario:** there is a 96% probability that the economy will perform better, and a 4% probability that it will perform worse.

Source: October 2010 U.K. Macroeconomic Outlook Alternative Scenarios from Moody's Economy.com

US Sales Growth vs. Unemployment Rate

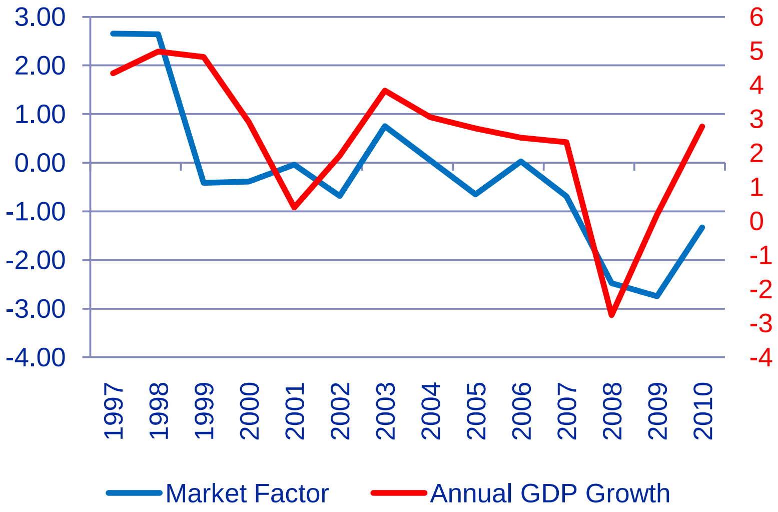


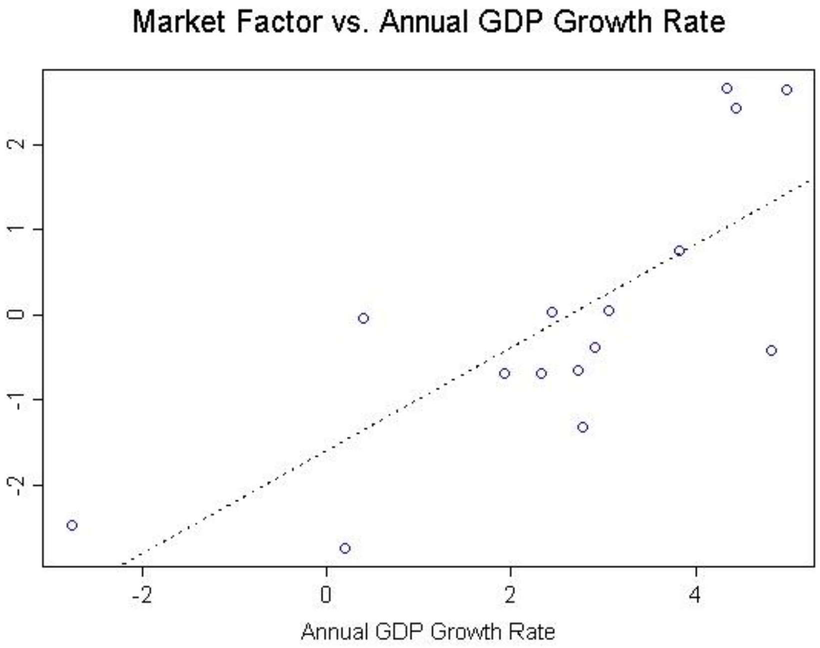


Sales Growth is Median Annual Sales growth from Moody's CRD

Unemployment Rate is US total Unemployment rate, (%, SA) from Moody's Economy.com

Market Index vs. Annual Changes in GDP



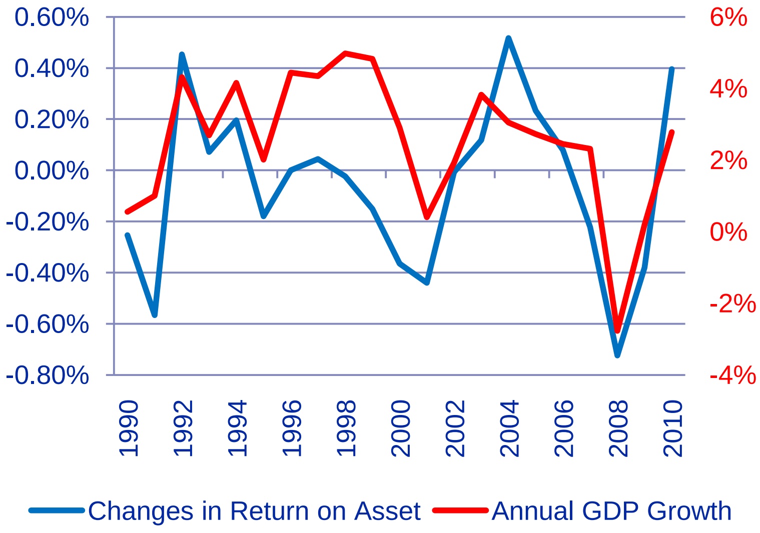


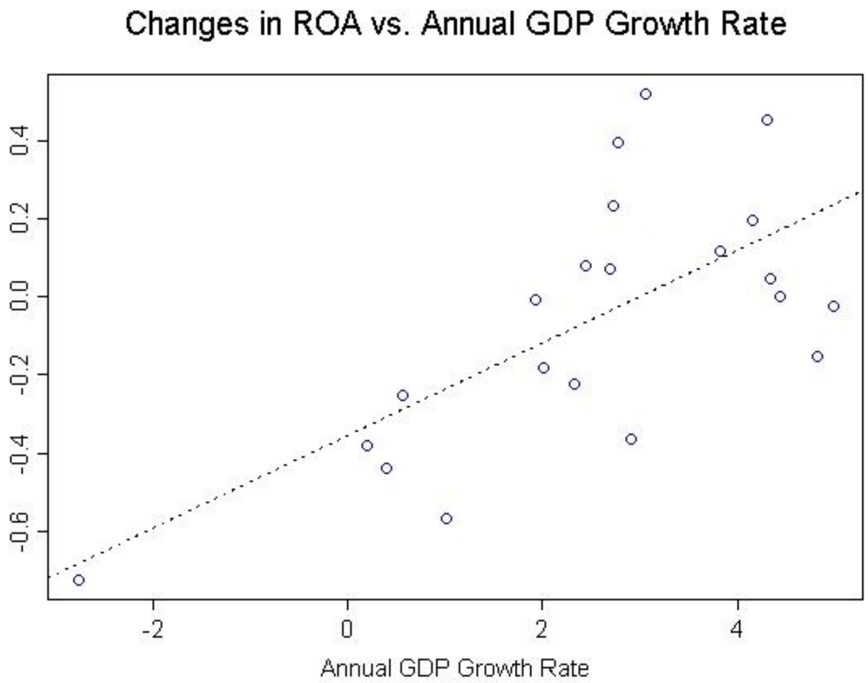
$$DR = \Pr\left(R\phi + \sqrt{1-R^2}\,\varepsilon \le N^{-1}\left(CDT\right)\right)$$

DR is realized default rate in the sample. CDT is Central Default Tendency (long run EDF).

With a market factor of ϕ and an idiosyncratic shock of ε.

Changes in ROA vs. Annual Changes in GDP

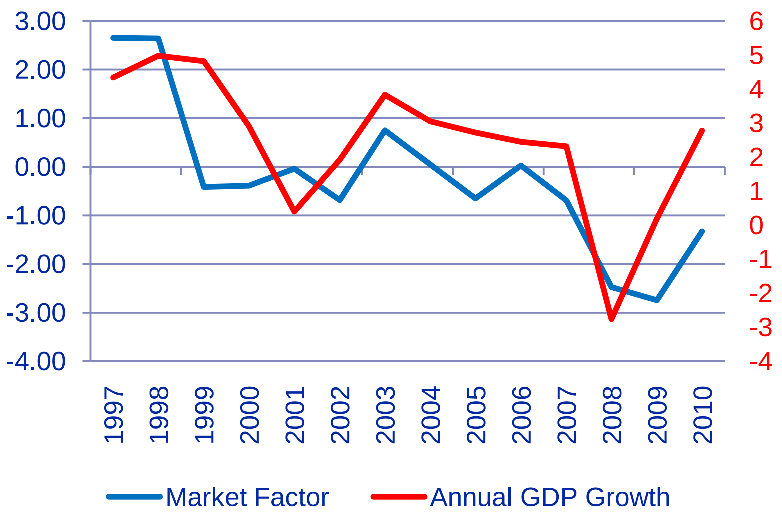


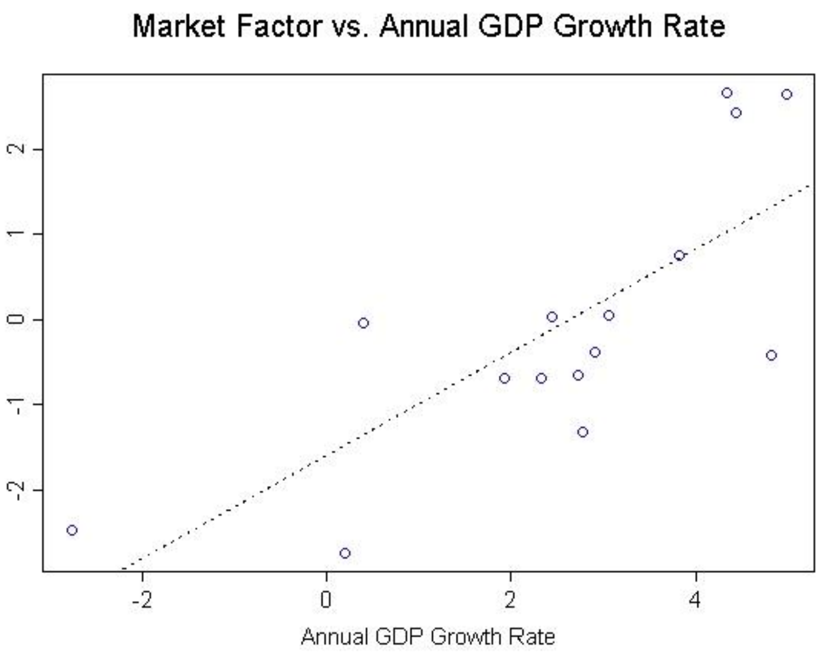


Changes in ROA is Median values from Moody's CRD

US Annual Change in Gross Domestic Product from Moody's Economy.com

Market Index vs. Annual Changes in GDP





Suppose unconditional PD is EDF, we have

$$EDF = \Pr\left(R\phi + \sqrt{1-R^2}\,\varepsilon \le N^{-1}(EDF)\right) = N\left(N^{-1}(EDF)\right)$$

With a market factor of ϕ an an idiosyncratic shock of ε.

Implementing Stress Testing in RiskCalc

Specify a set of stress scenarios based on macroeconomic variables

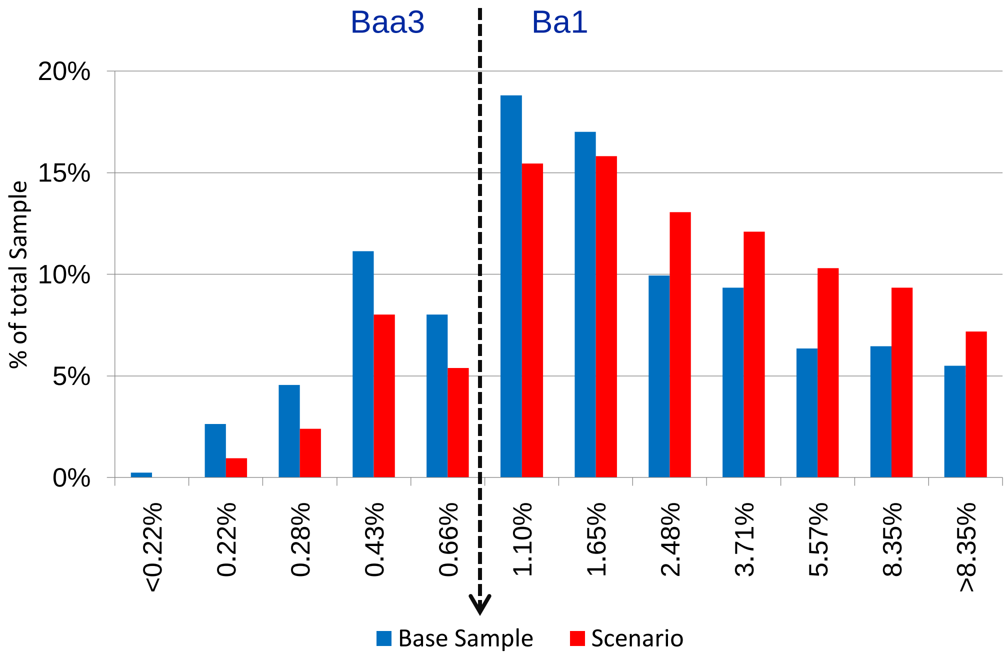
Estimate a series of multivariate models to link the relevant macroeconomic variables to the key financial statement risk drivers in Moody's KMV RiskCalc model

Forecast key EDF drivers under stress scenarios

For example,

- » Forecast sales growth based on stress scenario and back-out updated sales from sales growth
- » Assume costs remain the same
- » Forecast financial statement items based on stress scenario
- » Construct the forecast of default probabilities for private borrowers in various industries under the set of stress scenarios

EDF Distribution of Stressed Portfolio



The sample portfolio's average EDF is 2.36% and median is 1.22% (Median implied rating is Baa2). Under stress scenario, average EDF move up to 2.98% and median increased to 1.77% (Median implied rating is Ba3).

On average, the increase in EDF is over 25%. Median implied rating has move up a notch.

Sample portfolio with 835 borrowers.

Hypothetical Scenario: Unemployment Rate in March 2011 is 8.8%. What if unemployment rate continue to climb to 11% in the coming year?

Corporate sales would decline by 3%. Let us assume that the cost remains the same, EBITDA and NI decrease by 3% of total revenue

Adding a Behavioral Layer

We are testing the following hypotheses:

» Borrowers who have a long relationship with a specific bank are less likely to default with that bank

» Borrowers who deliver financial statements *late* are more likely to default

» Borrowers classified as *substandard* at some point are more likely to default

» Borrowers in industries with recently elevated default rates are more likely to default

» Borrowers who have *maxed-out* their credit lines are more likely to default

Combining Usage Data with RiskCalc EDF

Data is from eight US financial institutions

We collect usage information quarterly

We compute monthly EDF credit measures based on the latest available financial statement and credit cycle of that particular month

Sample Description

# Quarters	# Firms	# Defaults	Time Period
355033	40277	2684	2000-2010

Usage level is higher for defaulted firms

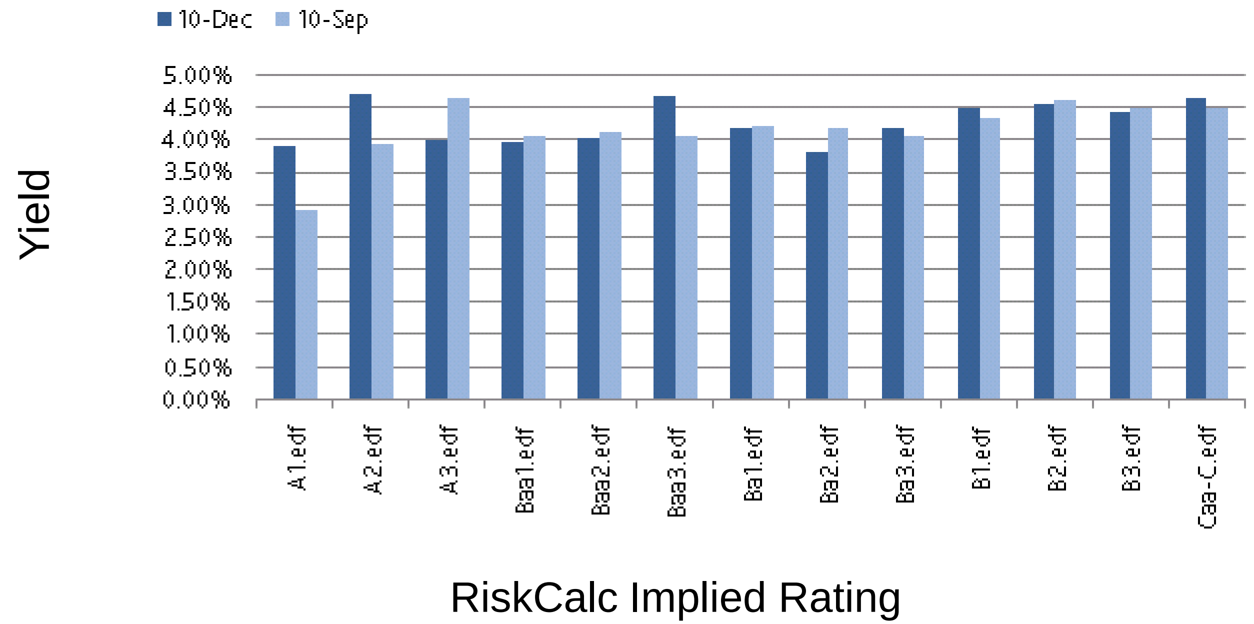
Usage ratio is defined as total draw-down amount scaled by the total commitment amount

	Usage Ratio
Overall	47.3%
Non-Defaulter	47.1%
Defaulter	71.7%

Usage Information Helps Improve the Accuracy of Default Prediction

Variable	AR
EDF only	53%
Usage only	39%
70% weight on EDF, 30% on Usage	57%

In the Middle Market, Risk-Based Pricing is Limited



Presents the yields on loans at in the US Credit Research Database

Overview

- We compare model performance of (i) using qualitatives alone (ii) internal ratings (iii) RiskCalc EDFs, and the (iv) combined score on their ability to distinguish defaulted firms and non-defaulted firms, using data from 2002 to 2010.
- The combined score's Accuracy Ratio is over 5 points higher than that of the other models on both the full sample and pass rating sample.
- We assess the economic value of a more powerful model and focus on the pass rating sample.
- Using the most powerful model can create to $22 million of economic value on a $10 billion portfolio (22bps).

Sample

Financial statements and internal ratings are from 11 US contributors to the Credit Research Database and have statements ending date between 6/2002-6/2009

Defaults are predicted 6 to 18 months after the statement date of the financial statements.

3808 defaults with a default date between 06/2003-6/2010

We exclude financial firms, real estate firms, non-for profit, and government organizations

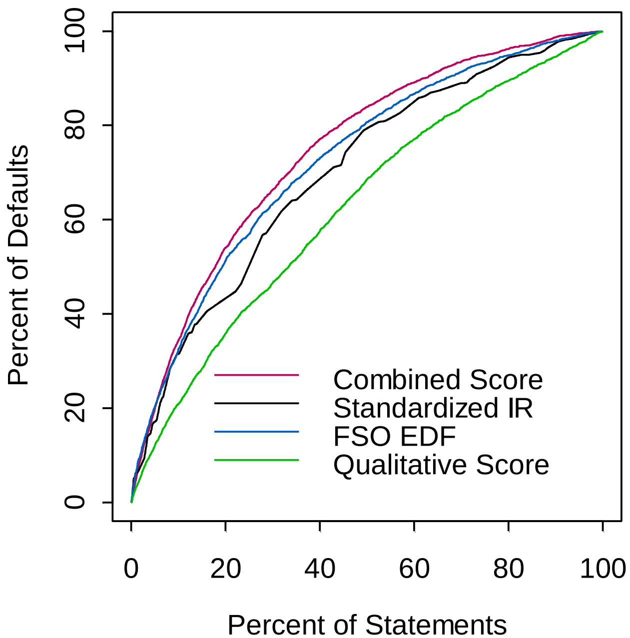
Sample Characteristics

Industry	Statements	Defaults
Agriculture	5,285	85
Business Products	23,703	381
Communication /High Tech	7,673	131
Construction	34,766	1,004
Consumer Products	10,659	209
Mining /Transportation/Utilities	12,807	168
Services	71,618	812
Trade	52,427	840
Unassigned	17,391	178
Total	**236,329**	**3,808**

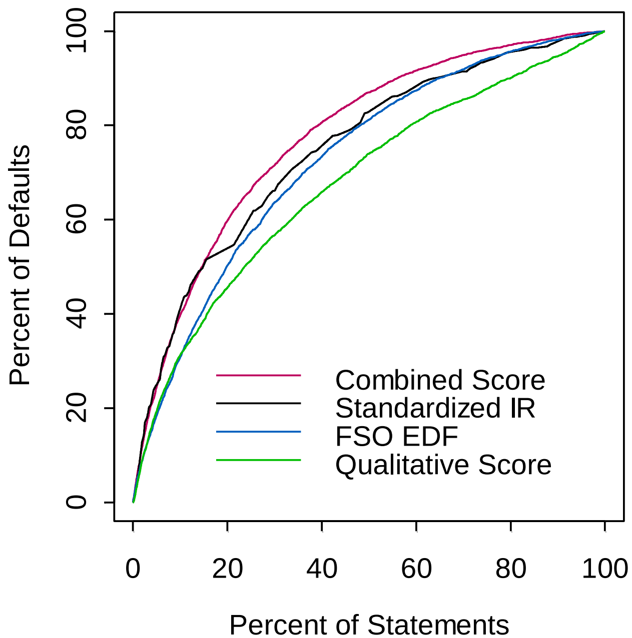
Assets in $million	Statements	Defaults
Less than 3mm	124,958	2,054
Greater than 3mm	111,371	1,754
Total	**236329**	**3808**

Model Performance

Pass Rating Sample



Full Sample



	#Statements	#Defaults	AR Combined	AR Qualitative	AR IR	AR EDF
Pass Sample	217,193	2,679	51.20%	24.20%	42.20%	44.20%
Full Sample	236,329	3,808	56.20%	36.10%	50.60%	46.60%

Moody's Analytics

The Incremental Economic Value of a More Powerful Model

- A better PD model allows a bank to take more informed actions on the exposures in their portfolio
- The actions a bank takes depends on both the risk and return profile of the exposure
- Suppose the LGD is 60% and that the spread for each bucket 200bps
- Suppose your strategy is to hedge/sell exposures for which the expected loss exceeds the spread income:
  - **IF** **THEN**

$$PD \times LGD > spread \qquad \qquad Sell\ or\ hedge$$

- Defaults avoided is equal to the probability of hedging the exposure multiplied by the average of the better PD conditional upon being hedged
- The savings is the defaults avoided multiplied by LGD less the loss in spread income
- We test 4 credit risk measures using this approach

We Construct a Theoretical Framework to Mimic the Power of the Qualitative Score

Risk Bucket	Qualitative Score PD	Spread	Probability of Selling	Probability of Default if Sold	Defaults Avoided	Value of Risk Mitigation (bps)
1	0.84%	2.00%	0.00%	0.00%	0.00%	0.00%
2	1.18%	2.00%	0.00%	0.00%	0.00%	0.00%
3	1.39%	2.00%	0.00%	0.00%	0.00%	0.00%
4	1.59%	2.00%	0.00%	0.00%	0.00%	0.00%
5	1.82%	2.00%	0.00%	0.00%	0.00%	0.00%
6	2.10%	2.00%	0.00%	0.00%	0.00%	0.00%
7	2.31%	2.00%	0.00%	0.00%	0.00%	0.00%
8	2.53%	2.00%	0.00%	0.00%	0.00%	0.00%
9	2.86%	2.00%	0.00%	0.00%	0.00%	0.00%
10	3.52%	2.00%	68.30%	3.91%	2.67%	0.24%
Average	2.01%					0.02%

Value on $10 Billion Dollar Portfolio

Value added by model → **$2,355,716**

We Construct a Theoretical Framework to Mimic the Power of the Internal Rating

Risk Bucket	Internal Rating PD	Spread	Probability of Selling	Probability of Default if Sold	Defaults Avoided	Value of Risk Mitigation (bps)
1	0.35%	2.00%	0.00%	0.00%	0.00%	0.00%
2	0.68%	2.00%	0.00%	0.00%	0.00%	0.00%
3	0.89%	2.00%	0.00%	0.00%	0.00%	0.00%
4	1.15%	2.00%	0.00%	0.00%	0.00%	0.00%
5	1.48%	2.00%	0.00%	0.00%	0.00%	0.00%
6	2.07%	2.00%	0.00%	0.00%	0.00%	0.00%
7	2.38%	2.00%	0.00%	0.00%	0.00%	0.00%
8	2.83%	2.00%	0.00%	0.00%	0.00%	0.00%
9	3.01%	2.00%	25.30%	4.80%	1.21%	0.22%
10	5.28%	2.00%	100.00%	4.64%	4.64%	0.78%
Average	2.01%					0.10%

Value on $10 Billion Dollar Portfolio

Value added by model → **$10,063,434**

We Construct a Theoretical Framework to Mimic the Power of the RiskCalc EDF

Risk Bucket	RC PD	Spread	Probability of Selling	Probability of Default if Sold	Defaults Avoided	Value of Risk Mitigation (bps)
1	0.62%	2.00%	0.00%	0.00%	0.00%	0.00%
2	0.76%	2.00%	0.00%	0.00%	0.00%	0.00%
3	0.92%	2.00%	0.00%	0.00%	0.00%	0.00%
4	1.15%	2.00%	0.00%	0.00%	0.00%	0.00%
5	1.38%	2.00%	0.00%	0.00%	0.00%	0.00%
6	1.64%	2.00%	0.00%	0.00%	0.00%	0.00%
7	1.96%	2.00%	0.00%	0.00%	0.00%	0.00%
8	2.49%	2.00%	0.00%	0.00%	0.00%	0.00%
9	3.43%	2.00%	57.28%	5.16%	2.96%	0.63%
10	5.55%	2.00%	100.00%	5.17%	5.17%	1.10%
Average	2.00%					0.17%

Value on $10 Billion Dollar Portfolio

Value added by model → **$17,296,674**

We Construct a Theoretical Framework to Mimic the Power of the Combined Score

Risk Bucket	Combined Score PD	Spread	Probability of Selling	Probability of Default if Sold	Defaults Avoided	Value of Risk Mitigation (bps)
1	0.32%	2.00%	0.00%	0.00%	0.00%	0.00%
2	0.53%	2.00%	0.00%	0.00%	0.00%	0.00%
3	0.76%	2.00%	0.00%	0.00%	0.00%	0.00%
4	0.98%	2.00%	0.00%	0.00%	0.00%	0.00%
5	1.25%	2.00%	0.00%	0.00%	0.00%	0.00%
6	1.59%	2.00%	0.00%	0.00%	0.00%	0.00%
7	2.01%	2.00%	0.00%	0.00%	0.00%	0.00%
8	2.62%	2.00%	0.00%	0.00%	0.00%	0.00%
9	3.66%	2.00%	74.72%	5.47%	4.09%	0.96%
10	6.09%	2.00%	100.00%	5.43%	5.43%	1.26%
Average	1.98%					0.22%

Value on $10 Billion Dollar Portfolio

Value added by model → **$22,186,011**

Academic Accounting Research Findings – Public Firms

Findings include:

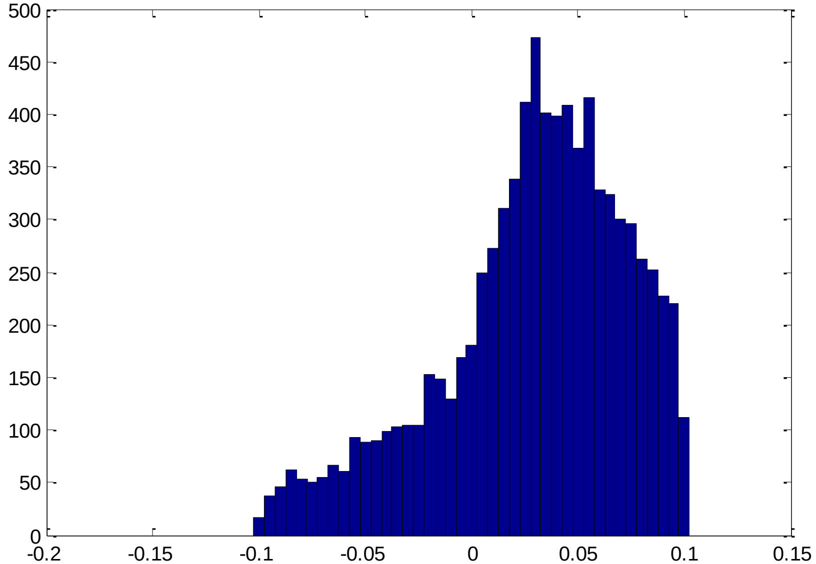
- Many firms “just” break even
- Cash better than accruals
- Asset composition matters

For public firms, research focuses on whether or not financial statement quality can be used to predict future cash flows, future earnings, restatements, lawsuits, and stock returns.

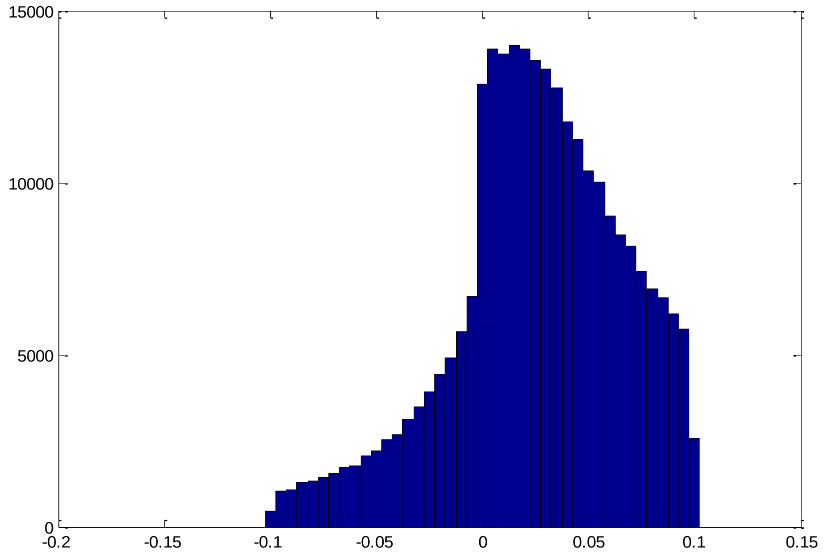
For private firms, we are testing whether or not financial statement quality can be used to predict future income, unexplained changes in retained earnings, qualified financial statements, and defaults.

Distribution of Return on Assets for Private Firms and Public Firms

Public Firms



Private Firms



Income from Accruals vs. Cash

NI can be decomposed into a *Cash from Operations* (CFO) component and an *accrual* component.

- Accrual is the non-cash component of NI:
  - Changes in Accounts Receivable + Changes in Inventories - Changes in Accounts Payable - Depreciation – Changes in Tax Payable
- Income derived from accruals is less persistent than income derived from cash.
- *Accrual Anomaly*: the stock market systematically overvalues firms that derive profitability from accruals rather than cash.
- We test to see whether or not this decomposition can be carried over to the CRD sample.

Persistence of Net Income

We look at firms with abnormal accrual levels, relative to their respective industries.

For these firms, the correlation between current and future ROA is lower.

For these firms, the correlation between current ROA and future CFO is lower as well.

	Corr(ROA_t, ROA_{t+1})	Corr(ROA_t, CFO_{t+1})
Normal Accrual Group	0.667	0.583
Abnormal Accrual Group	0.540	0.472

We See a Similar Pattern for UK Private Firms

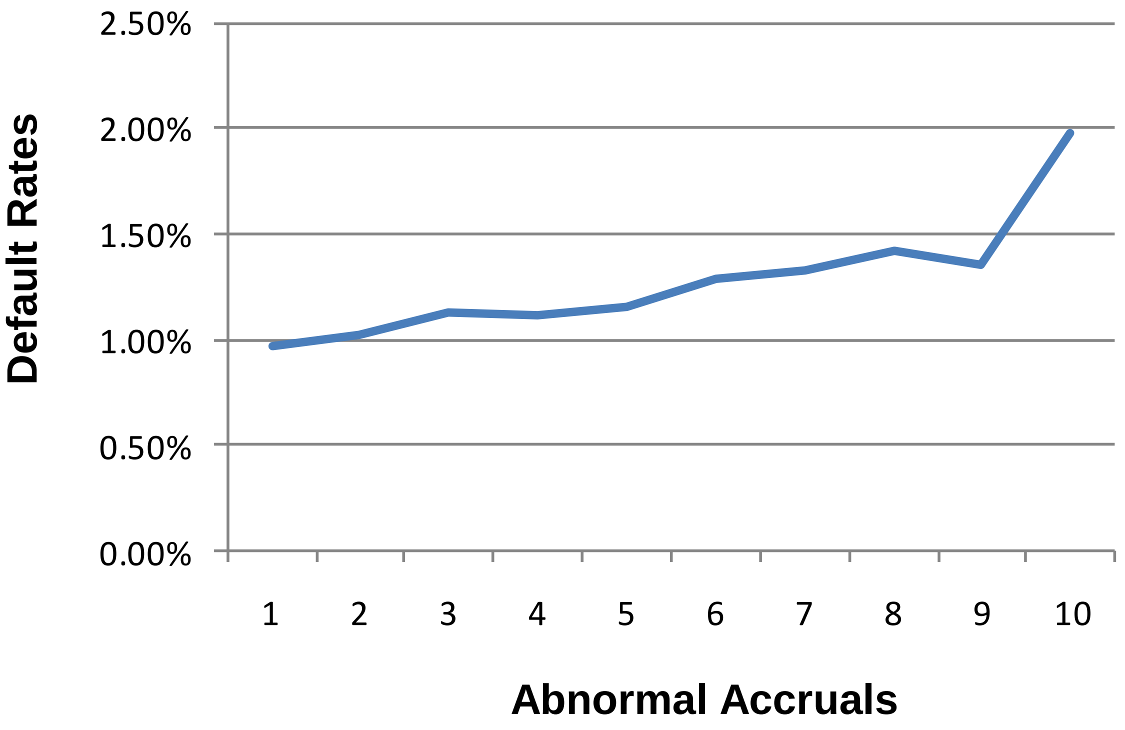
We look at UK firms with abnormal accrual levels, relative to their respective industries.

For these firms, the correlation between current and future ROA is lower than those with normal accrual levels.

Pearson Correlation	**Corr (ROA_t, ROA_{t+1})** Assets > 350K GBP	**Corr (ROA_t, ROA_{t+1})** Assets > 500K GBP
Normal Accrual Group	0.539	0.544
Abnormal Accrual Group	0.464	0.466

Moody's Analytics

Abnormal Accruals are Associated with Elevated Default Rates



Preliminary Findings

For private firms, measures of accounting quality are related to:

» Future income and cash flows

» Unexplained changes in retained earnings

» Defaults

This research could be useful in two ways:

» Identifying financial statements that require further review

» Enhanced default prediction

Not-for-Profits

We have not traditionally recommended RiskCalc for Not-for-Profit organizations

Not-for-Profits have a different business model and a different set of account

The process of default is different

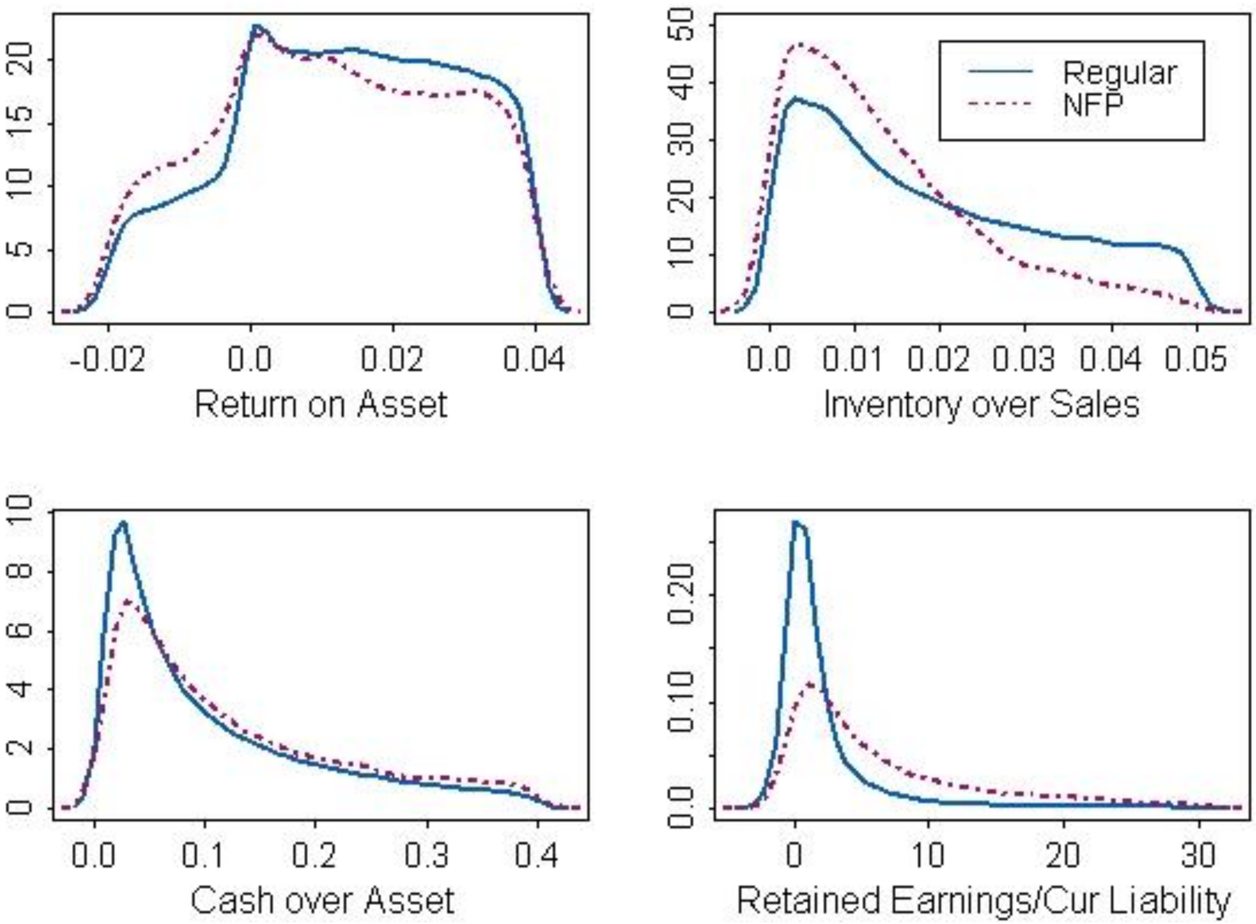
We now have “almost enough” data to build a Not-for-Profit model

Not-for-profits accounts use words like *Operating Results* and *Net Assets.* A Not-for-Profit does not *Retain Earnings*

Many banks will reconcile Not-for-Profit accounts with an RA chart of accounts

We are building a model designed to work well on both Not-for-Profit financial statements in their original format as well as once “spread” into RA

Not-for-Profits in the CRD differ from Corporates

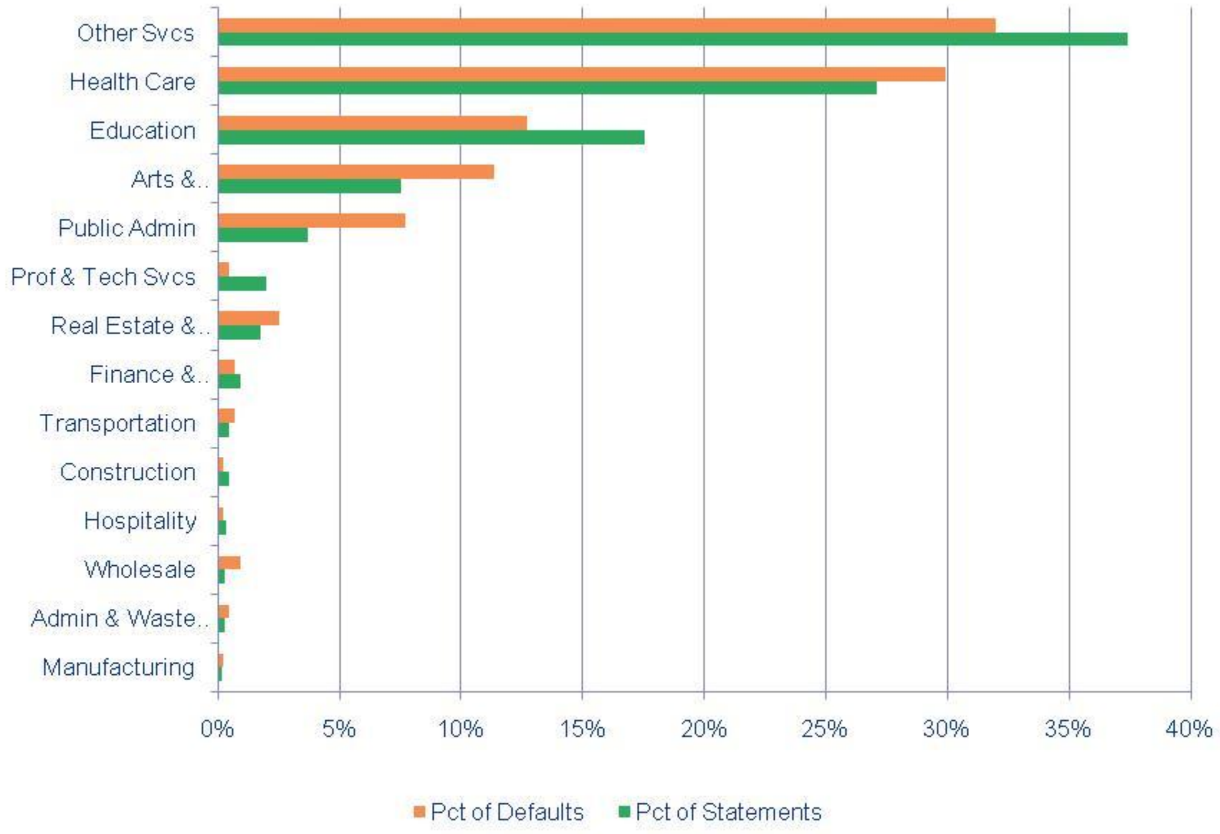


The nonprofit equivalent for retained earnings is “net assets” but, unlike retained earnings, net assets represent the entirety of the capital structure.

Banks try to fit NFP financial statement into regular corporate financial statement format usually would cause unexpected effect. For example, Retained Earnings are equivalent to NW in CRD database.

Moody's Analytics

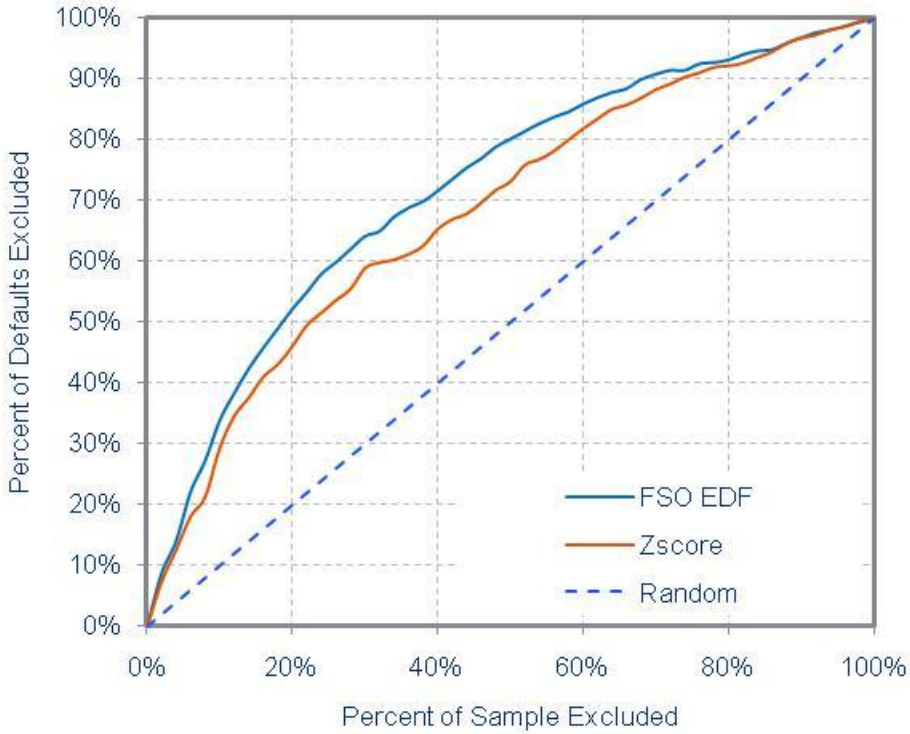
Not-for-Profits in the CRD



NAICSECTOR	Naics
Manufacturing	31/32/33
Admin & Waste Mgmt	56
Wholesale	42
Hospitality	72
Construction	23
Transportation	48/49
Finance & Insurance	52
Real Estate & Leasing	53
Prof & Tech Svcs	54
Public Admin	92
Arts & Entertainment	71
Education	61
Health Care	62
Other Svcs	81

Not-for-Profits in the CRD

Model	1- Year Accuracy Ratio
Financial Statements	~20,000
Defaults	~250
Time Horizon	1996-2009
US 3.1 EDF	50.68%
Z-SCORE	41.04%
3.1 – Z-SCORE (P-Value)	9.64% (0.0015)



MOODY'S ANALYTICS

Real Estate Firms

We have not traditionally recommended RiskCalc for real estate firms.

Real estate lending includes:

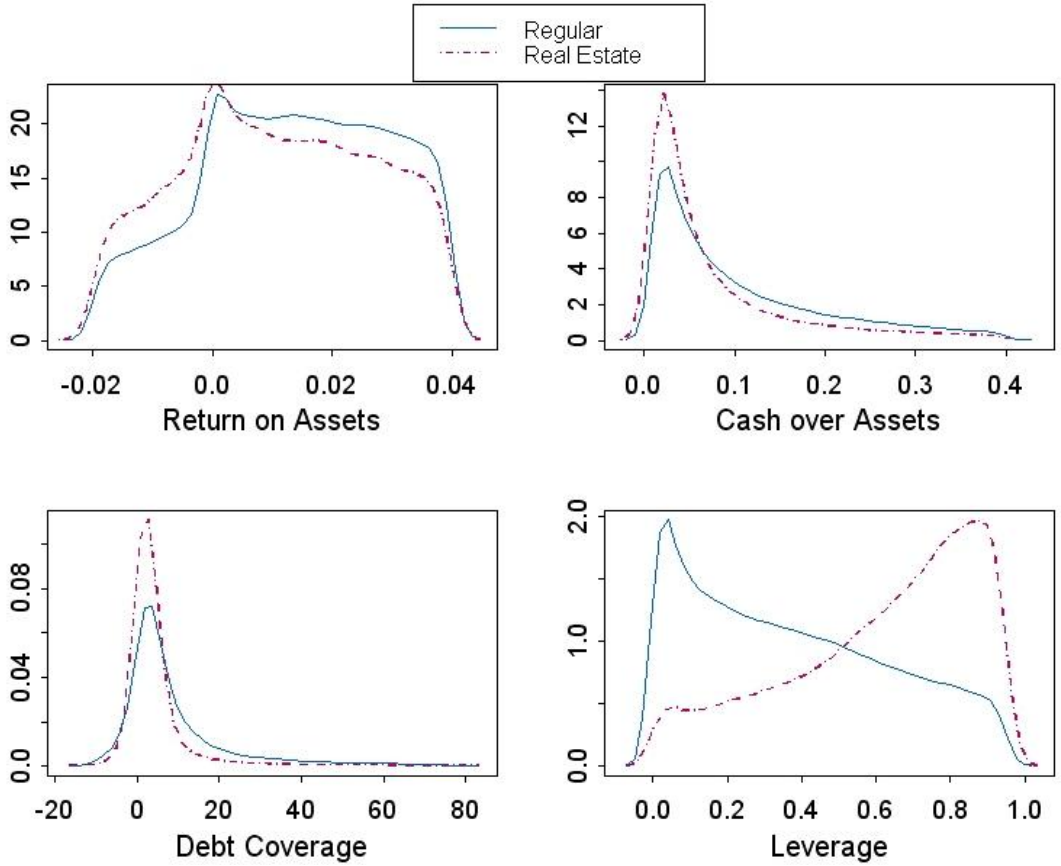
- » Non-Recourse Commercial Real Estate Loans
- » Project Finance
- » Real Estate Lessors
- » Real Estate Operators

For non-recourse commercial real estate loans, we now have CMM.

Real Estate Lessors and Operators both have more leverage and weaker debt coverage than their corporate counterparts.

Seek to build a model that is applicable to this population.

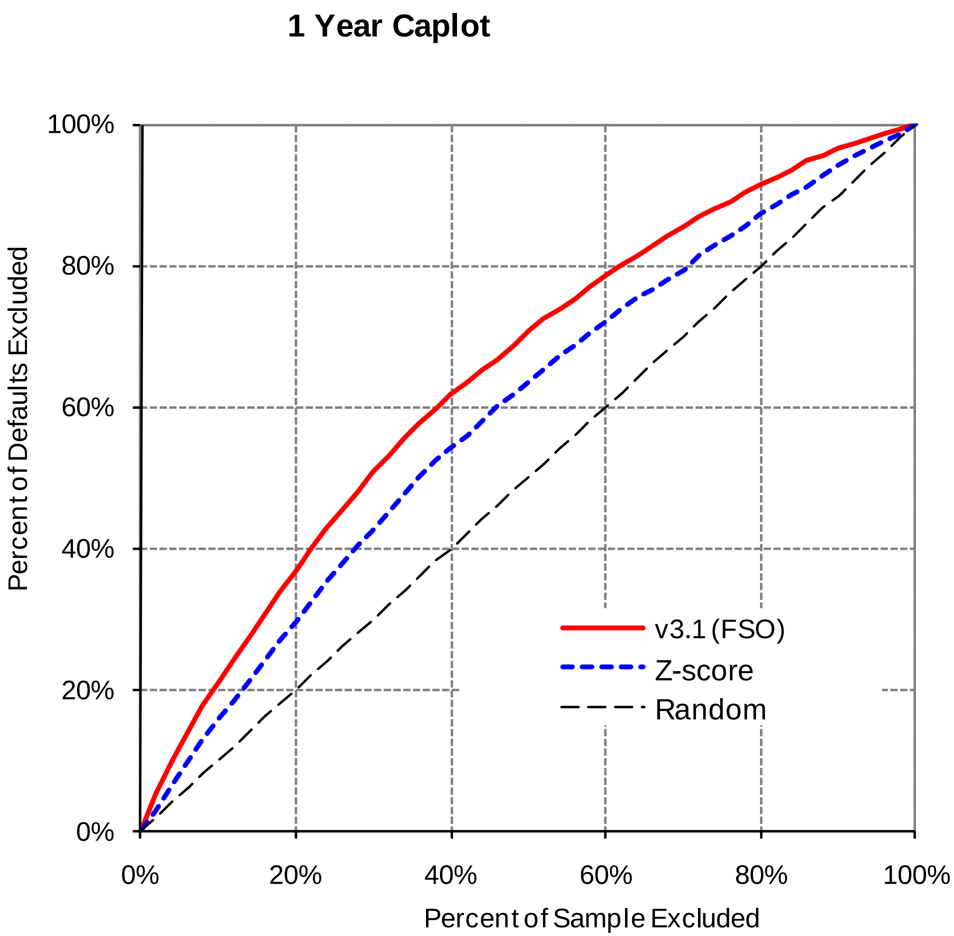
Real Estate in the CRD differ from Corporates



Statements	Firms	Defaults	Sample Period
99,500+	22,100+	3,100+	1995-2010

Power Comparison: Real Estate

1 Year Model	Real Estate Sample
RiskCalc US v3.1 (FSO)	30.01%
Z-SCORE	18.60%
1 Yr AR Difference	11.41%



Sample includes Lessors, Property Managers, REITs, and other types of real estate companies.

Validation Sample

Financial statements fiscal year: 1991-2009

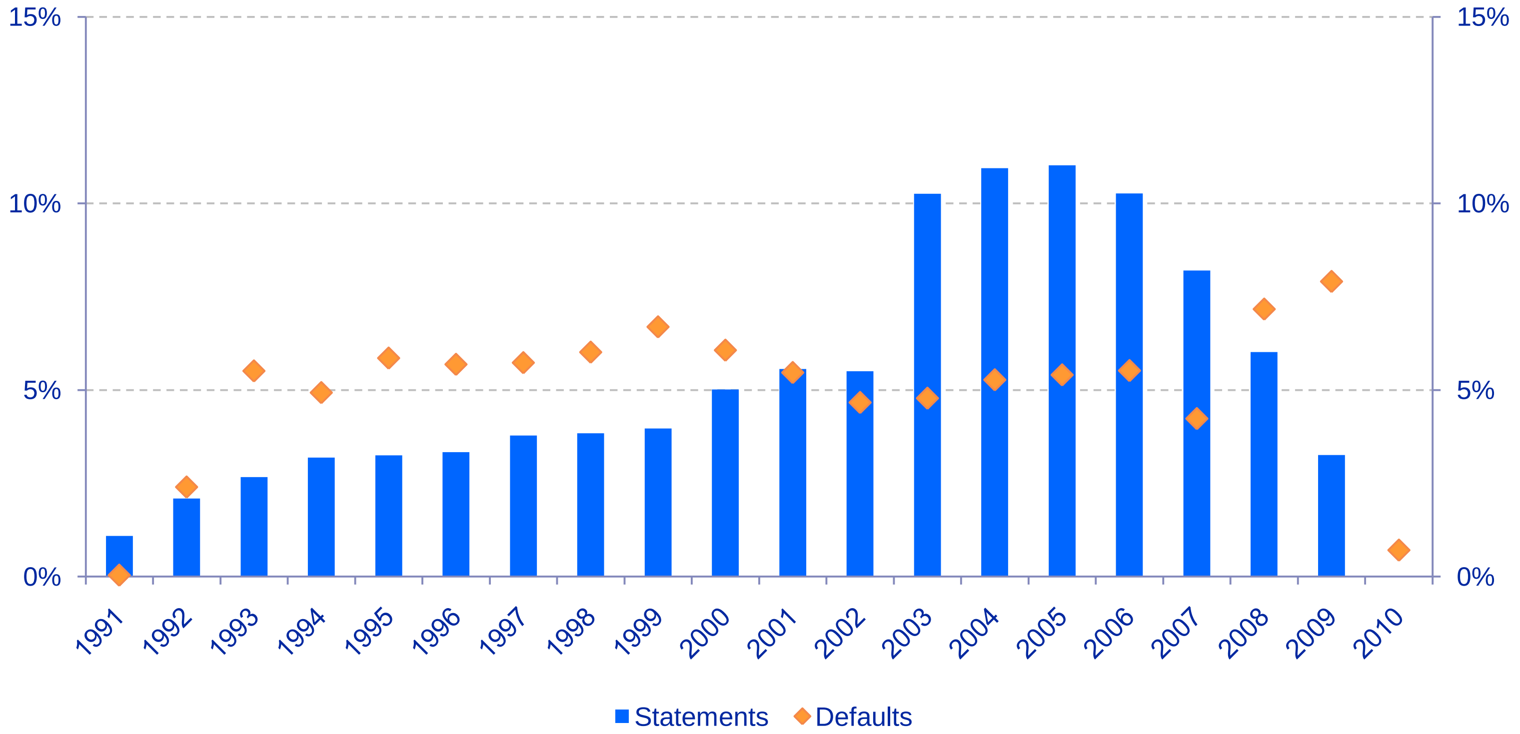
Defaults year: 1992-2010 (Aug 16, 2010)

Total # of statements: 1.2 Million +

Total # of defaults: 23,000+

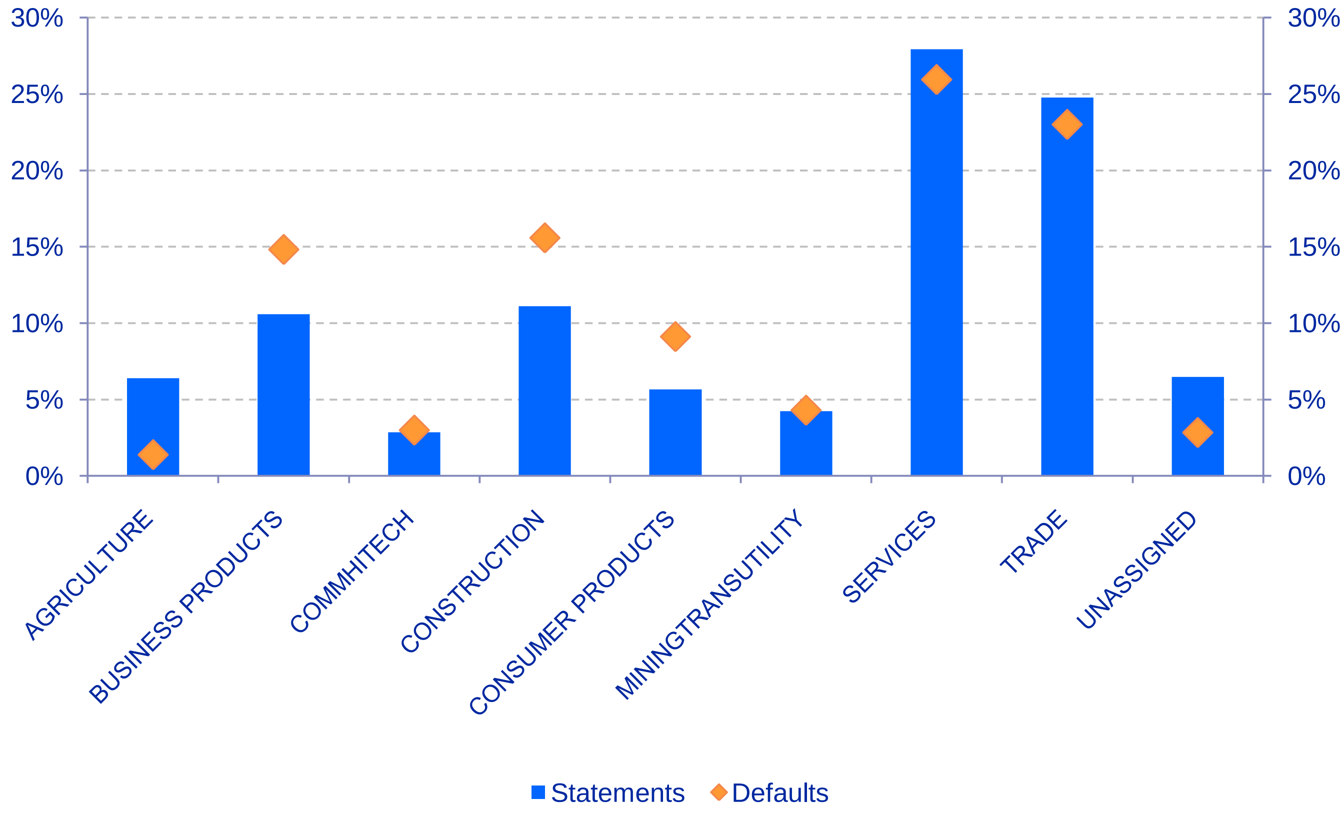
Total # of firms: 270,000+

Sample Characteristics – By Year

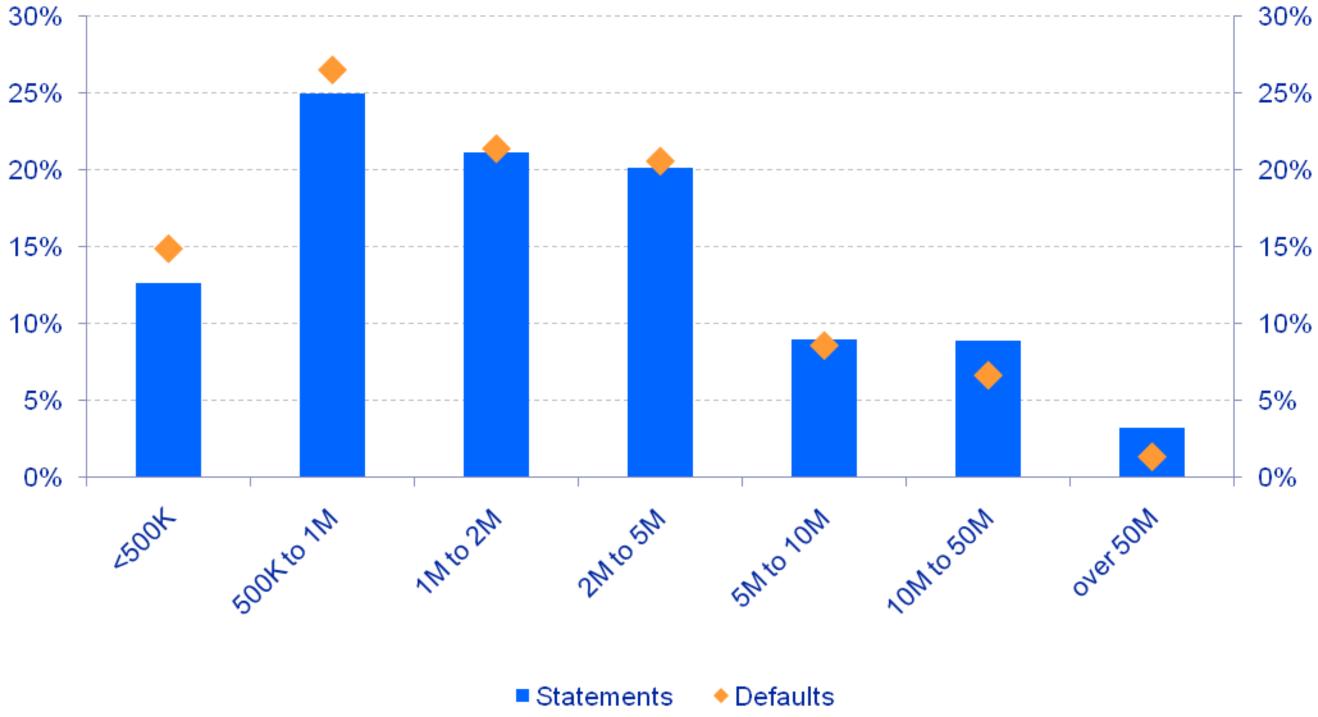


Statement years are fiscal years, which typically end in December. Default years are the years in which defaults occur.

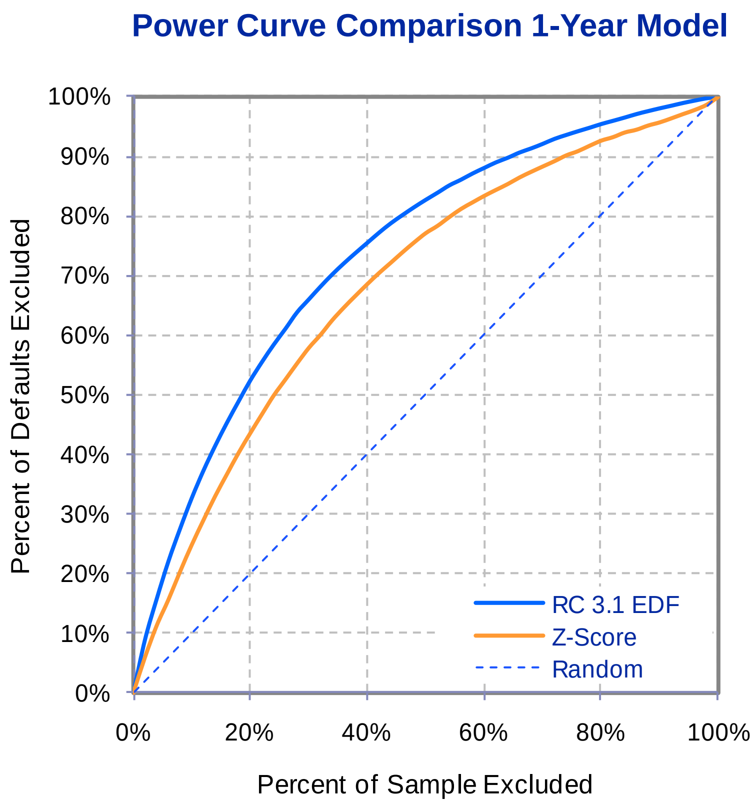
Sample Characteristics – By Industry



Sample Characteristics – By Real Assets

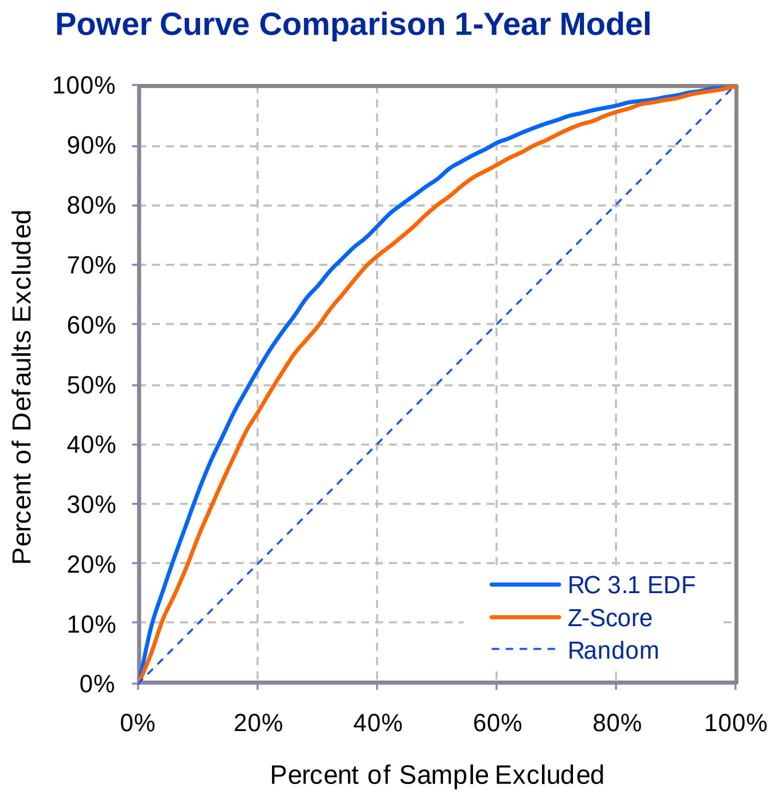


Power Comparison: 1-Year Horizon, Full Sample



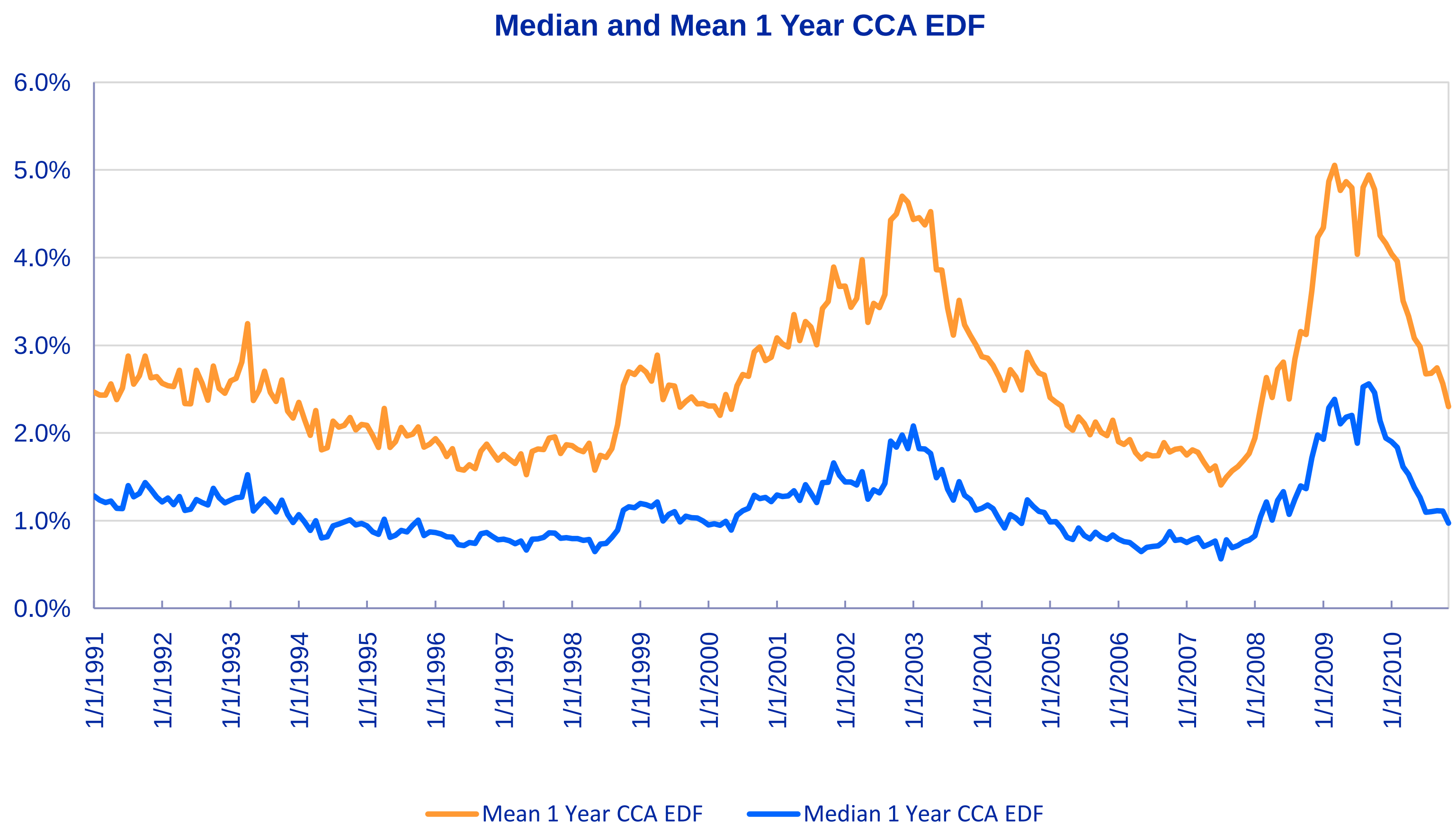
	RC UK v3.1	Z-Score	P-Value	Defaults	Firms	Number of Firm-Years
Full Sample	51.5%	40.3%	<.0001	11,346	148,217	542,081

Model Power on Bank-Provided Data

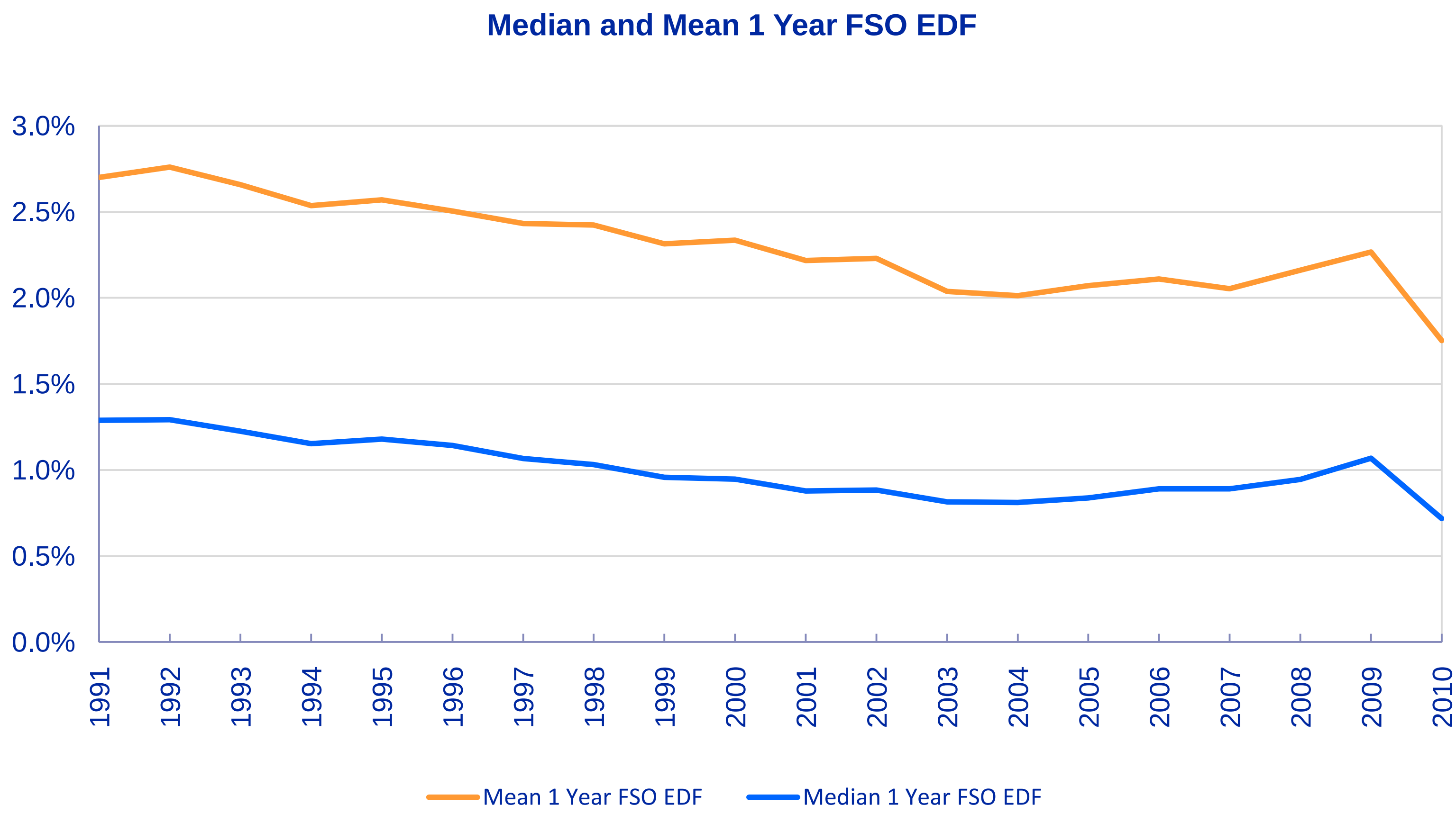


	RC UK v3.1	Z-Score	P-Value	Defaults	Firms	Number of Firm-Years
Bank-Provided Sample	52.6%	44.6%	<.0001	2,653	89,114	290,173

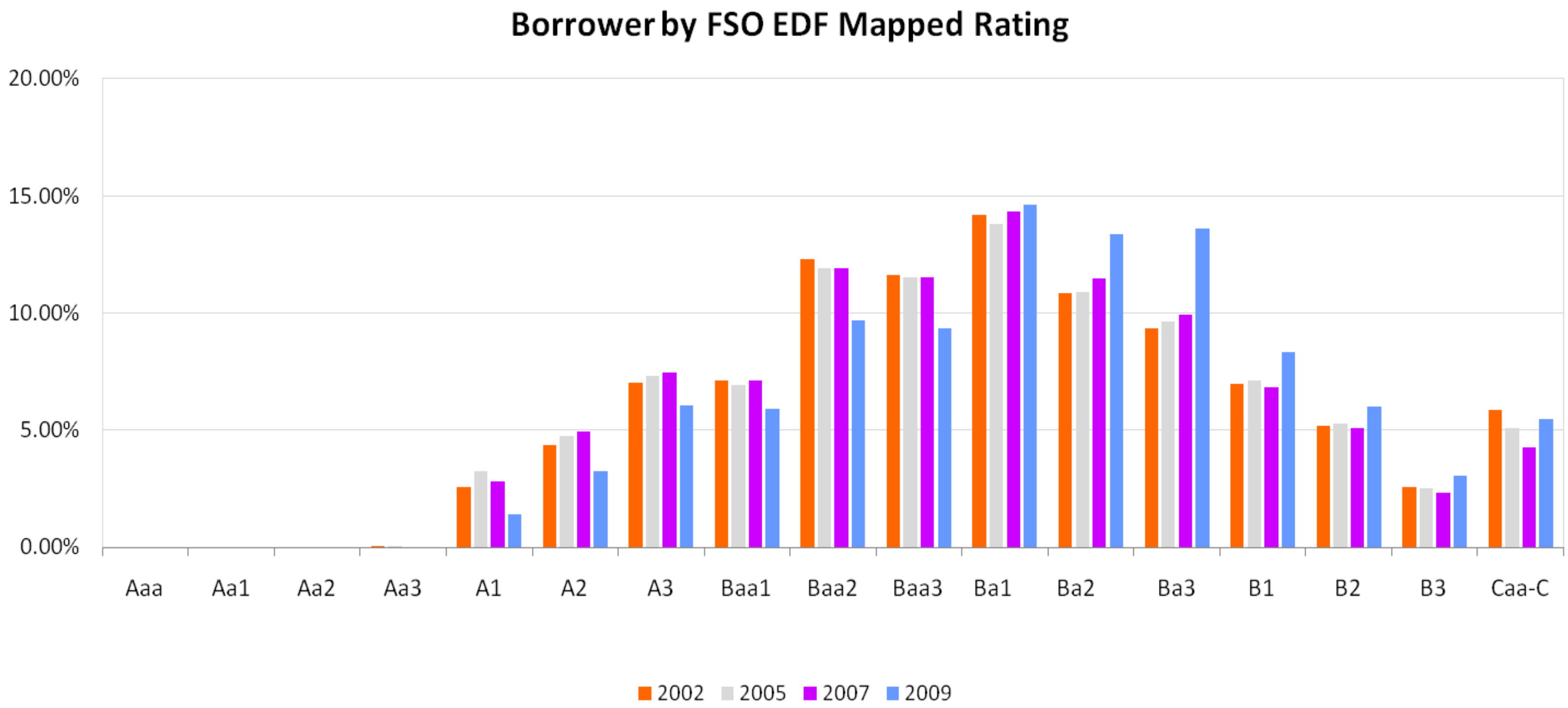
Recently, the CCA Based EDF Credit Measures Trended Upward at the Beginning of 2008 and Downward in the Middle of 2009



FSO is Declining

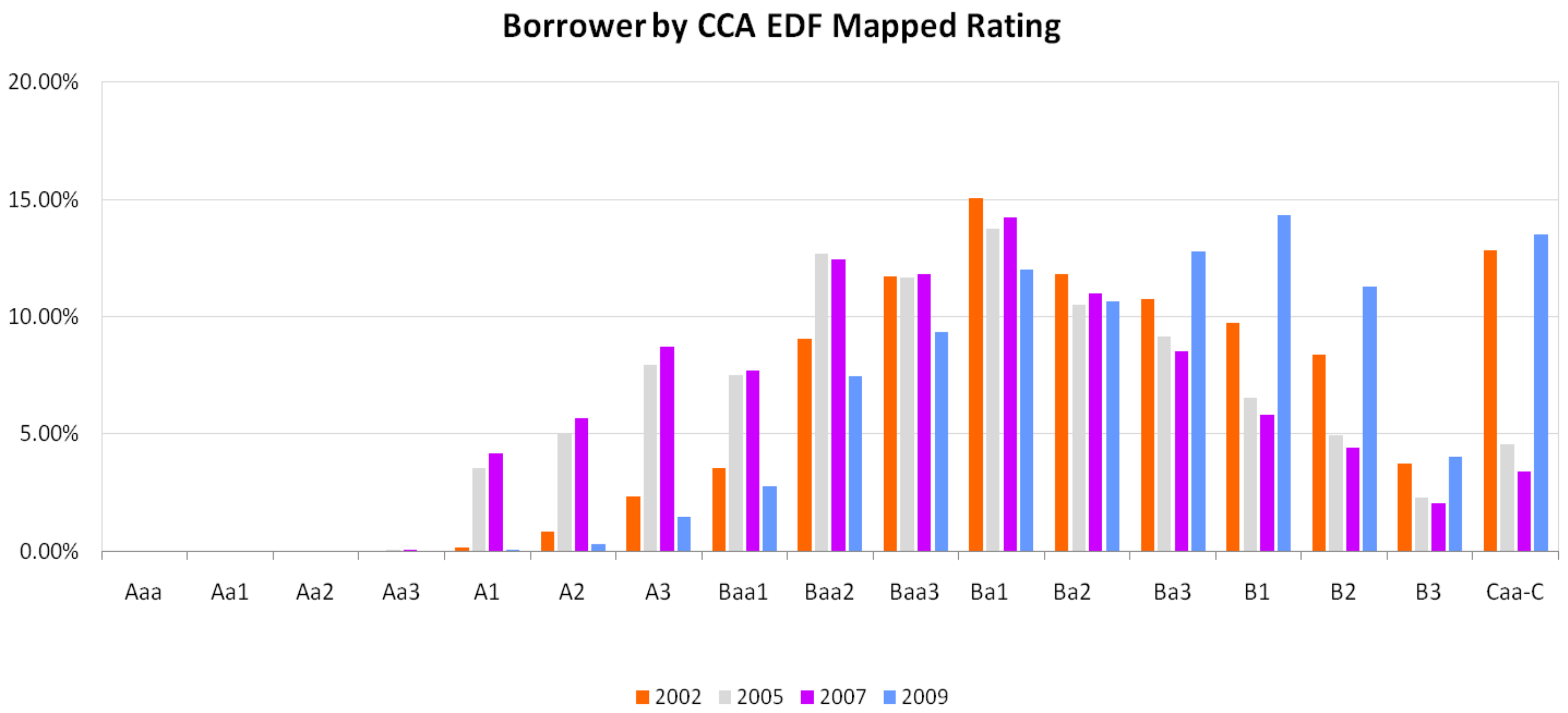


Distribution of FSO EDF Implied Ratings Continues to be Stable



The distribution of FSO EDF implied ratings is largely comparable to the development sample distribution.

The Distribution of CCA Implied Ratings is More Dynamic



» As expected, CCA pushed the distribution to the left during the expansionary year of 2007 and it pushed the distribution to the right during the recessionary year of 2009.

» The year of financial statement date is presented.

Defining a Default Rate with Private Firm Data

In CRD UK data, we currently have the following default types:

Default Type	% of Total Defaults
90 Days Past Due	5.18%
Administrative Order	47.74%
Bankruptcy	4.48%
Charge Off	0.88%
Liquidation	3.58%
Loss Provision	4.30%
Non Accrual	1.27%
Receivership	3.44%
Troubled Debt/Restructure	1.13%
Unknown	2.57%
Unlikely repayment of debt	0.03%
Winding-up	25.39%

We define the default date as the first occurrence of one of these default events.

Defining a Default Rate for Private Firm Data

We eliminate censored observations – observations for which the default window contains a time period in which we did not collect defaults.

On September 1 for each year, we count the number of firms that have a financial statement that is between 6 and 30 months old.

We count the number of firms that default between September 1 of that year and August 31 of the next year.

The ratio of these two numbers is the default rate.

UK Default Rates: 1992-2008

Year	Default (0-365) Vender Provided Data	Default (0-365) Bank Provided Data
1991	17.9%	
1992	7.9%	
1993	4.6%	
1994	3.6%	
1995	3.4%	
1996	3.3%	
1997	3.1%	1.8%
1998	3.4%	3.1%
1999	3.1%	1.7%
2000	2.9%	1.2%
2001	2.7%	0.1%
2002	2.5%	0.0%
2003	2.1%	0.7%
2004	1.9%	0.7%
2005	2.1%	0.7%
2006	2.0%	0.5%
2007	2.5%	0.7%
2008	2.9%	1.4%
Average 1992-2008	**3.2%**	**1.1%**
Average 2000-2008	**2.4%**	**0.7%**

*0-365 default is a default that occurs within 0 to 365 days of the date of September 1st of each year.

Is the Model Working as Intended?

Check the distribution of ratios entering into the model over time and compare with development sample

Examine the time series of mean and median EDF in CCA and FSO mode

Examine the distribution of EDF implied ratings over time in CCA and FSO mode

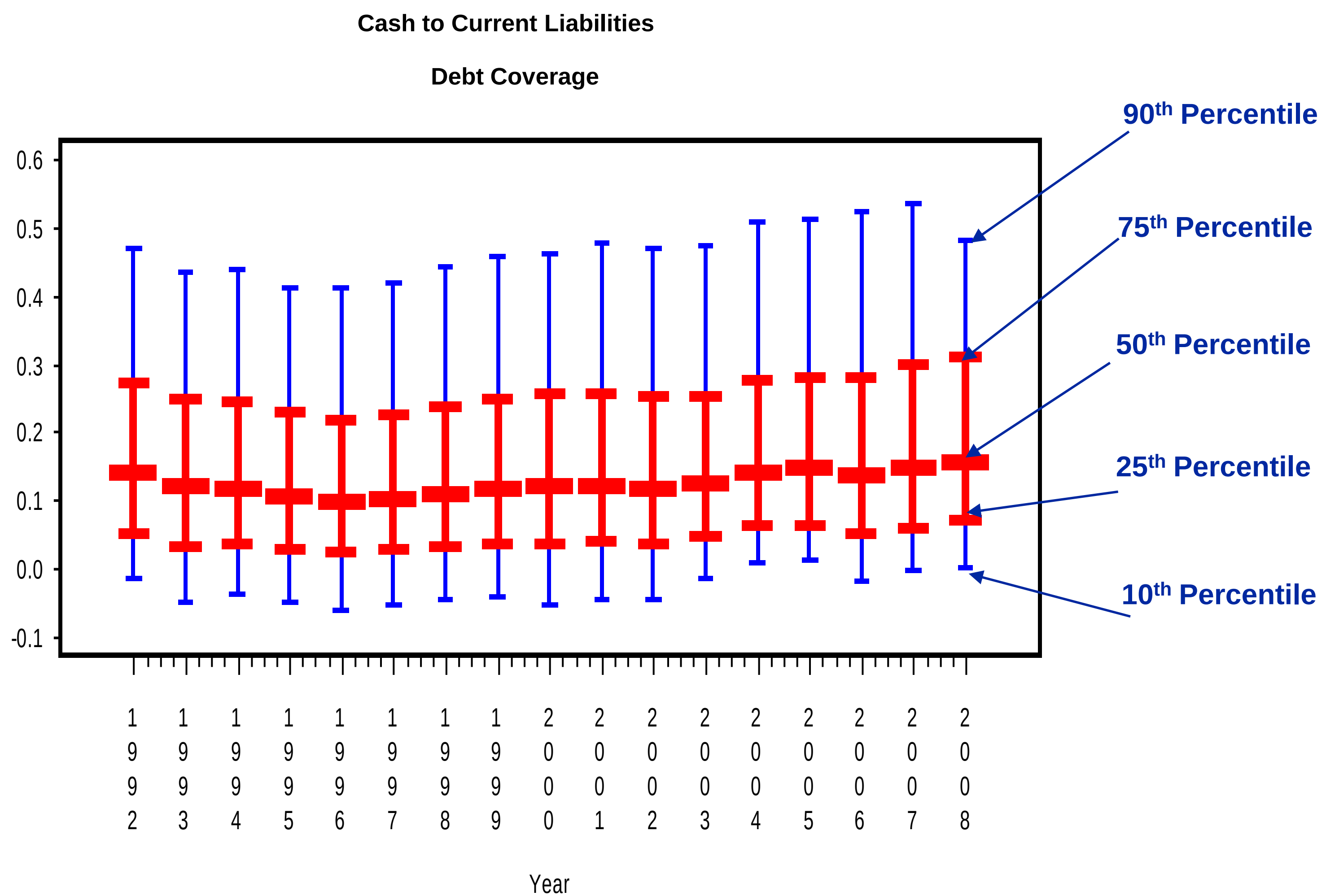
Ratio Percentiles (South Africa)

Ratio Percentile	% of Miss Obs.	P25	MEDIAN	P75
Inventory/Cost of Goods Sold	2.51%	2.00%	48.66%	74.67%
Cash Flow/Financial Charge	1.95%	20.77%	53.56%	84.29%
(Current Liabilities + Long Term Debt)/Assets	0.00%	19.72%	41.85%	68.38%
Sales Growth	0.00%	26.48%	50.46%	76.91%
Cash/Assets	1.62%	33.59%	60.45%	83.14%
Previous Yr Net Income/Previous Yr Assets	0.00%	31.42%	59.26%	82.97%
Net Income/Assets	0.00%	33.25%	59.91%	82.73%
Size	0.00%	34.85%	60.01%	81.70%

Distribution of percentiles for each ratio produced by the model are reasonably consistent with the development sample.

RiskCalc outputs a percentile score for each ratio in the model for each observation based on the development sample. If the distribution of the ratios in a sample that is scored through the model is consistent with the distributions of the ratios in the development sample, then the distribution of the percentiles should form a uniform distribution, i.e., P25=25%, median=50%, and P75=75%.

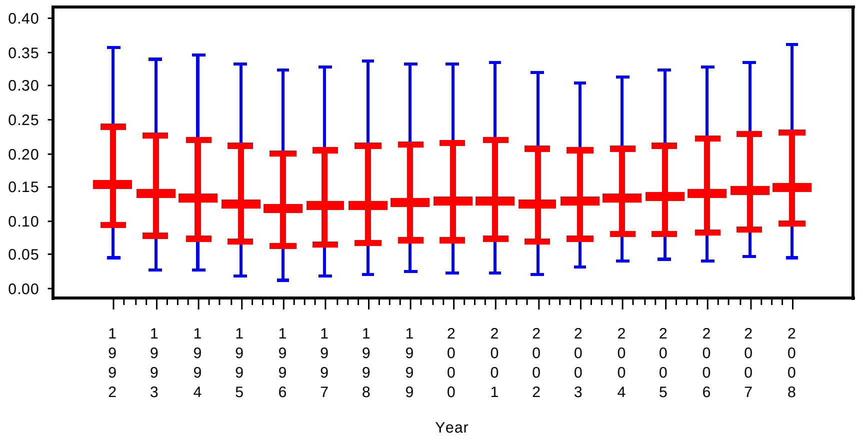
Checking Distributions of the Various Ratios (Germany)



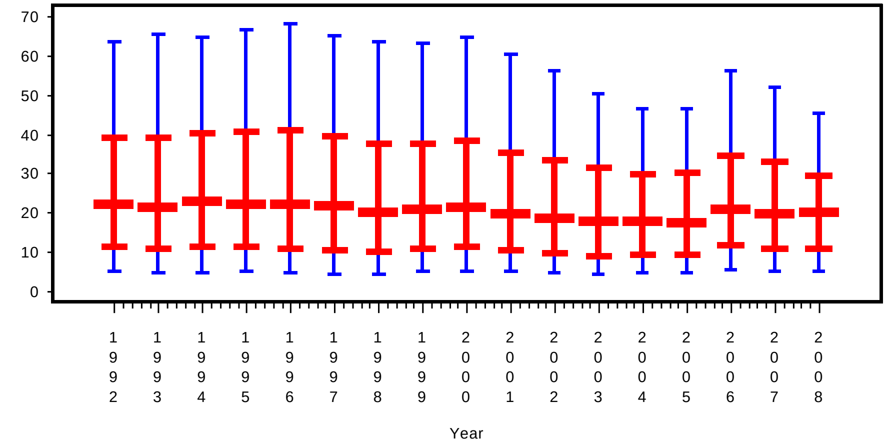
Year refers to the year in which the fiscal year ended.

Examine Ratio Distributions (Germany)

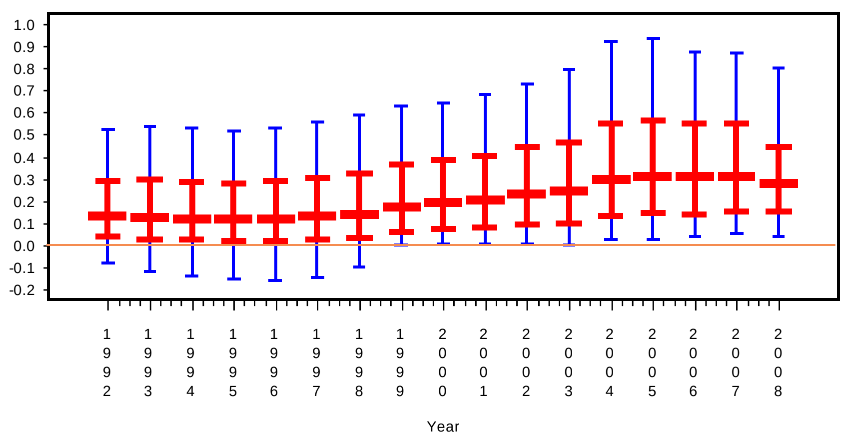
EBITD to Assets



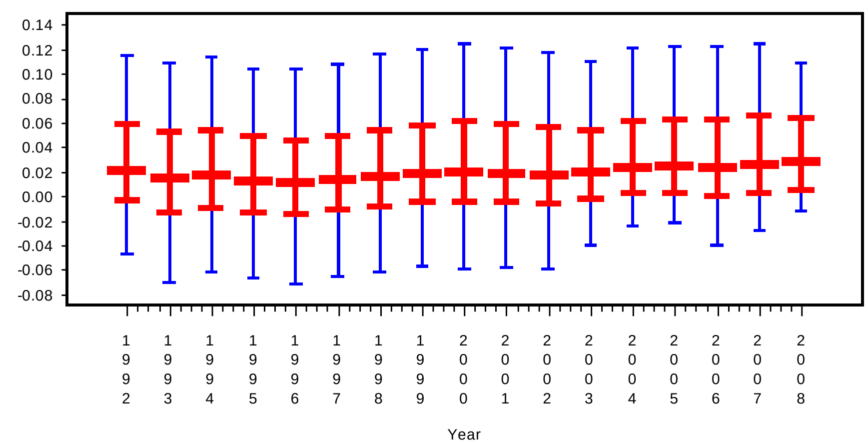
Trade Creditors Ratio



Equity Ratio

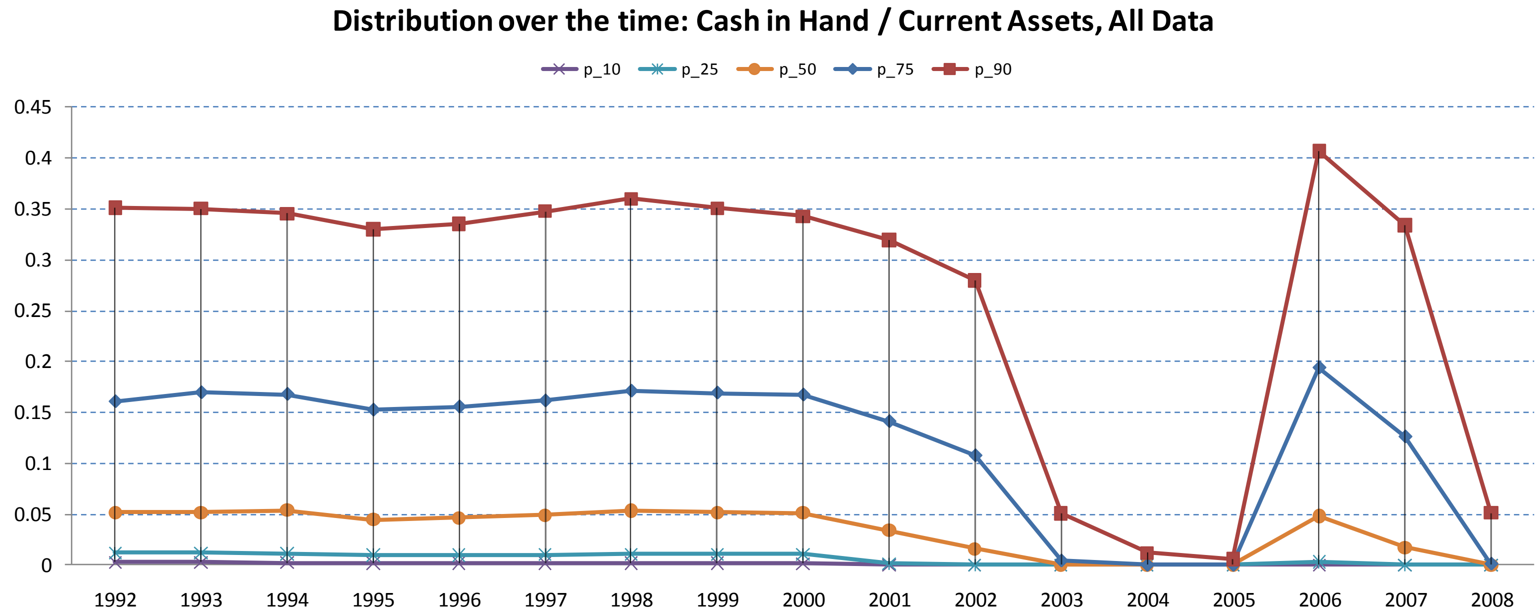


Ordinary Profit to Sales



Year refers to the year in which the fiscal year ended.

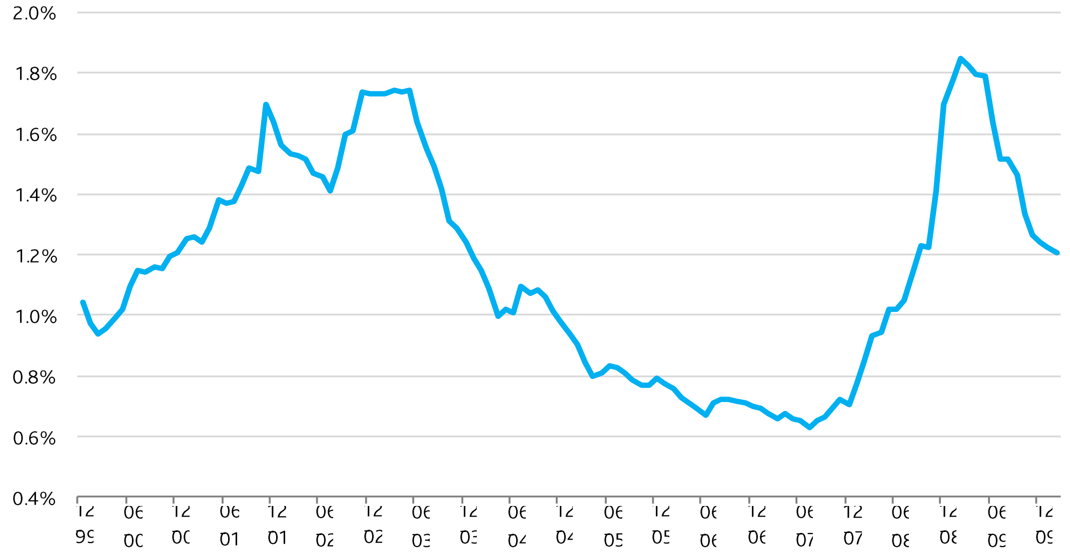
The "Cash in Hand / Current Assets" Does Not Have Consistent Distributions Over the Time for the Full Sample



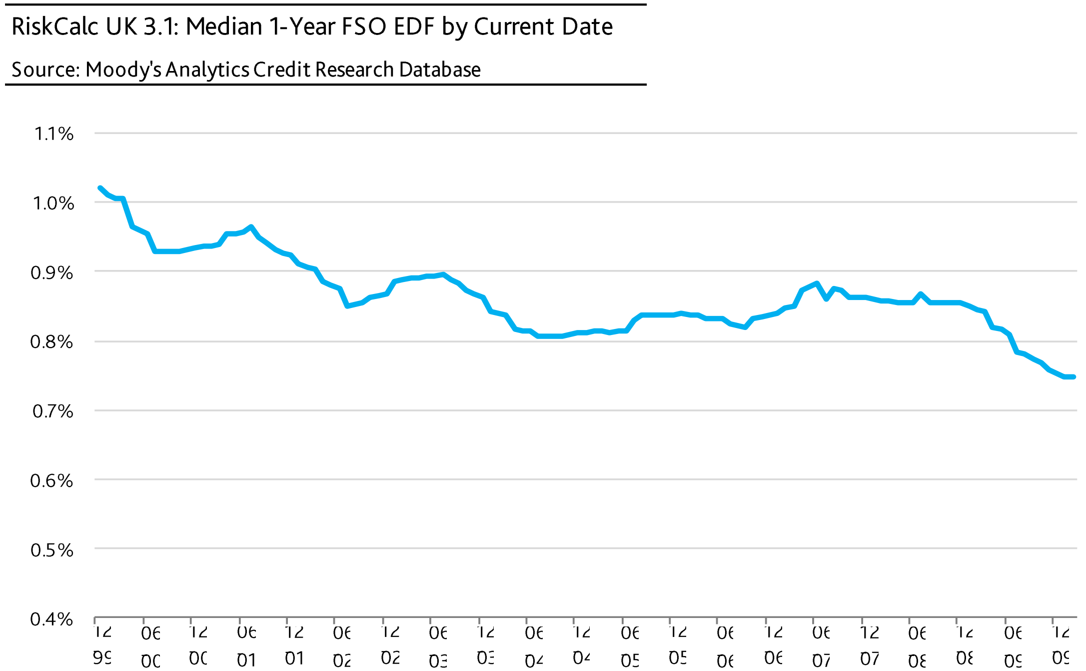
Check the Time Series of the Median CCA EDF (UK)

RiskCalc UK 3.1: Median 1-Year CCA EDF by Current Date

Source: Moody's Analytics Credit Research Database



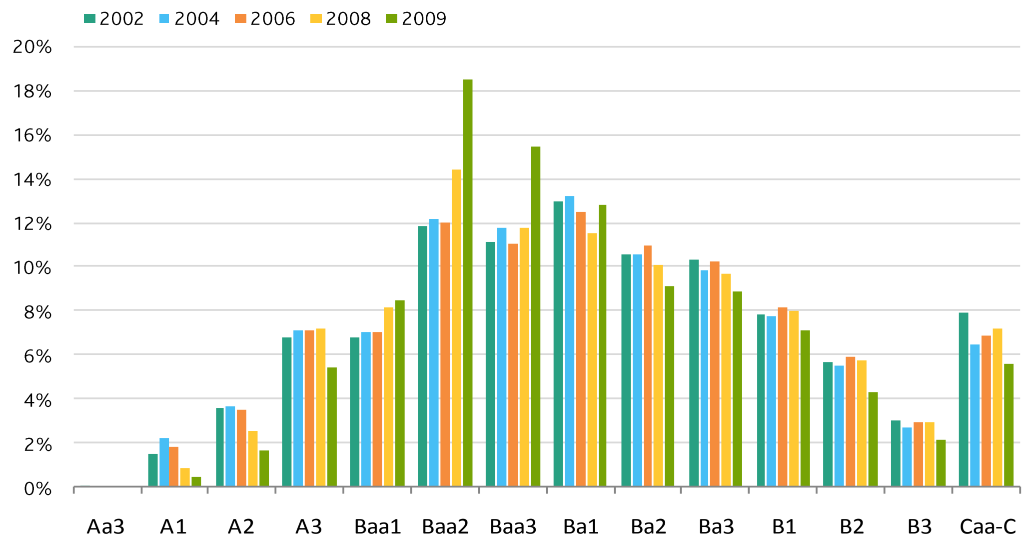
Check the Time Series of the Median FSO EDF (UK)



Check the Distribution of FSO EDF Implied Ratings (UK)

RiskCalc UK 3.1: Median 1-Year FSO EDF Mapped Rating by Year

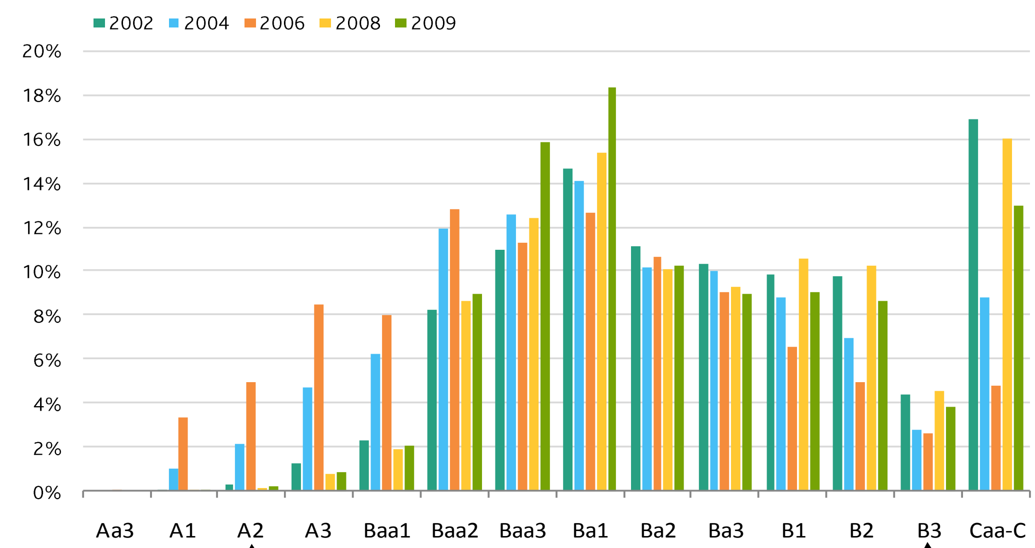
Source: Moody's Analytics Credit Research Database



Check the Time Series of CCA EDF Implied Ratings (UK)

RiskCalc UK 3.1: Median 1-Year CCA EDF Mapped Rating by Year

Source: Moody's Analytics Credit Research Database



Large amounts of A1, A2, A3
in 04, 06

Large amounts of B2, B3, Caa
in 02, 08, 09

Model Validation

Is the model working as intended?

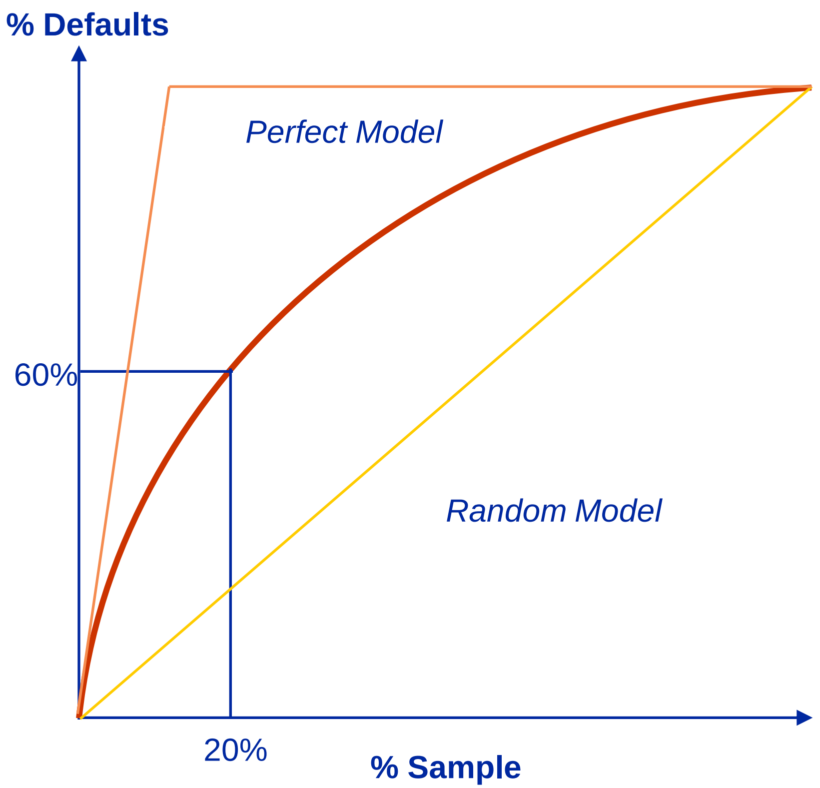
Is the discriminatory power being maintained?

Is the level of the PD appropriate?

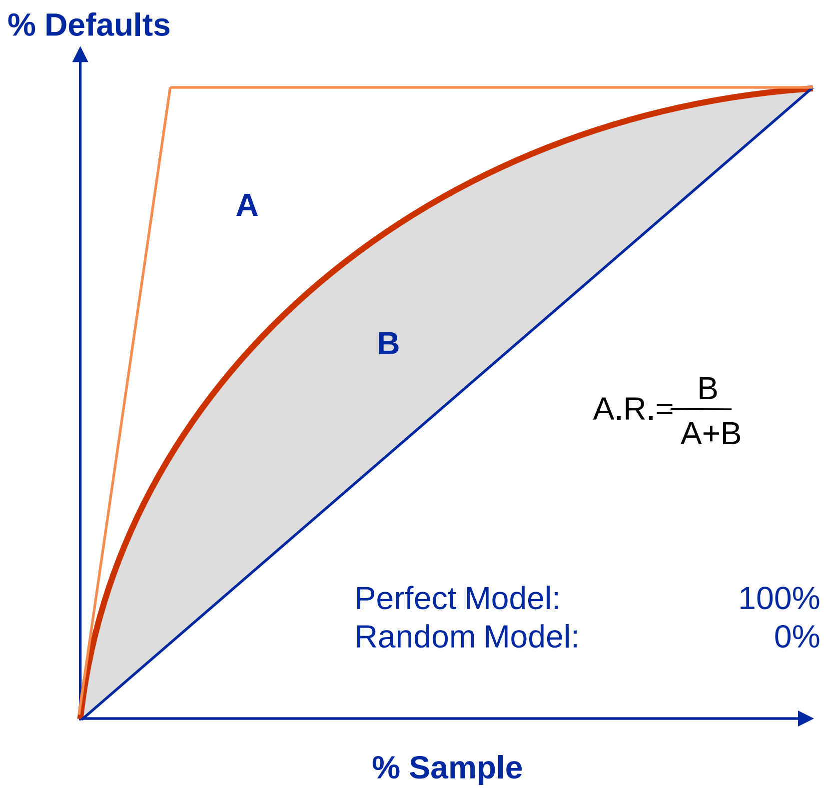
Can the model be improved?

PD Model Validation Dimension #1: Discriminatory Power

A POWER CURVE MEASURES HOW RAPIDLY DEFAULTS WOULD BE EXCLUDED



THE RELATION BETWEEN THE ACCURACY RATIO AND A POWER CURVE



An Accuracy Ratio of a Model on a Particular Sample Depends on Many Factors

The cleaner the data, the higher the power:

- Non-defaults misclassified as defaults will lower the power of the model as well as defaults misclassified as non-default.
- Inaccuracies in the financial statement information will lower model power.
- Mismatches between the default information and the financial statement information will lower power.

Timing of defaults matter:

- Default is a process of the borrower becoming “substandard” and/or “missing a payment” then becoming 90 days past due, being charged off, and being reorganized or liquidated. There are many variations.
- If we set the default date to the date of the first default event and we become more effective at capturing all default events we move the default date to an earlier stage of this process. Predicting an earlier stage default is harder than a later stage default.

The portfolio itself matters:

- In general, the more variability in the credit risk of the sample, the higher the power.

In practice, the age of the financial statement will matter:

- The older the financial statement, the less informative it is.

We See Higher ARs When We Work with "Insolvency-Based" Definitions of Default and Public Firms

» Insolvency-based defaults are latter stage defaults and, hence, easier to predict. Public firms are larger and have higher quality financial statements than small- and medium-sized enterprises. Consequently, the statements are more informative.

» In Belgium, Finland, and the Netherlands, the ARs of the RiskCalc v3.1 models were 72.3%, 74.3%, 70.2%, respectively. In these models, the default information sources were insolvency-based.

» The data underlying "Level and Rank Order Validation of the US v3.1 Model" (2009) is very close to the Basel definition of default. In this study, the Accuracy Ratio was 51.7% for defaults and 46.7% for "defaults and near defaults." The same model, when applied to public firms, produced an AR of 75.5%.

» In Austria v3.2, the AR of the model on "provisioned defaults" was 58.1%, while on "all defaults" it dropped to 51.0%.

» In the 2009 validation of RiskCalc UK v3.1, the AR was 53% on bank-provided data, which included some 90DPD defaults. The AR was 72%, however, when the same model was applied to public UK firms.

» In Germany, we have 90DPD information for the past five years, and the annual ARs range from 42% to 54%, when they are included, and 54% to 60% when they are excluded.

» In the 2009 validation of the South Africa model, the out-of-sample power was 45% on bank-provided private firm data, which included some 90DPD defaults. When the same model was applied to public South African firms, the power was 67.6%.

Cumulative Accuracy Profile: Germany

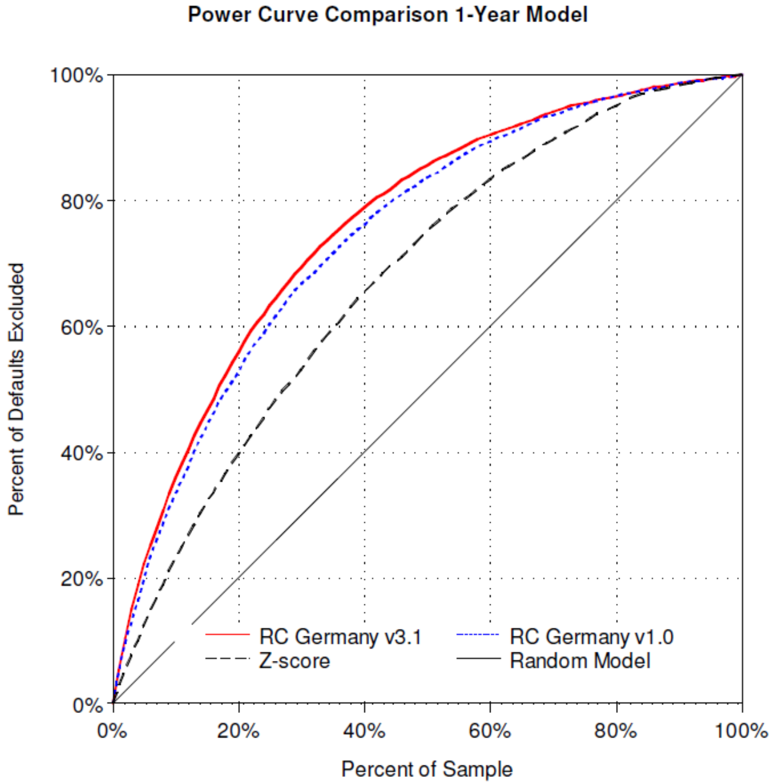
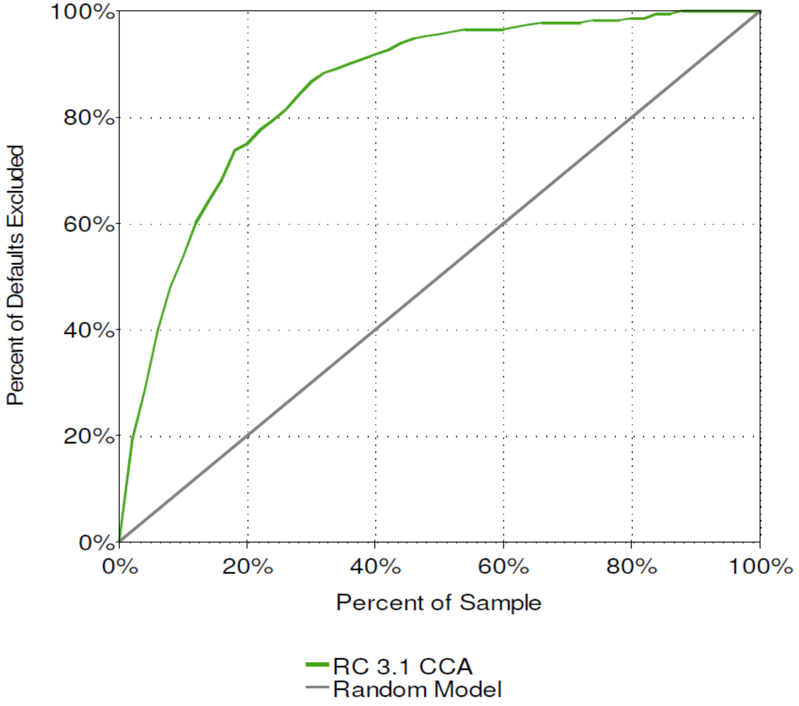


Figure 5 Cumulative Accuracy Profiles

Time Period: 1992-2009, AR 54.7%

Source: Assessment and Validation Evidence on RiskCalc Germany v3.1, 2010

Cumulative Accuracy Profile: Portugal

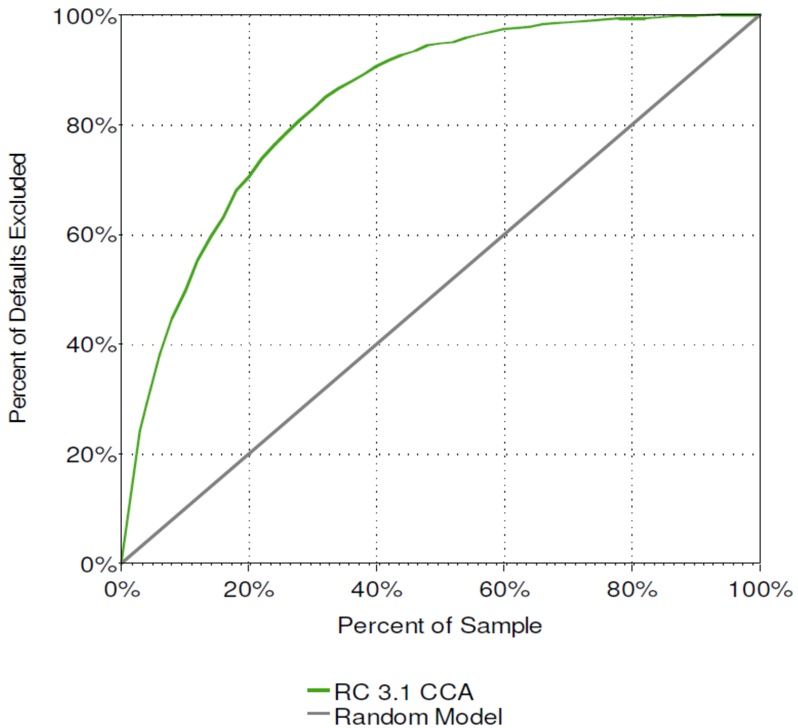


1-Yr EDF Accuracy Ratio: 71.4%

Time Period: 2006-2009

Source: RiskCalc Model Assessment, RiskCalc Portugal v3.1, 2010

Cumulative Accuracy Profile: Spain



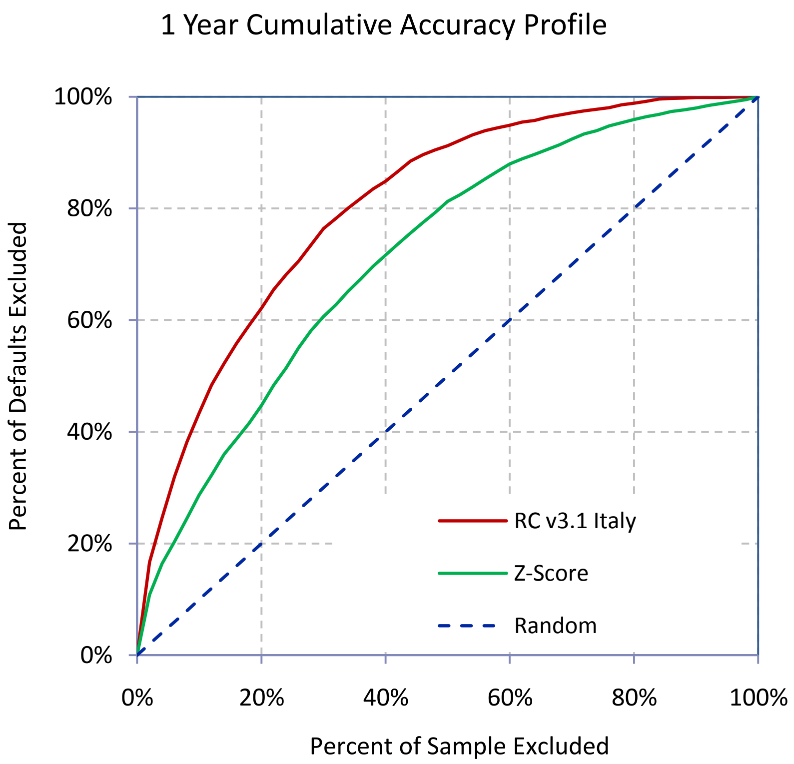
1-Yr EDF Accuracy Ratio: 69.2%

Time Period: 2006-2009

Source: RiskCalc Model Assessment, RiskCalc Spain v3.1, 2010

Cumulative Accuracy Profile: Italy

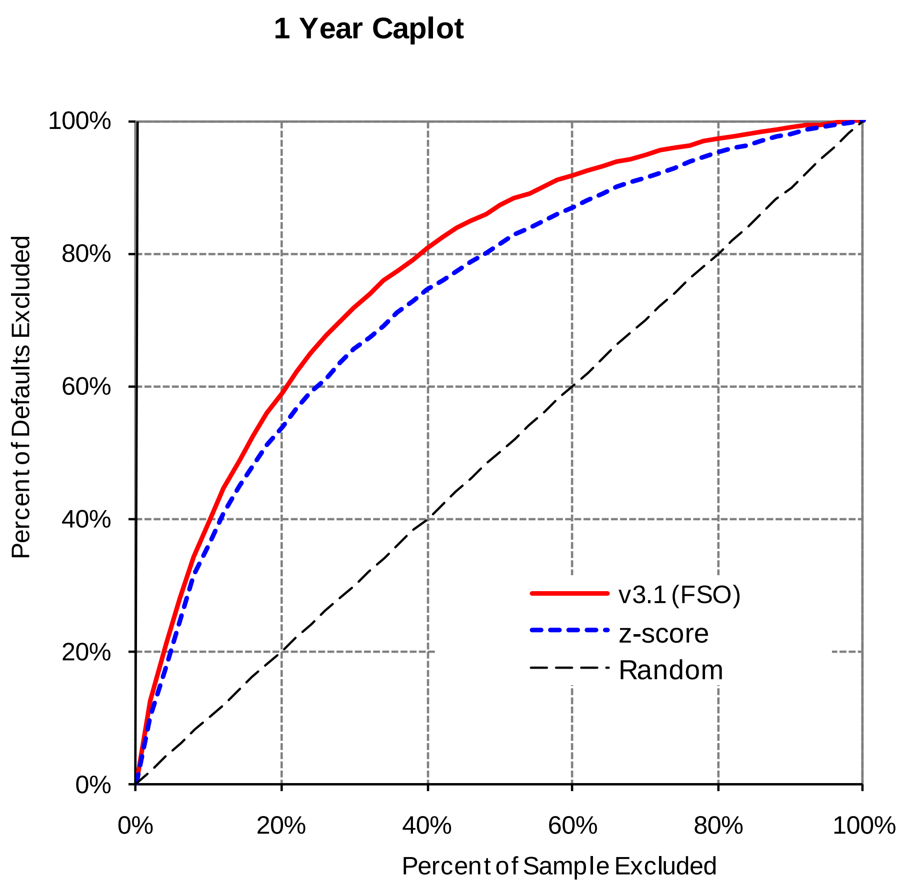
Accuracy Ratio	
RiskCalc v3.1 Model	63.88%
Z-score	44.89%



Time Period: 2003-2009

Cumulative Accuracy Profile: Norway

Model	Full Sample
Norway v3.1	60.5%
Z-Score	48.5%
Difference in Models	12%
Time Period	1994-2009

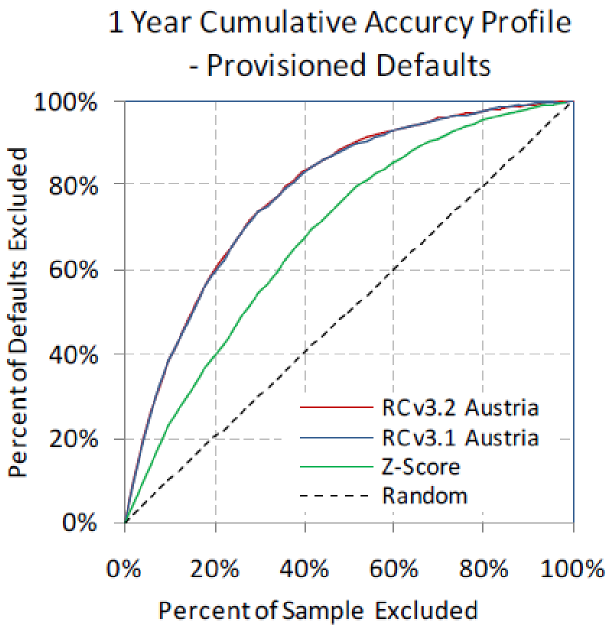


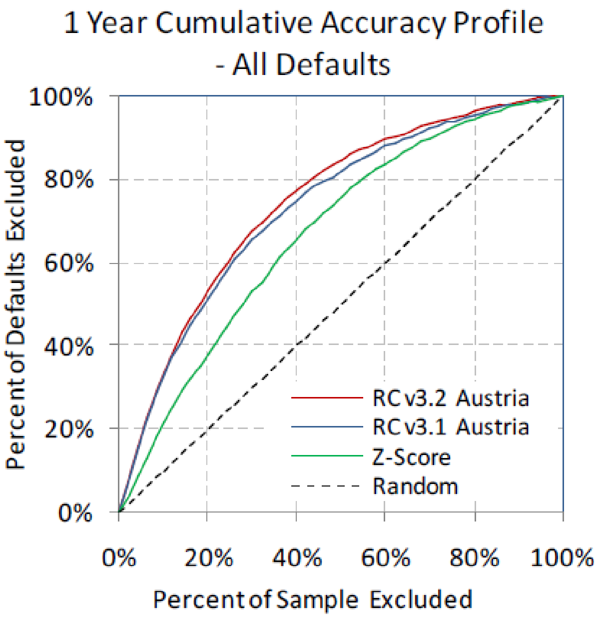
Time Period: 1994-2009

Cumulative Accuracy Profile: Austria v3.2

Table 5 Accuracy Ratio: One-year Model Horizon

	One-year Model Accuracy Ratio		
	RiskCalc v3.2 Austria	RiskCalc v3.1 Austria	P-value of Difference
Provisioned Defaults	58.1%	57.7%	0.2323
All Defaults	51.0%	48.3%	<.0001





Source: RiskCalc V3.2 Austria Model Methodology, 2010

Model Validation

Is the model working as intended?

Is the discriminatory power being maintained?

Is the level of the PD appropriate?

Can the model be improved?

Deriving the Central Default Tendency – Method 1

The default rate in a development sample depends on how it is measured.

Typically, we view the sample default rate from private firm data as a lower bound on the actual default rate.

Issues with Private Firm Data

For private firm data, we receive financial statement information and default information from separate, linked sources.

Coverage period of the two sources rarely overlap perfectly.

Default detection is generally improving in our samples, over time.

Often, there is a lag between the receipt of the final financial statement and a default event.

Defining a Default for Private Firm Data

We eliminate censored observations – observations for which the default window contains a time period during which we did not collect defaults.

On September 1 for each year, we count the number of firms that have a financial statement between 6 and 30 months old.

We count the number of firms that default between September 1 of that year and August 31 of the next year.

The ratio of these two numbers is the default rate.

Method 1: Sample Default Rates (Italy)

Year	Default Rate
1994	0.59%
1995	0.74%
1996	0.87%
1997	0.71%
1998	0.82%
1999	0.55%
2000	0.51%
2001	0.47%
2002	0.42%
2003	0.30%
2004	0.17%
2005	0.29%
2006	0.53%
2007	0.43%
2008	0.48%
2009	0.32%
Average 1994-2009	0.51%
Average 2004-2009	0.37%

***0-365 default is a default that occurs within 0 to 365 days of the date of September 1st of each year**

Deriving the Central Default Tendency – Method 2

One method is to look at the provisions rate and divide by an assumed value for LGD

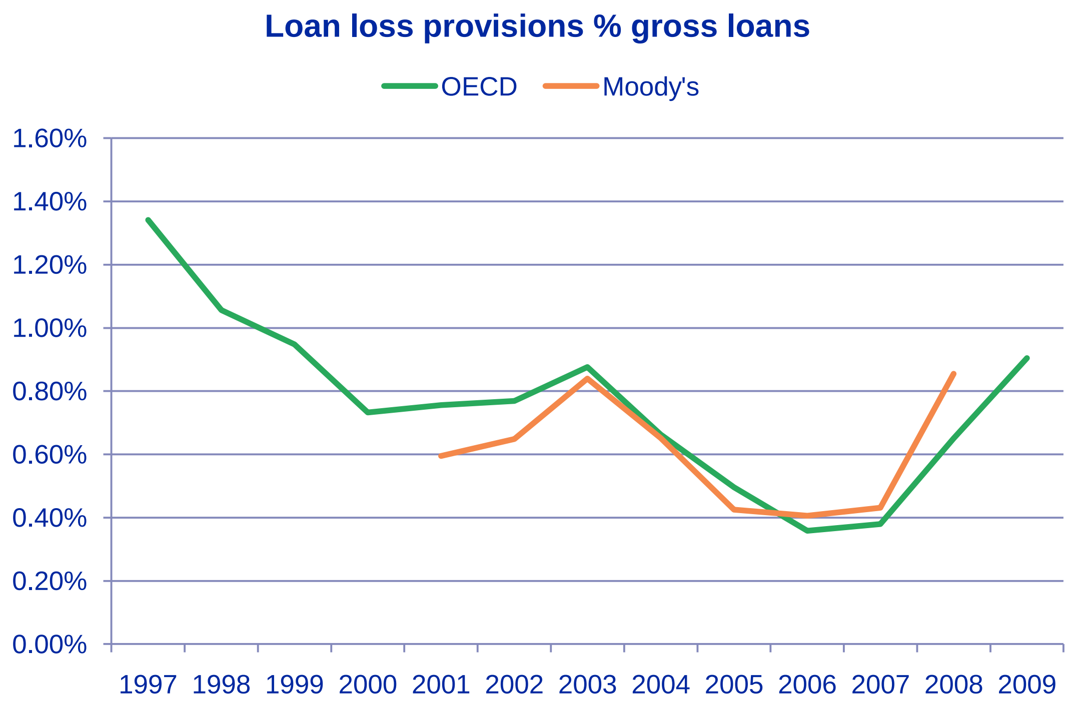
» *Probability of Default*LGD = Volume of Losses / (Volume of Loans)*

or

» *Probability of Default = Volume of Losses / (Volume of Loans*LGD)*

In implementing this approach, by convention, we take LGD to be 40% or 45% and use the average of the ratio of provisions to loans outstanding over a long time period.

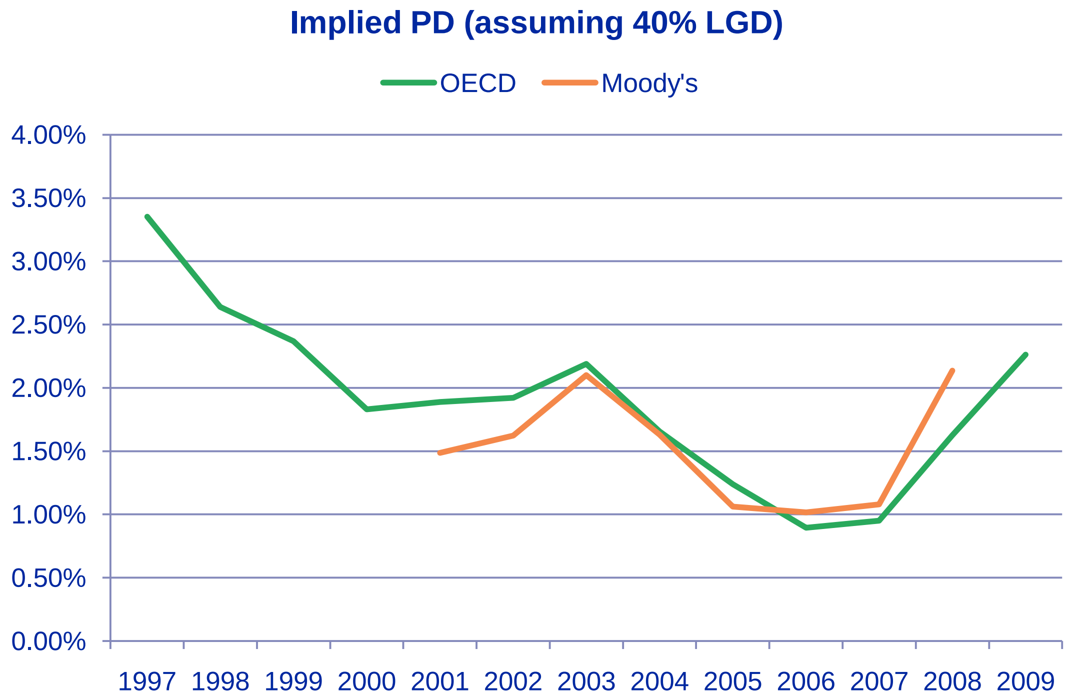
Method 2: CDT from Loan Loss Provisions



Source: OECD. *Bank Profitability*

Source: Banking Statistical Supplement, Italy, 2009, Moody's Investors Service.

Method 2: Implied Default Rate, Assuming 40% LGD



Source: OECD. *Bank Profitability*

Source: Banking Statistical Supplement, Italy, 2009, Moody's Investors Service.

Summary

Source	Default Rate Estimate Range	Average
OECD Provisioning Data	0.89%-3.35%	2.10%
Moody's Banking Statistical Supplement	1.02% to 2.14%	1.40%
Validation Sample	0.17%-0.87%	0.51%

Italy V3.1 Central Default Tendency Estimate – 2.1%

OECD provision data-implied default rates for the sample period are 0.89%-3.35%, and the average is 1.91%.

Recent (2001-2008) provisioning data compiled by Moody's Investors Service implies a default rate of 1.01% to 2.14%, and the average is 1.52%.

On the validation sample, the measure of default is 1.5%, after adjusting for missing defaults.

We view the current CDT, 2.1%, as appropriate.

Defaults rates have been trending downward during the past decade in Italy, but they increased during the 2008 and 2009 periods.

Model Validation

Is the model working as intended?

Is the discriminatory power being maintained?

Is the level of the PD appropriate?

Can the model be improved?

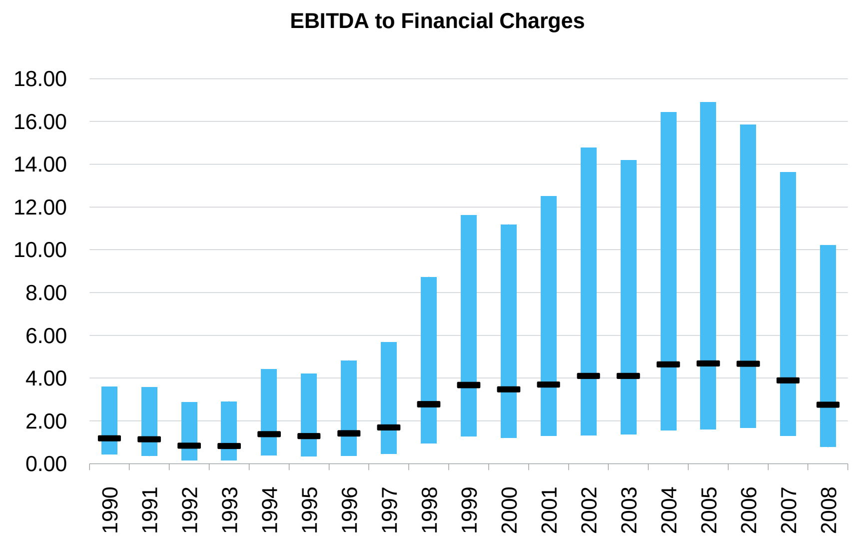
In Italy, the ARs for Both RC and the Benchmark Were Relatively Low from 2003 Until 2007

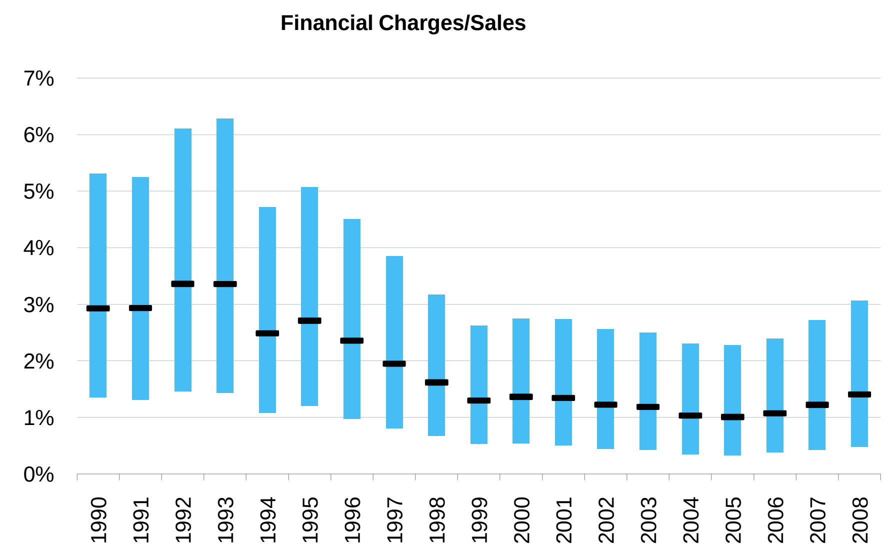
Year	% of defaults	AR RC 3.1	Z-Score
1992	1.18%	65.31%	49.88%
1993	2.13%	76.23%	55.47%
1994	2.82%	72.12%	56.03%
1995	3.79%	76.81%	57.44%
1996	4.28%	79.35%	56.51%
1997	10.21%	76.07%	55.90%
1998	10.65%	74.65%	54.75%
1999	10.95%	77.85%	61.71%
2000	9.13%	76.55%	55.48%
2001	4.70%	71.58%	48.41%
2002	4.26%	71.36%	53.63%
2003	4.12%	57.88%	39.58%
2004	7.81%	61.55%	41.97%
2005	11.05%	63.98%	42.58%
2006	5.73%	59.62%	39.55%
2007	5.25%	64.75%	46.72%
2008	1.94%	84.41%	77.80%

Euro Libor Rate Over Time

EUR Libor 3M, EU0003M, Bloomberg

Possible Reason for Recent Model Performance





EBITDA to Financial Charges improved during time period.

Financial Charges (Interest Expense)/Sales has decreased gradually.

The low interest rate environment in Italy may contribute.

Is it Possible to Further Increase the Model's AR

Can the model be improved by:

- » Keeping the original variables
- » Calibrating the model based on the most recent sample, 2004 -2008

Model	1- Year Accuracy Ratio
Calibrate model based on sample (2004-2008)	65.85%
Italy 3.1 EDF	64.64%
3.1 – Z-SCORE (P-Value)	1.21% (<0.0001)

Recalibrating RiskCalc Italy v3.1 with Most Recent Data Does Not Yield a Robust Improvement In AR

Year	% of defaults	Newly Calibrated Model	AR RC 3.1	Diff
2004	24.58%	63.10%	61.55%	1.56%
2005	34.77%	65.32%	63.98%	1.34%
2006	18.03%	61.28%	59.62%	1.66%
2007	16.53%	66.02%	64.75%	1.26%
2008	6.09%	83.11%	84.41%	-1.30%