5. Measurement and Management of Credit Risk

5.1. Credit Risk in Banking Management

Decision Process

1. Customer's financial capacity

2. Credit Rules

3. Minimum spread setting

4. Minimum spread adequacy

Financial Capacity

- The 1st step in credit risk analysis is the assessment of the ability to generate enough cash-flows to face the credit installments.

- The bank must impose credit limits to its larger customers/counterparties (in the corporate and institutional sectors), in line with their ability to absorb debt and the weight in that debt targeted by the bank.
- The limits must depend on the maturities (larger limits for larger maturities).
- For companies, the financial capacity is inferred from the cash-flows exhibited in the financial statements.
- For individual customers, that analysis is based on income and asset information, when the customer applies to a loan, or by bank's estimates (income models) based on relationship data.

Decision Filters

- Banks usually set credit rules, leading to the automatic loan approval or rejection.
- Regarding the former, the credit rules are motivated by commercial reasons (e.g. automatic offer of credit cards to private banking customers).
- Concerning the latter, banks usually reject loans whenever the applicants display negative credit events (e.g. non-performing loans).

Minimum Spread

- Conceptually, all loans can be accepted, as long as the spread charged to the performing customers is high enough to compensate for the losses with the remaining customers.

- It is necessary to calculate the minimum spread to be charged for a loan, reflecting the corresponding expected loss, as well as its administrative and funding costs and the shareholders' remuneration.

$$s = Ca + ROE \cdot K + Cf + EL$$

$$RAROC = \frac{s - Ca - Cf - EL}{K}$$

s = minimum spread (e.g. over the Euribor) for loans

Ca= administrative costs (% total credit).

ROE = return on equity (long-term goal).

K = capital requirement for the loan.

Cf = funding cost (spread over the Euribor).

EL = Expected Loss (PD x LGD x EAD)

- If the minimum spread is too high and the loan application is accepted, the bank may be incurring in adverse selection.

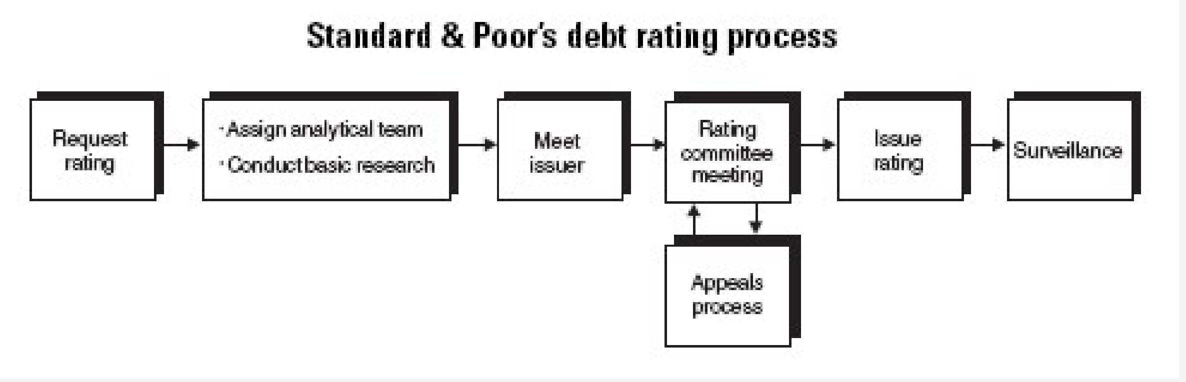
Minimum Spread

- The PDs are obtained from rating classifications provided by credit risk models.
- These classifications are characterized by a term structure of PDs.
- The bank must set a cut-off level for these PDs, based on the expected return.
- For loans that are profitable for all rating classes (e.g. credit cards), banks must impose a cap on the EL, by setting a maximum risk classification, in order to avoid the adoption of a less conservative credit policy leading to higher EL levels.

5.2. External Ratings

Key Features

- The rating is an opinion on the credit risk, associated to the possibility of a default by a debt issuer in any future payment.
- It is a qualitative assessment, even though based on financial information and often used to quantify credit risk, as rating agencies release statistics with frequencies of default.
- Its validity depends on the credibility of the underlying analysis, based on a very comprehensive process.



Source: S&P (2002), "Corporate Ratings Criteria".

Key Features

- Besides financial variables, the rating involves the assessment of the governance and the issuer's environment, namely its economic sector:
  - industrial companies– sector's growth perspectives, degree of exposure to technological changes, labor environment, existing and expected regulation;
  - financial companies – key role of reputation.

Key Features

- 2 main rating types:
  - issue-specific or facility rating – in this case, the rating is associated to the possibility of an issuer default in a given payment, considering the existing guarantees and collaterals, as well as the debt seniority.
  - borrower rating – respects only to the issuer credit risk, regardless bond features.
- The rating for collateralized debt may be different from the unsecured debt, if the collateral is relevant for the issuer's reimbursement ability.
- A strong shareholder structure may benefit the issuer's rating and the rating of a financial participation may be even higher than its parent's rating, if the latter doesn't have any incentive to use the former's assets.
- Usually the issuers face a sovereign rating ceiling and the foreign-currency debt has a lower rating.

Analysis

- The rating is usually based on the audited financial statements of the last 5 years, involving the comparison to the average sector ratios.
- Rating agencies perform a through-the-cycle, instead of a point-in-time analysis.
- The issuer is assessed according to its expected financial along the business cycle, considering its risk at its lowest point.
- Credit risk is assessed in order to smooth the impact of business cycle changes (through-the-cycle) vis-à-vis the models that explicitly relate credit risk to the business cycle (point-in-time).

Analysis

- The debtor is assessed according to his conditions in the lowest point of the credit cycle and downgraded companies are only those whose performance in these lowest points is worse than expected, being the rating migrations much less frequent and the PDs more volatile.
- Problems of “through-the-cycle” models:
  - difficulty in forecasting the business cycle stages of the different economic activities;
  - even the predictable cycles may have lasting effects on company’s credit risk, being frequent rating adjustments during the cycle.
- The rating analysis is performed for new and already existing debt issues, by an issuer’s request in the former case and the rating agency initiative in the latter.
- The rating monitoring may identify events potentially leading to rating changes, leading to a creditwatch (“positive”, “negative” or “developing”).

Classifications

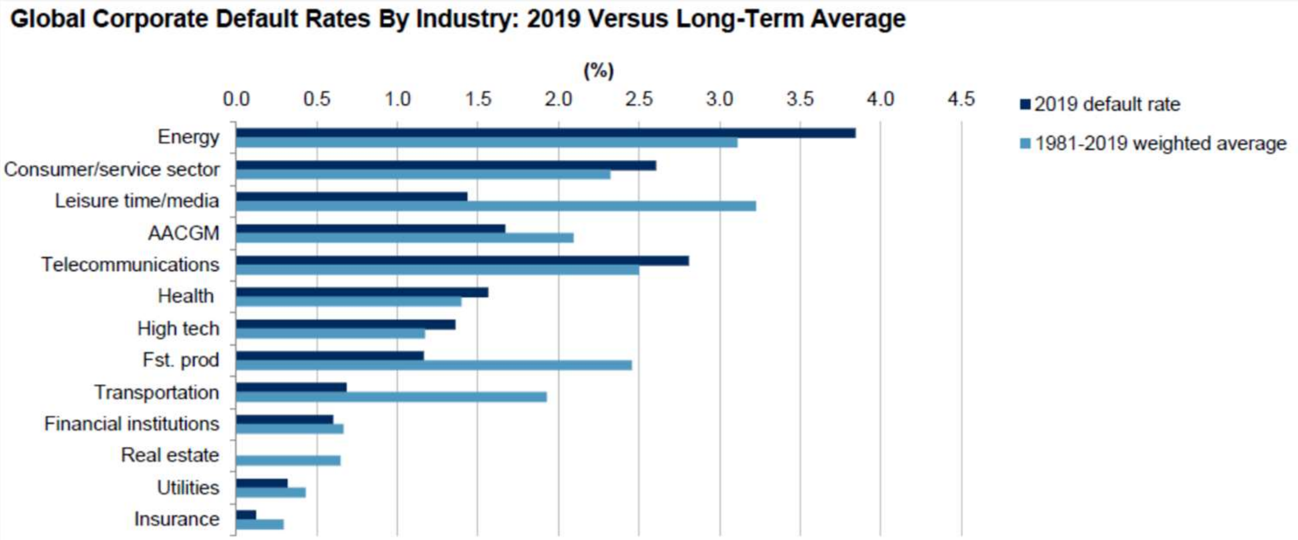
- Corporate rating analysis focus on business and financial risk:

(1) Business risk:
  - Industry characteristics;
  - Competitive position (regulation, marketing, efficiency, technology).

(2) Financial Risk:
  - Financial policy;
  - Profitability;
  - Capital Structure;
  - Access to liquidity.

Classificações

- Regarding corporate rating assessment, the industry assumes a relevant role.
- Therefore, companies in industries with risk levels above the average do not usually achieve the top ratings.
- When a company is involved in more than one sector, each business is assessed separately, with the classification resulting from the weighted average of each business classification.



Source: S&P (2020), "Default, Transition, and Recovery: 2019 Annual Global Corporate Default And Rating Transition Study".

Classifications

Annual default rates by broad industry group, 1970-2019

Year	Aerospace & Defense	Automotive	Banking	Beverage, Food, & Tobacco	Capital Equipment	Chemicals, Plastics, & Rubber	Construction & Building	Consumer goods: Durable	Consumer goods: Non-durable	Containers, Packaging, & Glass	Energy: Electricity	Energy: Oil & Gas	Environmental Industries	Finance	Forest Products & Paper	Healthcare & Pharmaceuticals
1970	0.00%	0.00%		0.00%	0.00%	0.00%	0.00%		0.00%	0.00%		0.00%			0.00%	0.00%
1971	0.00%	0.00%		0.00%	0.00%	0.00%	0.00%		0.00%	0.00%		0.00%			0.00%	0.00%
1972	0.00%	0.00%		0.00%	1.10%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%			0.00%	0.00%
1973	0.00%	0.00%		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.14%		0.00%			0.00%	0.00%
1974	0.00%	0.00%		0.00%	1.12%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%			0.00%	0.00%
1975	0.00%	3.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%		0.00%	0.00%	4.76%
1976	0.00%	0.00%	0.00%	0.00%	1.04%	0.00%	0.00%	0.00%	2.63%	0.00%		0.00%		0.00%	0.00%	0.00%
1977	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.70%	0.00%		0.00%		0.00%	0.00%	0.00%
1978	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.70%			1.32%		0.00%	0.00%	0.00%
1979	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%		0.00%	0.00%	0.00%
1980	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.23%	0.00%	0.00%	0.00%		0.00%		0.00%	0.00%	0.00%
1981	0.00%	0.00%	0.00%	0.00%	1.19%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%		0.00%	0.00%	0.00%
1982	0.00%	2.86%	0.00%	0.00%	0.00%	0.00%	3.33%	0.00%	0.00%	0.00%		0.98%		0.00%	0.00%	0.00%
1983	0.00%	8.11%	0.00%	1.47%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.44%		0.00%	0.00%	0.00%
1984	0.00%	2.94%	0.00%	1.45%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.01%		0.00%	0.00%	2.22%
1985	0.00%	0.00%	0.00%	0.00%	1.84%	2.04%	0.00%	0.00%	1.82%	0.00%	0.00%	3.43%		0.00%	0.00%	0.00%
1986	2.94%	0.00%	0.00%	1.20%	0.00%	1.85%	1.79%	5.88%	0.00%	0.00%	0.00%	8.37%		0.00%	0.00%	1.41%
1987	0.00%	1.82%	0.28%	0.00%	2.52%	0.00%	4.64%	0.00%	0.00%	0.00%	0.00%	5.54%		0.00%	0.00%	3.69%
1988	2.38%	0.00%	1.45%	0.00%	0.00%	1.64%	2.82%	4.35%	3.73%	0.00%	4.55%	2.13%	0.00%	0.00%	0.00%	4.71%
1989	0.00%	7.69%	1.49%	2.25%	0.00%	0.00%	8.85%	0.00%	3.85%	5.56%	0.00%	0.00%	0.00%	4.85%	0.00%	2.53%
1990	0.00%	3.97%	1.84%	5.61%	2.63%	0.00%	16.93%	4.76%	10.03%	0.00%	8.00%	1.47%	0.00%	0.00%	0.00%	1.15%
1991	2.22%	4.28%	1.40%	0.00%	4.54%	0.00%	7.55%	5.88%	6.18%	5.56%	4.17%	3.08%	0.00%	0.00%	3.33%	4.88%

Source: Moody’s (2020), “Default Trends – Global”.

Classifications

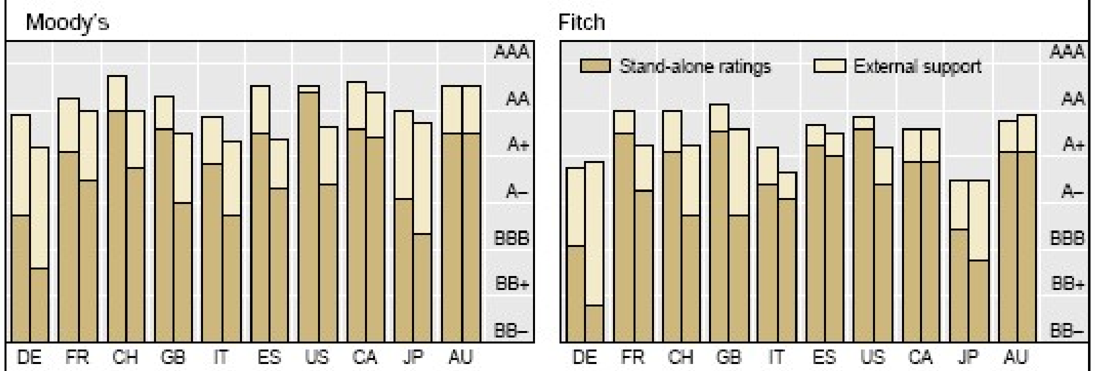
- Regarding the banking sector, a significant importance is attached to the potential support provided by the Government, considering the special role of the financial sector in the economy and the existing contagion risks.

Rating methodologies for banks

	Fitch	Moody's	Standard & Poor's[1]
Stand-alone assessments (intrinsic financial strength)	Focus on off-balance sheet commitments, funding and liquidity risk	Emphasis on forward-looking assessments of capital ratios, based on embedded expected losses	Focus on risk-adjusted performance and ability to grow capital from profits
All-in ratings (with external support)	Distinct ratings of sovereign support provide a floor	Based on a joint default analysis of banks and providers of support	Anticipated support increases with the bank's systemic importance
System-wide assessment			
Country rating	Based on: - macro indicators - average bank rating	None	Based on: - macro indicators - industry and regulatory environment
Does systemic risk affect banks' ratings?	Not explicitly; anticipated support increases with the bank's systemic importance but falls in times of generalised distress	Not explicitly; anticipated support increases with the bank's systemic importance	Yes, through: - macro indicators for countries where the bank operates - assessments of the industry and regulatory environment in the home country
Last major changes	2005: systemic risk analysis	2007: joint default analysis in support assessment	2011: overhaul of the rating methodology. Greater emphasis on: - system-wide risks - link from earnings to capital

[1] Refers to the agency's proposed methodology for bank ratings, as outlined in Standard & Poor's (2011). Table 1

Stand-alone ratings and the importance of external support[1]



DE = German banks (8; 8); FR = French banks (4; 2); CH = Swiss banks (2; 2); GB = UK banks (5; 5); IT = Italian banks (3; 3); ES = Spanish banks (4; 3); US = US banks (7; 6); CA = Canadian banks (5; 5); JP = Japanese banks (5; 3); AU = Australian banks (4; 4). The first figure in parentheses refers to the number of banks rated by Moody's, and the second to the number rated by Fitch.

[1] For each country, the first bar plots average ratings in mid-2007, and the second those in April 2011. The stand-alone rating plus the rise due to external support equals the all-in rating. See Table 2 for a definition of stand-alone and all-in ratings and an explanation of how they are mapped into numbers for the calculation of averages.

Sources: Fitch Ratings; Moody's Investors Service. Graph 3

Source: Packer, F. e N.Tarashev (2011), "Rating methodologies for banks", BIS Quarterly Review, June.

Classifications

- The long term ratings of the main agencies (S&P and Moody’s) is split by 7 classes, each of them (excluding AAA) with rating modifiers +/ /- (S&P) or 1/2/3 (Moody’s).
- The four first classes are the investment grade, while the remaining are speculative grade.

	S&P	**Moody's**
Investment Grade	AAA	Aaa
	AA	Aa
	A	A
	BBB	Baa
Speculative Grade	BB	Ba
	B	B
	CCC	Caa
	CC	Ca
	C	C

Classifications

54 M. Crouhy et al. / Journal of Banking & Finance 25 (2001) 47–95

Table 1
S&P ratings category definitions[a]

AAA	An obligation rated AAA has the highest rating assigned by Standard & Poor's. The obligor's capacity to meet its financial commitment on the obligation is extremely strong
AA	An obligation rated AA differs from the highest rated obligations only in small degree. The obligor's capacity to meet its financial commitment on the obligation is very strong
A	An obligation rated A is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligations in higher rated categories. However, the obligor's capacity to meet its financial commitment on the obligation is still strong
BBB	An obligation rated BBB exhibits adequate protection parameters. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitment on the obligation

Classifications

BB	An obligation rated BB is less vulnerable to nonpayment than other speculative issues. However, it faces major ongoing uncertainties or exposure to adverse business, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitment on the obligation
B	An obligation rated B is more vulnerable to nonpayment than obligations rated BB but the obligor currently has the capacity to meet its financial commitment on the obligation. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitment on the obligation
CCC	An obligation rated CCC is currently vulnerable to nonpayment, and is dependent upon favorable business, financial, and economic conditions for the obligor to meet its financial commitment on the obligation. In the event of adverse business, financial or economic conditions, the obligor is not likely to have the capacity to meet its financial commitment on the obligation
CC	An obligation rated CC is currently highly vulnerable to nonpayment.
C	The C rating may be used to cover a situation where a bankruptcy petition has been filed or similar action has been taken, but payments on this obligation are being continued

Short-Term Classifications

- Rating agencies have different classifications for the short term debt:

Table 3

(a) The short-term credit ratings of S&P[a]

A-1	A short-term obligation rated A-1 is rated in the highest category by S&P. The obligor's capacity to meet its financial commitment on the obligation is strong. Within this category, certain obligations are designated with a plus sign (+). This indicates that the obligor's capacity to meet its financial commitment on these obligations *is extremely strong*
A-2	A short-term obligation rated A-2 is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligations in higher rating categories. However, the obligor's capacity to meet its financial commitment on the obligation *is satisfactory*
A-3	A short-term obligation rated A-3 exhibits adequate protection parameters. However, adverse economic conditions or changing circumstances are more likely to lead to a *weakened capacity* of the obligor to meet its financial commitment on the obligation
B	A short-term obligation rated B is regarded as having significant speculative characteristics. The obligor currently has the capacity to meet its financial commitment on the obligation; however, it faces major ongoing uncertainties which could lead to the obligor's *inadequate capacity* to meet its financial commitment on the obligation
C	A short-term obligation rated C is *currently vulnerable to nonpayment* and is dependent upon favorable business, financial, and economic conditions for the obligor to meet its financial commitment on the obligation

Short-Term Classifications

(b) Moody's short-term debt ratings[b]

Prime 1	Issuers rated Prime-1 (or supporting institutions) have a superior ability for repayment of senior short-term debt obligations. Prime-1 repayment ability will often be evidenced by many of the following characteristics: Leading market positions in well-established industries High rates of return on funds employed Conservative capitalization structure with moderate reliance on debt and ample asset protection Broad margins in earnings coverage of fixed financial charges and high internal cash generation Well-established access to a range of financial markets and assured sources of alternate liquidity
Prime 2	Issuers rated Prime-2 (or supporting institutions) have a strong ability for repayment of senior short-term debt obligations. This will normally be evidenced by many of the characteristics cited above but to a lesser degree. Earnings trends and coverage ratios, while sound, may be more subject to variation. Capitalization characteristics, while still appropriate, may be more affected by external conditions. Ample alternate liquidity is maintained
Prime 3	Issuers rated Prime-3 (or supporting institutions) have an acceptable ability for repayment of senior short-term obligations. The effect of industry characteristics and market compositions may be more pronounced. Variability in earnings and profitability may result in changes in the level of debt protection measurements and may require relatively high financial leverage. Adequate alternate liquidity is maintained

Transition Matrices

- Transition matrices illustrate the significant stability of rating classifications, being this stability higher for higher ratings.

Average one-year letter rating migration rates, 1920-2019

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca-C	WR	Def
Aaa	86.99%	7.67%	0.80%	0.19%	0.03%	0.00%	0.00%	0.00%	4.32%	0.00%
Aa	1.03%	84.24%	7.70%	0.71%	0.15%	0.04%	0.01%	0.00%	6.05%	0.06%
A	0.07%	2.71%	85.29%	5.42%	0.61%	0.11%	0.03%	0.01%	5.68%	0.08%
Baa	0.03%	0.22%	4.12%	83.35%	4.38%	0.69%	0.12%	0.02%	6.84%	0.24%
Ba	0.01%	0.07%	0.47%	6.14%	74.32%	6.75%	0.66%	0.09%	10.40%	1.10%
B	0.00%	0.04%	0.15%	0.59%	5.58%	71.98%	6.15%	0.45%	12.01%	3.05%
Caa	0.00%	0.01%	0.02%	0.10%	0.46%	6.49%	68.56%	2.78%	14.18%	7.40%
Ca-C	0.00%	0.01%	0.09%	0.03%	0.54%	2.71%	8.81%	46.46%	17.86%	23.48%

Source: Moody's (2020), "Default Trends – Global".

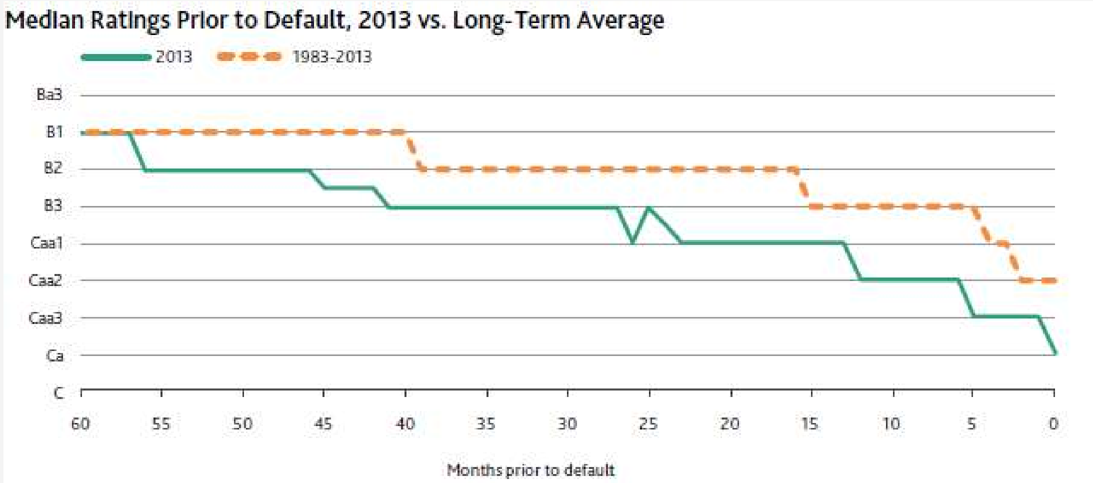
Transition Matrices

Average one-year alphanumeric rating migration rates, 1983-2019

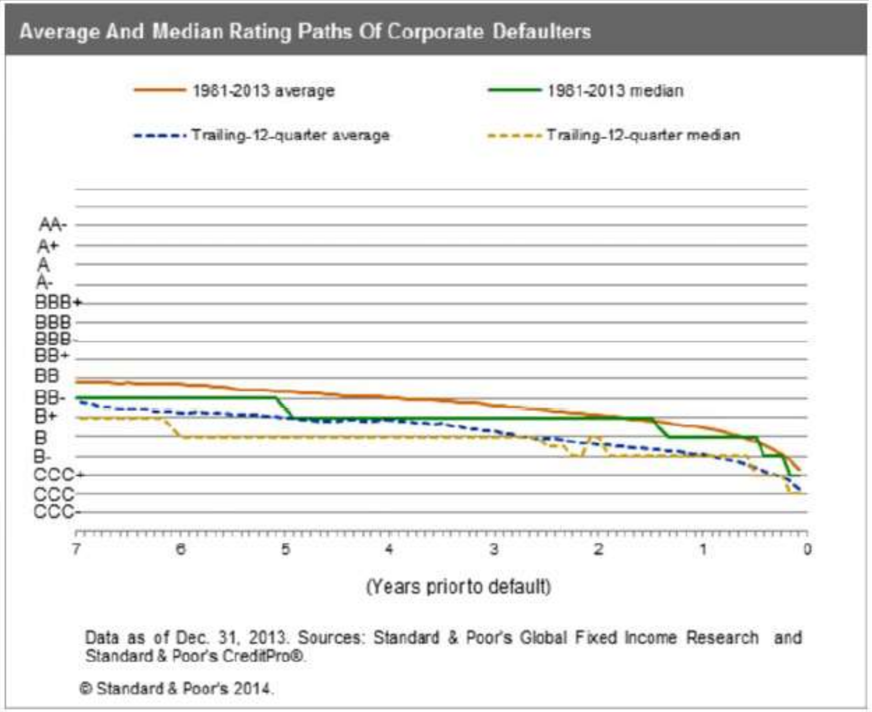
	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca-C	WR	PD
Aaa	87.07%	5.32%	2.27%	0.57%	0.30%	0.15%	0.02%	0.06%	0.00%	0.02%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.18%	0.00%
Aa1	1.64%	76.74%	7.99%	5.87%	1.43%	0.90%	0.18%	0.12%	0.08%	0.01%	0.04%	0.00%	0.01%	0.04%	0.03%	0.01%	0.02%	0.02%	0.00%	0.00%	4.87%	0.00%
Aa2	1.04%	4.30%	73.50%	10.14%	3.47%	1.65%	0.40%	0.09%	0.16%	0.07%	0.03%	0.02%	0.00%	0.03%	0.01%	0.02%	0.00%	0.02%	0.00%	0.00%	5.06%	0.00%
Aa3	0.16%	1.05%	4.17%	75.34%	8.74%	3.53%	0.83%	0.24%	0.24%	0.12%	0.03%	0.03%	0.01%	0.01%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	5.44%	0.04%
A1	0.05%	0.09%	1.10%	5.18%	76.10%	7.53%	2.73%	0.62%	0.44%	0.19%	0.17%	0.12%	0.04%	0.06%	0.01%	0.01%	0.01%	0.01%	0.01%	0.00%	5.46%	0.06%
A2	0.06%	0.03%	0.20%	1.03%	5.86%	76.40%	7.26%	2.55%	1.00%	0.37%	0.17%	0.13%	0.16%	0.05%	0.03%	0.01%	0.02%	0.02%	0.01%	0.00%	4.61%	0.04%
A3	0.04%	0.04%	0.09%	0.30%	1.49%	6.37%	75.35%	6.84%	2.64%	0.87%	0.35%	0.15%	0.12%	0.10%	0.03%	0.02%	0.03%	0.01%	0.00%	0.01%	5.08%	0.06%
Baa1	0.01%	0.02%	0.07%	0.11%	0.20%	1.56%	6.74%	75.57%	6.80%	2.25%	0.61%	0.31%	0.21%	0.25%	0.06%	0.03%	0.05%	0.03%	0.01%	0.02%	4.95%	0.12%
Baa2	0.03%	0.04%	0.02%	0.06%	0.16%	0.58%	1.90%	6.68%	75.57%	6.42%	1.32%	0.62%	0.43%	0.32%	0.19%	0.09%	0.10%	0.01%	0.02%	0.01%	5.29%	0.16%
Baa3	0.02%	0.01%	0.02%	0.04%	0.07%	0.17%	0.45%	1.83%	9.03%	72.93%	4.78%	2.02%	0.97%	0.69%	0.26%	0.25%	0.14%	0.07%	0.06%	0.04%	5.94%	0.22%
Ba1	0.02%	0.00%	0.02%	0.02%	0.16%	0.13%	0.21%	0.68%	2.38%	10.29%	65.57%	5.22%	4.00%	1.64%	0.59%	0.50%	0.13%	0.22%	0.04%	0.12%	7.68%	0.40%
Ba2	0.00%	0.00%	0.02%	0.02%	0.07%	0.11%	0.15%	0.35%	0.70%	3.73%	8.16%	64.35%	6.36%	3.73%	1.36%	0.91%	0.30%	0.19%	0.09%	0.13%	8.59%	0.68%
Ba3	0.00%	0.01%	0.02%	0.01%	0.06%	0.16%	0.17%	0.09%	0.44%	0.77%	2.87%	6.84%	64.32%	6.96%	3.17%	1.93%	0.67%	0.39%	0.09%	0.12%	9.64%	1.27%
B1	0.01%	0.01%	0.02%	0.01%	0.05%	0.03%	0.07%	0.09%	0.18%	0.35%	0.66%	2.89%	6.74%	63.66%	6.16%	4.40%	1.33%	0.70%	0.21%	0.25%	10.36%	1.82%
B2	0.00%	0.01%	0.00%	0.01%	0.02%	0.02%	0.09%	0.11%	0.13%	0.24%	0.22%	0.67%	2.12%	7.57%	62.11%	7.90%	3.59%	1.73%	0.41%	0.47%	9.75%	2.81%
B3	0.01%	0.00%	0.02%	0.00%	0.03%	0.03%	0.06%	0.03%	0.04%	0.10%	0.14%	0.23%	0.79%	2.39%	6.19%	60.60%	7.30%	3.26%	1.07%	0.80%	12.54%	4.37%
Caa1	0.00%	0.01%	0.00%	0.00%	0.00%	0.01%	0.00%	0.02%	0.01%	0.03%	0.06%	0.11%	0.25%	0.49%	1.29%	7.58%	59.48%	8.89%	2.57%	1.24%	13.97%	4.00%
Caa2	0.00%	0.00%	0.02%	0.00%	0.02%	0.01%	0.00%	0.00%	0.04%	0.08%	0.04%	0.04%	0.14%	0.37%	0.81%	2.15%	7.32%	56.35%	5.88%	2.87%	15.69%	8.17%
Caa3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.06%	0.03%	0.03%	0.16%	0.15%	1.04%	3.06%	8.74%	45.48%	8.62%	14.48%	18.15%
Ca-C	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.03%	0.00%	0.00%	0.00%	0.23%	0.13%	0.17%	0.09%	0.37%	1.70%	1.95%	3.29%	4.60%	38.13%	21.17%	28.13%

Source: Moody’s (2020), “Default Trends – Global”.

Transition Matrices



Source: Moody's (2014), "Corporate Default and Recovery Rates, 1920-2013".



Source: S&P (2014), "Default, Transition and Recovery: 2013 Annual Global Corporate Default Study and Rating Transitions".

Default Frequencies

- Default frequencies also tend to change along time, namely for lower ratings.

Annual issuer-weighted corporate default rates by letter rating, 1920-2019

Year	Aaa	Aa	A	Baa	Ba	B	Caa-C	IG	SG	All
1920	0.00%	0.00%	0.32%	0.94%	2.15%	4.38%	0.00%	0.43%	3.01%	1.23%
1921	0.00%	0.19%	0.35%	0.65%	0.44%	2.68%	13.33%	0.39%	2.15%	1.07%
1922	0.00%	0.18%	0.17%	1.10%	1.08%	1.71%	7.63%	0.51%	1.76%	1.01%
1923	0.00%	0.00%	0.00%	0.62%	0.93%	2.27%	5.93%	0.24%	1.70%	0.80%
1924	0.00%	0.37%	0.00%	0.13%	2.06%	2.70%	12.84%	0.14%	2.85%	1.15%
1925	0.00%	0.00%	0.14%	0.71%	1.74%	2.59%	14.40%	0.32%	2.56%	1.17%
1926	0.00%	0.40%	0.15%	0.11%	1.39%	2.90%	3.70%	0.19%	1.91%	0.77%
1927	0.00%	0.00%	0.21%	0.00%	1.30%	1.98%	12.84%	0.07%	1.83%	0.74%
1928	0.00%	0.00%	0.00%	0.00%	0.16%	1.32%	10.48%	0.00%	0.88%	0.36%
1929	0.00%	0.29%	0.00%	0.44%	0.82%	0.92%	9.73%	0.24%	1.40%	0.71%
1930	0.00%	0.00%	0.00%	0.40%	0.92%	3.16%	7.72%	0.15%	2.20%	1.04%
1931	0.00%	0.00%	0.27%	1.08%	3.00%	9.52%	31.67%	0.50%	7.90%	3.80%
1932	0.00%	0.67%	1.10%	0.92%	6.10%	13.98%	24.06%	0.86%	10.99%	5.50%
1933	0.00%	0.00%	0.26%	1.77%	11.71%	16.15%	25.92%	0.79%	15.77%	8.53%
1934	0.00%	0.62%	0.31%	0.86%	2.52%	4.22%	16.50%	0.59%	5.89%	3.40%
1935	0.00%	0.00%	1.43%	1.92%	5.12%	4.27%	13.02%	1.29%	6.25%	3.93%
1936	0.00%	0.85%	0.54%	0.33%	1.23%	2.38%	7.80%	0.48%	2.71%	1.63%
1937	0.00%	0.00%	0.51%	1.04%	0.99%	2.67%	9.07%	0.62%	2.74%	1.72%
1938	0.00%	0.85%	1.64%	1.99%	0.98%	1.47%	12.81%	1.55%	2.59%	2.11%
1939	0.00%	0.00%	0.00%	0.99%	0.62%	1.74%	6.07%	0.41%	1.77%	1.22%
1940	0.00%	0.00%	0.00%	1.37%	0.43%	3.29%	11.83%	0.59%	3.55%	2.47%
1941	0.00%	0.00%	0.00%	0.00%	0.97%	0.81%	5.07%	0.00%	1.71%	1.08%
1942	0.00%	0.00%	0.00%	0.00%	0.00%	0.78%	2.00%	0.00%	0.73%	0.45%
1943	0.00%	0.00%	0.00%	0.00%	0.00%	1.35%	0.00%	0.00%	0.61%	0.37%
1944	0.00%	0.00%	0.00%	0.00%	0.00%	0.49%	2.55%	0.00%	0.66%	0.39%
1945	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.57%	0.00%	0.56%	0.31%
1946	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1947	0.00%	0.00%	0.00%	0.00%	0.00%	0.71%	2.78%	0.00%	0.63%	0.31%
1948	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1949	0.00%	0.00%	0.00%	0.00%	1.36%	1.02%	8.57%	0.00%	1.92%	0.84%
1950	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1951	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.76%	0.00%	0.43%	0.18%
1952	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1953	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1954	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.14%	0.00%	0.47%	0.17%
1955	0.00%	0.00%	0.00%	0.00%	0.00%	1.61%	0.00%	0.00%	0.52%	0.17%
1956	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1957	0.00%	0.00%	0.00%	0.00%	0.00%	1.27%	0.00%	0.00%	0.45%	0.14%
1958	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1959	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1960	0.00%	0.00%	0.00%	0.00%	1.25%	0.00%	0.00%	0.00%	0.75%	0.25%
1961	0.00%	0.00%	0.00%	0.00%	0.60%	0.00%	8.70%	0.00%	1.07%	0.35%
1962	0.00%	0.00%	0.00%	0.00%	1.75%	1.47%	0.00%	0.00%	1.52%	0.47%
1963	0.00%	0.00%	0.00%	0.00%	1.16%	1.47%	0.00%	0.00%	1.15%	0.35%
1964	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1965	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1966	0.00%	0.00%	0.00%	0.00%	0.00%	2.44%	0.00%	0.00%	0.44%	0.12%
1967	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1968	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.00%	0.00%	0.37%	0.11%
1969	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1970	0.00%	0.00%	0.00%	0.54%	4.24%	19.44%	50.00%	0.27%	8.68%	2.63%
1971	0.00%	0.00%	0.00%	0.00%	0.89%	0.00%	12.50%	0.00%	1.16%	0.29%
1972	0.00%	0.00%	0.00%	0.00%	0.00%	6.90%	37.50%	0.00%	1.92%	0.45%

Source: Moody’s (2020), “Default Trends – Global”.

Default Frequencies

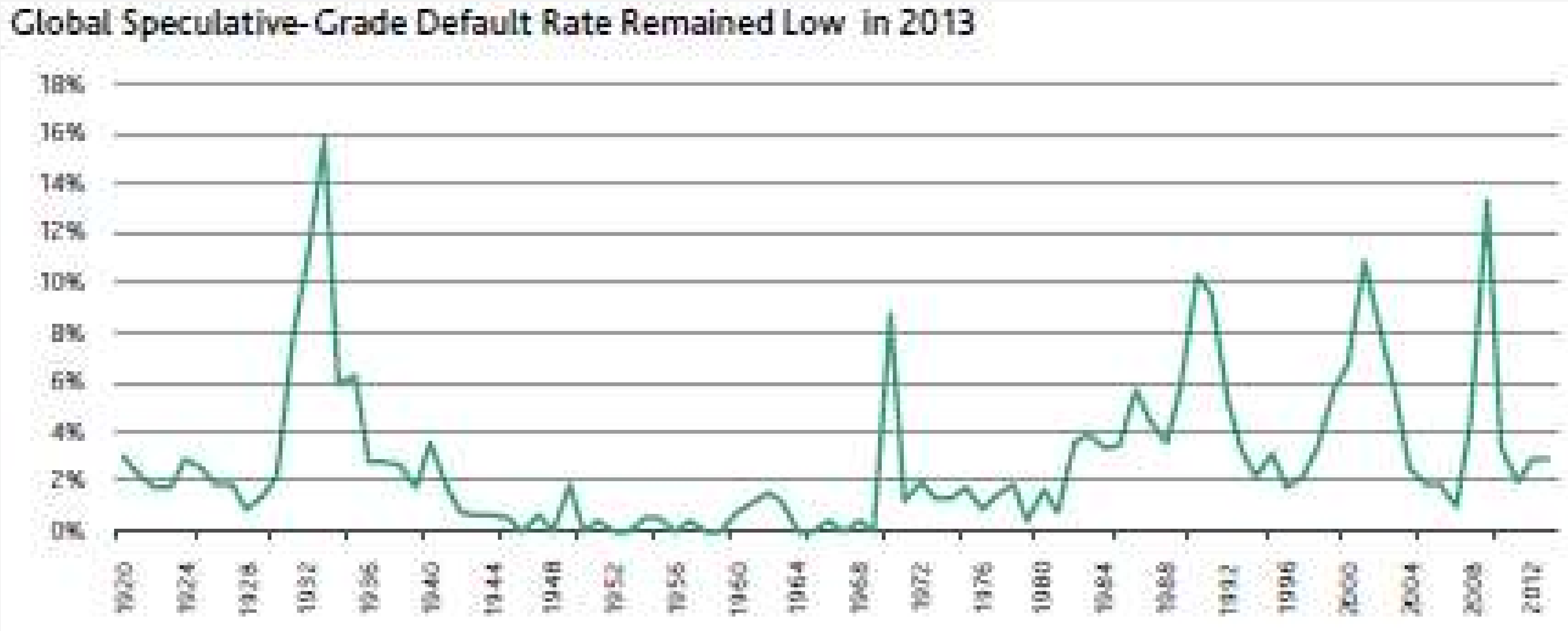
Annual issuer-weighted corporate default rates by letter rating, 1920-2019 (continued)

Year	Aaa	Aa	A	Baa	Ba	B	Caa-C	IG	SG	All
1973	0.00%	0.00%	0.00%	0.46%	0.00%	3.85%	37.50%	0.23%	1.28%	0.46%
1974	0.00%	0.00%	0.00%	0.00%	0.51%	7.16%	0.00%	0.00%	1.33%	0.28%
1975	0.00%	0.00%	0.00%	0.00%	1.03%	6.16%	0.00%	0.00%	1.74%	0.36%
1976	0.00%	0.00%	0.00%	0.00%	1.00%	0.00%	0.00%	0.00%	0.87%	0.18%
1977	0.00%	0.00%	0.00%	0.29%	0.54%	3.23%	33.33%	0.11%	1.36%	0.35%
1978	0.00%	0.00%	0.00%	0.00%	1.12%	5.41%	0.00%	0.00%	1.82%	0.35%
1979	0.00%	0.00%	0.00%	0.00%	0.51%	0.00%	0.00%	0.00%	0.43%	0.09%
1980	0.00%	0.00%	0.00%	0.00%	0.00%	5.00%	33.33%	0.00%	1.63%	0.34%
1981	0.00%	0.00%	0.00%	0.00%	0.00%	4.40%	0.00%	0.00%	0.70%	0.16%
1982	0.00%	0.00%	0.26%	0.33%	2.79%	2.22%	23.08%	0.21%	3.55%	1.04%
1983	0.00%	0.00%	0.00%	0.00%	1.16%	2.30%	42.31%	0.00%	4.06%	0.90%
1984	0.00%	0.00%	0.00%	0.62%	0.52%	5.34%	18.18%	0.18%	3.13%	0.87%
1985	0.00%	0.00%	0.00%	0.00%	0.87%	7.31%	6.67%	0.00%	3.76%	0.95%
1986	0.00%	0.00%	0.00%	0.87%	2.36%	10.54%	17.11%	0.21%	6.16%	1.83%
1987	0.00%	0.00%	0.00%	0.00%	3.04%	5.44%	9.82%	0.00%	4.31%	1.42%
1988	0.00%	0.00%	0.00%	0.00%	1.36%	5.93%	12.50%	0.00%	3.86%	1.39%
1989	0.00%	0.50%	0.00%	0.52%	2.97%	7.55%	20.33%	0.25%	5.91%	2.22%
1990	0.00%	0.00%	0.00%	0.26%	3.77%	13.71%	45.06%	0.06%	10.54%	3.57%
1991	0.00%	0.00%	0.00%	0.25%	3.84%	13.16%	15.97%	0.06%	9.10%	2.80%
1992	0.00%	0.00%	0.00%	0.00%	0.34%	7.67%	15.43%	0.00%	4.93%	1.34%
1993	0.00%	0.00%	0.00%	0.00%	0.62%	4.36%	13.74%	0.00%	3.40%	0.90%
1994	0.00%	0.00%	0.00%	0.00%	0.00%	4.20%	5.31%	0.00%	2.34%	0.65%
1995	0.00%	0.00%	0.00%	0.00%	0.27%	3.83%	11.55%	0.00%	3.07%	0.90%
1996	0.00%	0.00%	0.00%	0.00%	0.00%	1.51%	10.00%	0.00%	1.65%	0.51%
1997	0.00%	0.00%	0.00%	0.00%	0.18%	2.00%	9.16%	0.00%	1.89%	0.62%
1998	0.00%	0.00%	0.00%	0.11%	0.77%	3.77%	8.32%	0.03%	2.98%	1.11%
1999	0.00%	0.00%	0.00%	0.09%	1.39%	5.02%	15.14%	0.03%	5.33%	2.10%
2000	0.00%	0.00%	0.00%	0.35%	1.45%	5.52%	18.10%	0.13%	6.11%	2.45%
2001	0.00%	0.00%	0.16%	0.18%	1.18%	8.69%	28.72%	0.12%	9.32%	3.54%
2002	0.00%	0.00%	0.16%	1.01%	1.77%	4.44%	26.73%	0.43%	7.76%	2.95%
2003	0.00%	0.00%	0.00%	0.00%	0.89%	2.69%	20.26%	0.00%	5.32%	1.84%
2004	0.00%	0.00%	0.00%	0.00%	0.38%	0.80%	11.33%	0.00%	2.41%	0.83%
2005	0.00%	0.00%	0.00%	0.16%	0.00%	0.81%	7.15%	0.06%	1.72%	0.64%
2006	0.00%	0.00%	0.00%	0.00%	0.20%	1.06%	5.83%	0.00%	1.67%	0.59%
2007	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.90%	0.00%	0.94%	0.35%
2008	0.00%	0.51%	0.40%	1.03%	2.32%	4.02%	10.77%	0.62%	5.46%	2.51%
2009	0.00%	0.00%	0.24%	0.94%	1.75%	6.87%	26.49%	0.43%	12.09%	5.00%
2010	0.00%	0.00%	0.17%	0.08%	0.00%	0.39%	8.67%	0.10%	3.06%	1.25%
2011	0.00%	0.19%	0.00%	0.36%	0.16%	0.34%	6.06%	0.19%	2.03%	0.92%
2012	0.00%	0.00%	0.00%	0.07%	0.14%	0.55%	7.96%	0.03%	2.80%	1.25%
2013	0.00%	0.00%	0.09%	0.12%	0.58%	1.01%	6.26%	0.10%	2.67%	1.25%
2014	0.00%	0.00%	0.09%	0.06%	0.14%	0.49%	4.80%	0.06%	2.01%	0.97%
2015	0.00%	0.00%	0.00%	0.00%	0.29%	2.48%	6.56%	0.00%	3.67%	1.75%
2016	0.00%	0.00%	0.00%	0.00%	0.14%	1.57%	9.02%	0.00%	4.52%	2.17%
2017	0.00%	0.00%	0.00%	0.00%	0.51%	0.44%	7.55%	0.00%	3.54%	1.71%
2018	0.00%	0.00%	0.00%	0.00%	0.00%	0.68%	5.05%	0.00%	2.38%	1.15%
2019	0.00%	0.00%	0.00%	0.11%	0.00%	1.30%	6.16%	0.06%	3.05%	1.48%
Mean	0.00%	0.06%	0.09%	0.26%	1.01%	3.11%	10.40%	0.14%	2.82%	1.16%
Median	0.00%	0.00%	0.00%	0.00%	0.52%	1.86%	7.67%	0.00%	1.91%	0.83%
St Dev	0.00%	0.17%	0.26%	0.45%	1.59%	3.74%	11.08%	0.27%	2.92%	1.34%
Min	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Max	0.00%	0.85%	1.64%	1.99%	11.71%	19.44%	50.00%	1.55%	15.77%	8.53%

Source: Moody’s (2020), “Default Trends – Global”.

Default Frequencies

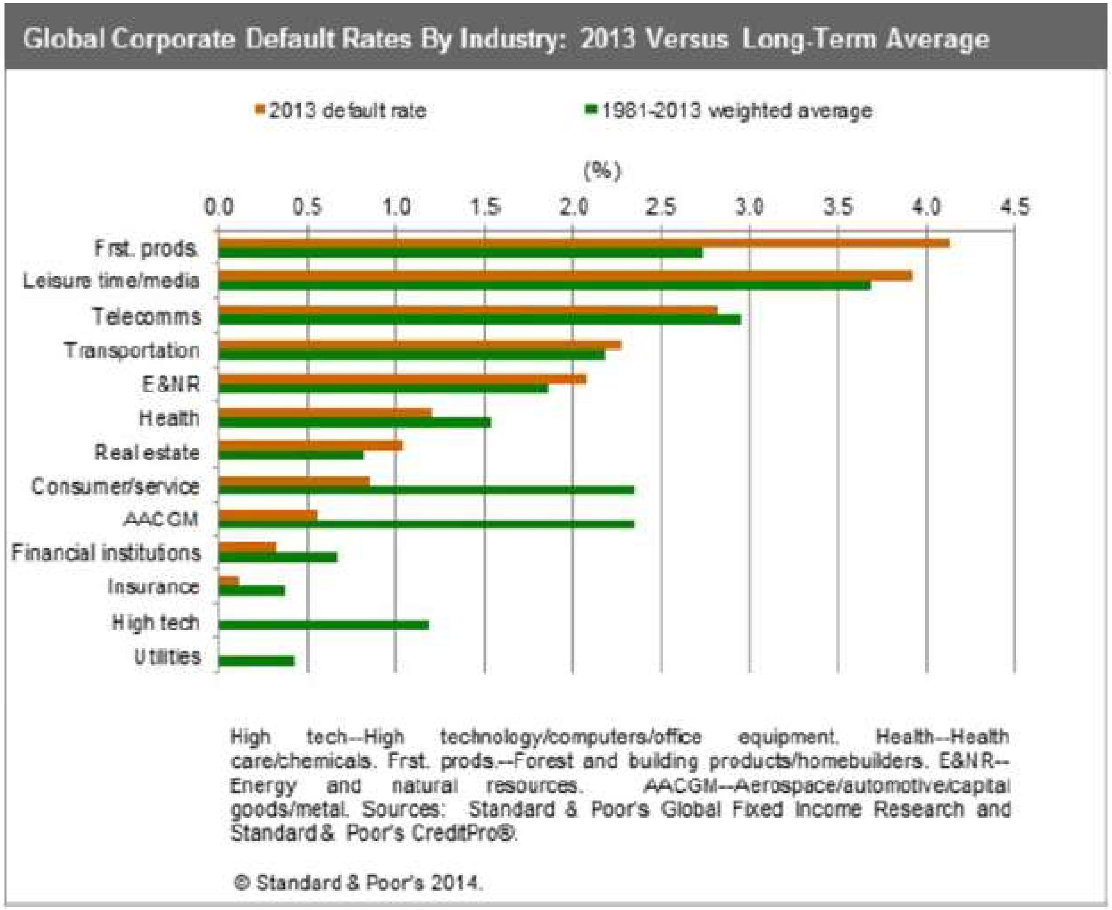
- Actually, the volatility of default frequencies for lower ratings (speculative grade) is significant.



Source: Moody's (2014), "Corporate Default and Recovery Rates, 1920-2013".

Default Frequencies

- Default frequencies also vary according to economic sectors.



Source: S&P (2014), "Default, Transition and Recovery: 2013 Annual Global Corporate Default Study and Rating Transitions".

Default Frequencies

- Default levels of sovereign issuers are lower than for corporates.

Fitch Sovereign IDR Average Annual Transition Rates — 1995–2013

(%)	AAA	AA	A	BBB	BB	B	CCC to C	D	Total
AAA	97.98	2.02	0.00	0.00	0.00	0.00	0.00	0.00	100.00
AA	3.56	91.56	3.11	1.33	0.00	0.44	0.00	0.00	100.00
A	0.00	2.84	91.47	5.21	0.47	0.00	0.00	0.00	100.00
BBB	0.00	0.00	5.12	89.76	4.33	0.39	0.39	0.00	100.00
BB	0.00	0.00	0.00	9.54	84.45	4.95	0.00	1.06	100.00
B	0.00	0.00	0.00	0.00	9.01	87.12	3.00	0.86	100.00
CCC to C	0.00	0.00	0.00	0.00	0.00	26.32	47.37	26.32	100.00

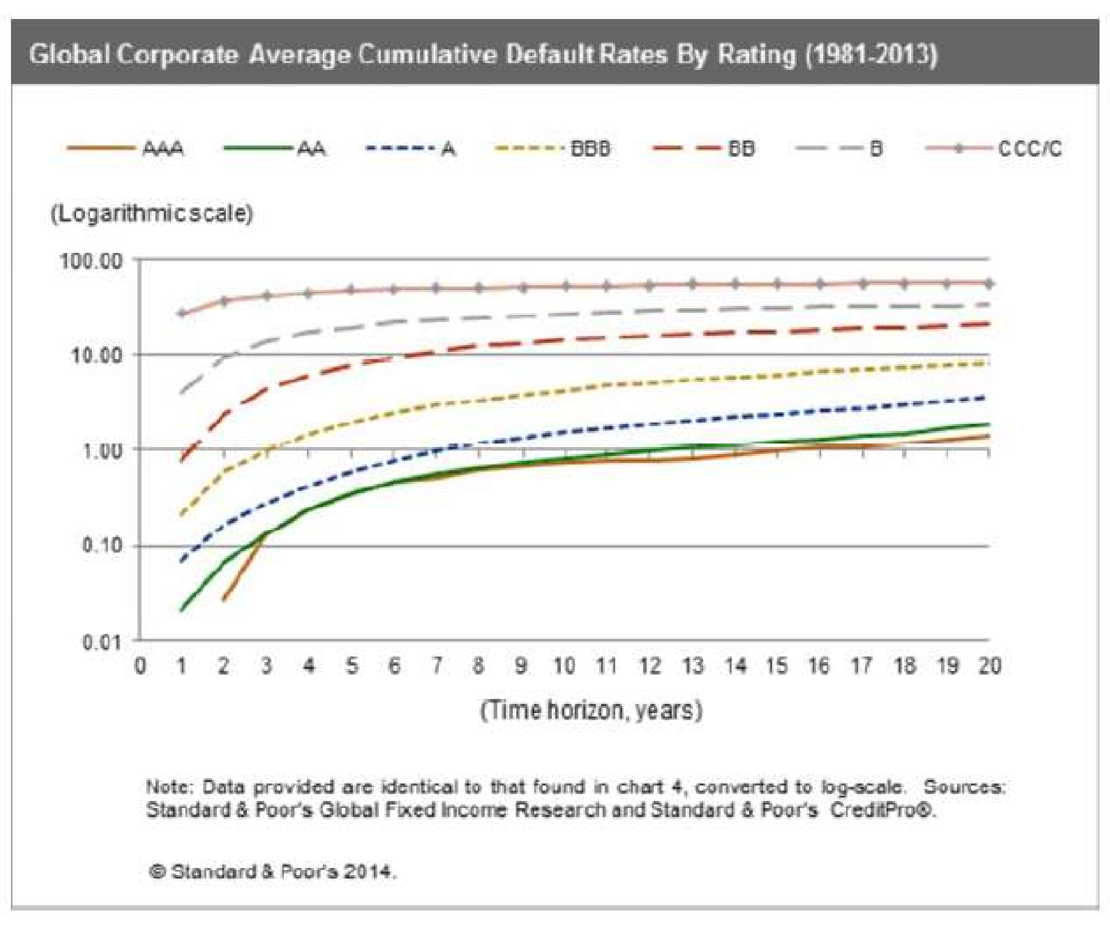
Fitch-Rated Sovereign IDR Defaults[a] 1995–2013

Year	Issuer Name	Rating at Beginning of Year	Region
1998	Indonesia, Republic of	BB+	Asia-Pacific
	Russian Federation	BB+	Europe
2001	Argentina	BB	Latin America
2002	Moldova	CC	Europe
2003	Uruguay	B	Latin America
2005	Dominican Republic	CCC+	Caribbean
2008	Ecuador	CCC	Latin America
2010	Jamaica	CCC	Caribbean
2012	Greece (Hellenic Republic)	CCC	Europe
2013	Jamaica	B–	Caribbean

Source: Fitch Ratings (2014), "Fitch Ratings Sovereign 2013 - Transition and Default Study", 12 Mar.

Default Frequencies

- Cumulative default frequencies usually exhibit a smooth shape:



Source: S&P (2014), "Default, Transition and Recovery: 2013 Annual Global Corporate Default Study and Rating Transitions".

Default Frequencies

Average Cumulative Issuer-Weighted Global Default Rates by Letter Rating, 1920-2013*

Rating	1	2	3	4	5	6	7	8	9	10
Aaa	0.000	0.009	0.030	0.084	0.162	0.248	0.357	0.508	0.666	0.851
Aa	0.072	0.213	0.342	0.539	0.834	1.167	1.498	1.815	2.118	2.464
A	0.099	0.306	0.634	0.996	1.379	1.790	2.233	2.683	3.167	3.644
Baa	0.282	0.841	1.491	2.195	2.943	3.687	4.398	5.122	5.876	6.632
Ba	1.348	3.204	5.263	7.428	9.485	11.440	13.216	14.946	16.595	18.333
B	3.714	8.437	13.124	17.273	20.944	24.229	27.260	29.808	32.074	34.088
Caa-C	13.830	23.374	30.462	35.936	40.375	43.751	46.417	48.728	50.961	52.850
Inv Grade	0.158	0.471	0.859	1.292	1.768	2.259	2.751	3.248	3.763	4.286
Spec Grade	3.863	7.807	11.493	14.784	17.682	20.242	22.521	24.552	26.422	28.220
All rated	1.579	3.225	4.767	6.150	7.388	8.494	9.487	10.393	11.253	12.086

Rating	11	12	13	14	15	16	17	18	19	20
Aaa	1.008	1.139	1.277	1.317	1.354	1.428	1.502	1.563	1.634	1.682
Aa	2.861	3.291	3.718	4.127	4.431	4.666	4.877	5.127	5.433	5.689
A	4.128	4.602	5.023	5.439	5.929	6.366	6.735	7.108	7.454	7.803
Baa	7.376	8.118	8.869	9.551	10.164	10.801	11.401	11.932	12.437	12.972
Ba	19.882	21.424	22.915	24.248	25.486	26.630	27.775	28.845	29.796	30.698
B	35.890	37.576	39.180	40.725	42.139	43.505	44.700	45.677	46.384	46.856
Caa-C	54.819	56.806	58.653	60.496	62.359	64.126	65.692	67.106	68.421	69.719
Inv Grade	4.814	5.341	5.849	6.319	6.772	7.199	7.582	7.950	8.312	8.672
Spec Grade	29.843	31.423	32.934	34.332	35.638	36.867	38.036	39.092	40.000	40.822
All rated	12.868	13.630	14.355	15.021	15.647	16.233	16.770	17.270	17.733	18.176

Source: Moody's (2014), "Corporate Default and Recovery Rates, 1920-2013".

Fitch Sovereign IDR Average Cumulative Default Rates — 1995–2013

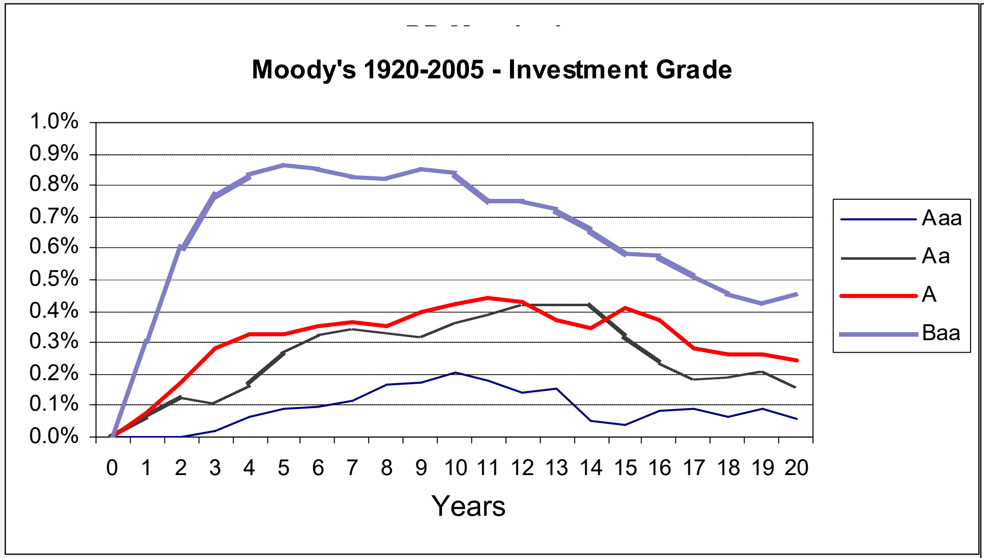
(%)	One-Year	Two-Year	Three-Year	Four-Year	Five-Year	10-Year
AAA	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.00	0.00	0.60	1.29	2.63
BBB	0.00	0.87	1.96	2.19	2.45	5.43
BB	1.06	1.90	2.45	3.08	3.38	8.18
B	0.84	2.71	4.00	6.18	6.88	7.58
CCC to C	23.81	26.32	22.22	22.22	25.00	37.50
Investment Grade	0.00	0.23	0.49	0.67	0.87	1.78
Speculative Grade	1.84	3.18	3.89	5.20	5.74	9.24
All Sovereigns	0.68	1.31	1.73	2.31	2.62	4.16

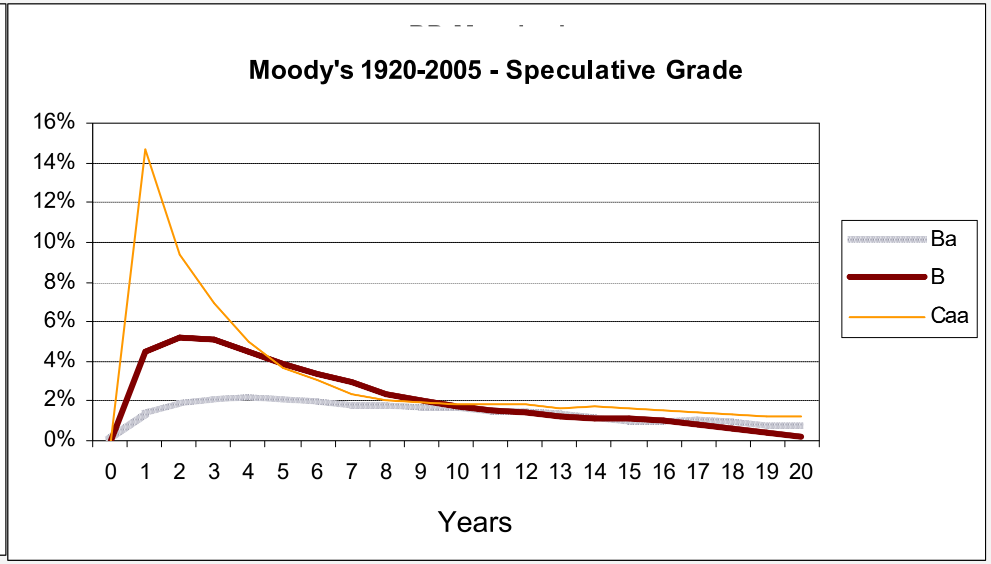
IDR – Issuer Default Rating.
Source: Fitch.

Source: Fitch Ratings (2014), "Fitch Ratings Sovereign 2010 - Transition and Default Study", 14 Mar.

Default Frequencies

- However, marginal frequencies obtained from the cumulative figures tend to exhibit a very irregular shape:





- It can be observed that marginal PD curves have different inflection points, depending on the *rating class*, with the lower inflection points for the higher risk classes.

5.3. Internal Credit Risk Models

5.3.1. General Issues

Best Practices

- Scoring and internal rating models belong to the set of best practice tools in credit risk management.
- These models rank bank customers according to their credit risk, segmenting them in homogeneous classes.
- A term structure of PDs is associated to each risk class, either through rating agency statistics (for corporates) or cumulative default frequencies (for individuals).
- Additionally, scorings differ from internal ratings because the former provide a risk classification for the customer in a given loan, while internal ratings are the same for all loans to a given corporate customer.

Best Practices

- Banks adopting best practices use internal ratings and scorings in:
  - credit proposals and limits' decisions;
  - securitizations;
  - pricing;
  - risk-adjusted performance measurement;
  - credit portfolio management;
  - economic capital;
  - impairments.

Governance

- Internal credit risk models must be integrated within a sound risk governance framework.

- Main features of a robust risk management model:
  - Full monitoring and understanding of risks by the Board, with regular updates:

. “A significant minority of banks has no plans to appoint individuals with deep practical risk experience to senior positions”, in KPMG(2009), “Never again? Risk Management in Banking Beyond the Credit Crisis”;

. “This theme of a lack of understanding between the risk function and the business certainly seems to be significant.”, “After the storm: A new era for risk management in financial services”, Economist Intelligence Unit, Jun.09.

Governance

– Adequacy of resources, structure and risk management policies, including Board members with experience and know-how in banking and risk management

. "One of the common characteristics of some of the collapsed or rescued banks appears to have been the low level of risk management (or even banking) expertise at the Chairman and board levels, in (2008), "Bank Liquidity: Running on Empty", Oliver Wyman.

. "It's a problem, because people are either very good at numbers or they're very good with people and to get someone with both is not easy," Dean Spencer, Barclays Simpson

. Risk management recruitment consultants say that HR units are asking for candidates with stronger interpersonal skills who would have the courage and the influence to stand up to bullish colleagues.

Governance

– Strong risk culture, led by the Board, mitigating "risk of irrelevance" of Risk function "For measures to be effective, the risk function must be allowed to have a significant voice in the organization".

"In banking, the risk function takes prime responsibility for dealing with risk, rather than for embedding risk management throughout the business and this surely can't be a sensible approach. The key is risk awareness and creating a risk culture."

"The function's role within the business is as important as the type of people employed to discharge it. Its role should be to embed risk, (…) making sure that every individual has personal objectives linked to risk. This has rarely been the case in the past".

- Source: After the storm: A new era for risk management in financial services", Economist Intelligence Unit", Jun.09

Governance

- BCBS (2010), "Principles for enhancing corporate governance " – focus:

(1) Board practices

(2) Senior management

(3) Risk Management

(4) Remunerations

(5) Lack of transparency of internal structures

(6) Disclosure and transparency

Governance

- It is key to ensure not only the direct report to the Board and the independence between risk and the commercial units, but also the involvement of non-executive bodies in the CRO's appointment and replacement decisions.
  - "The CRO should have sufficient stature, authority and seniority within the organization. This will typically be reflected in the ability of the CRO to influence decisions that affect the bank's exposure to risk".
- If the CRO is removed from his or her position for any reason, this should be done with the prior approval of the board and generally should be disclosed publicly. The bank should also discuss the reasons for such removal with its supervisor.

Governance

- Lehman Brothers Case (*in Risk*, Dec.06) – In 2006, the Risk Committee met twice, headed by an octogenarian professional; other Committee members: Broadway producer, ex- US Naval Forces Officer, Director of a TV channel in Spanish, former IBM CEO, retired since 1993 (on aggregate at Lehman's Board for 55 years). Committees seen as a bank's department or a social event.
- Santander Case - "Many are surprised to learn that the Banco Santander board's risk committee meets for half a day twice a week and that the board's 10-person executive committee meets every Monday for at least four hours, devoting a large portion of that time to reviewing risks and approving transactions. Not many banks do this. It consumes a lot of our directors' time. But we find it essential and it is never too much", *in* Botin, Emilio (2008), "Banking's mission must be to serve its customers", Financial Times, *16 Oct;*

Governance

– *One Milion Dollar Question*: the subprime crisis was motivated by risk management failures or resulted from the limited internal relevance of the Risk function?

"It would be a mistake to conclude that the only way to succeed in banking is through ever-greater size and diversity. Indeed, better risk management may be the only true necessary element of success in banking".

Alan Greenspan, Speech to the American Bankers Association, October 5, 2004.

5.3.2. Corporates

Types of models

- Credit scoring - relate with no theoretical background the credit behavior to selected variables illustrating the financial capacity of the company.
- Structural – based on the financial theory to explain the PDs as a function of the capital and the debt structure:
  - Default-at-maturity maturities (e.g. Merton) - the default occurs at that moment, as only at the maturity the credit may use the assets for their compensation in case of default.
  - First-passage time – the default occurs the first time the asset value becomes lower than the debt value.
- Reduced form models – assume that the default depends on an exogenous stochastic process exogenous to ant observable feature of the company (e.g. focused on PD estimation from credit spreads).

Credit Scoring

- Credit scoring models usually incorporate explanatory variables that illustrate the most relevant features of the company, namely profitability, liquidity and size:
  - EBIT(or EBITDA)/Interest Paid
  - Cash-flow/Total Debt
  - ROE
  - Income from activity/Sales
  - Long Term Debt/Own Funds
  - Total Debt/Capitalisation

Key industrial financial ratios for rating categories[a]

	AAA	AA	A	BBB	BB	B
US industrial three-year (1994–1996) *medians*						
1. EBIT[b] interest coverage (x)	16.05	11.06	6.26	4.11	2.27	1.18
2. EBITDA[c] interest coverage (x)	20.3	14.94	8.51	6.03	3.63	2.27
3. Funds from operations/total debt (%)	116.4	72.3	47.5	34.7	18.4	10.9
4. Free operating cashflow/total debt (%)	76.8	30.5	18.8	8.4	2.4	1.2
5. Pretax return on capital (%)	31.5	23.6	19.5	15.1	11.9	9.1
6. Operating income/sales (%)	24.0	19.2	16.1	15.4	15.1	12.6
7. Long-term debt/capital (%)	13.4	21.9	32.7	43.4	53.9	65.9
8. Total debt/capitalization (%)	23.6	29.7	38.7	46.8	55.8	68.9

Source: S&P (1998), Corporate Ratings Criteria.

Credit Scoring

- The traditional analysis of financial ratios started with the univariated analysis of Beaver (1968), whose goal was to identify the link between credit behavior and each financial ratio considered.
- It was concluded that some indicators were helpful to anticipate defaults until 5 years beforehand.
- However, this analysis didn't allow for the interaction of several indicators, problem that was overcome by Altman (1968) and Deakin (1972), with the first multivariate analysis.
- Altman Z-Score became the most well-know credit risk model for decades and it is still used nowadays.

Altman Z-score (1968)

- The model was developed for listed companies, using 22 financial ratios from 66 companies between 1946 and 1965, evenly split between defaulting and non-defaulting companies:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where:

X_1 = working capital (net) / total assets; X_2 = retained earnings/ total assets

X_3 = EBIT / total assets; X_4 = market capitalization/book value of long-term liabilities

X_5 = sales/total assets

- The PD decreases with the Z-Score:
  - Z<1,81 – defaulting companies
  - Z>2,99 – non-defaulting companies

Altman Z-score (1983)

- In order to allow the calculation of a Z-score for non-listed companies, the Z-score' model was developed in Altman (1983):

$$Z' = 0.717\ X_1 + 0.847\ X_2 + 3.107\ X_3 + 0.420\ X_4 + 0.998\ X_5.$$

- This model is similar to the previous one, with the numerator in X_4 replaced by the book value of own funds.
- The cut-off point corresponds to Z = 2.675, which is the level that minimizes the estimation errors.

Altman Z-score (1993)

- Aiming at reducing sector distortions for non-manufacturing companies, Altman (1993) Z''-score model was developed (eliminating X_5):

  $$Z'' = 6.56\,X_1 + 3.26\,X_2 + 6.72\,X_3 + 1.05\,X_4.$$

  where the variables have the same meaning of Altman (1983).

- For emerging markets, the constant 3.25 was added, in order to obtain a zero score for defaulting companies.

PDs from Z-Score

- The mapping of PDs to Z-scores is done through the rating classifications:

Panel D Average Z-Scores by S&P Bond Rating 1995 - 1999			
	Average Annual Number of Firms	Average Z-Score	Standard Deviation
AAA	11	5.02	1.50
AA	46	4.30	1.81
A	131	3.60	2.26
BBB	107	2.78	1.50
BB	50	2.45	1.62
B	80	1.67	1.22
CCC	10	0.95	1.10

Source: Compustat Data Tapes

Panel E
US Bond Rating Equivalent Based on EM Score

US Equivalent Rating	Average EM Score
AAA	8.15
AA+	7.60
AA	7.30
AA-	7.00
A+	6.85
A	6.65
A-	6.40
BBB+	6.25
BBB	5.85
BBB-	5.65
BB+	5.25
BB	4.95
BB-	4.75
B+	4.50
B	4.15
B-	3.75
CCC+	3.20
CCC	2.50
CCC-	1.75
D	0

Source: In-Depth Data Corp.; average based on over 750 U.S. Corporates with rated debt outstanding: 1995 data.

Source: Altman (2002)

Logit Models

- Split entities in two groups: 1 for defaults and 0 for performing.
- The models corresponds to:

$$P(Y=1)=\frac{\exp(\alpha+\beta X)}{1+\exp(\alpha+\beta X)}$$

being X the explanatory variables (continuous, binary or stepwise) and α and β the model coefficients.

- Given that $1-P(Y=1)=\dfrac{1}{1+\exp(\alpha+\beta X)}$ $\Leftrightarrow$ $P(Y=1)=\{1-[P(Y=1)]\}\cdot\exp(\alpha+\beta X)$

 in logs, one gets a linear model: $$\ln\left(\frac{P}{1-P}\right)=\alpha+\beta X$$

- Though the transformed model is linear, given that the endogenous variable is not continuous, its estimation is done by the maximum likelihood method and not by linear OLS.

Logit Models

- The Ohlson (1980) model is an example of a logit model, applied to industrial companies ($O = \alpha + \beta X$) :

  $O = -1.32 - 0.407\,X_1 + 6.03\,X_2 - 1.43\,X_3 + 0.076\,X_4 - 1.72\,X_5 - 2.37\,X_6 - 1.83\,X_7 + 0.285\,X_8 - 0.521\,X_9$

  where

  - X_1 = log(total assets / GDP price-level index)
  - X_2 = total liabilities / total assets,
  - X_3 = working capital / total assets
  - X_4 = short-term liabilities / short-term assets
  - X_5 = 1 (if total liabilities > total assets) or 0 (other cases)
  - X_6 = ROA = net income / total assets
  - X_7 = operational cash-flow / total liabilities
  - X_8 = 1 (if net income <0 in the last 2 years) or 0 (other cases)
  - X_9 = income volatility = net income variation in the previous year / sum of the absolute value of net income in the last 2 years.

Logit Models

- Altman and Sabato (2006):

Table4. **Model developed with logged predictors**
This table shows the model developed using the logged values of the variables to predict the probability of the firm being bankrupt.

$$
\begin{aligned}
Log(PD/1-PD) = &+ 53.48 \\
&+ 4.09 \quad -LN(1-Ebitda/Total\ Assets) \\
&- 1.13 \quad LN(Short\ Term\ Debt/Equity\ Book\ Value) \\
&+ 4.32 \quad -LN(1-Retained\ Earnings/Total\ Assets) \\
&+ 1.84 \quad LN(Cash/Total\ Assets) \\
&+ 1.97 \quad LN(Ebitda/Interest\ Expenses)
\end{aligned}
$$

RiskCalc

- A logit model for non-listed companies, developed by Moody's KMV for several countries.
- Provides PD estimates for 1 and 5-year maturities, as well as a mapping to Moody's' rating classes.
- The model is based on a set of financial ratios, specific for each country, illustrating the most relevant financial items.
- The databases used include credit performance data from banks in each country:

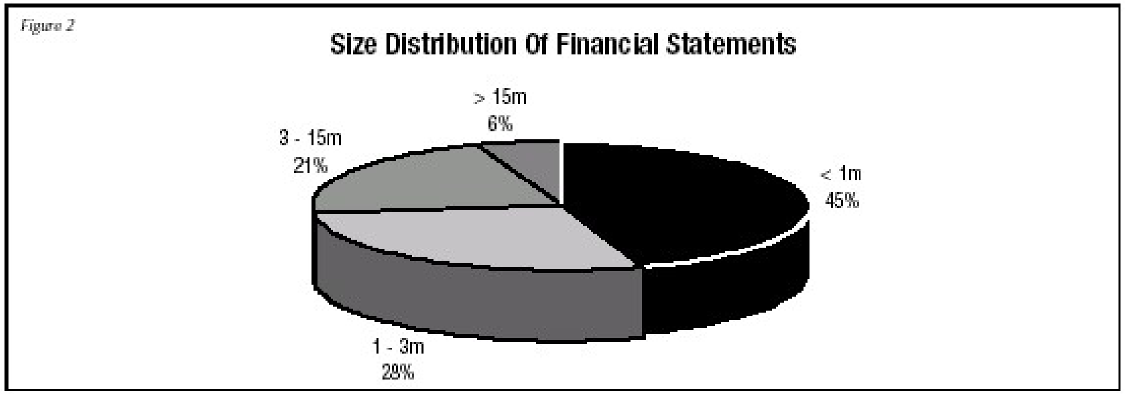
	Período Coberto	Nº. de empresas		Frequência de Incumprimento	Nº. de Demonstrações Financeiras
		Total	C/default		
Portugal	1993-2000	18137	416	2.3%	69.765
Bélgica	1992-1998	102594	6658	6.5%	523057
Reino Unido	1989-2000	64531	4723	7.3%	283522
Espanha	1992-1999	140790	2265	1.6%	569181
EUA	1989-1999	33964	1393	4.1%	139060

RiskCalc

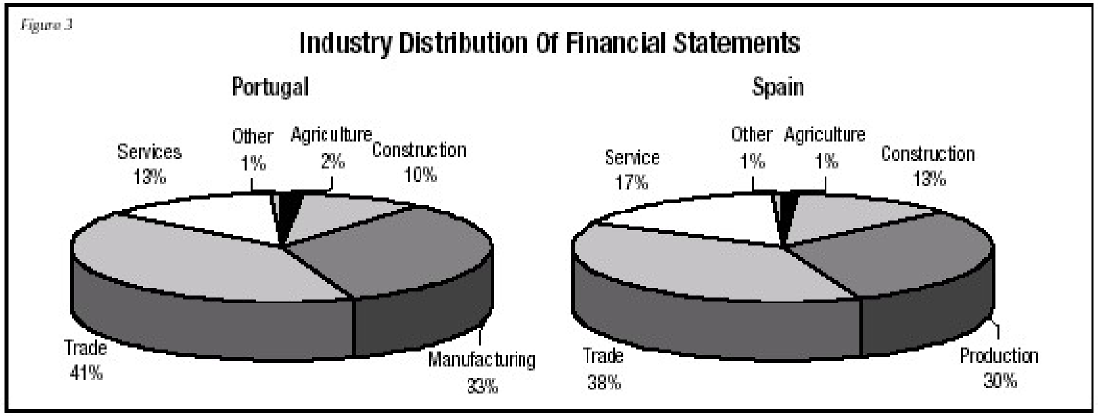
- Each observation corresponds to a year with observable credit performance for a given company.
- Main exclusions:
  - Small businesses (*turnover* < 500 k €);
  - *start-ups* (companies less than 2 years old);
  - Financial institutions
  - Real Estate brokers
  - Government-owned companies;
  - *holdings*.
  - Performing loans after a company's default.

RiskCalc

- Even after excluding the small business, the Portuguese database is dominated by companies with a *turnover* below 1M€, in line with other European countries.



- The industry distribution of companies included in the Portuguese model database is similar to the Spanish one:



Source: Moody's (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc

- The development of the RiskCalc models involves 5 main stages:

1. Data Preparation → 2. Univariate Analysis → 3. Multivariate Analysis → 4. Validation → 5. Calibration

RiskCalc

- 1st stage – Data preparation: consists in implementing the database exclusions planned, identifying the defaults and associating the adequate financial information:
  - in performing loans– the balance sheet of the previous year, if the loan was originated in the 2nd half of the year, or two years before, when loans were originated in the 1st half.
  - default loans – the balance sheet of the previous year, if the loan was originated in the 2nd half of the year, or two years before, when loans were originated in the 1st half, also identifying the two years before as defaults, in order to ensure better discrimination between performing and non-performing companies, as well as the increase in the number of defaults (usually low).

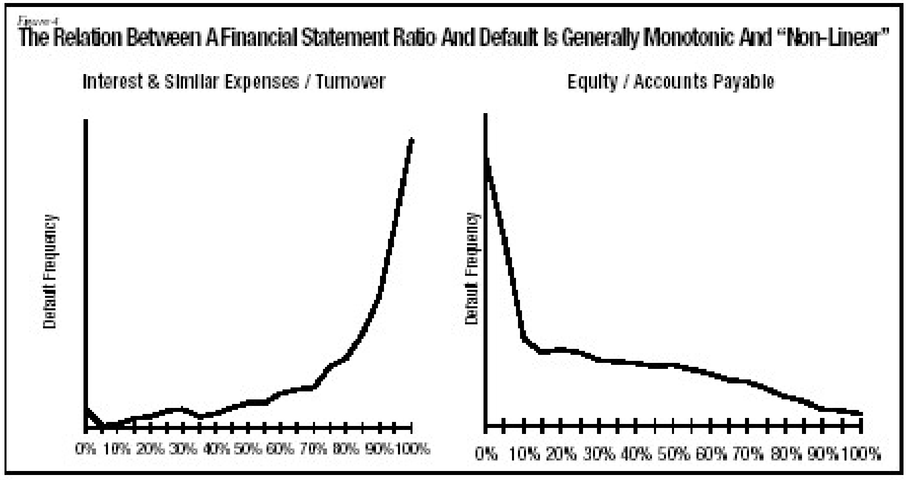
RiskCalc

- Example – company with 3 loans granted in 2001:
  - (i) 4th April 1997, 2-year maturity - regular;
  - (ii) 7th July 1999, 1-year maturity – default at maturity (7th July 2000);
  - (iii) 2nd February 2000, 2-year maturity - regular (until 2001).

Balance Sheet Year	Endogenous Variable	Relevant loan
1995	0	(i)
1996	0	(i)
1997	1	(ii)
1998	1	(ii)
1999	1	(ii)
2000	-	-
2001	-	-

RiskCalc

- 2nd Stage – Univariate analysis: consists in assessing the link between defaults and each potentially relevant explanatory variable, in two steps:
  - Univariate analysis – the link between the ratio percentiles and their corresponding default frequencies is assessed:
  - Mini-modeling of the ratios – a logit regression between the qualitative dependent variable and each pre-selected ratio in the previous stage is performed, after smoothing the default freq. curve.



Source: Moody's (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc

- 3rd Stage – Multivariate analysis: consists in the model estimation, by identifying the best combinations between the pre-selected ratios.
- Given the high number of potentially relevant ratios, the variable selection is done in one of the following two ways:

(i) forward selection – starts by including the independent variable with the highest univariate correlation and variables are added by ascending order of correlation, until they cease to increase the predictive power of the model.

(ii) backward selection – all variables are included and those with weaker predictive power are eliminated.

- Given the high number of potential variables, the forward selection is chosen.
- At this stage, a subsample of 750 default and regular observations is used, in order to improve the differentiation between these two groups, being the PD scale achieved through calibration.

RiskCalc

Results for Portugal:

Table 2

RiskCalc For Portuguese Private Companies: Relative Weights of Risk Factor Categories

Category	Factors	Contribution
Leverage / Gearing	Equity Ratio Bank Debt	21%
Profitability	Net P&L / Assets	17%
Debt Coverage	Debt Service Coverage Cash Flow/ Liabilities	34%
Liquidity	Current ratio	11%
Activity	Interest Expense/ Turnover	17%

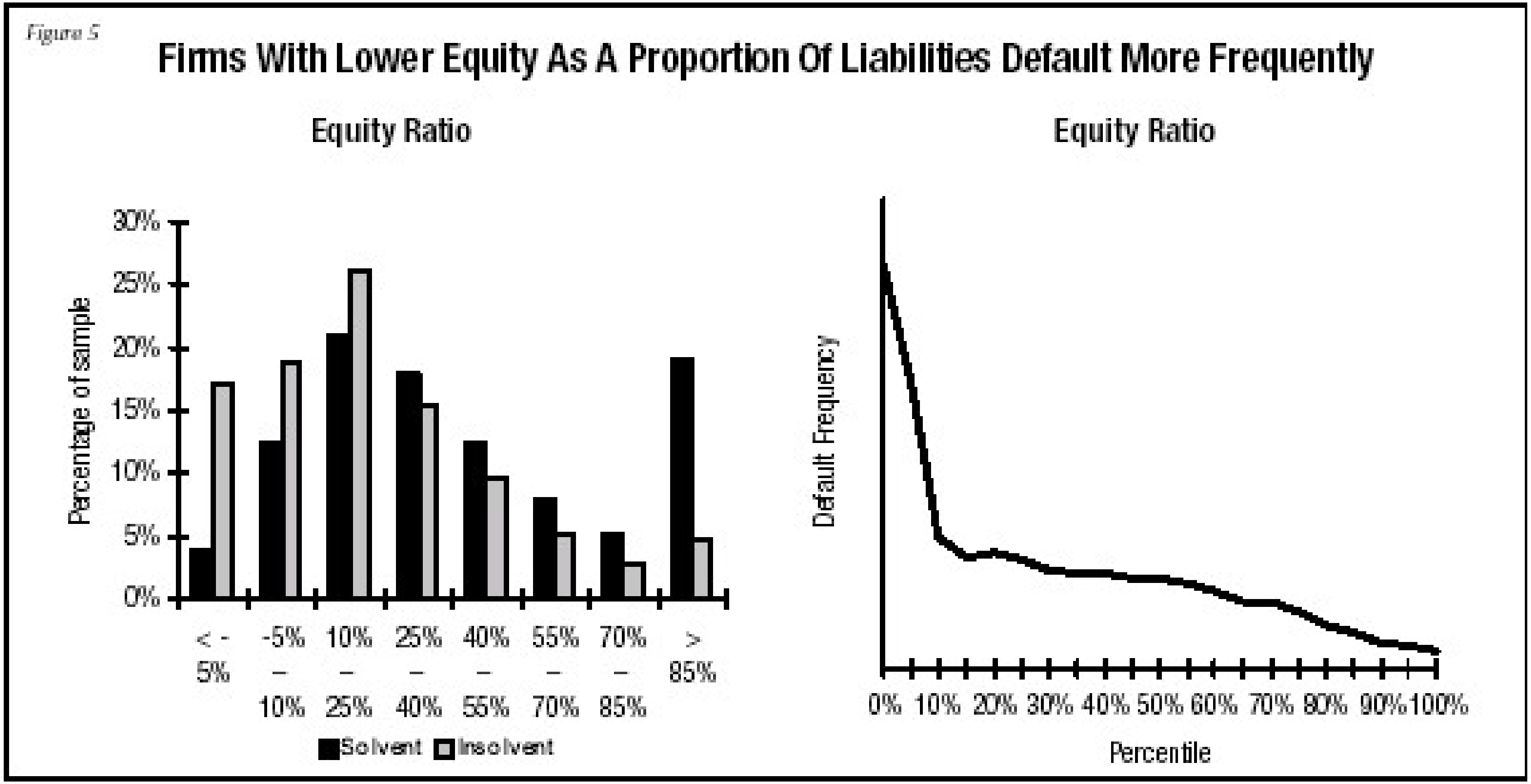
Table 8

RiskCalc™ For Portuguese Private Companies: Ratio Calculations

Category	Ratio Name	Definition
Leverage	Equity Ratio	Equity / Total Accounts Payable
	Bank Debt Ratio	Bank Debt / Total Liabilities
Profitability	Net P&L / Assets	Net P&L / Total Assets
Debt Coverage	Debt Service Coverage	(Ordinary P&L+ Depreciation)/ Interest and similar Expenses
	Cash Flow / Liabilities	(Ordinary P&L + Depreciation + Provisions) / Total Liabilities
Liquidity	Current Ratio	Current Assets / Accounts Payable (due within 1 year)
Activity	Interest expense / Sales	Interest and similar Expenses / Turnover

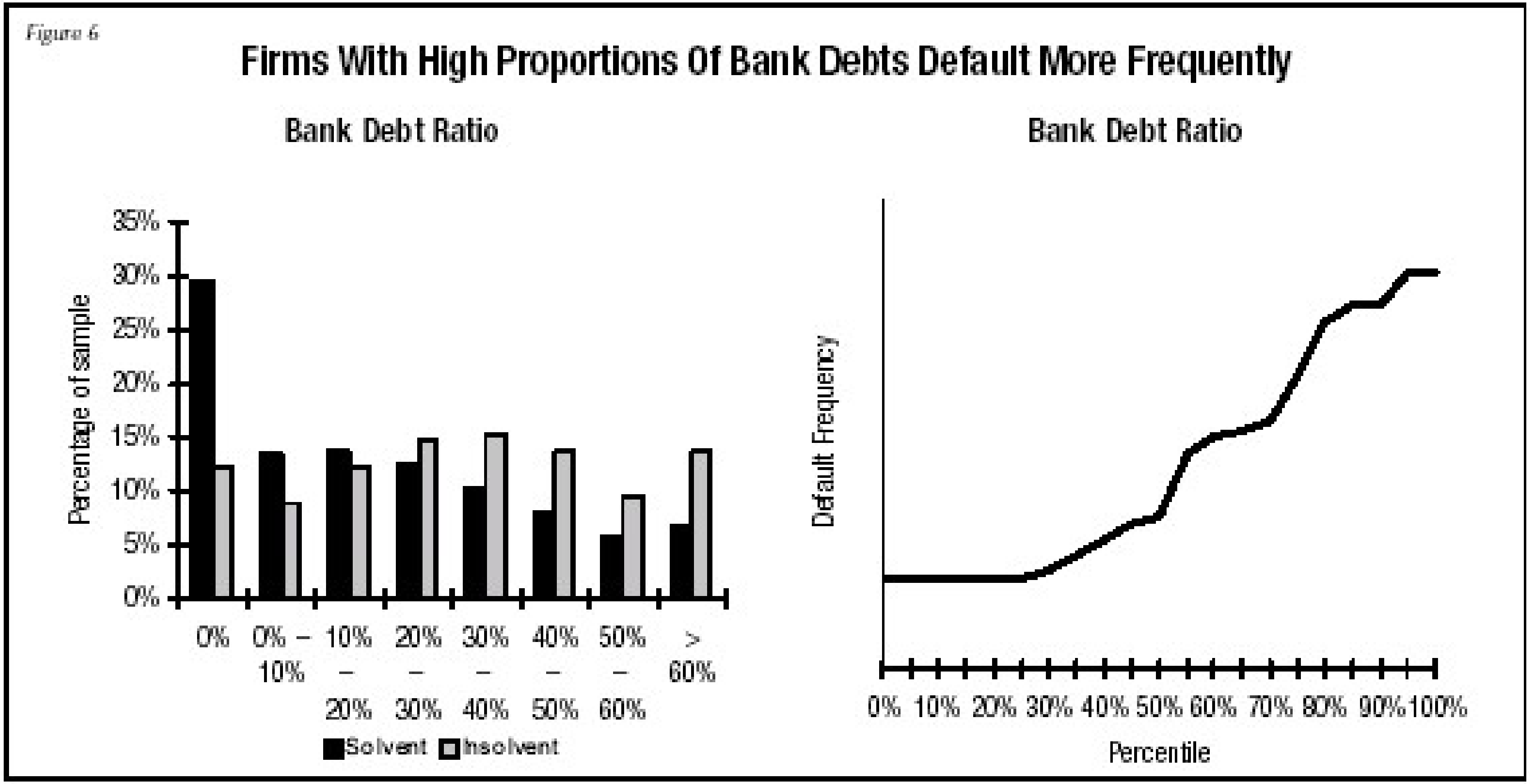
Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc



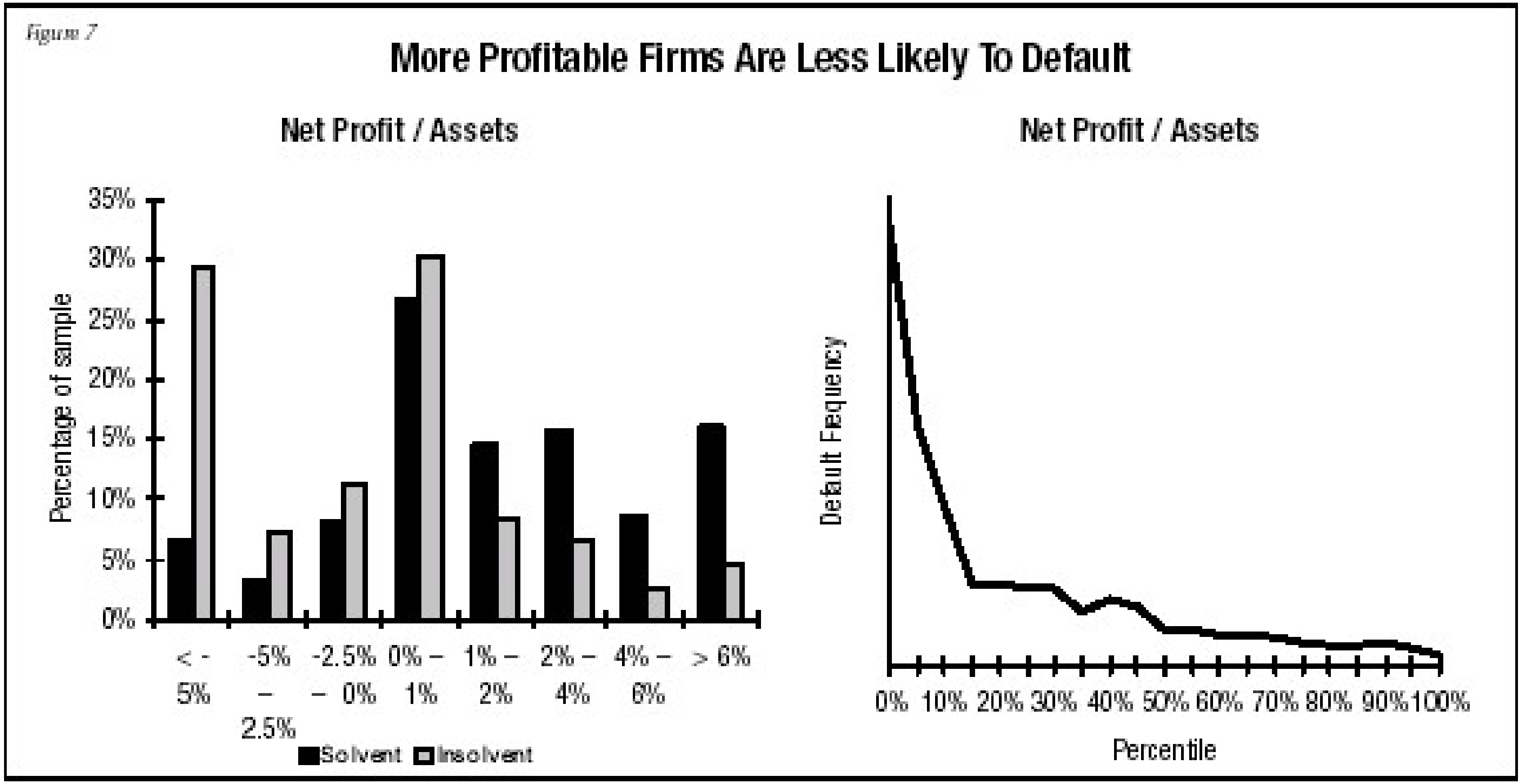
Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc



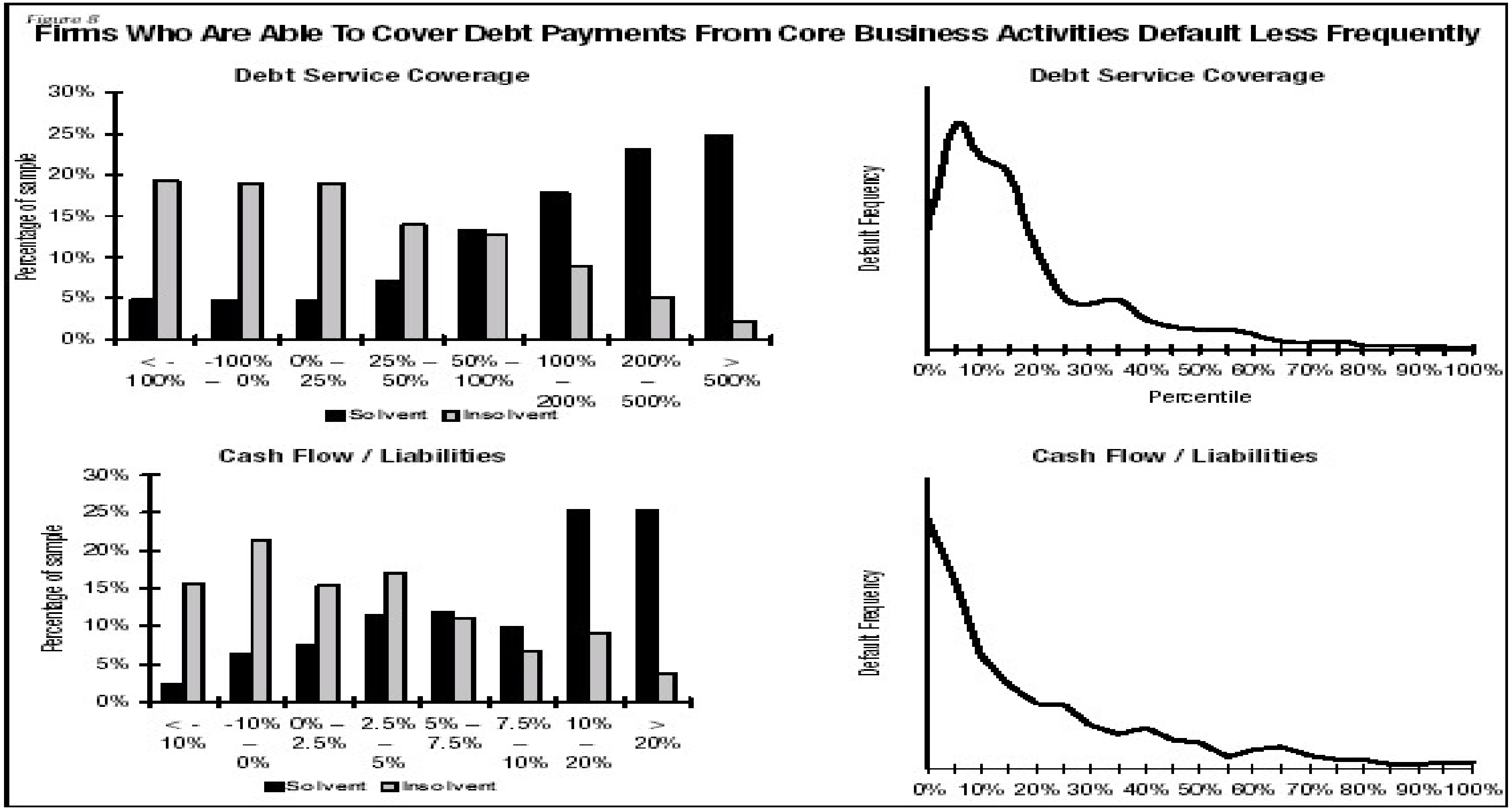
Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc



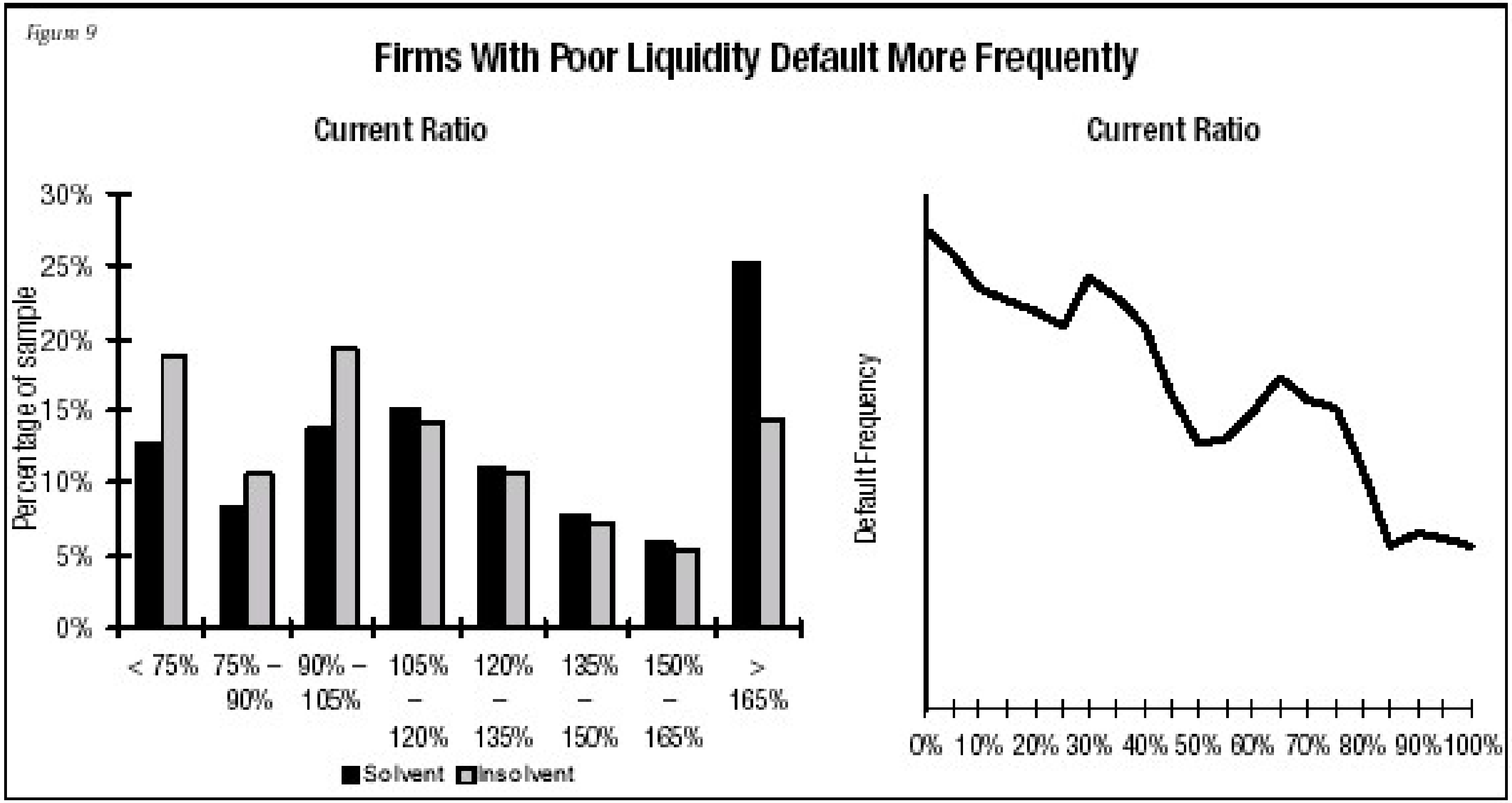
Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc



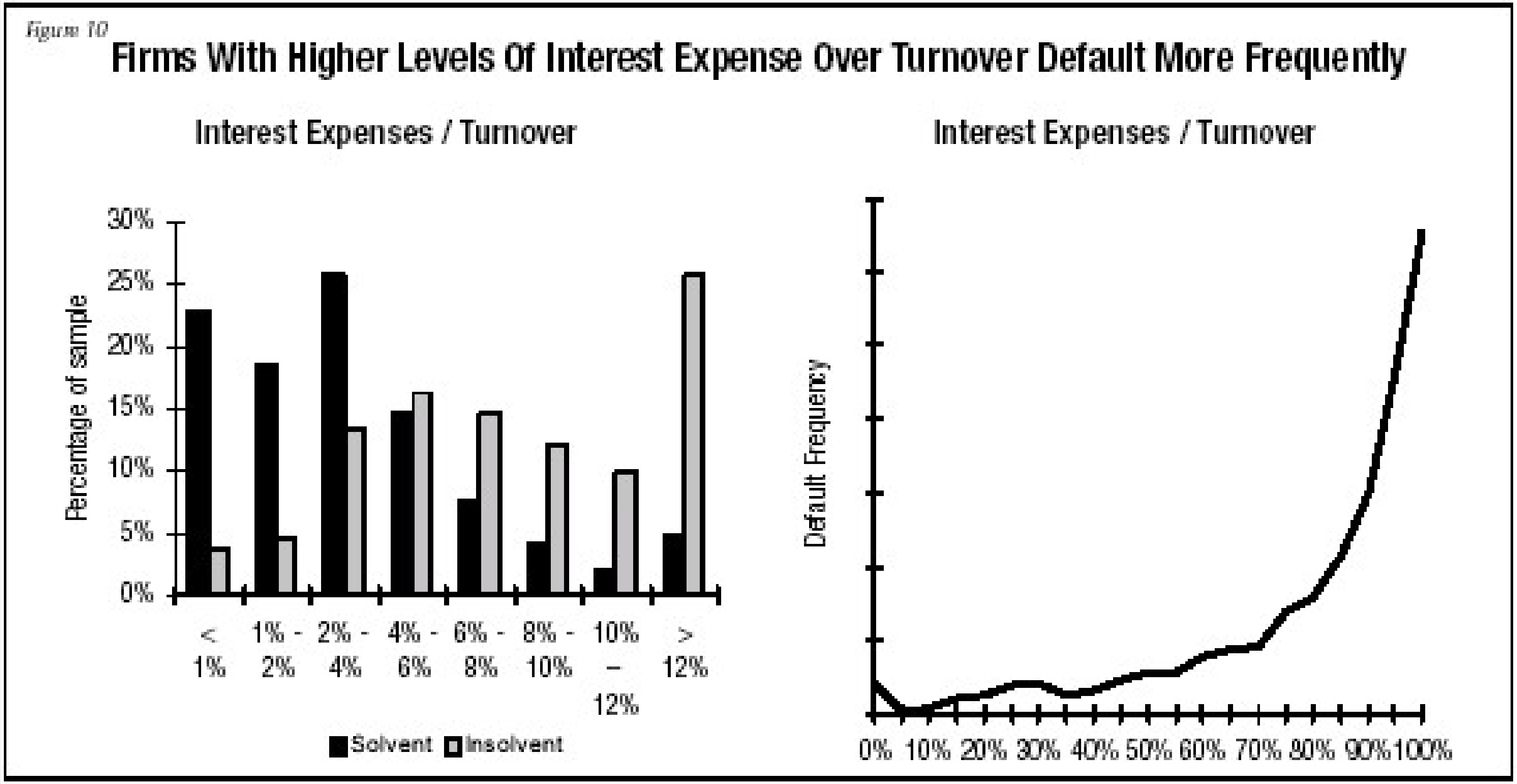
Source: Moody’s KMV (2002), “Moody’s RiskCalc for Private Companies: Portugal”.

RiskCalc



Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc



Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc

- 4th Stage - Validation: consists in analyzing the model ability to predict correctly the future behavior of loans.
- It involves the assessment of in- and out-of-sample model behavior, on aggregate and by economic sectors and periods.
- 5th Stage – Calibration: consists in the mapping between the model scores and PDs, in order to
  - obtain an expected loss level (regardless the collateral) close to market figures (for Portugal, Moody’s considered 1.5% and 6%, respectively to 1- and 5-year PDs);
  - obtain comparable figures between different countries;
  - map to the Moody’s rating scale.

RiskCalc

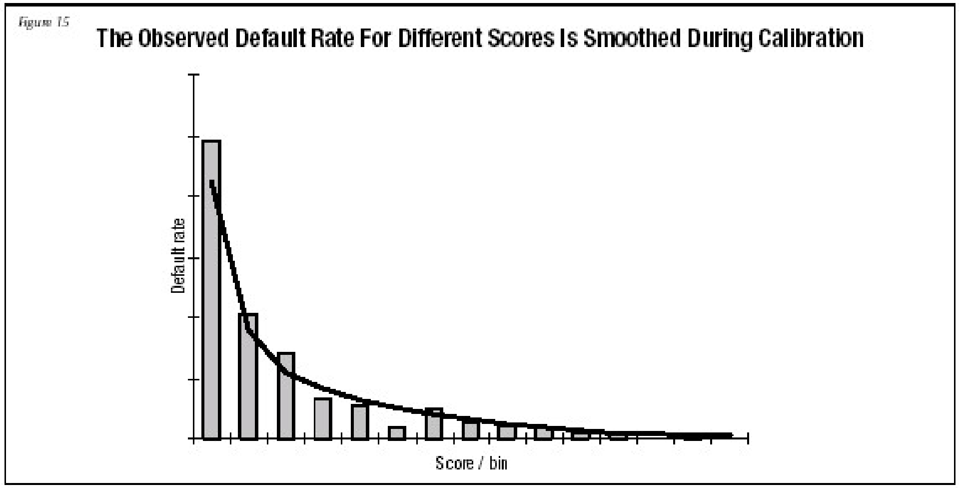
- Calibration is done in 2 steps and aims at getting constant PDs along the business cycle, with the EL moving as a consequence of rating migrations:

  (i) "run" the model for the whole sample, considering:

  - for regular observations, the financial statements closer to the loan decision;

  - for default observations, the financial statements closer to the default (12 to 35 months before, for the 1y PD and 6 to 65 months for the 5y PD).

  (ii) calculate the relative frequency of default for each percentile, smooth this curve and adjust it, considering the relative difference between the global estimated PD and the benchmark figure.



Source: Moody's KMV (2002), "Moody's RiskCalc for Private Companies: Portugal".

RiskCalc

- Ex: if a global PD = 0.75% is obtained from the chart, the model scores will have to be doubled (1,5%/0,75%) in order to correspond to a calibrated PD.
- Calibrated PDs may be used for mapping the RiskCalc classification to the agency ratings (if a sufficient number of rated companies with a RiskCalc classification exist).
- Given that the logit scores are in the range 0%-100%, the mapping may be done by grouping the scores, in order to get for each group a relative frequency of default similar to the historical PDs of rating classes, in a given maturity.

Structural Models

- The drawbacks of traditional credit risk models and rating updates by agencies in the recent past led to the development of new credit risk models, based on the prices of financial assets issued by the company.
- The rationale is that market prices are the best assessment available on the companies' capital or debt value.
- The first attempt to incorporate market prices in a credit risk model was done in the Z-Score model. Later, in 1974, Merton developed a corporate valuation approach based on financial options.
- In structural models, the default time is determined endogenously by the evolution of the company value ⇔ default occurs when the company's market value of assets falls below the notional liabilities value => the company does not keep an incentive to redeem the debt.
- The main problem with these models corresponds to the false alarms.

Merton Model

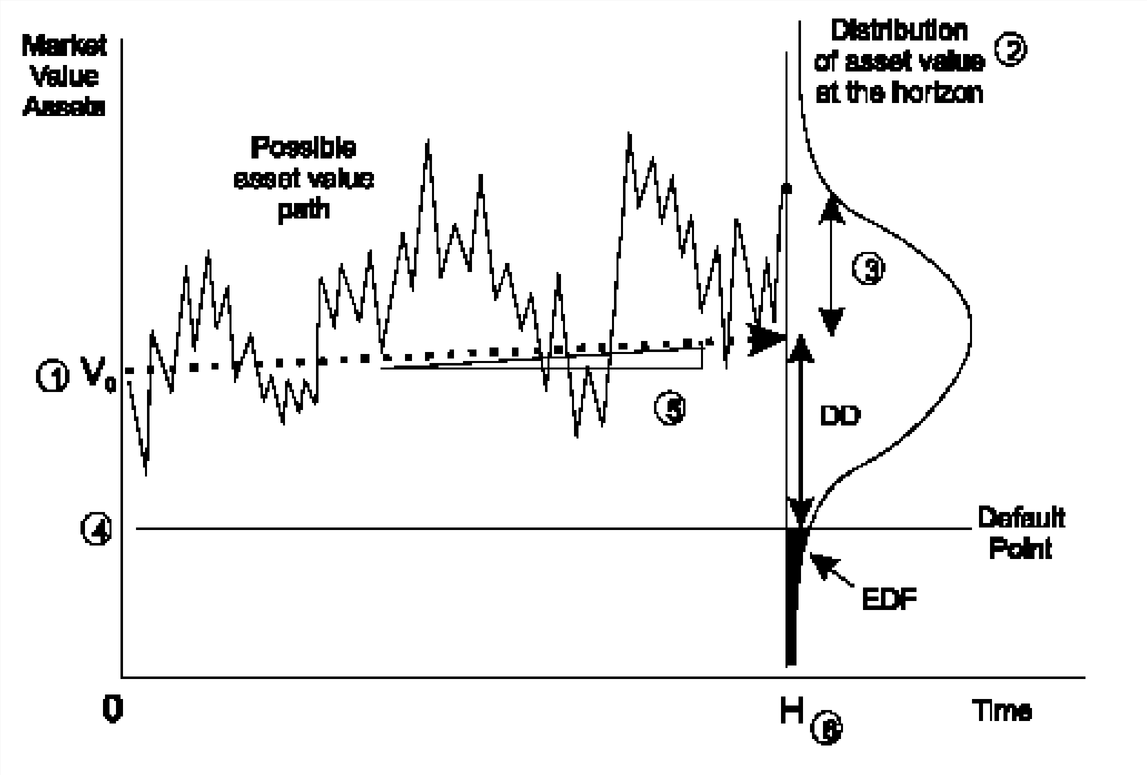
- The model is based on the idea that when a company is issuing debt, it is sharing the control of the company with its creditors.
- However, shareholders have the right to recover the full control of the company by ensuring the company redeems the debt.

$$\Downarrow$$

- Equity may be seen like owning a call-option on the market value of assets, with the strike price corresponding the liabilities' value.
- On the debt redemption date, if the company's market value of assets is lower than its debt value, the option is not exercised and the company defaults.
- Debt issuance may also be seen as selling a put-option on the market value of assets.

Merton Model

- Therefore, the PD will correspond to the probability of the company's asset market value to be lower than the nominal value of debt.



Source: Crosbie and Bohn (2002), "Modeling Default Risk", KMV.

Merton Model

- If the call-option can be valued, the PD will be obtained from the distribution function resulting from the stochastic process of the company's asset market value.
- Assuming that the option is European and the asset market value may be taken as the price of non-paying dividend asset, one can use the Black-Scholes formula and calculate the PD from the implied volatility of the company's asset value and an estimate for the respective growth rate.
- Hence, the Merton model is based on the assumption of the growth rates of the company's market value of assets being normally distributed:

$$dV_A = \mu V_A dt + \sigma_A V_A dz \Leftrightarrow \quad dV_A / V_A = \mu dt + \sigma_A dz$$

where V_A is the company's market value of assets, μ *and* σ_A the respective trend and instantaneous volatility and *dz* is a Wiener process (random shocks normally distributed).

Merton Model

- Consequently, the pricing formula for an European *call-option* on the company's market value of assets is:

$$V_E = V_A N(d1) - e^{-rT} X N(d2)$$

where

V_E is the market value of the company's own funds

N is the cumulative normal distribution function

r is the riskfree interest rate for the maturity T

X is the nominal value of the company's total debt payable in maturity T.

$$d1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}$$

$$d2 = d1 - \sigma_A \sqrt{T}.$$

Merton Model

- In the pricing formula, there are two unknowns - V_A and $\sigma_{A.}$
- Consequently, an additional equation is required, in order to determine the values for those two variables.
- This equation will result from the relationship between the volatility of assets and the volatility of capital:

(1) $$\sigma_E = \frac{V_A}{V_E} N(d1) \sigma_A$$

- In Jarrow and Rudd (1983), it is shown that:

(2) $$\sigma_E = \eta \sigma_A$$

Merton Model

- Given (1) and that

(3) $$\delta = \frac{\partial C(X)}{\partial V_A} = N(d_1)$$

one gets:

$$\frac{V_A}{V_E} N(d1)\sigma_A = \eta\sigma_A \Leftrightarrow$$

$$\Leftrightarrow \frac{V_A}{V_E}\delta = \eta \Leftrightarrow$$

$$\Leftrightarrow \delta = \frac{\eta}{V_A / V_E}$$

- Therefore, from inputs V_E, σ_E , X, r and T, the equation system including the option pricing formula and (1) provides the following outcome:

$$V_E = V_A N(d1) - e^{-rT} X N(d2)$$

$$\delta = \frac{\sigma_E / \sigma_A}{V_A / V_E}$$

Merton Model

- The PD is thus the probability of the market prices of assets falling below the nominal value of debt at the expiry date:

$$p_t = \Pr\left[V_A^t \le X_t \mid V_A^0 = V_A\right] = \Pr\left[\ln V_A^t \le \ln X_t \mid V_A^0 = V_A\right]$$

- Given that the market value of assets follows a log-normal distribution, one gets (with *m* = expected asset returns):

$$\ln V_A^t = \ln V_A + \left(\mu - \frac{\sigma_A^2}{2}\right)t + \sigma_A \sqrt{t}\varepsilon$$

- Therefore, the PD is:

$$p_t = \Pr\left[\ln V_A + \left(\mu - \frac{\sigma_A^2}{2}\right)t + \sigma_A\sqrt{t}\varepsilon \le \ln X_t\right] = \Pr\left[-\frac{\ln\frac{V_A}{X_t} + \left(\mu - \frac{\sigma_A^2}{2}\right)t}{\sigma_A\sqrt{t}} \ge \varepsilon\right] \quad \Leftrightarrow p_t = N\left[-\frac{\ln\frac{V_A}{X_t} + \left(\mu - \frac{\sigma_A^2}{2}\right)t}{\sigma_A\sqrt{t}}\right]$$

- Risk-neutral PD ($\mu = r$): $p_t = N\left[-d_2\right]$

Merton Model

- Open issues:
  - How to estimate μ and σ_E?
  - How to deal with complex debt structures, with different maturities, seniority degrees and installments?
  - How to deal with the sensitivity of PDs to the leverage ratio?
  - How to solve the kurtosis problem in the market value of assets?
  - How to use the PD estimates as a leading indicator of rating changes?

KMV Model

- KMV overcomes the distribution problems by using a database of loans providing empirical PDs as a function of the distance-to-default measure.
- According to Oderda et al. (2002), Moody's KMV model anticipates defaults with a lead of around 15 months (11 months for RiskCalc).

$$DD = \left[\frac{\ln \frac{V_A}{X_t} + \left(\mu - \frac{\sigma_A^2}{2} \right) t}{\sigma_A \sqrt{t}} \right]$$

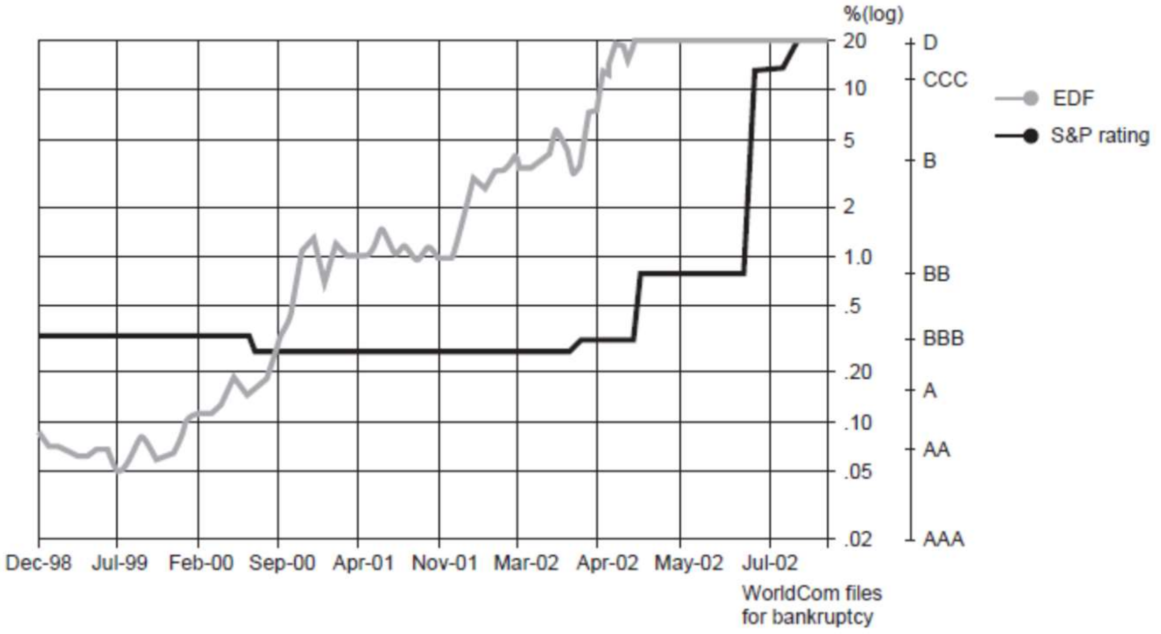
- However, it also produces false alarms in 88% of the cases.

KMV Model

- Nonetheless, KMV model was able to anticipate important defaults, like Worldcom, before rating agencies:

FIGURE 11–13 **KMV and S&P Ratings for WorldCom**

Source: KMV Corporation, San Francisco, California. *www.moodyskmv.com*



Saunders, Anthony and Marcia Millon Cornett (2006), Financial Institutions Management – A Risk Management Approach, 5th Edition, McGraw-Hill International.

KMV Model

- In this model, σ_A is a linear combination of a modeled and an empirical volatility (the latter weighting 70%, 80% for Financial Institutions).

- Empirical vols are calculated as the annualized standard deviation of the growth rates of the nominal value of assets, using 3 years of weekly observations for US companies (5 years of monthly data for European companies), excluding extreme values and adjusting for effects of M&A.

- The modeled vols are obtained from a regression between the observed vol and size, revenues, profitability, sector and region variables.

KMV Model

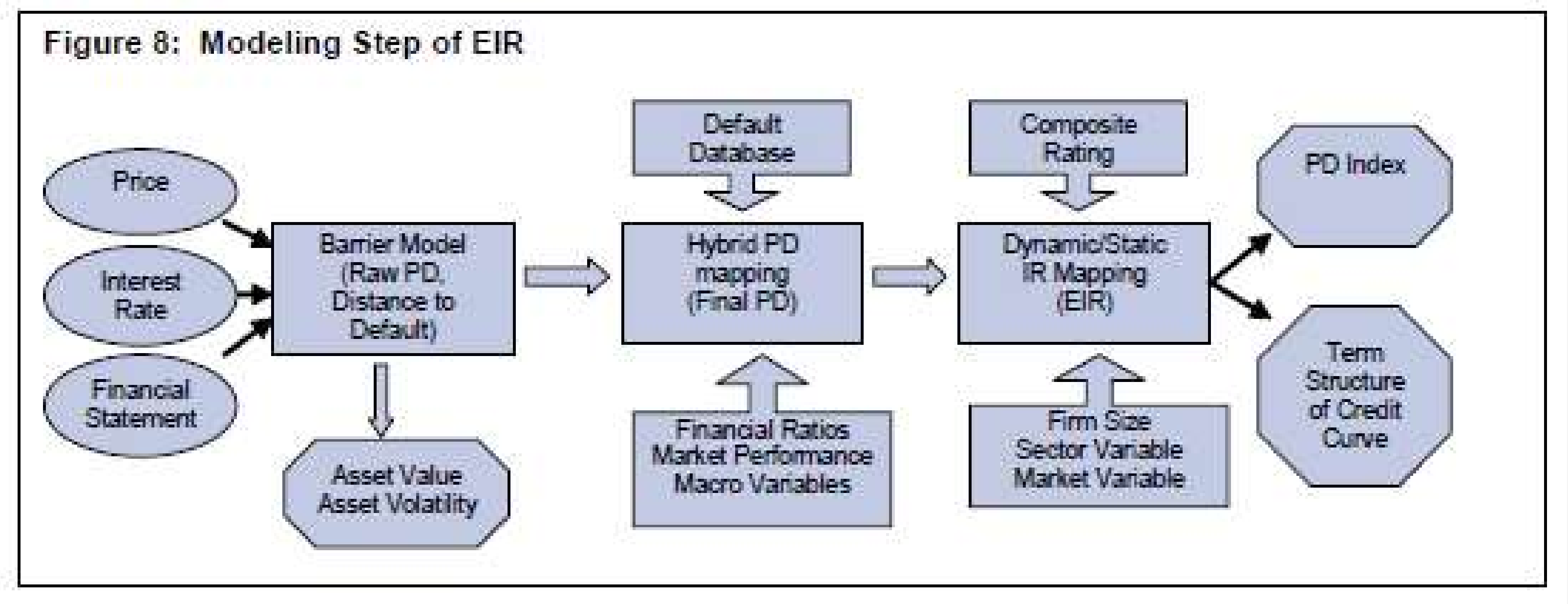
- For FIs, the PD is harder to estimate, given the diversity and uncertainty of the liabilities' maturities.
- On the other hand, by definition, banks are highly leveraged companies.
- Thus, Moody's KMV proposes the *default point* (the value of the payable liabilities in the maturity considered) to be calculated as a % of the total liabilities, being that % differentiated according to the type of institution.
- In Chan-Lau and Sy (2006), it is proposed an adjustment to the KMV model, in order to accommodate the possibility of a bail-out. Consequently, the "*Distance-Risk measure*" concept is created, with L_t being the bank's liabilities (λ=1 => DR=DD) and PCAR the planned capital ratio:

$$DR_T = \frac{\ln\left(\frac{V_t}{\lambda L_t}\right) + \left(\mu - \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}},$$

$$\lambda = \frac{1}{1 - PCAR_i}$$

Fitch EIR

- Fitch also developed a Merton-based model, the Equity Implied Rating (EIR), relating the DD with a set of financial ratios and macroeconomic variables:



Source: Fitch (2007).

Bondscore

- In order to smooth the excessive volatility of PDs obtained from equity prices, hybrid models have been developed, with the PD being obtained simultaneously from corporate financial and market information.
- One of these models is the Bondscore, developed by CreditSights:

$$p = -9.593 + 7.366X_1 - 3.989X_2 - 5.308X_3$$
$$-6.333X_4 - 2.501X_5 + 3.807X_6 + 5.469X_7$$

being:
X_1 = Total Liabilities/Market Value of Capital
X_2 = EBITDA/Sales
X_3 = Sales/ Total Assets
X_4 = Working Capital / Total Assets
X_5= log(Assets)
X_6= Vol of EBITDA/Sales
X_7= Vol of Market Value of Capital

Reduced-form Models

- Given that *credit spreads* can be decomposed in default risk (PD) and recovery risk (LGD), the PD can be modeled from the credit spreads and LGDs.
- Considering several maturities, one can obtain a term structure of PDs.
- However, one must have in mind that spreads are not only a function of PDs and LGDs, but also of liquidity.

5.3.3. Small Business and Individuals

Small Business

- Small business models include a wider range of variables, comparing to individual and corporate models:
  - variables illustrating the entrepreneurs' credit risk and professional features;
  - behavioral variables (for customers).
- Typically, the credit track record of the entrepreneurs exhibits higher predictive power.
- Variables usually considered:
  - Income and financial and real estate portfolio of the entrepreneurs;
  - Credit track record of the entrepreneurs;
  - Age and seniority of the entrepreneurs;
  - Loan purpose;
  - Debt, solvency and revenue growth variables.

Individuals

- A relevant issue in these models is the difficulty in updating credit risk, comparing to the corporate segment.
- Therefore, in revolving loans, the following models are used:
  - Application scorings, based on the information provided by the customer when applying for a loan;
  - Behavioral scorings, incorporating relationship data of the customer, namely for revolving loans.
- The higher difficulty in obtaining updated information may lead to the integration of macroeconomic variables, in order to get model with some sensitivity to the business cycle.
- Therefore, variables as the real growth rate of GDP, coincident and leading indicators of the business cycle and the unemployment rate can be included in scoring models.

Individuals

- Variables usually considered:
  - Income
  - Age
  - Sex
  - Civil Status
  - Profession
  - Job seniority
  - Job contract
  - Academic degrees
  - Residence region
  - Type of residence
  - Loans obtained
  - Nº. of household persons

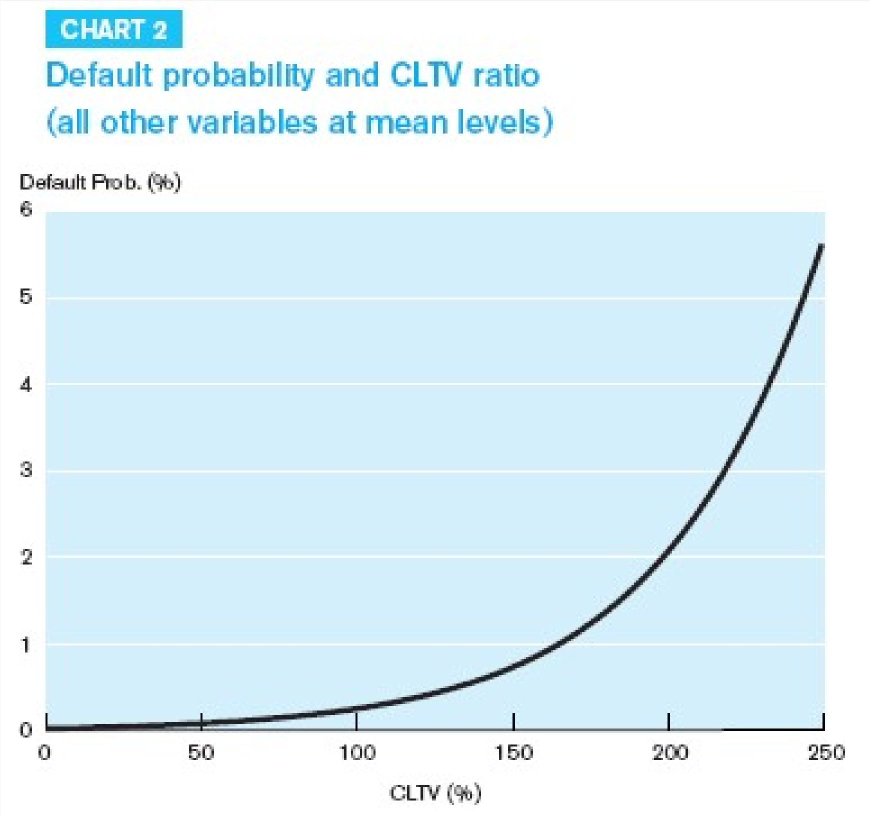
Individuals

- The variables in the scoring models are defined as follows:

  - continuous variables;
  - discrete variables (e.g. sex, civil status, profession or academic degrees);
  - *stepwise variables* (e.g., age, job seniority, No household members or income);
  - interacted variables, conciliating features of more than one variable (e.g., older than 35 years and living in Lisbon).

Individuals

- For residential mortgage loans, the most relevant variables are usually the LTV and the DTI.



Source: Wong et al (2004)

Maturity adjustments

- The loans included in the scoring development samples have different maturities.
- Therefore, the PD term structure has to be obtained from these different maturities, usually through a formula for the cumulative survival probability:

$$\hat{S}(T_k) = \prod_{i=1}^{k} \frac{n_i - h_i}{n_i}$$

where n_i is the total number of active loans until time i and h_i the total number of *defaults*.

5.4. Severity of Loss

Loss determinants

- Collateral
- Debt seniority
- Loan type (namely for individuals)
- Region
- Business cycle
- Economic sector
- PD

Estimation Methods

- NPV of recoveries
- Recovery distributions
- Bond prices after default
- LGD implied in bond prices
- LGD implied in observed losses and in PD estimates.
- Econometric adjustment of the LGD as a function of several variables (LossCalc, Moody's (2002)).

Table 9

Classification of the objective methods to obtain LGDs

Source	**Measure**	**Type of facilities in the RDS**		**Most applicable to**
		Defaulted facilities	**Non-defaulted facilities**	
Market values	Price differences	Market LGD		Large corporate, sovereigns, banks
	Credit spreads		Implied market LGD	Large corporate, sovereigns, banks
Recovery and cost experience	Discounted cash flows	Workout LGD		Retail, SMEs, large corporate
	Historical total losses and estimated PD	Implied historical LGD		Retail

Source: Basel Committee on Banking Supervision (2005)

Statistics

- Recoveries exhibit a bimodal distribution:

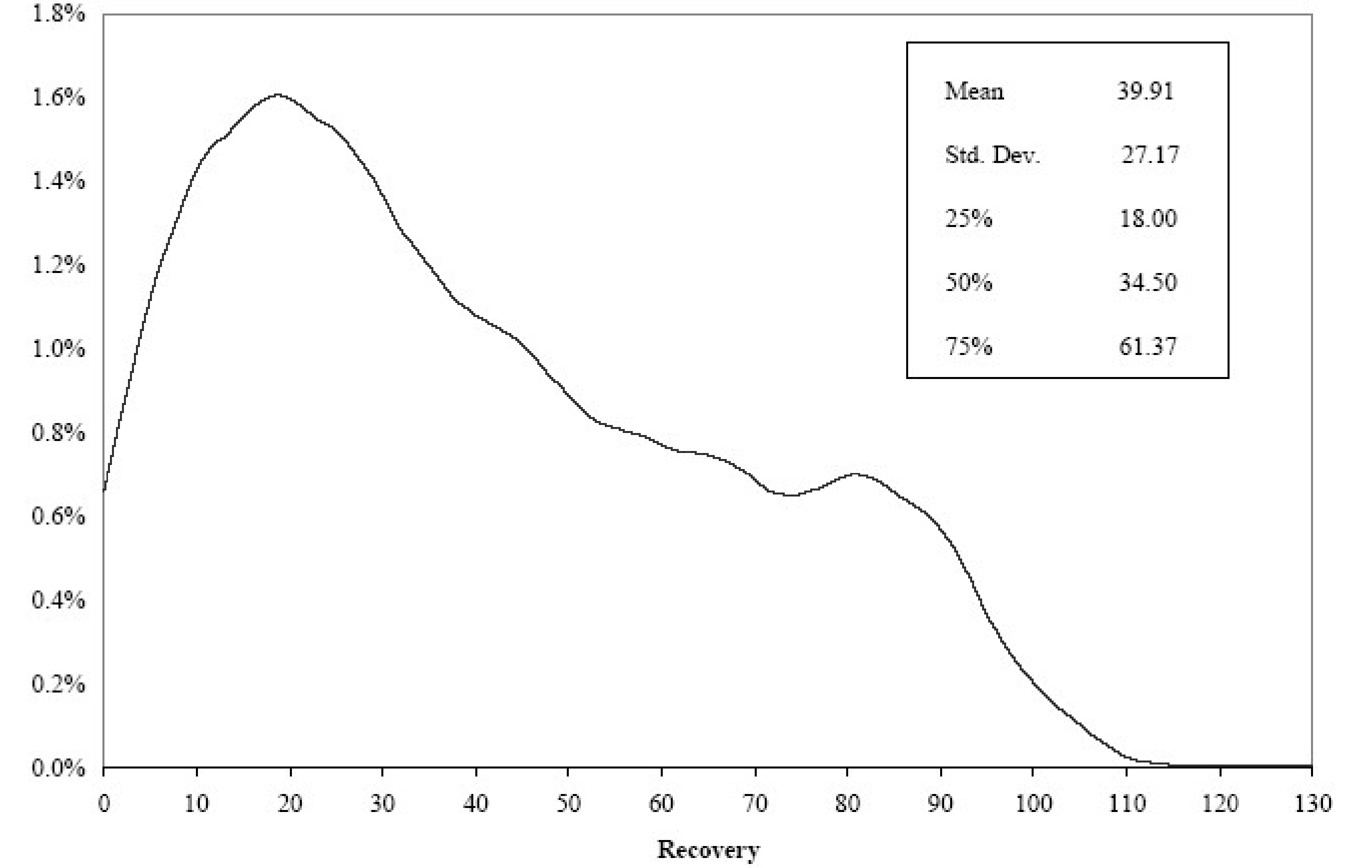


Figure 1: Probability Distribution of Recoveries, 1970-2003: All Bonds & Loans (Moody's)

Source: Schuermann (2004)

Seniority

- Higher recoveries in senior debt:

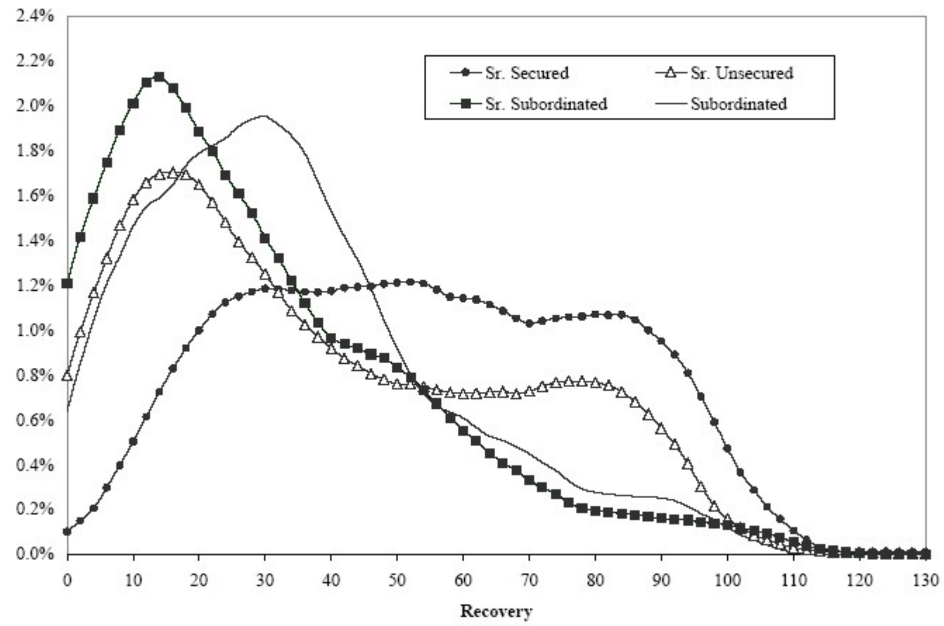


Figure 2: Probability Densities of Recovery by Seniority (Moody's, 1970-2003)

Source: Schuermann (2004) and Moody's (2009)

Average Annual Bond and Loan Recovery Rates[1]

	Loan	Bond					
Year	Sr. Sec.[2]	Sr. Sec.	Sr. Unsec.	Sr. Sub.	Sub.	Jr. Sub.	All Bonds
1982	n.a.	72.50%	35.79%	48.09%	29.99%	n.a.	35.57%
1983	n.a.	40.00%	52.72%	43.50%	40.54%	n.a.	43.64%
1984	n.a.	n.a.	49.41%	67.88%	44.26%	n.a.	45.49%
1985	n.a.	83.63%	60.16%	30.88%	39.42%	48.50%	43.66%
1986	n.a.	59.22%	52.60%	50.16%	42.58%	n.a.	48.38%
1987	n.a.	71.00%	62.73%	44.81%	46.89%	n.a.	50.48%
1988	n.a.	55.40%	45.24%	33.41%	33.77%	36.50%	38.98%
1989	n.a.	46.54%	43.81%	34.57%	26.36%	16.85%	32.31%
1990	75.25%	33.81%	37.01%	25.64%	19.09%	10.70%	25.50%
1991	74.67%	48.39%	36.66%	41.82%	24.42%	7.79%	35.53%
1992	61.13%	62.05%	49.19%	49.40%	38.04%	13.50%	45.89%
1993	53.40%	n.a.	37.13%	51.91%	44.15%	n.a.	43.08%
1994	67.59%	69.25%	53.73%	29.61%	38.23%	n.a.	45.57%
1995	75.44%	62.02%	47.60%	34.30%	41.54%	n.a.	43.28%
1996	88.23%	47.58%	62.75%	43.75%	22.60%	n.a.	41.54%
1997	78.75%	75.50%	56.10%	44.73%	35.96%	30.58%	49.39%
1998	51.40%	46.82%	41.63%	44.99%	18.19%	62.00%	39.25%
1999	75.82%	43.00%	38.04%	28.01%	35.64%	n.a.	34.33%
2000	68.32%	39.23%	23.81%	20.75%	31.86%	15.50%	25.18%
2001	64.87%	37.98%	21.45%	19.82%	15.94%	47.00%	22.21%
2002	58.80%	48.37%	29.69%	21.36%	24.51%	n.a.	29.95%
2003	73.43%	63.46%	41.87%	37.18%	12.31%	n.a.	40.72%
2004	87.74%	73.25%	52.09%	42.33%	94.00%	n.a.	58.50%
2005	83.78%	71.93%	54.88%	26.06%	51.25%	n.a.	55.97%
2006	83.60%	74.63%	55.02%	41.41%	56.11%	n.a.	55.02%
2007	68.63%	80.54%	53.25%	54.47%	n.a.	n.a.	54.69%
2008	63.38%	57.98%	33.80%	23.02%	23.56%	n.a.	34.83%

1. Issuer-weighted, based on 30-day post-default market prices.

2. Second-lien loans excluded.

Region

- Often regions where customers are based exhibit different recovery perspectives:

Figure 4: LGD over Loss Years by State

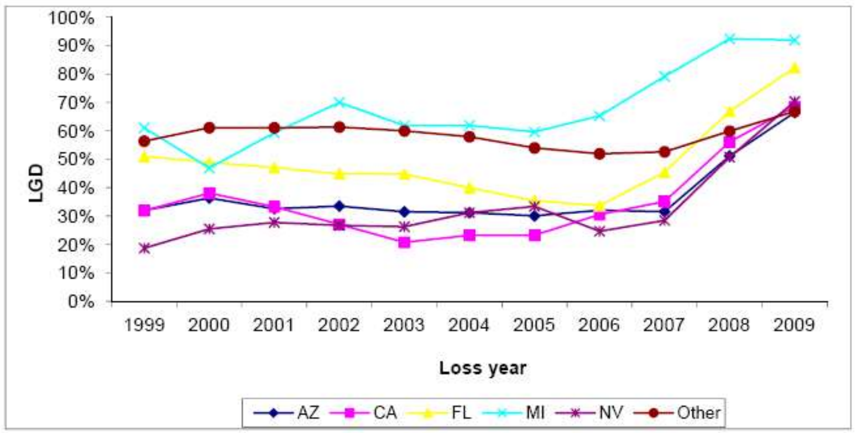


Table 5.5: Discounted recovery rates by country (12%)

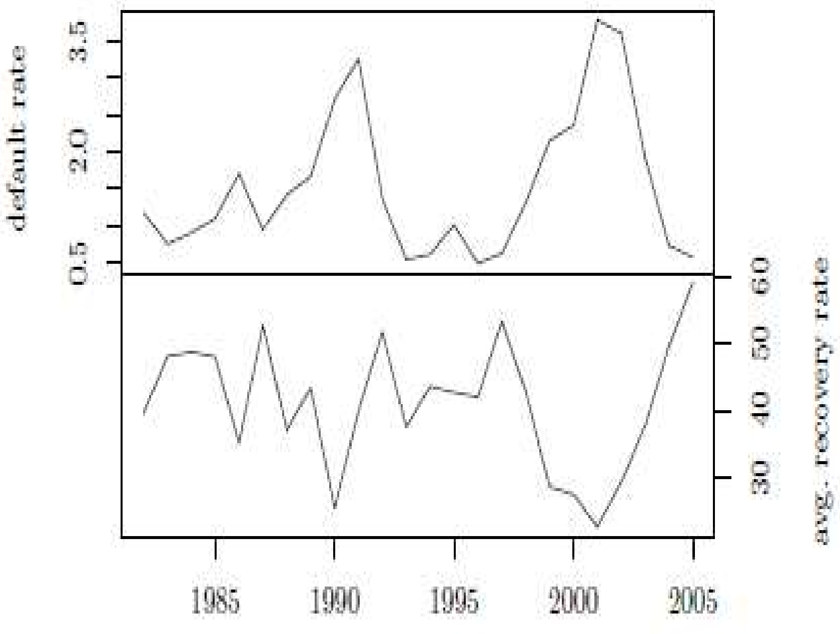
	Mean	Median	Std. dev.	No. in sample
U.K.	65.8%	82.8%	36.4%	92
France	38.0%	31.9%	33.6%	336
Germany	54.9%	56.7%	24.0%	35
Total				463

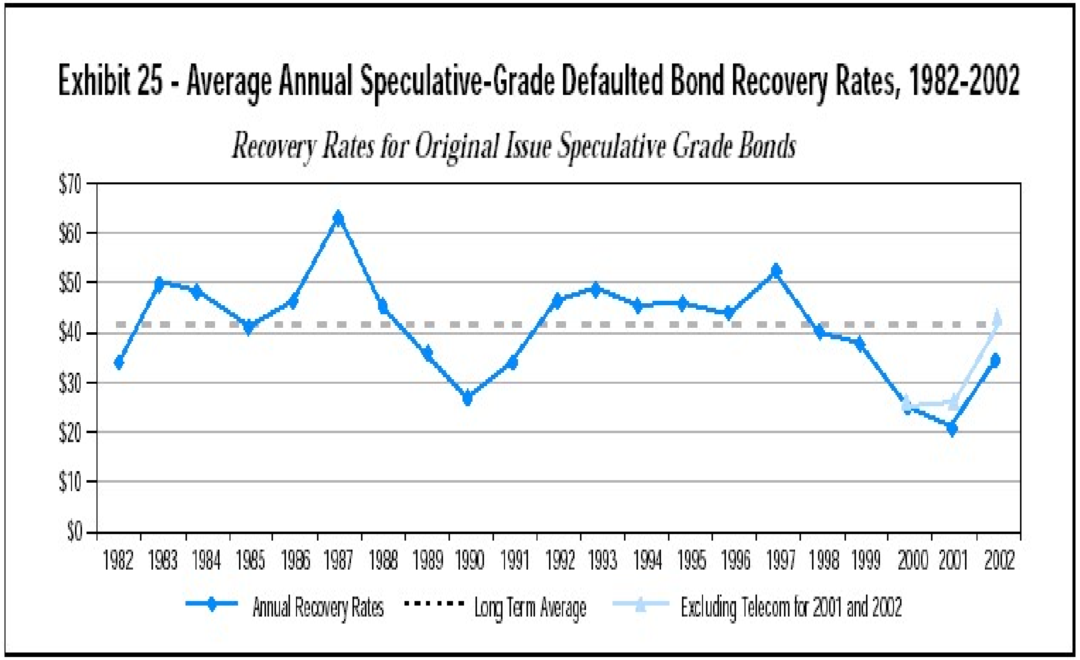
Source: Zhang, Yanan Lu Ji and Fei Liu (2010), "Local Housing Market Cycle and Loss Given Default: Evidence from Sub-Prime Residential Mortgages", IMF WP WP/10/167.

Source: Franks *et al* (2004).

Business Cycle

- LGD is typically higher during the lower stages of the business cycle.





Source: Bruche, Max and Carlos Gonzalez-Aguado (2007), "Recovery Rates, Default Probabilities and the Credit Cycle".

Source: Moody's (2003).

Business Cycle

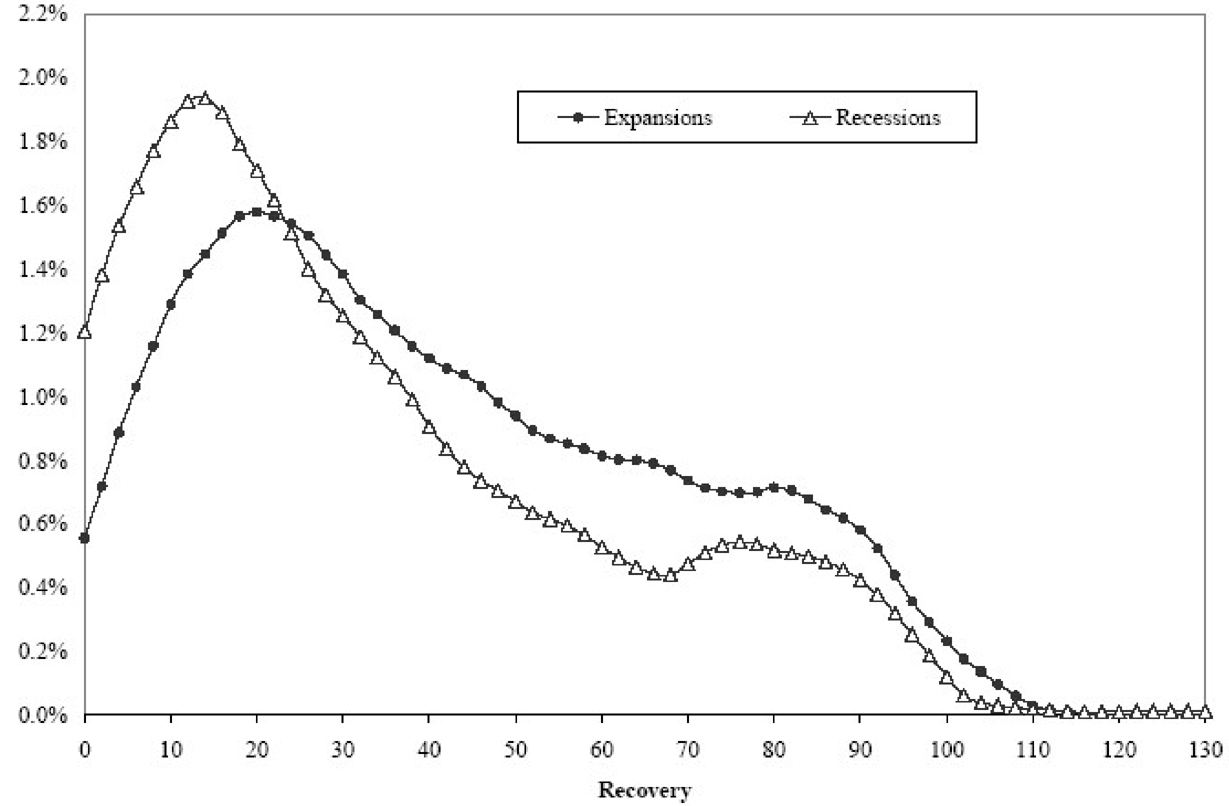


Figure 4: Probability Densities of Recoveries across the Business Cycle (Moody's, 1970-2003)

Source: Schuermann (2004)

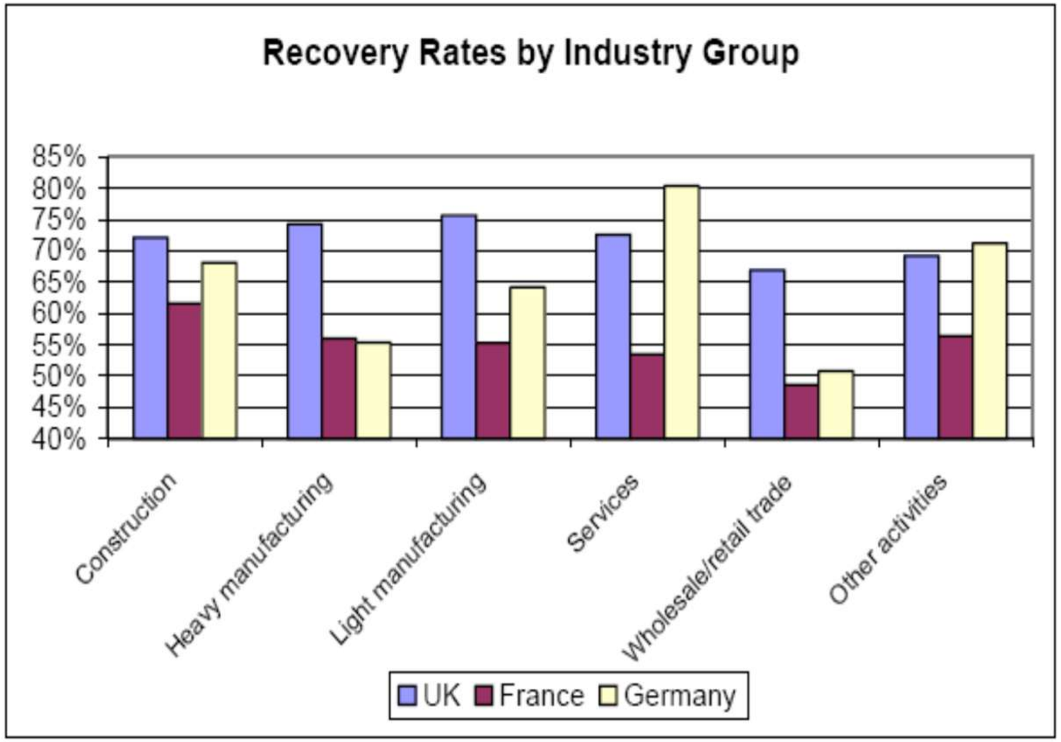
Economic Sectors

- In Altman and Kishore (1996), differences between sectors are identified.
- The LGD is usually higher for sectors with higher PD.

Exhibit 16 - Average Recovery Rates by Industry Category

Industry	Issuer Weighted Mean Recovery Rate 2003	2002	1982-2003
Utility-Gas	48.0	54.6	51.5
Oil and Oil Services	NA	44.1	44.5
Hospitality	64.5	60.0	42.5
Utility-Electric	5.3	39.8	41.4
Transport-Ocean	76.8	31.0	38.8
Media, Broadcasting and Cable	57.5	39.5	38.2
Transport-Surface	NA	37.9	36.6
Finance and Banking	18.8	25.6	36.3
Industrial	33.4	34.3	35.4
Retail	57.9	58.2	34.4
Transport - Air	22.6	24.9	34.3
Automotive	39.0	39.5	33.4
Healthcare	52.2	47.0	32.7
Consumer Goods	54.0	22.8	32.5
Construction	22.5	23.0	31.9
Technology	9.4	36.7	29.5
Real Estate	NA	5.0	28.8
Steel	31.8	28.5	27.4
Telecommunications	45.9	21.4	23.2
Miscellaneous	69.5	46.5	39.5

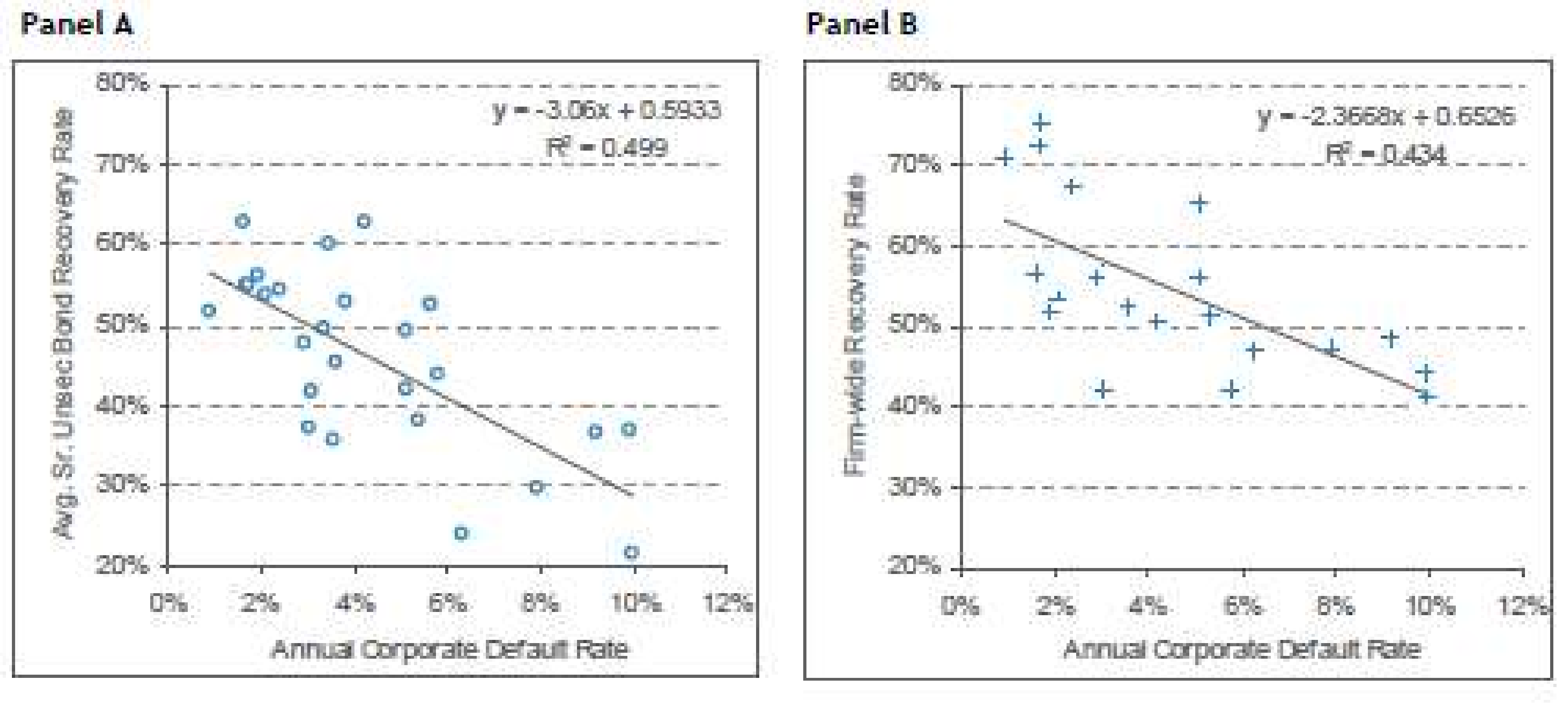
Source: Moody's (2004).



Source: Franks *et al* (2004).

PD

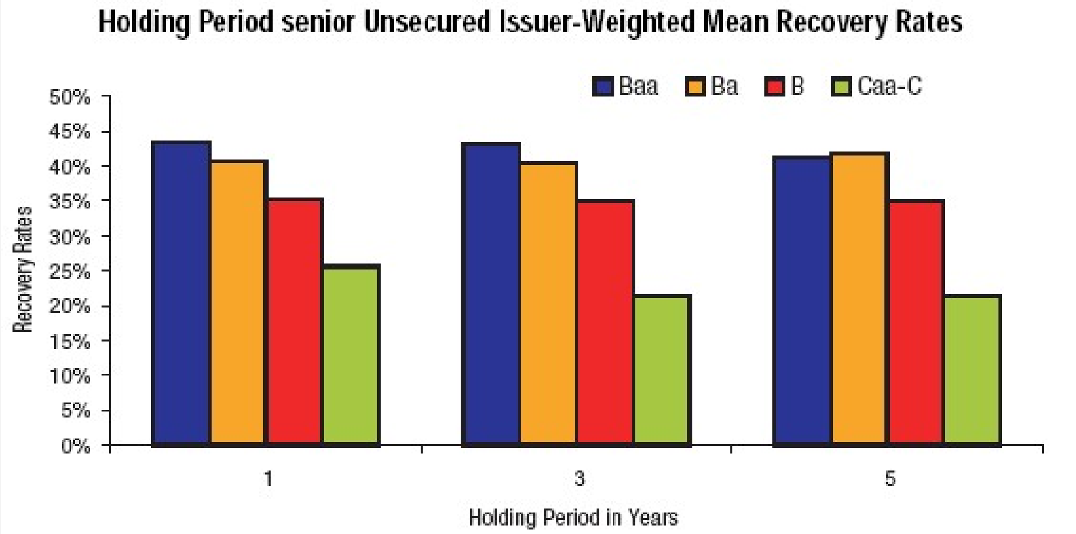
- The correlation between LGD and PD along time is high (0.66 according to S&P (2007)).



Source: Moody's (2008).

PD

- Higher ratings exhibit lower LGDs:



Average Sr. Unsecured Bond Recovery Rates by Year Prior to Default, 1982-2008[1]

	Year 1	Year 2	Year 3	Year 4	Year 5
Aaa	n.a.	3.33%[2]	n.a.	97.00%	85.55%
Aa	43.60%	40.15%	43.45%	57.61%	43.40%
A	42.48%	45.45%	44.50%	38.28%	40.95%
Baa	41.85%	44.56%	44.09%	45.44%	42.68%
Ba	48.00%	42.68%	41.58%	41.15%	41.12%
B	36.98%	35.41%	35.88%	36.91%	40.68%
Caa-C	33.96%	33.25%	33.11%	39.59%	41.94%
Investment-Grade	42.05%	44.23%	44.24%	44.57%	43.37%
Speculative-Grade	36.26%	35.71%	36.30%	38.26%	40.90%
All Rated	36.56%	36.65%	37.50%	39.52%	41.51%

1. *Issuer-weighted, based on 30-day post default market prices.*
2. *Based on three Icelandic bank defaults.*

Source: Moody's (2003; 2008).

Listed bonds

- Usually, in these exposures the LGD is measured as 1-Price (as a % of EAD) in a given period (usually 1 month after the default).
- Empirical evidence points to LGDs between 30% and 40% in non-colateralized exposures (around 60% for collateralized loans).

Average Corporate Debt Recovery Rates Measured by Post-Default Trading Prices

	ISSUER-WEIGHTED			VALUE-WEIGHTED		
LIEN POSITION	2009	2008	1982-2009	2009	2008	1982-2009
1st Lien Bank Loan	54.0%	61.7%	65.6%	56.6%	46.9%	59.1%
2nd Lien Bank Loan	16.0%	40.4%	32.8%	20.5%	36.6%	31.9%
Sr. Unsecured Bank Loan	34.5%	31.6%	48.7%	38.1%	22.8%	40.0%
Sr. Secured Bond	37.5%	54.9%	49.8%	29.5%	40.3%	48.5%
Sr. Unsecured Bond	37.7%	33.8%	36.6%	35.5%	26.2%	32.6%
Sr. Subordinated Bond	22.4%	23.7%	30.7%	17.9%	10.4%	25.0%
Subordinated Bond	46.8%	23.6%	31.3%	24.7%	7.3%	23.5%
Jr. Subordinated Bond	n.a.	n.a.	24.7%	n.a.	n.a.	17.1%

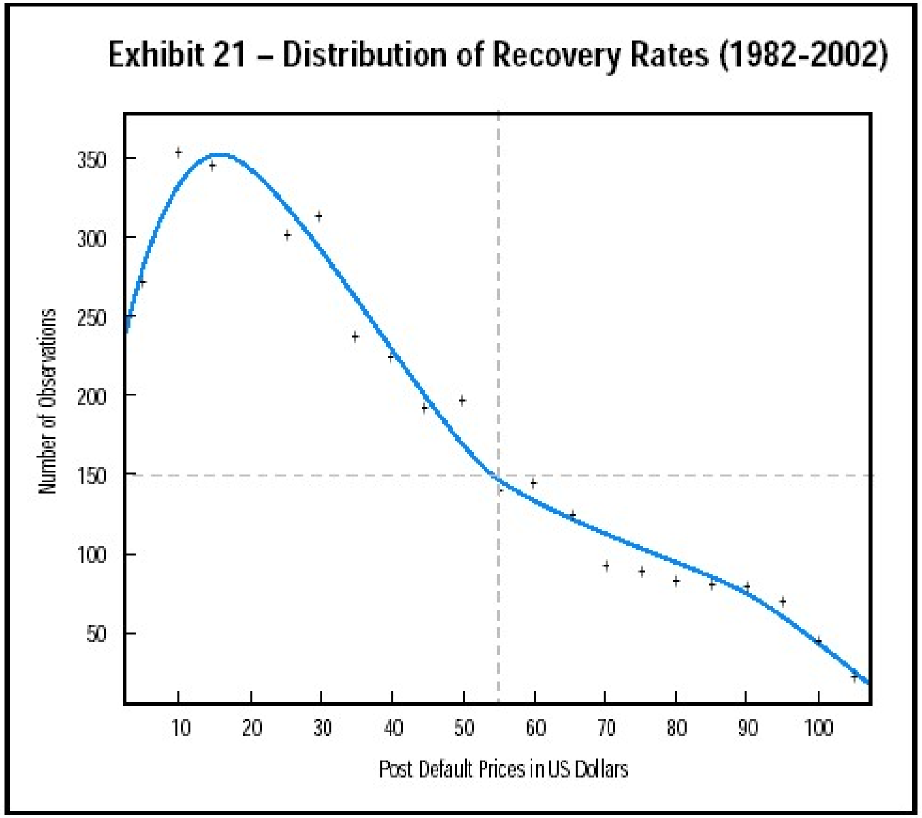
Source: Moody's (2010).

Listed bonds

Senior Unsecured Bond Recovery Rates for Financial Institution Defaults in 2008[1]

Company	Domain	Default Volume ($Mil)	Sr. Unsecured Bond Recovery
Lehman Brothers Holdings, Inc.	United States	120,164	9.3%
Kaupthing Bank hf	Iceland	20,063	4.0%
Glitnir banki hf	Iceland	18,773	3.0%
GMAC LLC	United States	17,190	69.9%
Washington Mutual Bank	United States	13,600	26.5%
Residential Capital, LLC	United States	12,315	51.7%
Landsbanki Islands hf	Iceland	12,161	3.0%
Washington Mutual, Inc.	United States	5,746	57.0%
GMAC of Canada Ltd	Canada	265	70.7%
Downey Financial Corp.	United States	200	0.5%
Fremont General Corporation	United States	166	46.0%
Luminent Mortgage Capital, Inc.	United States	131	27.3%
Triad Financial Corporation	United States	89	76.5%
Franklin Bank Corp.	United States	80	0.0%
GMAC International Finance B.V.	Netherlands	51	85.5%
Average	35.4%	Median	27.3%

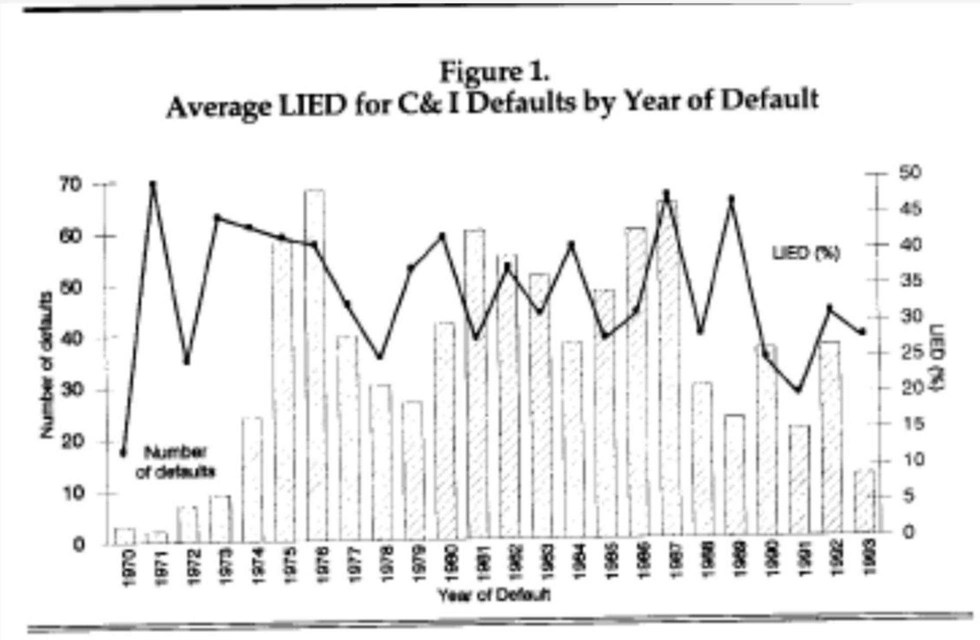
Source: Moody's (2009).



Source: Moody's (2003).

Corporate loans

- According to Renault (2006), the LGD in loans is usually lower than in bonds (mostly between 30% and 40%, as concluded in Asarnow and Edwards).



Source: Asarnow e Edwards (1995).

Recovery Ratings

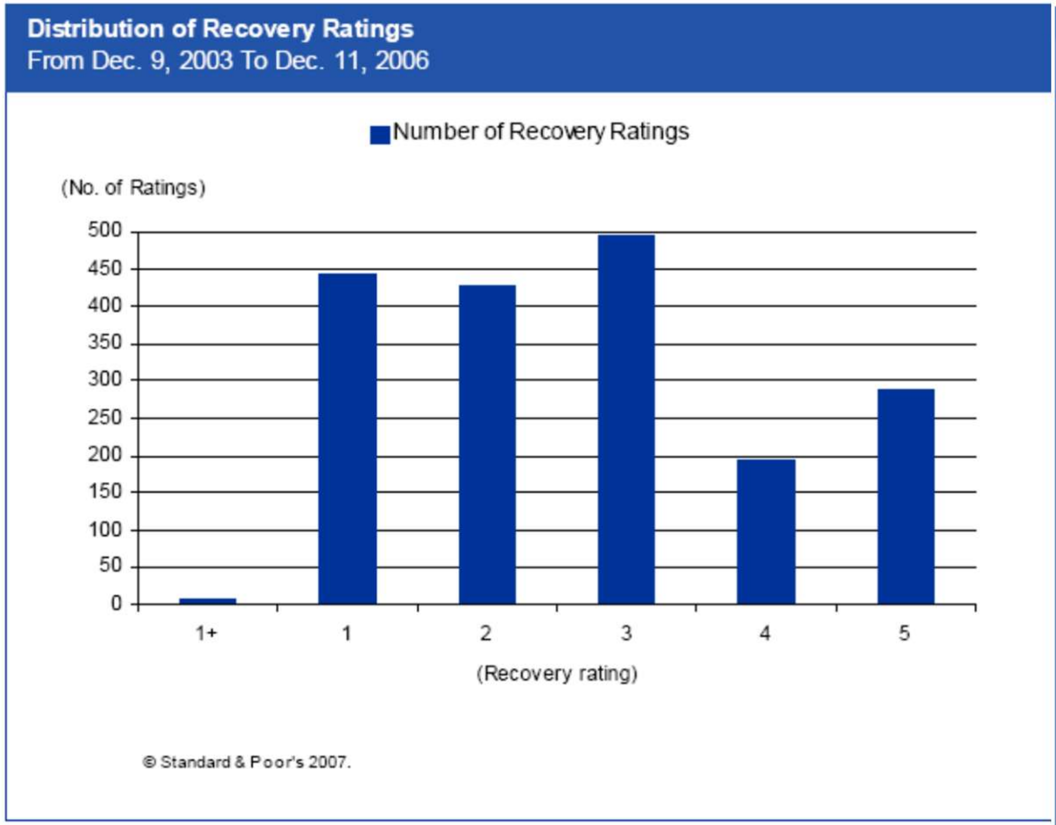
- In Dec.03, S&P introduced recovery ratings:

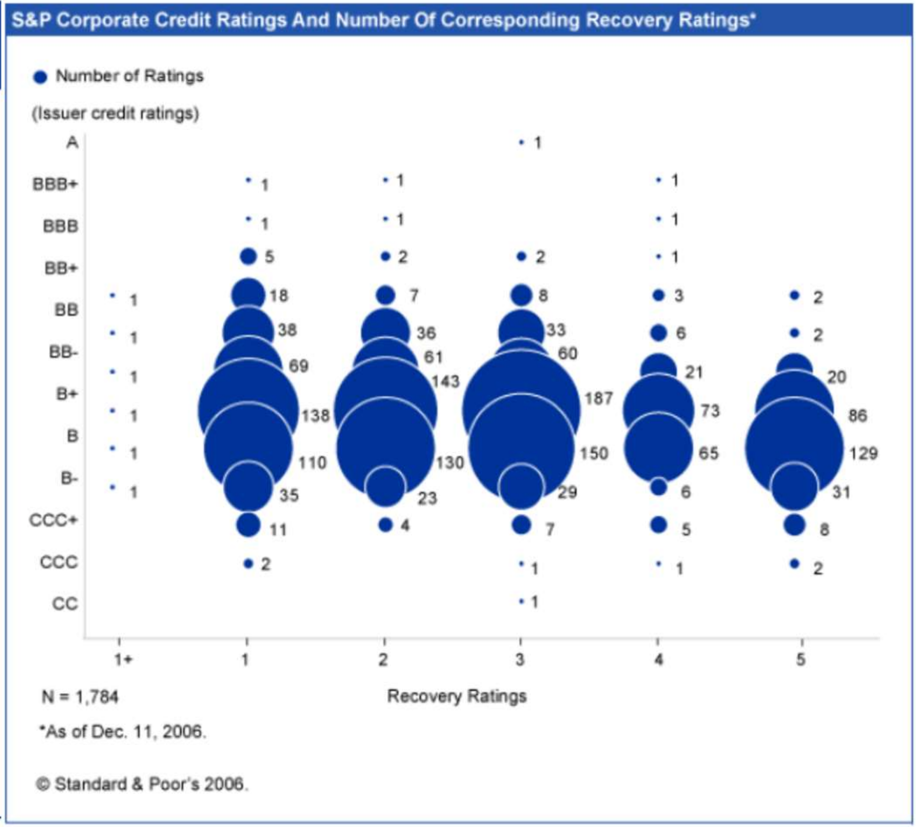
Standard & Poor's Recovery Ratings		
Rating	*Analytical description*	*Indicative recovery expectation*
1+	Highest expectation for full recovery of principal	100% of principal
1	High expectation for full recovery of principal	100% of principal
2	Substantial recovery of principal	80%-100% of principal
3	Meaningful recovery of principal	50%-80% of principal
4	Marginal recovery of principal	25%-50% of principal
5	Negligible recovery of principal	0%-25% of principal

Source: S&P (2007).

Recovery Ratings

- These ratings exhibited some dispersion and weak correlation with the issuer rating:





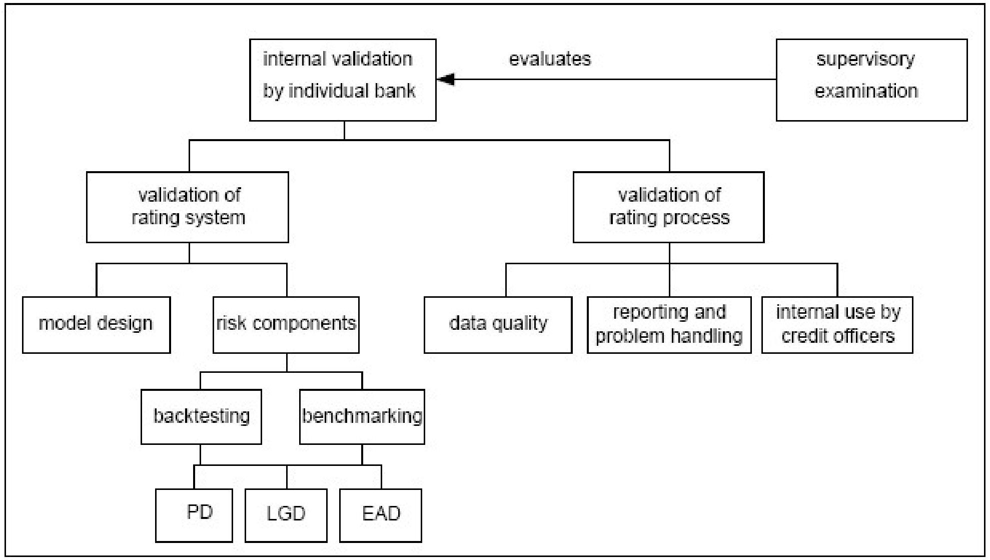
Source: S&P (2007).

5.5. Model Validation

Validation Principles in Basel II

- Each bank is the first responsible for model validation.
- The validation focus essentially on the predictive power of internal models and the utilization of internal ratings in the decision processes.
- The validation is an iterative process.
- There is no single validation method.
- The validation must include both quantitative and qualitative issues.
- The validation processes and the results must be subjected to an internal independent assessment.

Figure 1. Validation components.



Source: Basel Committee on Banking Supervision (2005)

Assessment Methodologies

- In sample:
  - (i) predictive power – statistical tests;
  - (ii) calibration:
    - comparison between estimated and observed PDs and LGDs (on average and along time);
    - comparison between EL and observed loss (on average and along time);
    - comparison between several estimates of PDs and LGDs (statistical models vs market prices' models or rating agencies).
    - Comparison between rating transition matrices (on average and along time).
- Out-of-sample:
  - assessment of the model behavior in a sample not used in its estimation.
- Stress tests:
  - assessment of the model behavior under a stress scenario.

Error Types

- Usually these tests intend to assess the model's ability to adequately order the credit counterparties, in order to minimize decision errors.

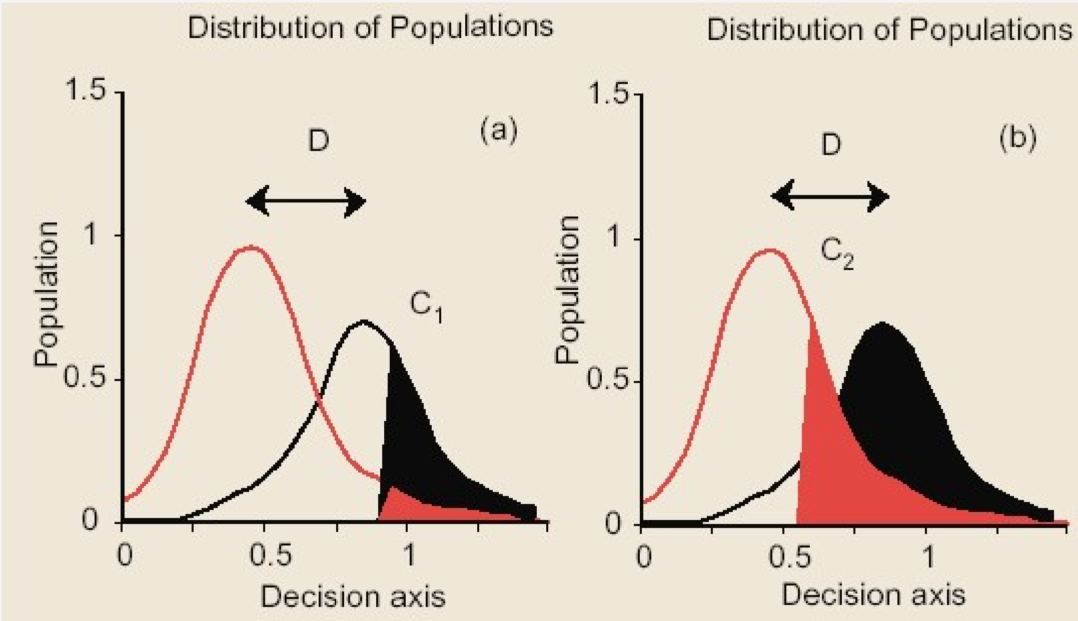
- These errors can be of two types:

  (i) type I – high rating classification to a counterparty that eventually defaults;

  (ii) type II – low rating classification to a counterparty with low credit risk.

Error Types

- Loans (red) and defaults distribution (black), with a more conservative loan granting criteria on the right hand side.
- <u>Type I error</u> – % of the non-anticipated defaults, i.e. ratio between the non-filled area under the defaults density function and the total area under the same function (larger on the LHS)
- <u>Type II error</u> – % of loans incorrectly anticipated as defaults, i.e. ratio between the filled area under the density function of total loans over the density function of defaults and the total filled area under the density function of total loans (larger on the RHS).



Source: Keenan and Sobehart (1999).

- A significant overlap between the 2 density function means that the predictive power of the model is weak.

Contingency Tables

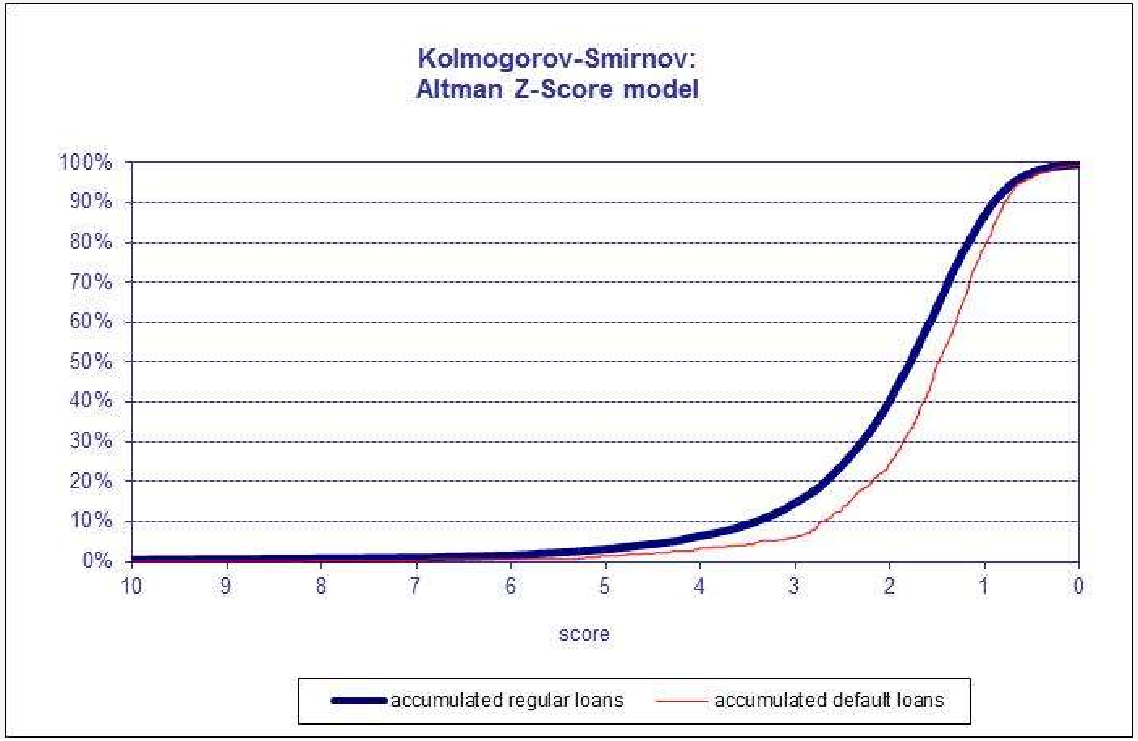
- These are used to condensate information on type I and II errors (or Confusion Matrix).

	Observed Defaults	Observed Regular
Estimated Defaults	TP (“true positive”)	FP (“false positive”)
Estimated Regular	FN (“false negative”)	TN (“true negative”)

- A usual indicator to aggregate this information is the ratio between the number of defaults correctly anticipated (TP) and the total number of defaults (TP+FN).

Kolmogorov-Smirnov

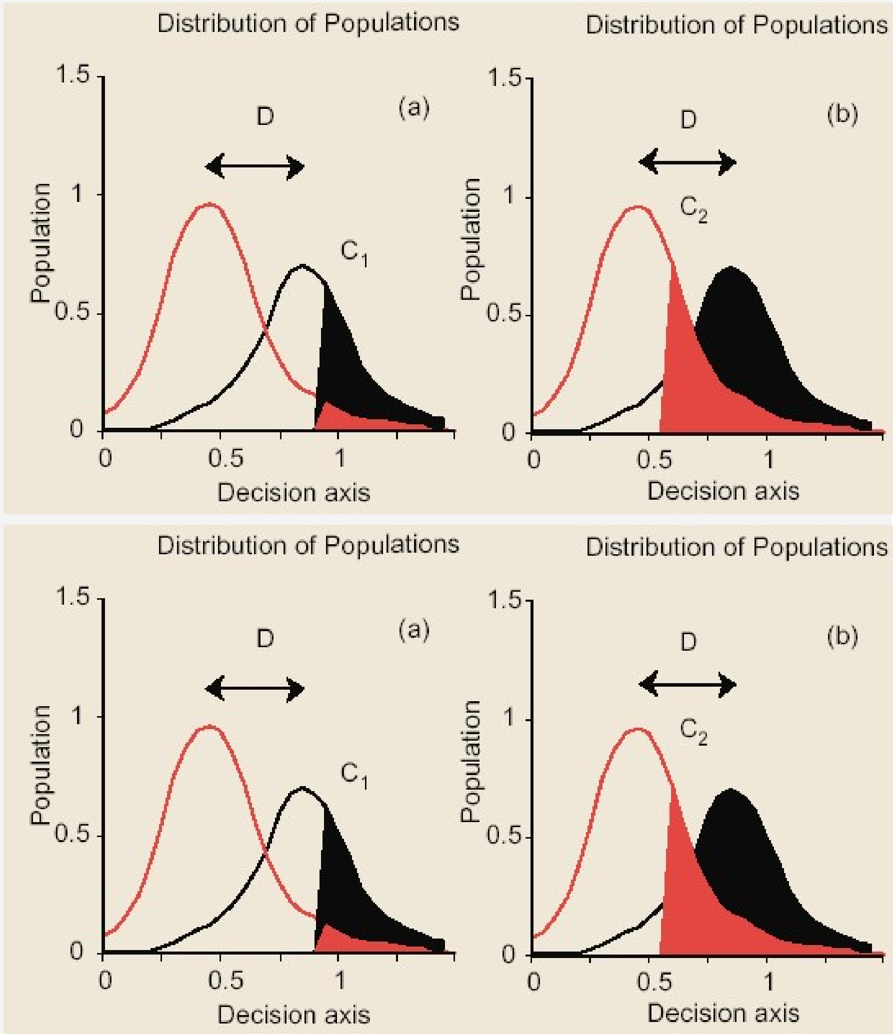
- Another relatively simple way of assessing the discriminating power of a model consists in the Kolmogorov-Smirnov indicator, that corresponds to the maximum difference between the cumulative % of regular and default loans according to the scores.



- <20 - bad
- 20-40 – fair
- 41-50 - good
- 51-60 – very good
- 61-75 - excellent
- >75 - too good to be true

Additional indicators

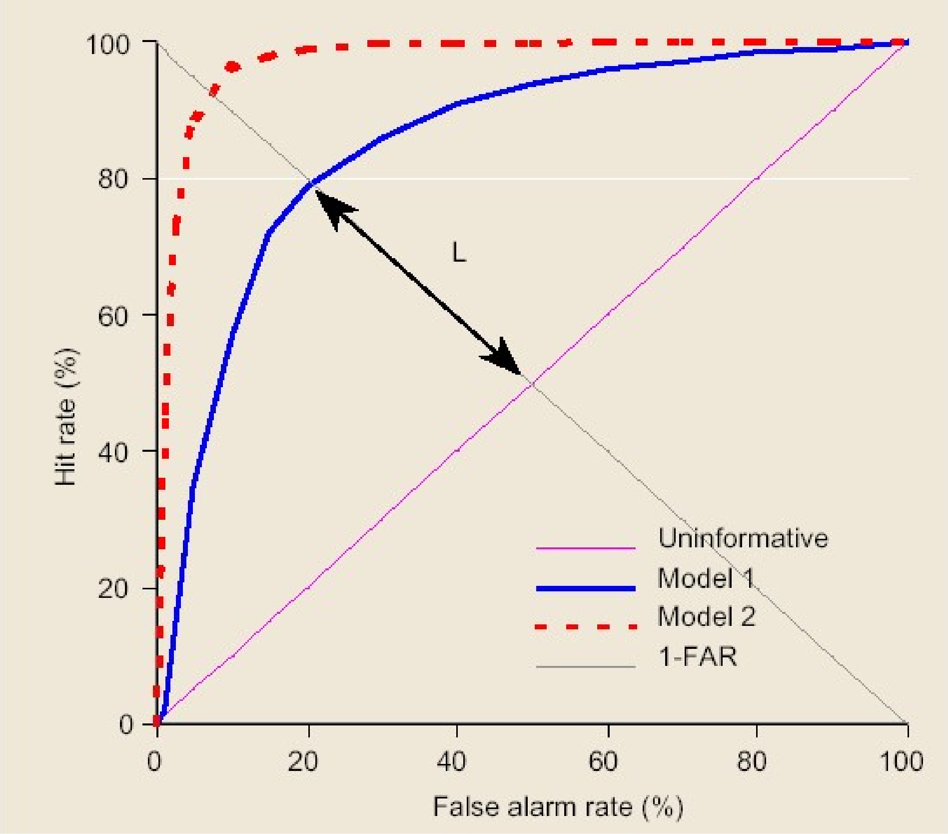
- Hit rate - % of defaults anticipated (1-type I error), i.e. the ratio between the shaded area below the defaults density function and the total number of defaults.
- False alarm rate - % of regular loans anticipated as defaults, i.e. the ratio between the number of wrongly anticipated defaults (shaded area below the density function of total loans and above the defaults' density function) and the total number of regular loans (area under the density function of total loans).
  - Differs from type II error as it is calculated as a % of the total number of loans and not the total number of anticipated defaults.



Source: Keenan and Sobehart (1999).

ROC Curve

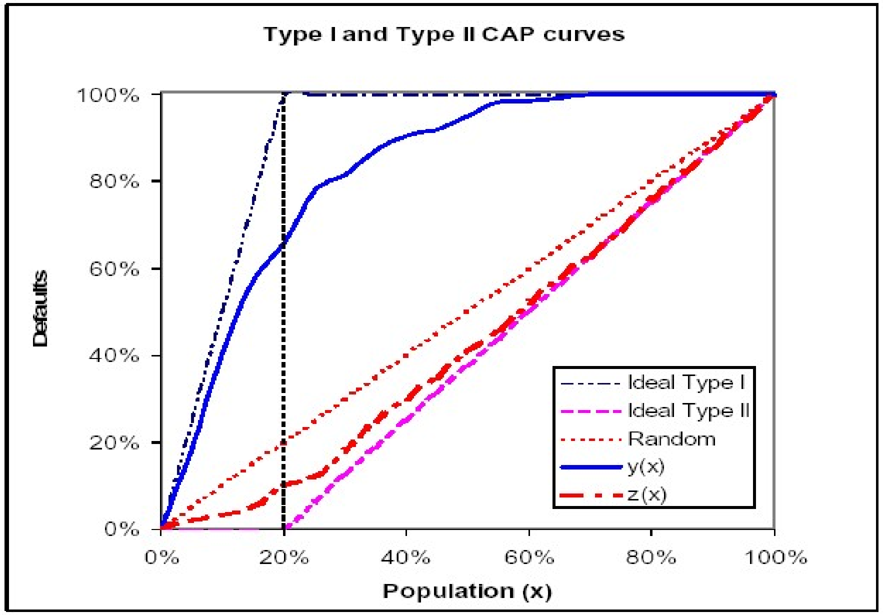
- In order to assess the ability of a rating model in anticipating defaulting companies, the ROC (*receiver operating characteristics*) curve can be used, corresponding to the (FAR, HR) points associated to different *cut-offs*.
- An optimal model must exhibit high figures for HR to any given FAR level, i.e. the ROC curve must have a pronounced curvature.



Source: Keenan and Sobehart (1999).

CAP Curve

- The predictive power of a model can also be assessed by the ability to provide the worst classifications to most of the defaults with, i.e. the ability to avoid type I errors.
- Conversely, a good model must also be able to provide the best classifications to most of the performing loans (avoiding type II errors).
- These properties can be visualized through the Cumulative Accuracy Profile (CAP) curves, aka Gini, Power or Lorenz Curves, representing the accumulated default or performing loans % as a function of the risk classification, in a decreasing order of risk.



Source: Keenan and Sobehart (1999).

Accuracy Ratios

- The ratio of the areas between the diagonal and the type I error curve, on one hand, and the area between the same diagonal and the ideal type I error curve, on the other hand, corresponds to the accuracy ratio.

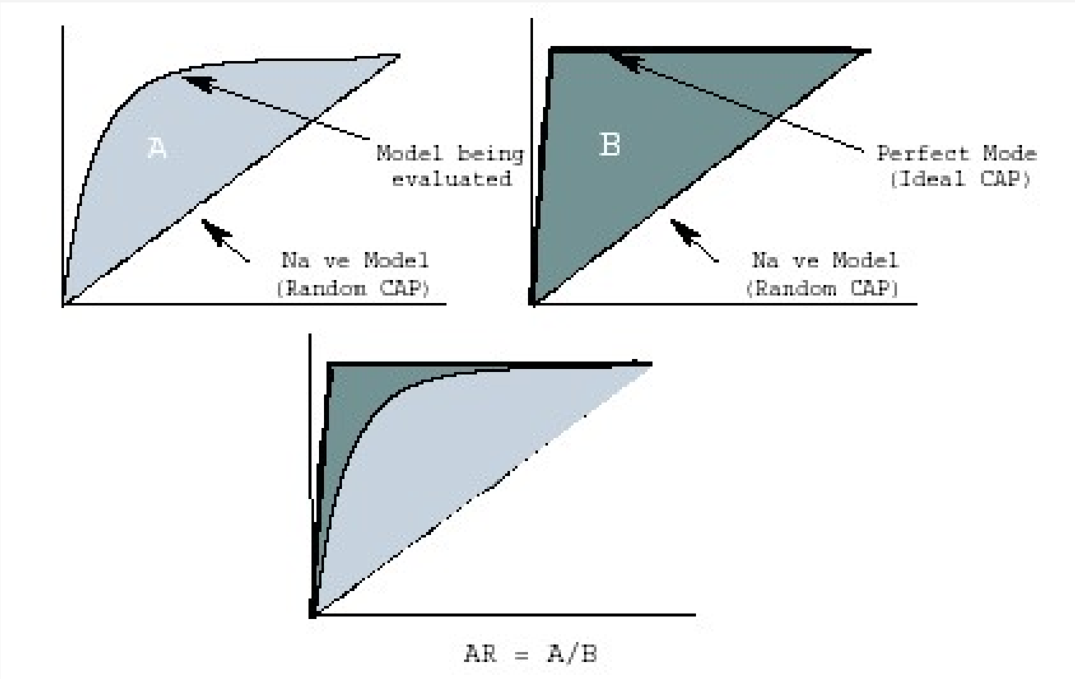


Table 1. Selected Accuracy Ratios

	In-sample AR	Validation AR
ROA	0.53	0.53
Reduced Z'-Score	0.56	0.53
Z'-Score	0.48	0.43
Hazard Model	0.59	0.58
Merton Model Variant	0.67	0.67
Moody's Model	0.76	0.73

Source: Sobehart *et al*. (2000).

Chi-Squared

- The Chi-Squared (Hosmer-Lemeshow) test allows for the assessment of the model calibration quality, comparing the observed to the estimated frequencies of default:

$$HL = \sum_{i=1}^{k} \left(r - \hat{r}\right)^2 + \left(d - \hat{d}\right)^2 \sim X^2_{(8;0.95)}$$

being r and d the relative frequencies of performing and defaulting loans in each risk class k, with ^ denoting the estimated values.

$$H_0 : r = \hat{r}; d = \hat{d}$$

rejecting the model if HL>X^2.

Transition Matrices

- The quality of a credit risk model must also be assessed through the features of the transition matrices.

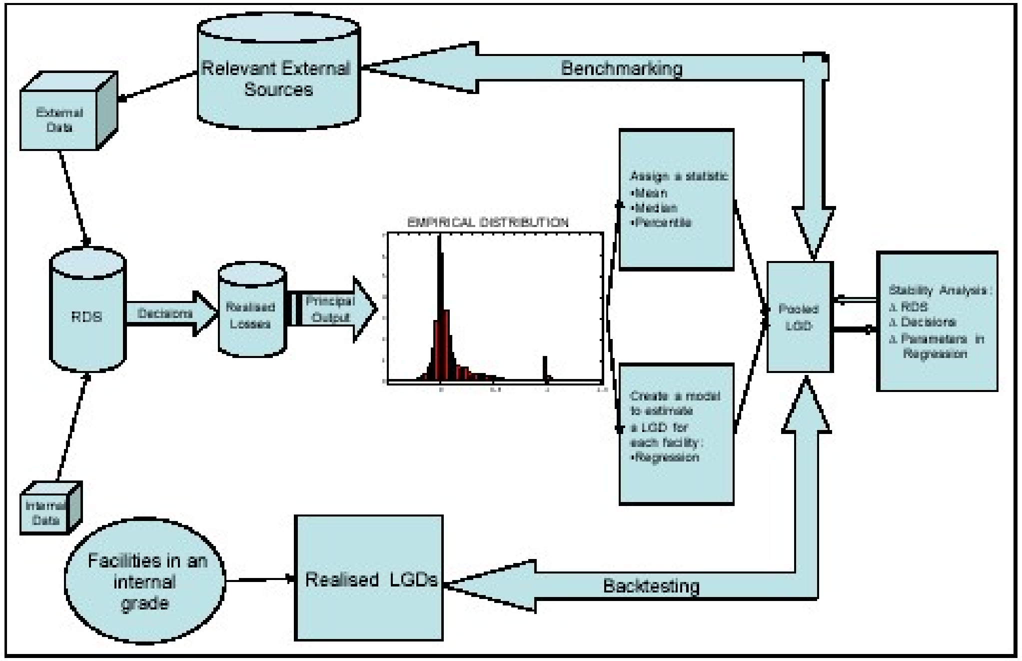
- One must expect to find the highest figures in the main diagonal and similarities between the frequency of upgrades and downgrades, with the highest transition figures near the diagonal

- The transition frequencies must also be monotonous for each side of the main diagonal, with figures close to zero for the transitions more distant to the main diagonal.

LGD Validation

- The validation of LGD estimates also requires the assessment of the models and the data used.
- The assessment must involve 3 key steps:
  - Stability analysis – impact on LGD estimates of changes in data and assumptions;
  - Comparisons between estimated LGDs and relevant external data;
  - Comparisons between observed LGDs out of sample and estimated LGDs.

Figure 10. An example of the validation process.



Source: Basel Committee on Banking Supervision (2005)