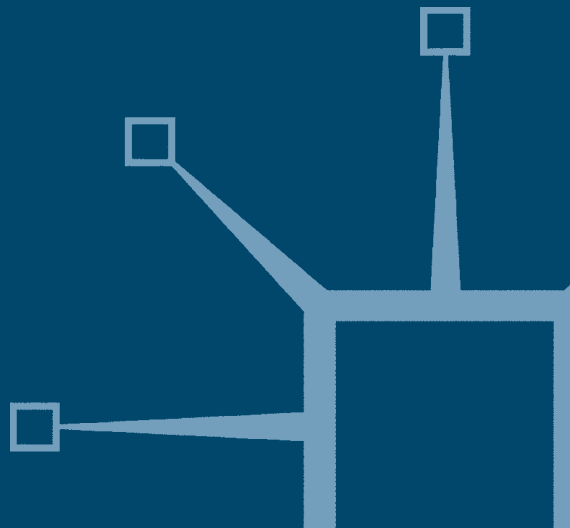


From Basel 1 to Basel 3

The Integration of State-of-the-Art
Risk Modeling in Banking Regulation

Laurent Balthazar



FROM BASEL 1 TO BASEL 3

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From Basel 1 to Basel 3: The Integration of State-of-the-Art Risk Modeling in Banking Regulation

LAURENT BALTHAZAR

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Contents

<i>List of Figures, Tables, and Boxes</i>	ix
<i>Acknowledgments</i>	xiv
<i>List of Abbreviations</i>	xv
<i>Website</i>	xix
<i>Introduction</i>	1
Part I Current Banking Regulation	
1 <i>Basel 1</i>	5
Banking regulations and bank failures: a historical survey	5
The Basel 1988 Capital Accord	16
2 <i>The Regulation of Market Risk: The 1996 Amendment</i>	23
Introduction	23
The historical context	24
Amendment to the Capital Accord to incorporate market risk	27
3 <i>Critics of Basel 1</i>	32
Positive impacts	32
Regulatory weaknesses and capital arbitrage	33
Part II Description of Basel 2	
4 <i>Overview of the New Accord</i>	39
Introduction	39
Goals of the Accord	39
Open issues	40
Scope of application	41

Treatment of participations	42
Structure of the Accord	44
The timetable	47
Summary	47
5 Pillar 1: The Solvency Ratio	49
Introduction	49
Credit risk – unstructured exposures – standardized approach	50
Credit risk – unstructured exposures – IRB approaches	58
Credit risk: securitization	63
Operational risk	73
Appendix: Pillar 1 treatment of double default and trading activities	76
6 Pillar 2: The Supervisory Review Process	89
Introduction	89
Pillar 2: the supervisory review process in action	90
Industry misgivings	93
7 Pillar 3: Market Discipline	95
Introduction	95
Pillar 3 disclosures	95
Links with accounting disclosures	96
Conclusions	99
8 The Potential Impact of Basel 2	101
Introduction	101
Results of QIS 3	101
Comments	104
Conclusions	105
Part III Implementing Basel 2	
9 Basel 2 and Information Technology Systems	109
Introduction	109
Systems architecture	109
Conclusions	112
10 Scoring Systems: Theoretical Aspects	114
Introduction	114
The Basel 2 requirements	115
Current practices in the banking sector	117
Overview of historical research	119

The data	123
How many models to construct?	126
Modelization steps	127
Principles for ratio selection	130
The logistic regression	133
Performance measures	136
Point-in-time versus through-the-cycle ratings	142
Conclusions	144
11 Scoring Systems: Case Study	145
Introduction	145
The data	145
Candidate explanatory variables	148
Sample selection	154
Univariate analysis	155
Model construction	171
Model validation	175
Model calibration	178
Qualitative assessment	179
Conclusions	181
Appendix 1: hypothesis Test for PD estimates	182
Appendix 2: comments on low-default portfolios	187
12 Loss Given Default	188
Introduction	188
LGD measures	188
Definition of workout LGD	189
Practical computation of workout LGD	190
Public studies	194
Stressed LGD	198
Conclusions	199
13 Implementation of the Accord	200
Introduction	200
Internal ratings systems	201
The quantification process	201
The data management system	202
Oversight and control mechanisms	203
Conclusions	204
 Part IV Pillar 2: An Open Road to Basel 3	
14 From Basel 1 to Basel 3	209
Introduction	209
History	209

Pillar 2	211
Basel 3	211
Conclusions	212
15 <i>The Basel 2 Model</i>	214
Introduction	214
A portfolio approach	214
The Merton model	217
The Basel 2 formula	219
Conclusions	235
16 <i>Extending the Model</i>	237
Introduction	237
The effect of concentration	237
Extending the Basel 2 framework	238
Conclusions	247
17 <i>Integrating Other Kinds of Risk</i>	248
Introduction	248
Identifying material risks	248
Quantification and aggregation	276
Typical capital composition	279
Conclusions	280
Conclusions	283
Overview of the book	283
The future	284
<i>Bibliography</i>	286
<i>Index</i>	291

List of Figures, Tables, and Boxes

FIGURES

2.1	DJIA: yearly trading volume	24
3.1	Securitization with recourse	34
3.2	Remote-origination securitization	35
4.1	Scope of application for a fictional banking group	42
4.2	Treatment of participations in financial companies	43
4.3	Treatment of participations in insurance companies	43
4.4	Treatment of participations in commercial companies	44
4.5	The three pillars	45
4.6	Solvency ratio	45
5.1	Capital using the SF	71
5.2	Capital rate using the SF	71
5.3	RWA for securitization and corporate exposures	73
5A.1	EE and EPE	77
5A.2	EPE, EE, and PFE	78
5A.3	EE, EPE, and effective EE and EPE	79
9.1	Incremental IT architecture	111
9.2	Integrated IT architecture	112
10.1	Current bank practices: rating systems	118
10.2	A decision tree	121
10.3	A neural network	121
10.4	A CAP curve	140

10.5	A ROC curve	141
11.1	Rating distribution	146
11.2	Frequency of total assets	151
11.3	Frequency of LN(Assets)	152
11.4	ROA:rating dataset	156
11.5	ROA:default dataset	156
11.6	ROA before exceptional items and taxes:rating dataset	157
11.7	ROA before exceptional items and taxes:default dataset	157
11.8	ROE:rating dataset	157
11.9	ROE:default dataset	158
11.10	EBITDA/Assets:rating dataset	158
11.11	EBITDA/Assets:default dataset	158
11.4A	ROA:rating dataset	159
11.12	Cash/ST debts:rating dataset	160
11.13	Cash/ST debts:default dataset	161
11.14	Cash and ST assets/ST debts:rating dataset	161
11.15	Cash and ST assets/ST debts:default dataset	161
11.16	Equity/Assets:rating dataset	163
11.17	Equity/Assets:default dataset	163
11.18	Equity (excl. goodwill)/Assets:rating dataset	164
11.19	Equity (excl. goodwill)/Assets:default dataset	164
11.20	Equity/LT fin. debts:rating dataset	164
11.21	Equity/LT fin. debts:default dataset	165
11.22	EBIT/Interest:rating dataset	166
11.23	EBIT/Interest:default dataset	166
11.24	EBITDA/Interest:rating dataset	166
11.25	EBITDA/Interest:default dataset	167
11.26	EBITDA/ST fin. debts:rating dataset	167
11.27	EBITDA/ST fin. debts:default dataset	167
11.28	LN(Assets):rating dataset	169
11.29	LN(Assets):default dataset	169
11.30	LN(Turnover):rating dataset	170
11.31	LN(Turnover):default dataset	170
13.1	Rating model implementation	204
15.1	Simulated default rate	215
15.2	S&P historical default rates, 1981–2003	216
15.3	Distribution of asset values	218
15.4	Loss distribution	223
15.5	Cumulative bivariate normal distribution	228
15.6	Asset correlation for corporate portfolios	229
15.7	Maturity effect	233
15.8	Loss distribution	234
16.1	Potential asset return of a BBB counterparty	241
17.1	A stylized bank economic capital split, percent	280

TABLES

1.1	A definition of capital	18
1.2	Risk-weight of assets	18
1.3	CCFs	19
1.4	PFE	20
4.1	The Basel 2 timetable	47
5.1	Pillar 1 options	49
5.2	RWA in the Standardized Approach	50
5.3	RWA of past due loans	52
5.4	CCF for the Standardized Approach	52
5.5	RWA for short-term issues with external ratings	53
5.6	Simple and comprehensive collateral approach	54
5.7	Supervisory haircuts (ten-day holding period)	55
5.8	Minimum holding period	55
5.9	Criteria for internal haircut estimates	56
5.10	Risk parameters	58
5.11	Source of risk estimations	58
5.12	RWA for Specialized Lending	60
5.13	CRM in IRBF	62
5.14	RWA for securitized exposures: Standardized Approach	66
5.15	CCF for off-balance securitization exposures	67
5.16	CCF for early amortization features	68
5.17	Risk-weights for securitization exposures under the RBA	69
5.18	The Standardized Approach to operational risk	74
5A.1	CCF for an underlying other than debt and forex instruments	79
5A.2	CCF for an underlying that consists of debt instruments	80
5A.3	Swap 1 and 2	80
5A.4	CCF multiplication	81
5A.5	Application of the double default effect	84
5A.6	Capital requirements for DVP transactions	88
6.1	CEBS high-level principles for pillar 2	93
7.1	Pillar 3 disclosures	97
8.1	Results of QIS 3 for G10 banks	102
8.2	Results of QIS 3 for G10 banks: maximum and minimum deviations	103
8.3	Results of QIS 3 for G10 banks: individual portfolio results	103
10.1	Summary of bankruptcy prediction techniques	122
10.2	Key criteria for evaluating scoring techniques	124
10.3	Bankruptcy models: main characteristics	131
10.4	Accuracy ratios	132
10.5	ROC and AR: indicative values	142
11.1	Explanatory variables	150

11.2	Ratio calculation	153
11.3	Profitability ratios: performance measures	160
11.4	Liquidity ratios: performance measures	162
11.5	Leverage ratios: performance measures	165
11.6	Coverage ratios: performance measures	168
11.7	Size variables: performance measures	170
11.8	Correlation matrix: rating dataset	172
11.9	Correlation matrix: default dataset	173
11.10	Performance of the Corporate model	176
11.11	Performance of the Midcorp model	177
11.12	Typical rating sheet	180
11.13	Impact of qualitative score on the financial rating	181
12.1	LGD public studies	195
15.1	Simulated standard deviation of DR	217
15.2	Estimated default correlation	227
15.3	Implied asset correlation	228
16.1	A non-granular portfolio	238
16.2	The concentration effect	238
16.3	The credit VAR-test	239
16.4	An average one-year migration matrix	240
16.5	Corporate spreads	243
16.6	A stylized transition matrix	244
16.7	Comparison between the Basel 2 formula and the credit VAR MTM results	245
16.8	VAR comparison between various sector concentrations	246
17.1	Benchmarking results: credit risk	251
17.2	Benchmarking results: market risk	254
17.3	Benchmarking results: operational risk	260
17.4	Benchmarking results: strategic risk	263
17.5	Benchmarking results: reputational risk	265
17.6	Benchmarking results: business risk	268
17.7	Benchmarking results: liquidity risk	270
17.8	Benchmarking results: other risk	274
17.9	Summary of benchmarking study	276
17.10	Determination of the confidence interval	277
17.11	Correlation matrix: ranges	279

BOXES

1.1	A chronology of banking regulation: 1 – 1863–1977	6
1.2	A chronology of banking regulation: 2 – 1979–99	9
2.1	The regulation of market risk, 1922–98	24
5.1	Categories of RWA	51

5.2	Calculating a haircut for a three-year BBB bond	56
5.3	Calculating adjusted exposure for netting agreements	57
5.4	Classification of exposures	59
5.5	Calculating LGD	62
5A.1	Calculating the final exposure	80
10.1	The key requirements of Basel 2: rating systems	115
10.2	Overview of scoring models	119
10.3	Data used in bankruptcy prediction models	124
10.4	Construction of the scoring model	127
10.5	Five statistical tests	136
10.6	Five measures of economic performance	138
11.1	Steps in transforming ratios	151
11.2	Estimating a PD	178
12.1	Example of calculating workout LGD	190

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Braine L'Alleud, Belgium

LAURENT BALTHAZAR

List of Abbreviations

ABA	American Bankers Association
ABCP	Asset Backed Commercial Paper
ABS	Asset Backed Securities
ADB	Asian Development Bank
AI	Artificial Intelligence
ALM	Assets and Liabilities Management
AMA	Advanced Measurement Approach
ANL	Available Net Liquidity
AR	Accuracy Ratio
BBA	British Bankers Association
BCBS	Basel Committee on Banking Supervision
BIA	Basic Indicator Approach
BIS	Bank for International Settlements
BoJ	Bank of Japan
bp	Basis Points
CAD	Capital Adequacy Directive
CAP	Cumulative Accuracy Profile
CCF	Credit Conversion Factor
CD	Certificate of Deposit
CDO	Collateralized Debt Obligation
CDS	Credit Default Swap
CEBS	Committee of European Banking Supervisors
CEM	Current Exposure Method (Basel 1988)
CI	Confidence Interval
CND	Cumulative Notch Difference

CP	Consultative Paper
CRE	Commercial Real Estate
CRM	Credit Risk Mitigation
CSFB	Credit Suisse First Boston
DD	Distance to Default
df	Degrees of Freedom
DJIA	Dow Jones Industrial Average
DR	Default Rate
DVP	Delivery Versus Payment
EAD	Exposure at Default
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciations, and Amortizations
EBRD	European Bank for Reconstruction and Development
EC	Economic Capital
ECA	Export Credit Agencies
ECAI	External Credit Assessment Institution
ECB	European Central Bank
ECBS	European Committee of Banking Supervisors
EE	Expected Exposure
EL	Expected Loss
EPE	Expected Positive Exposure
ERC	Economic Risk Capital
ETL	Extracting and Transformation Layer
FDIC	Federal Deposit Insurance Corporation
FED	Federal Reserve (US)
FSA	Financial Services Act (UK)
FSA	Financial Services Authority (UK)
GAAP	Generally Accepted Accounting Principles (US)
HVCRE	High Volatility Commercial Real Estate
IAA	Internal Assessment Approach
IAS	International Accounting Standards
ICAAP	Internal Capital Adequacy Assessment Process
ICCMCS	International Convergence of Capital Measurements and Capital Standards
IFRS	International Financial Reporting Standards
ILSA	International Lending and Supervisory Act (US)
IMF	International Monetary Fund
IMM	Internal Model Method (Basel 1988)
IOSCO	International Organization of Securities Commissions
IRBA	Internal Rating-Based Advanced (Approach)
IRBF	Internal Rating-Based Foundation (Approach)
IRRBB	Interest Rate Risk in the Banking Book
IT	Information Technology
JDP	Joint Default Probability

KRI	Key Risk Indicator
LED	Loss Event Database
LGD	Loss Given Default
LOLR	Lender of Last Resort
LT	Long Term
LTCB	Long Term Credit Bank (Japan)
M	Maturity
M&A	Mergers and Acquisitions
MDA	Multivariate Discriminant Analysis
MTM	Marked-to-Market
MVA	Market Value Accounting
NBFI	Non-Bank Financial Institution
NIB	Nordic Investment Bank
NIF	Note Issuance Facilities
NYSE	New York Stock Exchange
OCC	Office of the Comptroller of the Currency (US)
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
ORM	Operational Risk Management
ORX	Operational Riskdata eXchange
OTC	Over the Counter
P&L	Profit and Loss Account
PD	Probability of Default
PFE	Potential Future Exposure
PIT	Point-in-Time
PSE	Public Sector Entities
PV	Present Value
QIS	Quantitative Impact Studies
RAROC	Risk Adjusted Return on Capital
RAS	Risk Assessment System
RBA	Rating-Based Approach
RCSA	Risk and Control Self-Assessment
RIFLE	Risk Identification for Large Exposures
ROA	Return on Assets
ROC	Receiver Operating Characteristic
ROE	Return on Equities
RRE	Residential Real Estate
RUF	Revolving Underwriting Facilities
RW	Risk Weighting
RWA	Risk Weighted Assets
S&L	Savings and Loan (US)
S&P	Standard and Poors
SA	Standardized Approach
SEC	Securities and Exchange Commission (US)

SF	Supervisory Formula
SFBC	Swiss Federal Banking Commission
SFT	Securities Financing Transaction
SIPC	Securities Investor Protection Corporation
SL	Specialized Lending
SM	Standardized Method (Basel 1988)
SME	Small and Medium Sized Enterprises
SPV	Special Purpose Vehicle
SRP	Supervisory Review Process
ST	Short Term
TTC	Through-the-Cycle
UCITS	Undertakings for Collective Investments in Transferable Securities
UNCR	Uniform Net Capital Rule
USD	US Dollar
VAR	Value at Risk
VBA	Visual Basic Application
VIF	Variance Inflation Factor

Website

If you would like to be informed about the author's latest papers, receive free comments on Basel 2 developments, new software, updates on the book, or even to ask questions directly of the author, register freely on his website: www.creditriskmodels.com. All the workbook files that illustrate examples in this book can be freely downloaded from the website.

Introduction

Banks have a vital function in the economy. They have easy access to funds through collecting savers' money, issuing debt securities, or borrowing on the inter-bank markets. The funds collected are invested in short-term and long-term risky assets, which consist mainly of credits to various economic actors (individuals, companies, governments ...). Through centralizing any money surplus and injecting it back into the economy, large banks are the heart maintaining the blood supply of our modern capitalist societies. So, it is no surprise that they are subject to so much constraint and regulations.

But if banks often consider regulation only as a source of the costs that they have to assume to maintain their licenses, their attitudes are evolving under the pressure of two factors.

First, *risk management discipline* has seen significant development since the 1970s, thanks to the use of sophisticated quantification techniques. This revolution first occurred in the field of market risk management, and more recently credit risk management has also reached a high level of sophistication. Risk management has evolved from a passive function of risk monitoring, limit-setting, and risk valuation to a more proactive function of performance measure, risk-based pricing, portfolio management, and economic capital allocation. Modern approaches desire not only to limit losses but to take an active part in the process of "shareholder value creation," which is (or, at least, should be) the main goal of any company's top management.

The second factor is that *banking regulation* is currently under review. The banking regulation frameworks in most developed countries are currently based on a document issued by a G10 central bankers' working group (see Basel Committee on Banking Supervision, 1988, p. 28). This document, "International convergence of capital measurement and capital standards,"

was a brief set of simple rules that were intended to ensure financial stability and a level playing field among international banks. As it quickly appeared that the framework had many weaknesses, and even sometimes perverse effects, and thanks to the evolution that we mentioned above, a revised proposition saw the light in 1999. After three rounds of consultation with the sector, the last document, supposed to be the final one (often called the “Basel 2 Accord”) was issued in June 2004 (Basel Committee on Banking Supervision, 2004d, p. 239). The level of sophistication of the proposed revision is a tremendous progress by comparison with the 1988 text, which can be seen just by looking at the document’s size (239 pages against 28). The formulas used to determine the regulatory capital requirements are based on credit risk portfolio models that have been known in the literature for some years but that few banks, except the largest, have actually implemented.

Those two factors represent an exceptional opportunity for banks that wish to improve their risk management frameworks to make investments that will both match the regulators’ new expectations and, by adding a few elements, be in line with state-of-the-art techniques of shareholder value creation through risk management.

The goal of this book is to give a broad outline of the challenges that will have to be met to reach the new regulatory standards, and at the same time to give a practical overview of the two main current techniques used in the field of credit risk management: *credit scoring* and *credit value at risk*. The book is intended to be both pedagogic and practical, which is why we include concrete examples and furnish an accompanying website (www.creditriskmodels.com) that will permit readers to move from abstract equations to concrete practice. We decided not to focus on cutting-edge research, because little of it ends up becoming an actual market standard. Rather, we preferred to discuss techniques that are more likely to be tomorrow’s universal tools.

The Basel 2 Accord is often criticized by leading banks because it is said not to go far enough in integrating the latest risk management techniques. But those techniques usually lack standardization, there is no market consensus on which competing techniques are the best, and the results are highly sensitive to model parameters that are hard to observe. Our sincere belief is that today’s main objective of the sector should be the wide-spread integration of the main building blocks of credit risk management techniques (as has been the case for market risk management since the 1990s); to be efficient for everyone, these techniques need wide and liquid secondary credit markets, where each bank will be able to trade its originated credits efficiently to construct a portfolio of risky assets that offers the best risk–return profile as a function of its defined risk tolerance. Many initiatives of various banks, researchers, or risk associations have contributed to the educational and standardization work involved in the development of these markets, and this book should be seen as a small contribution to this common effort.

PART I

Current Banking Regulation

Basel 1

BANKING REGULATIONS AND BANK FAILURES: A HISTORICAL SURVEY

Before describing the Basel 1 Accord, we begin by giving a (limited) historical overview of banking regulation and bank failures, which are intimately linked, focusing mainly on recent decades. Our goal is not to be exhaustive, but to have a broad overview of the patterns of banking history helps to better understand the current state of regulation, and to anticipate its possible evolution. A study of bank failures is also very instructive in permitting a critical examination of the ability of proposed legislative adaptations to prevent systemic crises.

Should a bank run into liquidity problems, the competent authorities can, most of the time, provide the necessary temporary funds to solve the problem. But a bank becoming insolvent can have more devastating effects. If governments have to intervene it may be with taxpayers' money, which can displease their populations. Being insolvent means not being able to absorb losses, and the main means to absorb losses is through capital. This is why when regulators have tried to develop various policies, solvency ratios (that have had various definitions) have often been one of the main quantitative requirements imposed.

The history of banking regulation has been a succession of waves of deregulation and tighter policies following periods of crises. Nowadays many people think that banks in developed countries are exempt from bankruptcy risk and that their deposits are fully guaranteed, but looking at the two or three last decades this is far from evident (see Box 1.1).

Box 1.1 A chronology of banking regulation: 1 – 1863–1977

- 1863** In the US, before 1863, banks were regulated by the individual states. At that time, the government needed funds because the Civil War was weighing heavily on the economy. A new law, the National Currency Act, was voted to create a new class of banks: the “charter national banks.” They could issue their own currency if it was backed by holdings in US treasury bonds. These banks were subject to one of the first capital requirements, which was based on the population in their service area (FDIC, 2003a). Two years later, the Act was modified in the National Banking Act. The Office of the Comptroller of the Currency (OCC) was created. It was responsible for supervision of national banks, and this was the beginning of a dual system with some banks still chartered and controlled by the states, and some controlled by the OCC. This duality was the beginning of later developments that led to today’s highly fragmented US regulatory landscape.
- 1913** Creation of the US Federal Reserve (FED) as the lender of last resort (LOLR). This allowed banks that had liquidity problems to discount assets rather than being forced to sell them at low prices and suffer from consequent loss.
- 1929** Crash: the Dow Jones went from 386 in September 1929 to 40 in July 1932, the beginning of the Great Depression that lasted for ten years. Wages went down and unemployment reached record rates. As many banks were involved in stock markets, they suffered heavy losses. The population began to fear that they would not be able to reimburse their deposits, and bank “runs” caused thousand of bankruptcies. A “run” occurs when all depositors want to retrieve their money from the bank at the same time: the banks, most of whose assets are liquid and medium to long term, are not able to get the liquidity they need. Even solvent banks can then default. When such panic moves strike one single financial institution, central banks can afford the necessary funds, but in 1929, the whole banking sector was under pressure.
- 1933** In response to the crisis, the Senate took several measures. Senator Steagal proposed the creation of a Federal Deposit Insurance Corporation (FDIC), which would provide government guarantee to almost all banks’ creditors, with the goal of preventing new bank runs. Senator Glass proposed to build a “Chinese wall” between the banking and securities industries, to avoid deposit-taking institutions being hurt by any new stock market crash. Banks had to choose between *commercial* banking and *investment* banking activities: Chase National Bank and City Bank dissolved their securities business, Lehman Brothers stopped collecting deposits, JP Morgan became a commercial bank but some managers left to create the investment bank Morgan Stanley.

These famous measures are known as the Glass–Steagall Act and the separation of banking and securities business was peculiar to the US. Similar measures were adopted in Japan after the Second World War, but Europe kept a long tradition of universal banks.

- 1930s** In the 1930s and 1940s, several different solvency ratios were tried by US federal and states' regulators. Capital:deposits or capital:assets ratios were discussed, but none was finally retained at the country level because all failed to be recognized as effective solvency measures (FDIC, 2003a).
- 1944** After the war, those responsible for post-war reconstruction in Europe considered that floating exchange rates were a source of financial instability which could encourage countries to proceed towards devaluations, which then encouraged protectionism and were a brake on world growth. It was decided that there should be one reference currency in the world, which led to the creation of the *Bretton Woods* system. The price of a US dollar (USD) was fixed against gold (35 USD per ounce) and all other currencies were to be assigned an exchange rate that would fluctuate in a narrow 1 percent band around it. The International Monetary Fund (IMF) was created to regulate the system.
- 1954** In the Statement of Principles of the American Bankers Association (ABA) of that year, the use of regulatory ratios for prudential regulation was explicitly rejected (FDIC, 2003a). This illustrates the fact that until the 1980s, the regulatory framework was mainly based on a case-by-case review of banks. Regulatory ratios, which were to later become the heart of the Basel 1 international supervisory framework, were considered inadequate to capture the risk level of each financial institution. A (subjective) individual control was preferred.
- 1957** Treaty of Rome. This was the first major step towards the construction of a unique European market. It was also the first stone in the construction of an integrated European banking system.
- 1973** A pivotal year in the world economy. This was the end of the "golden 1960s." The Bretton Woods system was trapped in a paradox. As the USD was the reference currency, the US was supposed to defend the currency–gold parity, which meant having a strict monetary policy. But at the same time, they had to inject high volumes of USD into the world economy, as that was the currency used in most international payments. The USD reserves that were owned by foreign countries went from 12.6 billion USD in 1950 to 53.4 billion USD in 1970, while the US gold reserves went, over the same period, from 20 billion USD to 10 billion USD. Serious doubts arose about the capacity of the US to ensure the USD–gold parity. With the Vietnam War weighing heavily on the US deficit, President Nixon decided in 1971 to suspend the system, and the

USD again floated on the currency markets. The Bretton Woods system was officially wound up in 1973.

In the same year, the European Commission issued a new Directive that was the first true step in the deregulation of the European banking sector. From that moment, it was decided to apply “national treatment” principles, which meant that all banks operating in one country were subject to the same rules (even if their headquarters were located in another European country), which ensured a “level playing field.” However, competition remain limited because regulations on capital flows were still strict.

1974 The Herstatt crisis. The Herstatt bank was a large commercial bank in Germany, with total assets of 2 billion DEM (the thirty-fifth largest bank in the country), with an important business in foreign exchange. Before the collapse of Bretton Woods, such business was a low-risk activity, but this was no longer the case, following the transition to the floating-exchange rate regime. Herstatt speculated against the dollar, but got its timing wrong. To cover its losses, it opened new positions, and a vicious circle was launched. When rumors began to circulate in the market, regulators made a special audit of the bank and discovered that while the theoretical limit on its foreign exchange positions was 25 million DEM, the open positions amounted to 2,000 million DEM, three times the bank’s capital. Regulators ordered the bank to close its positions immediately: final losses were four times the bank’s capital and it ended up bankrupt. The day the bank was declared bankrupt, a lot of other banks had released payments in DEM that arrived at Herstatt in Frankfurt but never received the corresponding USD in New York, because of time zone difference (this has since been called the “Herstatt risk”). The whole débâcle shed light on the growing need for harmonization of international regulations.

1977 A second step in European construction of the banking sector was the new Directive establishing the principle of home-country control. Supervision of banks that were operating in several countries was progressively being transferred from the *host* country to the *home* country of the mother company.

We now interrupt our discussion of the flow of events to make a point about the situation at the end of the 1970s. The world economic climate was very bad. Between 1973 and 1981, average yearly world inflation was 9.7 percent against an average world growth of 2.4 percent (Trumbore, 2002). Successive oil crises had pushed up the price of a barrel of oil from 2 USD in 1970 to 40 USD in 1980. The floating exchange rate had created a lot of disturbance on financial markets, although that was not all bad. Volatile foreign exchange and interest rates attracted a number of non-bank financial

institutions (NBFIs) that began to compete directly against banks. At the same time, there was an important development of capital markets as an alternative source of funding, leading to further disintermediation. This was bad news for the level of banking assets – as companies were no longer dependent only on bank loans to finance themselves – but also for banking liabilities, as depositors could invest more and more easily in money market funds rather than in savings accounts. As margins went down and funding costs went up, banks began to search for more lucrative assets. The two main trends were to invest in real estate lending and in loans or bonds of developing countries that were increasing their international borrowings because they had been hurt by the oil crises.

What had traditionally been a protected and stable industry, with in many countries a legal maximum interest rate on deposits, ensuring lucrative margins, was now under fire. Through the combination of a weak economy, a volatile economic environment, and increased competition, banks were under pressure. The only possible answer was deregulation. Supervisory authorities all over the world at the end of the 1970s began to liberalize their banking sector to allow financial institutions to reorganize and face the new threat. Deregulation was not a bad thing in itself: in many countries where banking sectors were heavily protected, it was generally at the cost of inefficient financial systems that were not directing funds towards more profitable investments, which hampered growth. But the waves of deregulations were often made in a context where neither regulators nor banks' top management had the necessary skills to accompany the transition process. Deregulation, then, was a time bomb that was going to produce an important number of later crises, particularly when coupled with "asset bubbles" (see Box 1.2).

Box 1.2 A chronology of banking regulation: 2 – 1979–99

- 1979** In the US, the OCC began to worry about the amounts of loans being made to developing countries by large US commercial banks. It imposed a limit: the exposure on one borrower could not be higher than 10 percent of its capital and reserves.
- 1980** This was the beginning of the US Savings and Loans (S&L) crises that would last for ten years. S&L institutions developed rapidly after 1929. Their main business was to provide long-term fixed-rate mortgage loans financed through short-term deposits. Mortgages had a low credit risk profile, and interest rate margins were comfortable because a federal law limited the interest rate paid on deposits. But the troubled economic environment of the 1970s changed the situation. In 1980, the effective interest rate obtained on a mortgage portfolio was around

9 percent while the inflation was at 12 percent and government bonds at 11 percent. Money market funds grew from 9 billion USD in 1978 to 188 billion USD in 1981, which meant that S&L faced growing funding problems. To solve this last issue, the regulators removed the maximum interest rate paid on deposits. But to compensate for more costly funding, S&L had to invest in riskier assets: land, development, junk bonds, construction ...

- 1981** Seeing the banking sector deteriorating, US regulators for the first time introduced a capital ratio at the federal level. Federal banking agencies required a certain level of leverage ratio on primary capital (basically equity and loan loss reserves: total assets).
- 1982** Mexico announced that it was unable to repay its debt of 80 billion USD. By 1983, twenty-seven countries had restructured their debt for a total amount of 239 billion USD. Although the OCC had tried to impose limits on concentration (see entry for 1979), a single borrower was defined as an entity that had its own funds to pay the credit back. But as public entities' borrowers were numerous in developing countries, consolidated exposures on the public sector for many banks were far beyond the 10 percent limit (some banks had exposure equal to more than twice their capital and reserves). The US regulators decided not to oblige banks to write off all bad loans directly, which would have led to numerous bankruptcies, but the write-off was made progressively. It took ten years for major banks completely to clear their balance sheets of those bad assets.
- 1983** The US International Lending and Supervisory Act (ILSA) unified capital requirements for the various bank types at 5.5 percent of total assets and also unified the definition of capital. It highlighted the growing need for international convergence in banking regulation. The same year, the Rumasa crisis hit Spain. The Spanish banking system had been highly regulated in the 1960s. Interest rates were regulated and the market was closed to foreign banks. In 1962, new banking licenses were granted: as the sector was stable and profitable, there were a lot of candidates. But most of the entrepreneurs that got licenses had no banking experience, and they often used the banks as a way to finance their industrial groups, which led to a very ineffective financial sector. Regulation of doubtful assets and provisions was also weak (Basel Committee on Banking Supervision, 2004a), which gave a false picture of the sector's health. When the time for deregulation came, the consequences were again disastrous. Between 1978 and 1983 more than fifty commercial banks (half of the commercial banks at the time) were hit by the crisis. Small banks were the first to go bankrupt, then bigger ones, and in 1983 the Rumasa group was severely affected. Rumasa was a holding that controlled twenty banks and several other financial institutions, and the crisis looked likely to have systemic implications. The crisis was

finally resolved by the creation of a vehicle that took over distressed banks, absorbed losses with existing capital (to penalize shareholders), then received new capital from the government when needed. There were also several nationalizations. The roots of the crisis were economic weakness, poor management, and inadequate regulation.

1984 The Continental Illinois failure – the biggest banking failure in American history. With its 40 billion USD of assets, Continental Illinois was the seventh largest US commercial bank. It had been rather a conservative bank, but in the 1970s the management decided to implement an aggressive growth strategy in order to become Number One in the country for commercial lending. It reached its goal in 1981: specific sectors had been targeted, such as energy, where the group had significant expertise. Thanks to the oil crises, the energy sector had enjoyed strong growth, but at the beginning of the 1980s, energy prices went down, and banks involved in the sector began to experience losses. An important part of Continental's portfolio was made up of loans to developing countries, which did not improve the situation. Continental began to be cited regularly in the press. The bank had few deposits because of regulation that prevented it from having branches outside its state, which limited its geographic expansion. It had to rely on less stable sources of funding and used certificates of deposits (CDs) on the international markets. In the first quarter of 1984, Continental announced that its non-performing loans amounted to 2.3 billion USD. When stock and rating analysts began to downgrade the bank, there was a run because the federal law did not protect international investors' deposits. The bank lost 10 billion USD in CDs in two months. This posed an important systemic threat as 2,299 other banks had deposits at Continental (of which 179 might have followed it into bankruptcy if it had been declared insolvent following a FDIC study). It was decided to rescue the bank: 2 billion USD was injected by the regulators, liquidity problems were managed by the FED, a 5.3 billion USD credit was granted by a group of twenty-four major US banks, and top management was laid off and replaced by people chosen by the government. The total estimated cost of the Continental case was 1.1 billion USD, not a lot considering the bank's size, thanks to the effectiveness of the way the regulators had handled the case.

1985 In Spain, following the crises of 1983, a new regulation was issued: criteria of experience, independence, and integrity were introduced for the granting of new banking licenses; the rules for provisions and doubtful assets were reviewed; and the old regulatory ratio of equity:debt was abandoned in favor of a ratio of equity:assets weighted in six classes by function of their risk level, three years before Basel 1.

In Europe, a White Paper from the European Commission was issued on the creation of a Single Market. Concerning the banking sector, there

was a call for a unique banking license and a regulation made from the home country and universally recognized.

- 1986** The riskier investments and funding problems that began to affect the S&L in 1980 steadily eroded the financial health of the sector. In 1986, a modification of the fiscal treatment of mortgages was the final blow. The federal insurer of S&L went bankrupt: 441 S&Ls became insolvent, with total assets of 113 billion USD; 553 others had capital ratios under 2 percent for 453 billion USD assets. Together, they represented 47 percent of the S&L industry. To deal with the crisis, the regulators assured depositors that their deposits would be guaranteed by the federal state (to avoid bank runs) and they bought the distressed S&Ls to sell them back to other banking groups. Entering the 1990s, only half of the S&Ls of the 1980s were still there.

In the UK, the Bank of England was supervising banks while the securities market was largely self-regulating. The Financial Service Act (FSA) (1986) changed the situation by creating separated regulatory functions. UK regulation was thus deviating from the continental model to become closer to the US post-Glass–Steagall framework.

- 1987** Crash on the stock exchange. The Dow Jones index lost 22.6 percent in one day (Black Monday) – its maximum one-day loss in the 1929 crash had been 12.8 percent. (But this was far from being as severe as in 1929, as five months later the Dow Jones had already recovered.) In Paris, the CAC40 lost 9.5 percent and in Tokyo the Nikkei lost 14.9 percent. Japan had fared relatively well in the 1970s crises. In 1988 its GDP growth was 6 percent with inflation at only 0.7 percent. Its social model was very specific (life-long guaranteed jobs in exchange for flexibility for wages and working time). The Japanese management style was cited as an exemplar and Japanese companies, including banks, rapidly developed their international presence. Japanese stock and real estate markets were growing, and there were strong American pressures to oblige Japan to open its markets, or even to guarantee some market share for American companies on the domestic market (in the electronic components industry, for example).

- 1988** A major Directive on the construction of a unique European market for the financial services industry: the Directive on the Liberalization of Capital Flows.

Calls for the creation of unified international legislation were finally resolved by a concrete initiative. The G10 countries (in fact eleven countries: Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the UK, and the US) and Luxembourg created a committee of representatives from central banks and regulatory authorities at a meeting at the Bank for International Settlements (BIS) in Basel, Switzerland. Their goal was to define the role of the different regulators in the case of international banking groups, to ensure that such groups

were not avoiding supervision through the creation of holding companies and to promote a fair and level playing field. In 1988, they issued a reference paper that, a few years later, became the basis of national regulation in more than 100 countries: the 1988 Basel Capital Accord.

1989 Principles defined in 1985 in the European Commission White Paper were incorporated in the second Banking Directive. It ignored the need for national agreement on opening branches in other countries; it reaffirmed the European model of universal banking (no distinction between securities' firms and commercial banks); it divided the regulatory function between home country (solvency issues) and host country (liquidity, advertising, monetary policy). The home-country principle allowed the UK to maintain its existing dual system.

1991 In Japan, the first signs of inflation appeared in 1989. The Bank of Japan (BoJ) had reacted by increasing interest rates five times during 1990. The stock market began to react and had lost 50 percent by the end of 1990, and the real estate market began also to show signs of weaknesses, entering a downward trend that would last for ten years. In 1991 the first banking failures occurred, but only small banks were concerned and people were still optimistic about the economy's prospects. The regulators adopted a "wait-and-see" policy.

In Norway, the liberalization of the 1980s had led the banks to pursue an aggressive growth strategy: between 1984 and 1986 the volume of credit granted grew 12 percent per year (inflation-adjusted). In 1986, the drop in oil prices (since oil was one of the country's main exports) hit the economy. The number of bankruptcies increased rapidly and loan losses went from 0.47 percent in 1986 to 1.6 percent in 1989. The deposits insurance system was used to inject capital into the first distressed banks, but in 1991 the three largest Norwegian banks announced important loan losses and an increased funding cost. The insurance fund was not enough to help even one of those banks: the government had to intervene to avoid a collapse of the whole financial system. It injected funds in several banks and eventually controlled 85 percent of all banking assets. The total net cost (funds invested minus value of the shares) of the crisis was estimated at 0.8 percent of GDP at the end of 1993.

Sweden followed a similar pattern: deregulation, high growth of lending activity (including mortgage loans), and an asset price bubble on the real estate market. In 1989 the first signs of weakness appeared: over the following two years the real estate index of the stock exchange dropped 50 percent. The first companies that suffered were NBFIs that had granted a significant level of mortgages. Due to legal restrictions they were funded mainly through short-term commercial paper, and when the panic gripped the market, they soon ran out of liquidity. The crisis was then propagated to banks because they had important exposures to finance companies without knowing what they had in their balance sheets (because they were competing, little information was

disclosed by finance companies). Loan losses reached 3.5 percent in 1991, then 7.5 percent in the last quarter of 1992 (twice the operating profits of the sector). Real estate prices in Stockholm collapsed by 35 percent in 1991 and by 15 percent in the following year. By the end of 1991, two of the six largest Swedish banks needed state support to avoid a financial crisis.

The crisis in Switzerland from 1991 to 1996 was also driven by a crash of the real estate market. The Swiss Federal Banking Commission (SFBC) estimated the losses at 42 billion CHF, 8.5 percent of the credits granted. By the end of the crisis, half of the 200 regional banks had disappeared.

1992 The Basel Banking Accord, which was not mandatory (it is not legally binding) was transposed into the laws of the majority of the participating countries (Japan requested a longer transition period).

1994 The Japanese financial sector situation did not improve as expected. Bankruptcies hit large banks for the first time – two urban cooperative banks with deposits of 210 billion JPY. The state guaranteed deposits to avoid a bank run and a new bank was created to take over and manage the doubtful assets.

1995 The *Jusen* companies in Japan had been founded by banks and other financial companies to provide mortgages. But in the 1980s they began to lend to real estate developers without having the necessary skills to evaluate the risks of the projects. In 1995 the aggregated losses of those companies amounted to 6.4 trillion JPY and the government had to intervene with taxpayers' money.

In the same year, Barings, the oldest merchant bank in London, collapsed. The very specific fact about this story, in comparison to the other failures, is that it can be attributed to only one man (and to a lack of rigorous controls). The problem here was not credit risk-related, but market and operational risk-related (matters not covered by the 1988 Basel Accord). Nick Leeson was the head trader in Singapore, controlling both the trading and the documentation of his trades, which he could then easily falsify. He made some operations on the Nikkei index that turned sour. To cover his losses, he increased his positions and disguised them so that they appeared to be client-related and not proprietary operations. In 1995 the positions were discovered, although the real amount of losses was hard to define as Leeson had manipulated the accounts. The Bank of England was called upon to rescue the bank. After some discussion with the sector, it was decided that although it was large, Barings was not causing systemic risk. It was decided not to use taxpayers' money to cover the losses, which were finally evaluated at 1.4 billion USD, three times the capital of the bank.

1997 In Japan, Sanyo Securities, a medium-sized securities house, filed an application for reorganization under the Insolvency Law. It was not

considered to pose systemic problems, but its bankruptcy had a psychological impact on the inter-bank market. The inter-bank market quickly became dry and three weeks later Yamaichi Securities, one of the four largest securities houses in Japan, became insolvent. There were clearly risks of a systemic crisis, so the authorities provided the necessary liquidity and guaranteed the liabilities. Yamaichi was finally declared bankrupt in 1999.

- 1998** The bankruptcy of the Long-Term Credit Bank (LTCB) was the largest in Japan's history: the bank had assets for 26 trillion JPY and a large derivatives portfolio. An important modification of the legislation, the "Financial Reconstruction Law," followed.
- 1999** Creation of the European Single Currency. With an irrevocably fixed exchange rate, the money and capital markets moved into the euro.

This short and somewhat selective overview of the history of banking regulation and bank failures allows us to get some perspective before examining current regulation in more detail, and the proposed updating. We can see that, at least, an international regulation answers to a growing need for both a more secure financial system and some standards to develop a level playing field for international competition. Boxes 1.1 and 1.2 show that the use of capital ratios to establish minimum regulatory requirements has been tested for more than a century. But only after the numerous banking crises of the 1980s was it imposed as an international benchmark. Until then, even the banking sector was in favor of a more subjective system where the regulators could decide which capital requirements were suited for a particular bank as a function of its risk profile. We shall see later in the book that the Basel 2 proposal incorporates both views, using a solvency ratio as in the Basel Accord 1988 and at the same time putting the emphasis on the role of the regulators through the pillar 2 (see Chapter 6).

Boxes 1.1 and 1.2 also showed that even if each banking crisis had its own particularities, some common elements seemed to be recurrent: deregulation phases, the entry of new competitors which caused an increased pressure on margins, an asset prices boom (often in the stock market or in real estate), and tighter monetary policy. Often, solvency ratios do not act as early warning signals – they are effective only if accounting rules and legislation offer an efficient framework for early recognition of loan losses and provisions. Then, the current trend leading to the development of international accounting standards (IASs) can be considered positive (although some principles such as those contained in IAS 39 that imposed a marked-to-market (MTM) valuation of all financial instruments, have been largely rejected by the European financial sector because of the volatility created).

Researchers have often concluded that the first cause of bankruptcy in most cases has been bad management. Of course, internal controls are the first layer of the system. Inadequate responses by the regulators to the first signs of a problem often worsen the situation. In addition to the simple determination of a solvency ratio, banking regulators and central banks (which in a growing number of countries are integrated in a single entity) have a large toolbox to monitor and manage the financial system: macro-prudential analysis (monitoring of the global state of the economy through various indicators), monetary policy (for instance, injecting liquidity into the financial markets in periods of trouble), micro-prudential regulation (individual control of each financial institution), LOLR measures, communication to the public to avoid panics and to the banking sector to help them manage a crisis, and in several countries monitoring of payment systems.

Considering a little further the role of LOLR, we might wonder whether it is possible for big banks to fail. We have seen that when the bankruptcy of a bank was a risk of a systemic nature, central banks often rescued the bank and guaranteed all its liabilities. Has the expression “too big to fail” some truth? When should regulators intervene and when should they let the bank go bankrupt? There is a consensus among regulators that liquidity support should be granted to banks that have liquidity problems but that are still solvent (Padoa-Schioppa, 2003). But in a period of trouble, it is often hard to distinguish between banks that will survive after temporary help and those that really are insolvent. The reality is that regulators decide on a case-by-case basis and do not assure the market in advance that they will support a bank, in order to prevent moral hazard issues (if the market was sure that a bank would always be helped in case of trouble, it would remove all the incentives to ensure that the bank was safe before dealing with it).

If one thing is clear from Boxes 1.1 and 1.2, it is that “banks can go bankrupt.” There is often a false feeling of complete safety about the financial systems of developed countries. Recent history has shown that an adequate regulatory framework is essential, as even Europe and the US may have to face dangerous banking crises in the future. We have to think only a little to find potential stress scenarios: a current boom in the US real estate market that may accelerate and then explode; terrorist attacks causing a crash in the stock market; the heavy concentration in the credit derivatives markets that could threaten large investment banks; growing investments in complex structured products whose risks are not always appreciated by investors ...

THE BASEL 1988 CAPITAL ACCORD

The “International convergence of capital measurement and capital standards” (Basel Committee on Banking Supervision, 1988) document was as we saw the outcome of a Committee working group of twelve countries’

central banks' representatives. It is not a legally binding text as it represents only recommendations, but members of the working group were morally charged to implement it in their respective countries. A first proposition from the Committee was published in December 1987, and then a consultative process was set up to get feedback from the banking sector. The Accord focuses on *credit risk* (other kinds of risks are left to the purview of national regulators) by defining capital requirements by the function of a bank's on- and off-balance sheet positions. The two stated main objectives of the initiative were:

- To strengthen the *soundness and stability* of the international banking system.
- To diminish existing sources of *competitive inequality* among international banks.

The Committee's proposals had to receive the approbation of all participants, each having a right of veto. The Basel 1 framework was thus a set of rules fully endorsed by participants. To reach consensus, there were some options that were left to national discretion, but the impact was not material on the way the solvency ratio was calculated. The rules were designed to define a *minimum capital level*, but national supervisors could implement stronger requirements. The Accord was supposed to be applied to internationally active banks, but many countries applied it also at national bank level.

The main principle of the solvency rule was to assign to both on-balance and off-balance sheet items a weight that was a function of their estimated risk level, and to require a capital level equivalent to 8 percent of those weighted assets. Thus, the main innovations of this ratio compared to the others that had been tested earlier was that it differentiated the assets by function of their *assumed risk* and also incorporated requirements for off-balance sheet items that had grown significantly in the 1980s with the development of derivatives instruments.

The first step in defining the capital requirement was to determine what could be considered as *capital* (Table 1.1). The Committee recognized two classes of capital by function of its quality: Tier 1 and Tier 2. Tier 2 capital was limited to a maximum 100 percent of Tier 1 capital. Goodwill had then to be deducted from Tier 1 capital and investments in subsidiaries had to be deducted from the total capital base. Goodwill was deducted because it was often considered as an element whose valuation was very subjective and fluctuating and it generally had a low value in the case of the liquidation of a company. The investments in subsidiaries that were not consolidated were also deducted to avoid several entities using the same capital resources. The Committee was divided on the question of deduction of all banks' holdings

Table 1.1 A definition of capital

Tier 1	<ul style="list-style-type: none"> – Paid-up capital – Disclosed reserves (retained profits, legal reserves ...)
Tier 2	<ul style="list-style-type: none"> – Undisclosed reserves – Asset revaluation reserves – General provisions – Hybrid instruments (must be unsecured, fully paid-up) – Subordinated debt (max. 50% Tier 1, min. 5 years – discount factor for shorter maturities)
Deductions	<ul style="list-style-type: none"> – Goodwill (from Tier 1) – Investments in unconsolidated subsidiaries (from Tier 1 and Tier 2)

of capital issued by other banks to prevent the “double-gearing” effect (when a bank invests in the capital of another while the other invests in the first bank capital at the same time, which artificially increases the equity). The Committee did not retain the deduction, but it has since been applied in several countries by national supervisors.

When the capital was determined, the Committee then defined a number of factors that would weight the balance sheet amounts to reflect their assumed risk level. There were five broad categories (Table 1.2).

Table 1.2 Risk-weight of assets

%	Item
0	<ul style="list-style-type: none"> – Cash – Claims on OECD central governments – Claims on other central governments if they are denominated and funded in the national currency (to avoid country transfer risk)
20	<ul style="list-style-type: none"> – Claims on OECD banks and multilateral development banks – Claims on banks outside OECD with residual maturity <1 year – Claims on public sector entities (PSE) of OECD countries
50	<ul style="list-style-type: none"> – Mortgage loans
100	<ul style="list-style-type: none"> – All other claims: claims on corporate, claims on banks outside OECD with a maturity >1 year, fixed assets, all other assets ...

So, for instance, if a bank buys a 200 EUR corporate bond on the capital market, the required capital to cover the risk associated with the operation would be:

$$200 \text{ EUR} \times 100\% \text{ (the weight for a claim on a corporate)} \\ \times 8\% = 16 \text{ EUR}$$

Finally, the Committee also defined weighting schemes to be applied to off-balance sheet items. Off-balance sheet items can be divided in two broad categories:

- First, there are engagements that are similar to unfunded credits, which could transform assets should a certain event occur (for instance, the undrawn part of a credit line that will be transformed into an on-balance sheet exposure if the client uses it, or a guarantee line for a client that will appear in the balance sheet if the client defaults and the guarantee is called in).
- Second, there are derivatives instruments whose value is a function of the evolution of the underlying market parameters (for instance, interest rate swaps, foreign exchange contracts ...).

For the first type of operations, a number of Credit Conversion Factors (CCFs) (Table 1.3) are applied to transform those off-balance sheet items into their on-balance equivalents. These “on-balance equivalents” are then treated as the other assets. The weights of these CCFs are supposed to reflect the risk in the different operations, or the probability that the events that would transfer them into on-balance sheet items may occur.

Table 1.3 CCFs

%	Item
0	– Undrawn commitments with an original maturity of max. 1 year
20	– Short-term self-liquidating trade-related contingencies (e.g. a documentary credit collateralized by the underlying goods)
50	– Transaction-related contingencies (e.g. performance bonds) – Undrawn commitments with an original maturity > 1 year
100	– Direct credit substitutes (e.g. general guarantees of indebtedness ...) – Sale and repurchase agreements – Forward purchased assets

For instance, if a bank grants a two-year revolving credit to another OECD bank of 200 EUR, and the other bank uses only 50 EUR, the weighting would be:

$$\begin{aligned}
 & 50 \text{ EUR} \times 20\% \text{ (risk-weight for OECD bank)} + 150 \text{ EUR} \\
 & \quad \times 50\% \text{ (CCF for the undrawn part of credit lines } > 1 \text{ year)} \\
 & \quad \times 20\% \text{ (risk-weight for OECD bank)} = 25
 \end{aligned}$$

25 EUR of risk-weighted assets (RWA) would lead to a capital requirement of:

$$25 \text{ EUR} \times 8\% = 2 \text{ EUR}$$

For the second type of operation, a first treatment was proposed in the 1988 Accord, but the current methodology is based on a 1995 amendment. For derivatives contracts, the risk can be decomposed into two parts:

- The *current replacement cost*. This is the current market value (or model value if not available) of the position.
- The *potential future exposure* (PFE) (Table 1.4), which expresses the risk of the variation of the current value as a function of the value of market parameters (interest rates, equities ...).

The sum of the two is the credit-equivalent amount of the derivatives contract. But current replacement cost is considered only if it is positive (otherwise it is taken as if it were 0) because a negative amount signifies that the bank is the debtor of its counterpart, which means that there is no credit risk. The PFE applies to the notional amount of the contract and is a function of the operation type and of the remaining maturity.

Table 1.4 PFE

Residual maturity	Interest rate (%)	Exchange rate and gold (%)	Equity (%)	Precious metal (%)	Other commodities (%)
≤1 year	0.0	1.0	6.0	7.0	10.0
1–5 years	0.5	5.0	8.0	7.0	12.0
≥ 5 years	1.5	7.5	10.0	8.0	15.0

For instance, if a bank has concluded a three-year interest rate swap with another OECD bank, on a notional amount of 1,000 EUR whose market value is currently 10 EUR, the credit-equivalent would be:

$$10 \text{ EUR (MTM value)} + 1,000 \text{ EUR} \times 0.5\% \text{ (PFE)} = 15 \text{ EUR}$$

The required regulatory capital would be:

$$15 \text{ EUR} \times 20\% \text{ (risk-weight for OECD bank)} \\ \times 8\% = 0.24 \text{ EUR}$$

Finally, the 1995 update introduced a better recognition for *bilateral netting agreements*. Those contracts between two banks create a single legal obligation, covering all relevant transactions, so that the bank would have either a claim to receive or an obligation to pay only the net sum of the positive and negative MTM values of individual transactions in the event that one of the banks fails to perform due to any of the following: default, bankruptcy,

liquidation, or similar. It then reduces the effective credit risk associated with those derivatives contracts by mitigating the potential exposure. The current exposure is taken into account on a net basis (if positive). The PFE is adapted by the following formula:

$$0.4 + 0.6 \times \text{NGR}$$

where NGR is the ratio of the netted MTM value (set to zero if negative) to the gross positive MTM values. For instance, two banks *A* and *B*, having signed a bilateral netting agreement, could have the following contracts (from bank *A*'s perspective):

Contract	Notional (EUR)	CCF (%)	MTM (EUR)
1	1,000	1.0	+100
2	2,000	5.0	-30
3	3,000	6.0	-40

The capital requirements for bank *A* would be calculated as follows:

$$\text{NGR} = 30 \text{ EUR (netted MTM of } 100 - 30 - 40) / 100 \text{ EUR (sum of positive MTM)} = 0.3$$

$$\text{PFE (without netting)} = (1,000 \times 1\% + 2,000 \times 5\% + 3,000 \times 6\%) = 290 \text{ EUR}$$

$$\text{PFE (corrected for netting)} = (0.4 + 0.6 \times 0.3) \times 290 \text{ EUR} = 168.2 \text{ EUR}$$

$$\text{Credit-equivalent} = 30 \text{ EUR (net current exposure)} + 168.2 \text{ EUR} = 198.2 \text{ EUR}$$

$$\text{RWA} = 198.2 \text{ EUR} \times 20\% \text{ (if bank } B \text{ is an OECD bank)} = 39.64 \text{ EUR}$$

$$\text{Capital requirement} = 39.64 \text{ EUR} \times 8\% = 3.17 \text{ EUR}$$

This method can be used at the counterparty level or at a sub-portfolio level (the determination of NGR).

To end this review of the Basel 1988 Accord, a few words are needed on the recognition of *collateral* and *guarantees*. A few words should be enough because in the absence of international consensus (due to the very different practices in collateral management and in historical experience of collateral recovery values), they were recognized to a very limited extent. The only collateral types that were considered were cash and securities issued by OECD central governments and specified multilateral development banks.

The part of the loan covered by such collateral received the weight of the issuer (e.g. 0 percent for a loan secured by US treasury notes). The guarantees given by OECD central governments, OECD public sector entities, and OECD banks are recognized in a similar way (substitution of the risk-weight). In addition, guarantees of banks outside the OECD for loans with a residual maturity inferior to one year received a 20 percent weight.

The Regulation of Market Risk: The 1996 Amendment

INTRODUCTION

Commercial banking (taking deposits and granting loans) and *investment banking* (being active on securities markets for clients and for the banks' proprietary activity) expose banks to different types of risk. While commercial banks have very illiquid portfolios and are exposed to systemic risk – which means that they need a broad capital base made up of long-term instruments – securities firms fund themselves mainly via Repos (borrowing cash using securities as collateral) and usually have very liquid assets, which means that they can have more volatile and short-term capital instruments. Banking regulations have historically been very different for both types of firms, and the regulators themselves were often different entities. But today the frontier between the two activities has narrowed as more and more banks have become very active in both fields. The increased competition and the internationalization of the industry has also highlighted the need for universal and uniform rules, and in this sense the creation of the market risk capital rules were a natural extension of the 1988 Basel working group's initial work.

We give first a broad picture in this chapter of the historical developments of market risk regulation prior to the 1996 Market Risk Amendment. Then we review briefly the main features of the new regulation.

THE HISTORICAL CONTEXT

Box 2.1 shows the development of market risk regulation.

Box 2.1 The regulation of market risk, 1922–98

- 1922** Before 1933, US securities markets were largely self-regulated. In 1922, the New York Securities Exchange (NYSE) was already imposing capital requirements on its members.
- 1933** After the 1929 stock market crash, the Glass–Steagall Act divided the industry into commercial banks (bearing essentially credit risk) and securities firms (also called investment banks, bearing essentially market risk) (see Chapter 1). In 1933, the Securities Act improved the quality of disclosed information on publicly offered securities on the primary market.
- 1934** The US Securities Exchange Act was passed to ensure that brokers and dealers were really acting in the interest of their clients and created the Securities and Exchange Commission (SEC) as the primary regulator of the US securities market.
- 1938** The Securities Exchange Act was modified to allow the SEC to impose its own capital requirements on securities firms.
- 1969** From 1966, there was an important increase in trading volumes on the NYSE, as illustrated by Figure 2.1, showing the Dow Jones Industrial Average (DJIA) from 1960 to 1974.

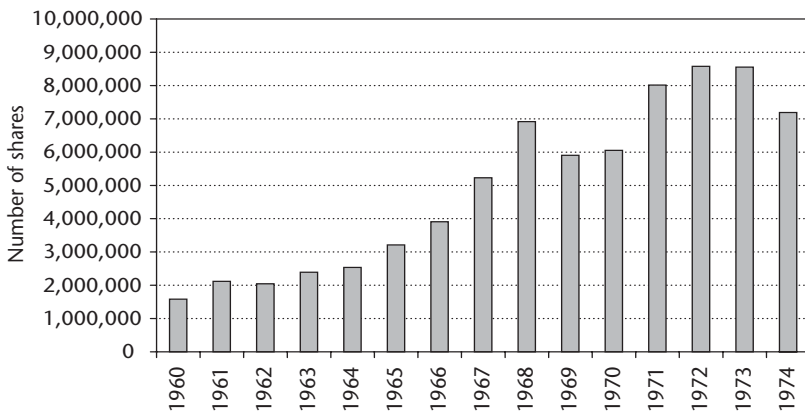


Figure 2.1 DJIA: yearly trading volume

Securities firms were not prepared and had a lot of back-office problems. This led to “paperwork crises.” The NYSE had to decrease the number of trading hours and even closed one day per week. In 1969, while securities firms had started to invest heavily to face this problem, the trading volume decreased and the exponential growth was over. As a consequence, revenues went down while costs went up; twelve companies went bankrupt and seventy were forced to merge with others. In response, the US Congress founded the Securities Investor Protection Corporation (SIPC) to insure the accounts of securities firms’ clients.

1975 The SEC implemented the Uniform Net Capital Rule (UNCR), whose main target was to ensure that securities firms had enough liquid assets to reimburse their clients in case of any problem.

1980s In the 1970s and 1980s, European and US banks came to carry more and more market risk. In Europe, the collapse of Bretton Woods and the economic crises (see Chapter 1) led to much more volatile exchange and interest rates. The increased competition following deregulation also pushed the banks to invest in new businesses, and they turned to investment banking. In the US, the Glass–Steagall Act was being undermined as exchange rate activities were allowed for commercial banks (the Act preceded the collapse of the fixed-exchange rate system), and international commercial banks became active in investment banking outside the US domestic market. At the same time, securities firms were increasingly active on Over The Counter (OTC) derivatives markets, which are less liquid (which meant they were now also facing credit risk).

This highlighted the growing need for international rules that could be applied to all types of banks: the main reasons were the need for a more secure financial system and a more level playing field.

1986 In the UK, as in continental Europe, there had been no distinction between commercial banks and investment banks. In 1986, the Financial Services Act (FSA) changed this by establishing separated regulatory functions.

1989 In Europe, the second Banking Coordination Directive that harmonized European regulatory frameworks was issued. It fixed the principle of home-country supervision which allowed continental banks to pursue investment banking activities in the UK while the UK could maintain a separate regulatory framework for its non-bank securities firms.

- 1991** The Basel Committee began to discuss with the International Organization of Securities Commissions (IOSCO) how to develop a common market risk framework. At the European level, people were also working on such an initiative, with the goal of creating a new Capital Adequacy Directive (CAD) to incorporate market risk. The European regulators hoped that the two initiatives could be completed simultaneously.
- 1993** The CAD and Basel-IOSCO amendments were very similar. The new CAD was issued because Europe had fixed 1992 as a deadline for reaching agreement on significant Single Market legislation. Unfortunately, the Basel-IOSCO initiative ran into trouble because the adoption of the proposal would have meant that the SEC had to abandon its UNCR, which determined capital for securities' firms, in favor of weaker requirements. A study of the SEC showed that it would have translated globally into a capital release of more than 70 percent for the US securities' firms sector (see Holton, 2003).
- After the failure of the joint proposal, the Basel Committee released a package of proposed amendments to the 1988 Accord. Banks were to identify a "trading book" where market risk was mainly concentrated and capital requirements had to be calculated using a crude Value At Risk (VAR) measure (we shall discuss VAR models on p. 29). The simple VAR model proposed recognized hedging but not diversification. Comments received on the proposal were very negative as banks had already been using more advanced VAR models for some years, and it was considered a backward step.
- 1994** JP Morgan launched its free Riskmetrics service, intended to promote the use of VAR among the firm's institutional clients. The package included technical documentation and a covariance matrix for several hundred key factors updated daily on the Internet.
- 1995** An updated proposition of the Basel Committee was issued, proposing the use of a more advanced standard VAR model and, more importantly, allowing banks to use their internal VAR models to compute capital requirements (if they satisfied a set of quantitative and qualitative criteria).
- 1996** After having received the comments of the sector, the final text was issued. The same year, the European Commission released a new Capital Adequacy Directive "CAD 2", that was similar to the Basel proposal.
- 1998** The new market risk rules were incorporated in most national legislation.

AMENDMENT TO THE CAPITAL ACCORD TO INCORPORATE MARKET RISK

In the Basel Committee document, market risk was defined as “the risk of losses in on- and off-balance sheet positions arising from movements in market prices.” The risks concerned were:

- The interest rate risk and equities risk in the *trading book* (see below).
- The foreign exchange risk and commodities risk *throughout the bank*.

The trading book is the set of positions in financial instruments (including derivatives and off-balance sheet items) held for the purpose of:

- Making short-term profits due to the variation in prices.
- Making short-term profits from brokering and/or market-making activities (the bid–ask spread).
- Hedging other positions of the trading book.

All positions have to be valued at MTM. The bank has then to calculate the capital requirements for credit risk under the 1988 rules on all on- and off-balance sheet positions excluding debt and equity securities in the trading book and excluding all positions in commodities, but including positions in OTC derivatives in the trading book (because these are less liquid instruments).

To support market risk, a new kind of capital was eligible: *Tier 3 capital*. The Market Risk Amendment recognizes short-term subordinated debts as capital instruments, but they are subject to some constraints:

- They must be unsecured and fully paid-up.
- They must have an original maturity of at least two years.
- They must not be repayable before the agreed repayment date (unless with the regulators’ approval).
- They must be subject to a lock-in clause which stipulates that neither interest nor principal may be paid if this would mean that the bank’s capital would fall below the minimum capital requirements.
- Tier 3 is limited to 250 percent of the Tier 1 capital allocated for market risk, which means that at least 28.5 percent of market risk capital is supported by Tier 1 capital.

Market risk is thus defined as the risk coming from only a part of a bank’s on- and off-balance sheet positions. The underlying philosophy is

to differentiate assets held to maturity from assets held for the purpose of a short-term sale. For instance, bonds that are bought for a few weeks in order to speculate on quick prices movements bear risks if the market moves in a direction that was not expected. Conversely, loans are usually held to maturity: even if interest rates go up, which causes the theoretical MTM value of the loan to decrease, if the bank keeps the loan on its balance sheet and if the debtor does not default before maturity, the interest rate move will not have translated in an actual loss for the bank (if on the liabilities side the funding was matched with the loan-amortizing profile, which is the role of the assets and liabilities management (ALM) department). The amendment requires the bank to define a trading book where the short-term positions in interest rates and equities are identified. Regarding foreign exchange and commodities risks, they are of course not offset by the fact that the underlying instruments are held to maturity. This explains why the market risk capital requirements for them apply throughout the bank, and not only on a limited trading book.

We have also seen that the Basel 1996 text recognizes other forms of capital because market risk is essentially a short-term risk and most positions can be cut easily as they are liquid. Short-term subordinated debt can to some extent be a valuable capital instrument.

The most striking innovation of the Accord update is the way that the required capital is calculated. There are two main options: the *Standardized Approach* and the *Internal Models Approach*. The first bases the requirements on some standard rules and formulas, as in the 1988 Accord for credit risk. The second, however, bases the capital requirements on the bank's proprietary internal models – the so-called VAR models.

Standardized Approach

In this framework, capital requirements for interest rate and equity positions are designed to cover two types of risks: specific risks and general risks. *Specific* risks are defined as movements in market value of the individual security owing to factors related to the individual issuer (rating downgrade, liquidity tightening ...). *General* risks are the risks of loss arising from changes in market interest rates, or from general market movements in the case of equities.

For specific risk, interest rate-sensitive instruments receive a risk-weight by function of their type (government securities, investment grade, speculative grade, or unrated) and their maturity. There is no benefit from offsetting positions except in the same issue. For general risk, securities are then categorized into several buckets by function of their maturity and another capital requirement is estimated, this time integrating some recognition of long and short positions in the same currency.

For equities, in a nutshell, each net individual position in an equity or index receives an 8 percent capital requirement for specific risk (or 4 percent at a national regulator's discretion if the portfolio is estimated to be sufficiently liquid and diversified). For general risk, the net position is calculated as the sum of long and short positions in all the equities of a national market. The result represents the amount at risk to general market fluctuations and receives a risk-weight of 8 percent.

For foreign exchange risks and commodities risks, there is no distinction between general and specific risks. The bank has to measure the net position in each currency, and the greater of the sum of net short positions or the sum of long positions receives an 8 percent risk-weight. The net position in gold is also subject to the 8 percent ratio. For commodities, two basic approaches are available, the simplest being a capital requirement of 15 percent on net positions. But we can notice that, for both risk types, the use of internal models are authorized (under certain conditions) and are even mandatory if those activities are important ones for the bank.

Finally, we can mention the fact that the 1996 Amendment has a specific chapter on the treatment of options. It is recognized that their risk is hard to estimate and two approaches of increasing complexity are proposed. The more advanced approach uses the Greeks (measures of sensitivities of option prices to underlying factors). The Delta is used to convert options in equivalent positions in the underlying asset, which permits calculating the capital requirements as explained above. Gamma and Vega risks are subject to specific capital requirements, thereby recognizing the "non-linear" risk component of options.

Internal Models Approach

In this framework, banks are allowed to use their own VAR model to calculate their capital requirements. We will not detail how market risk VAR models are constructed because it would take an entire book to do so, and a lot of excellent references are already available (see, for instance, Holton, 2003). However, we shall show how to construct credit risk VAR models later in this book (Chapter 15). The general philosophy can be summarized as follows:

- Each position is first valued with a *pricing model* (for instance, an option can be valued using the well-known Black–Scholes formula).
- Then the underlying *risk parameters* are simulated: interest rates, exchange rates, equities values, implied volatilities ... One can define the statistical distribution of each risk parameter and correlation between the different risk factors and generate correlated pseudo-random outcomes

(parametric VAR), or use historical time series and select randomly observations in the datasets collected (historical VAR).

- At each simulation, the generated outcomes of the *risk drivers* are injected in the pricing models and all positions are re-evaluated (note that simpler implementations of VAR models rely on analytical solutions rather than Monte Carlo simulations, but they cannot handle complex derivatives products).
- Thousands of simulations are done, which allows us to simulate a whole distribution of the *potential future values*.
- Various risk *metrics* can then be derived such as average value, standard deviation, percentiles ...

To be allowed to use its own internal VAR model, the bank must fulfill a range of qualitative and quantitative criteria. The main *qualitative* requirements are that:

- The model should be implemented and tracked by an independent unit.
- There should be frequent back-testing of model results against actual outcomes.
- The VAR model must be integrated into day-to-day risk management tools and daily reports should be reviewed by senior management that have the authority to reduce positions.
- The model construction and underlying assumptions should be fully documented.

The main *quantitative* requirements are that:

- VAR must be computed daily.
- The regulatory capital is the maximum cumulative loss on ten trading days at the 99th percentile one-tailed confidence level multiplied by a factor of 3 or 4 (at national discretion, depending on the quality of the model and of the back-testing results).
- Banks' datasets should be updated not less frequently than every three months.
- Banks will be allowed to use correlations within broad risk categories (interest rate, exchange rate, equity prices, commodity prices ...).
- Banks' models must capture the unique risks associated with options (non-linear risks).

To be complete, we need to mention the fact that VAR models, as any risk models, get their share of criticism in the industry. They are said to have a lot of drawbacks (summarizing risk in an over-simplistic single number, being highly dependent on underlying assumptions ...). Some of these are true, others not. But VAR models are indubitably widely used, recognized by regulators, and have at least greatly contributed to a better understanding and a better diffusion of market risk management issues. In our view this last benefit alone makes them worthwhile.

Critics of Basel 1

In this chapter, we give a short overview of the positive impacts and the weaknesses of the 1988 Basel Capital Accord.

POSITIVE IMPACTS

Despite a lot of criticism, the Basel 1 Accord was successful in many ways. The first and incontestable achievement of the initiative was that it created a *worldwide benchmark* for banking regulations. Designed originally for internationally active banks of the G10 countries, it is now the basis of the inspiration for banking regulations in more than 100 countries and is often imposed on national banks as well. Detractors will say that it does not automatically produce a level playing field for banks, which was one of the Accord targets, because banks with different risk profiles can end up with the same capital requirement. But, at least, international banks are now facing a uniform set of rules, which avoids them having to discuss with each national regulator what the correct capital level should be for conducting the same business in many different countries. Additionally, banks of different countries competing on the same markets have equivalent regulatory capital requirements. That is clearly an improvement in comparison with the situation before 1988.

The introduction of different risk-weights for different assets' classes, although not reflecting completely the true risks of banks' credit portfolios, is a clear improvement on the previous regulatory ratios that were used in some countries – such as equity:assets or equity:deposits ratios.

Has the Basel 1 Accord succeeded in making the banking sector a safer place? A lot of research has been carried out on the subject (see, for instance,

Jackson, 1999), but the answer is still unclear. The capital ratios of most banks indeed increased at the beginning of the 1990s (the capital ratios of the large G10 banks went from an average of 9.3 percent in 1988 to 11.2 percent in 1996), and bank failures diminished (for instance, yearly failures of FDIC-insured banks in the US went from 280 in 1988 to fewer than 10 a year between 1995 and 2000). But to what extent this amelioration of the situation is attributable to Basel 1 or to other factors (such as better economic conditions) is still an open question. But even without empirical evidence, one can reasonably think that the capital ratio has forced banks under the 8 percent value to get some fresh capital (or to decrease their risk exposures) and that the G10 initiative has contributed to a greater focus and a better understanding of the risks associated with banking activities.

REGULATORY WEAKNESSES AND CAPITAL ARBITRAGE

Aside from the merits that we have emphasized above, we have to recognize that the Basel 1988 Accord has a lot of deficiencies, which are only increasing as time passes, bringing a constant flow of innovations in financial markets. Since the 1990s, research on credit risk management-related topics have brought tremendous innovations in the way that banks handle their risk. Quantification techniques have allowed sophisticated banks to make continuously more reliable and precise estimates of their internal economic capital needs. Economic capital (EC), as opposed to the regulatory capital that is required by the regulating bodies, is the capital needed to support the bank's risk-taking activities as estimated by the bank itself. It is based on the bank's internal models and risk parameters. The result is that when a bank estimates that its economic capital is above the regulatory capital level, there is no problem. But if the regulatory capital level is higher than economic capital, it means that the bank has to maintain a capital level in excess of what it estimates as an adequate level, thereby destroying shareholder value. The response of sophisticated banks is what is called "capital arbitrage." This means making an arbitrage between regulatory and economic capital to align them more closely – it can be done by engaging in new operations that consume more economic than regulatory capital. As long as these new operations are correctly priced, they will increase the returns to the shareholders. Capital arbitrage in itself is not a bad thing, as it allows banks to correct the regulatory constraints' weaknesses that are recognized even by the regulators themselves. However, the more this practice spreads and the more it is facilitated by financial innovations, the less the 1988 Basel Capital Accord remains efficient.

Banks use various capital arbitrage techniques. The simpler one consists of investing, inside a risk-weight band, in riskier assets. For instance, if the bank wants to buy bonds on the capital markets, it can buy speculative-grade

bonds that provide high interest rates while requiring the same regulatory capital as investment-grade bonds (that they could sell to finance the operation). The economic capital consumed by the deal should be higher than the regulatory capital, allowing the bank to use the excess economic capital it has to hold because of regulatory constraints. The more sophisticated techniques that are now used are a recourse to securitization and to credit derivatives. The banks show an innovative spirit in creating new financial instruments that allow them to lower their capital requirements even if they don't really lower their risk. The regulators then adapt the 1988 rules to cover these new instruments, but always with some delay.

Securitization

Securitization consists generally of transferring some illiquid assets, such as loans, to an independent company called a Special Purpose Vehicle (SPV). The SPV buys the loans to the bank and funds itself by issuing securities that are backed by them (Asset Backed Securities, ABS). Usually, the bank provides some form of credit enhancement to the structure – by, for instance, granting a subordinated loan to the SPV. Or, simply, the SPV-issued debts are structured in various degrees of seniority, and the bank buys the lowest one. The result is that the repayment of the SPV's debts is made with the cash flows generated by the securitized loans. The more senior loans are paid first, and so on, until the so-called "equity tranche" (the more junior loans) that is often kept by the bank. The securities bought by investors have a better quality than the underlying loans because the first losses of the pool are absorbed by the equity tranche. This creates attractive investment opportunities for investors but it means that the main part of the risk is still in the bank's balance sheet (see Figure 3.1).

With the structure in Figure 3.1, the bank sells 100 EUR of loans, lowering its regulatory capital requirements of 8 EUR to 4 EUR (assuming that loans were weighted at 100 percent). The subordinated loan is currently risk-weighted at 1250 percent, which imposes a capital requirement of 100

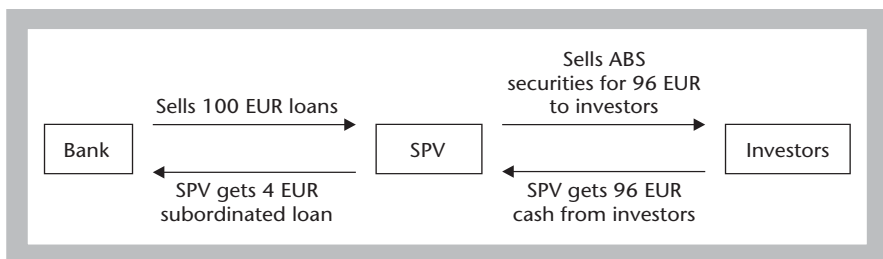


Figure 3.1 Securitization with recourse

percent (8 percent of 1250 percent). In this example, the regulators have correctly adapted the rules of the 1988 Accord for securitization because the subordinated loan is effectively highly risky as it absorbs the losses of all the pool. But if the risk linked to the structure of the operation is correctly captured, it nevertheless creates negative incentives, as to keep a good reputation on the marketplace banks tend to securitize good-quality loans. Loans remaining on the balance sheet are low-quality ones, which damage the bank's risk profile.

Other more pernicious structures existed in previous years. By structuring the operation as if the loans were directly granted by the SPV (a process termed "remote-origination securitization"), the bank provided only the credit enhancement and got the "excess spread" (the remaining cash flows after the payment of senior investors); the subordinated loan provided by the bank to the SPV could be risk-weighted as a classical guarantee line, at 100 percent (thus requiring 8 percent of capital) (see Figure 3.2).

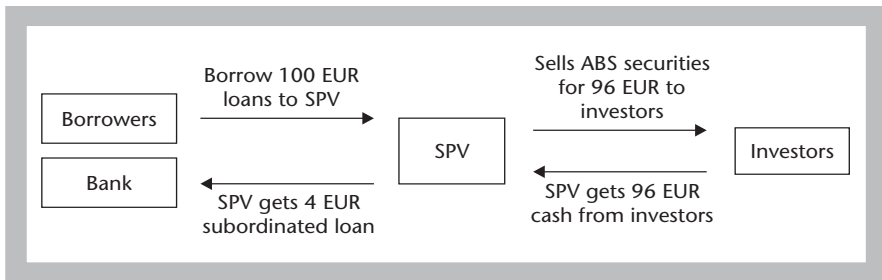


Figure 3.2 Remote-origination securitization

Until recently, virtually all asset-backed commercial paper programs were structured as remote-origination vehicles. An update of regulatory requirements corrected this bias in 2002 but no doubt banks will find new ways to manipulate the rules.

Other main weaknesses of the Accord, besides the possibility to lower capital requirements while keeping the risk level almost unchanged are:

- *The lack of risk sensitivity.* For instance, a corporate loan to a small company with high leverage consumes the same regulatory capital as a loan to a AAA-rated large corporate company (8 percent, because they are both risk-weighted at 100 percent).
- *A limited recognition of collateral.* As we saw in Chapter 1, the list of eligible collateral and guarantors is rather limited in comparison to those effectively used by the banks to mitigate their risks.
- *An incomplete coverage of risk sources.* Basel 1 focused only on credit risk. The 1996 Market Risk Amendment filled an important gap, but there

are still other risk types not covered by the regulatory requirements: operational risk, reputation risk, strategic risk . . .

- A “*one-size-fits all*” approach. The requirements are virtually the same, whatever the risk level, sophistication, and activity type, of the bank.
- An *arbitrary measure*. The 8 percent ratio is arbitrary and not based on explicit solvency targets.
- No recognition of *diversification*. The credit-risk requirements are only additive and diversification through granting loans to various sectors and regions is not recognized.

In conclusion, although Basel 1 was beneficial to the industry, the time has come to move to a more sophisticated regulatory framework. The Basel 2 proposal, despite having already received its share of criticism, is a major step in the right direction. It addresses a lot of Basel 1’s criticisms and, in addition to ameliorating the way the 8 percent capital ratio is calculated, emphasizes the role of regulators and of banks’ internal risk management systems. It creates a positive ascending spiral that is forcing many actors in the sector to increase their knowledge level, or – at least for those that already use sophisticated approaches – to discuss openly the various existing techniques that are far from receiving a consensus among either industry or researchers.

PART II

Description of Basel 2

Overview of the New Accord

In this chapter we discuss in broad terms the new Basel 2 Capital Accord.

INTRODUCTION

CP1 (the first Consultative Paper) was issued in June 1999. It contained the first set of proposals to modify the 1988 Basel Capital Accord and was the result of a year of work and contacts with the sector from various Basel Committee task forces. Eighteen months later, in January 2001, CP2 integrated the first set of comments from the sector and further work of the Committee. The last Consultative Paper (CP3) was issued by mid-2003 and in June 2004 the final proposal was published.

The so-called “Basel 2 Accord” that will replace the 1988 framework is the result of more than six years of regulators’ work and active discussion with the sector. This elaboration process was punctuated by three Quantitative Impact Studies (QIS). These consisted of collecting the main data inputs necessary to evaluate what could be the new capital requirements for various types of banks in the new Capital Accord. The explicitly stated goal of the regulators was to ensure that the global level of capital in the banking sector remained close to the current level (the main change being a different allocation to banks to reflect more closely their respective risk levels).

GOALS OF THE ACCORD

It is instructive to look at the three stated Committee objectives:

- To increase the *quality* and the *stability* of the international banking system.

- To create and maintain a level playing field for internationally active banks.
- To promote the adoption of *more stringent practices* in the risk management field.

The first two goals are those that were at the heart of the 1988 Accord. The last is new, and is said by the Committee itself to be the most important. This is the sign of the beginning of a shift from ratio-based regulation, which is only a part of the new framework, towards a regulation that will rely more and more on *internal data, practices, and models*. This evolution is similar to what happened in market-risk regulation, where internal models became allowed as the basis for capital requirements. That is why, backstage, people are already speaking of a “Basel 3 Accord” that would fully recognize internal credit risk models. Numerous contacts had to be created between regulators and the sector through joint forums and consultations to set up Basel 2; this built precious communications structures that are expected to be maintained even after Basel 2’s implementation date to keep working on what will be the regulation for the 2010s. This evolution is even highlighted in the final text itself:

The Committee understands that the IRB [Internal Rating-Based] approach represents a point on the continuum between purely regulatory measures of credit risk and an approach that builds more fully on internal credit risk models. In principle, further movements along that continuum are foreseeable, subject to an ability to address adequately concerns about reliability, comparability, validation and competitive equity. (Basel Committee on Banking Supervision, 2004d)

OPEN ISSUES

At the time of writing, there are still some open issues that the Committee plans to fix before the implementation date. The five most important ones are:

- The *recognition of double default*. In a nutshell, the current proposal treats exposures that benefit from a guarantee or that are covered by a credit derivative (which means that to lose money the bank would have to incur a “double default,” that of its counterparty and that of its protection provider) as if the exposure was directly held against the guarantor. Of course, this treatment understates the true protection level as it supposes a perfect correlation between the risk of the counterparty and the risk of the hedge. This could lead to a weak incentive for banks to effectively hedge their risk from a regulatory capital consumption perspective.
- The *definition of Potential Future Exposures (PFEs)*. This point has been actively debated with IOSCO as it is especially important for banks with

large trading books of derivative exposures (securities firms). Since the new Accord introduces a credit risk capital requirement for some trading book positions, the way PFE are evaluated will have a material impact on this sector.

- The definition of *eligible capital*. The definition currently applicable is the one of 1988 updated by a 1998 press release: “Instruments eligible for inclusions in Tier 1 capital” (Basel Committee on Banking Supervision, 1998) but further work is expected on this issue.
- The *scaling factor*. As mentioned above, the regulators’ target is to maintain the global level of capital in the banking sector. As the last tests made on QIS 3 data seem to show a small decrease under the IRB approach (following the Madrid Compromise that accepted that capital requirements could be based only on the unexpected loss part of a credit portfolio, excluding the expected loss: we shall discuss this in detail later (Chapter 15), the regulators should require a scaling factor currently estimated at 1.06. This means that IRB capital requirements would be scaled up by 6 percent. The exact value of this adjustment will be fixed after the “parallel run” period (see the discussion of transitional arrangements on p. 47).
- *Accounting issues*. The Committee is aware of possible distortions arising from the application of the same rules under different accounting regimes, and will keep on monitoring these issues. The trend is toward international standardization, mainly with the new International Accounting Standards (IAS) that will be implemented in banks in the same time frame as the new Accord. But if this helps to limit the problems associated with different accounting practices, it raises new questions, one of the most important being the definition of capital, that could become a much more volatile element if all gains and losses on assets and liabilities are valued MTM and passed through the profit and loss (P&L) accounts, as required by the controversial IAS 39 rule.

SCOPE OF APPLICATION

As with the 1988 Accord, Basel 2 is only a set of recommendations for the G10 countries. But as with the 1988 Accord also, it is expected to be translated into laws in Europe, North America, and Japan, and should reach finally the same coverage, which means that it will be the basis of regulation in more than 100 countries. The Accord is supposed to be applied on a consolidated basis for internationally active banks, including at the levels of the holdings shown in Figure 4.1.

National banks that are not within the scope of the Accord are, however, supposed to be under the supervision of their national authorities,

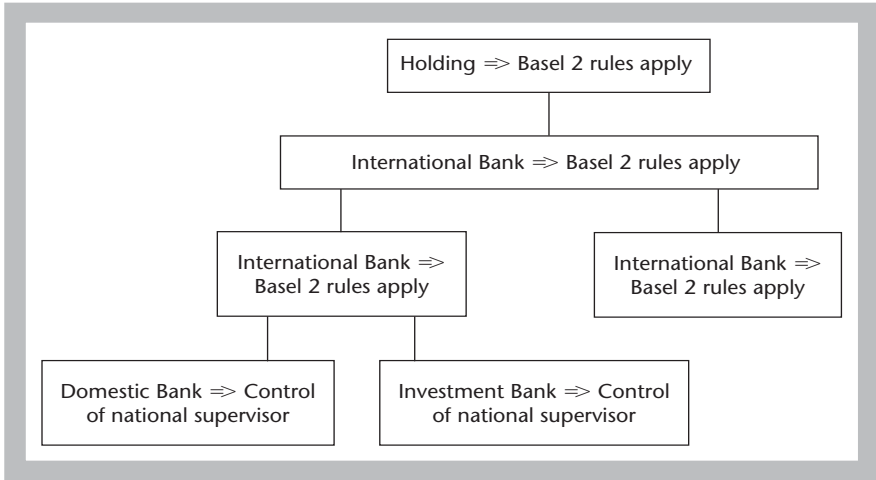


Figure 4.1 Scope of application for a fictional banking group

that should ensure that they have a sufficient capital level. That is the theory. In practice, the Accord will be mandatory for all banks and securities firms, even at the national level, in many countries. This will certainly be the case in Europe. On the other hand, in the US, the most advanced options of Basel 2 will be imposed only on a small group of very large banks (it is the position of US regulating bodies at the time of writing) while all the others will remain subject to the current approach (the 1988 Accord).

TREATMENT OF PARTICIPATIONS

The risk of “double gearing” has always been an issue for the regulators. Important participations that are not consolidated are treated as a function of their nature in the way shown in Figure 4.2.

Majority-owned financial companies that are not consolidated have to be deducted from equity. If the subsidiary has any capital shortfall, it will also be deducted from the parent company’s capital base. Minority investments that are significant (to be defined by the national regulators, in Europe the criterion is between 20 percent and 50 percent) have to be deducted or can be consolidated on a *pro rata* basis when the regulators are convinced that the parent company is prepared to support the entity on a proportionate basis.

Significant participations in insurance companies (Figure 4.3) have in principle to be deducted from equity. However, some G10 countries will apply other methods because of competitive equality issues. In any case, the

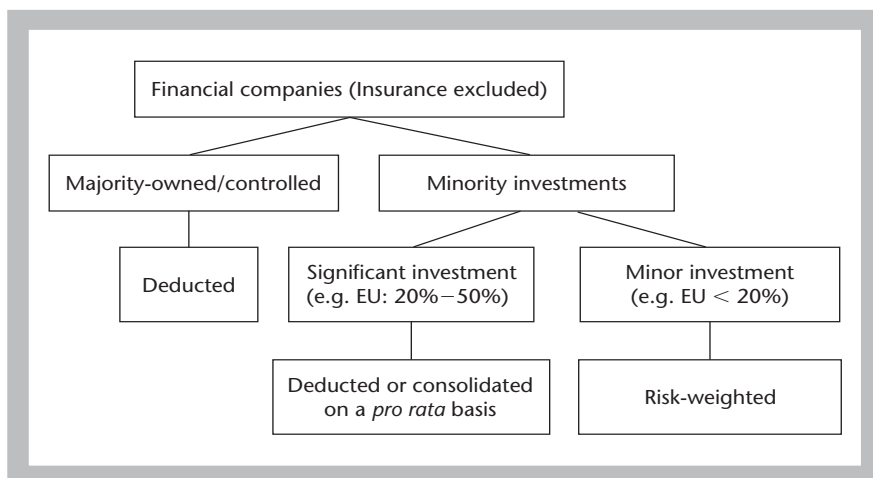


Figure 4.2 Treatment of participations in financial companies

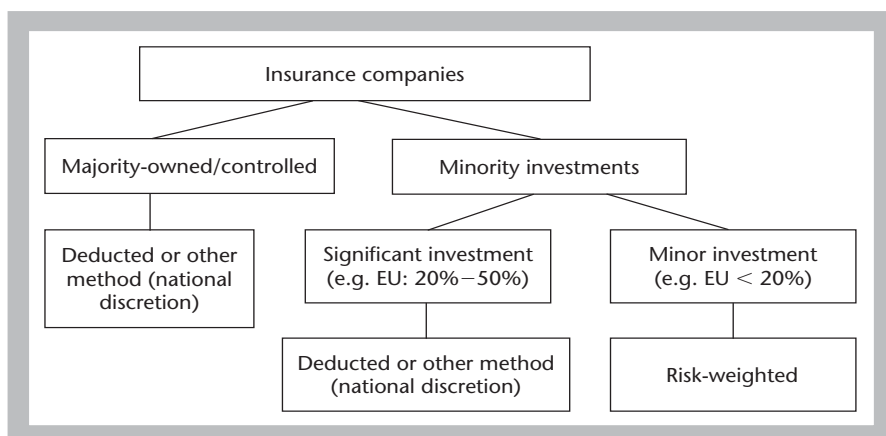


Figure 4.3 Treatment of participations in insurance companies

Committee requires that the method include a group-wide perspective and avoid double counting of capital.

Participations in commercial companies receive a normal risk-weight (with a minimum of 100 percent) up to an individual (15 percent of capital) and an aggregated (60 percent of capital) threshold. Amounts above those reference values (or a stricter level at national discretion) will have to be deducted from the capital base.

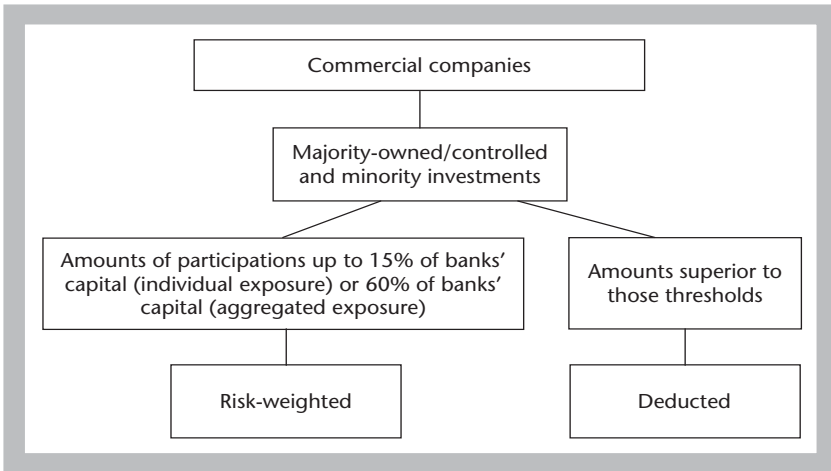


Figure 4.4 Treatment of participations in commercial companies

Deductions have to be made for 50 percent on Tier 1 and 50 percent on Tier 2 capital (except if there is a goodwill part related to those participations that has to be deducted 100 percent from Tier 1 capital).

STRUCTURE OF THE ACCORD

The Basel 2 Accord is structured in three main pillars (pillars 1–3) – the three complementary axes designed to support the global objectives of financial stability and better risk management practices (see Figure 4.5 opposite).

Pillar 1

This is the update of the 1988 *solvency ratio*. Capital: RWA is still viewed as the most relevant control ratio, as capital is the main buffer against losses when profits become negative. The 8 percent requirement is still the reference value, but the way assets are weighted has been significantly refined. The 1988 values were rough estimates while the Basel 2 values are directly and explicitly derived from a standard simplified credit risk model. Capital requirements should now be more closely aligned to internal economic capital estimates (the adequate capital level estimated by the bank itself, through its internal models). There are three approaches, of increasing complexity, to compute the risk-weighted assets (RWA) for credit risk. The more advanced are designed to consume less capital while they impose heavier qualitative

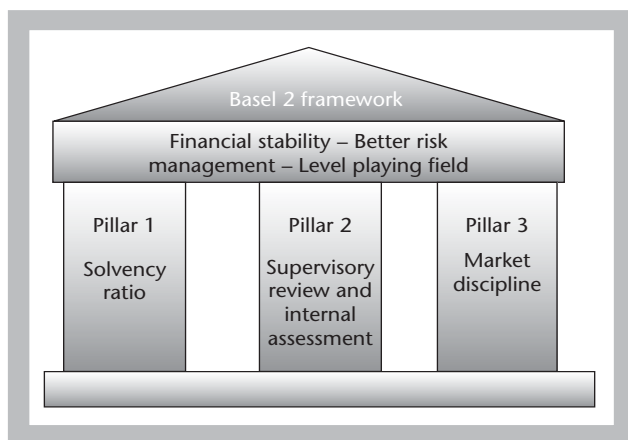


Figure 4.5 The three pillars

and quantitative requirements on internal systems and processes. This is an incentive for banks to increase their internal risk management practices. As well as more explicit capital requirements by function of risk levels, an important extension of the types of collateral that are recognized to offset the risks is another incentive to produce a more systematic collateral management practice. This is also significant improvement on the current Accord, where the scope of eligible collateral is rather limited.

Another important innovation in pillar 1 is a new requirement for *operational risk*. In the new Accord there is an explicit capital requirement for risks related to possible losses arising from errors in processes, internal frauds, information technology (IT) problems . . . Again, there are three approaches, of increasing complexity, that are available.

The eligible capital must cover at least 8 percent of the risk-weighted requirements related to three broad kinds of risks (see Figure 4.6).

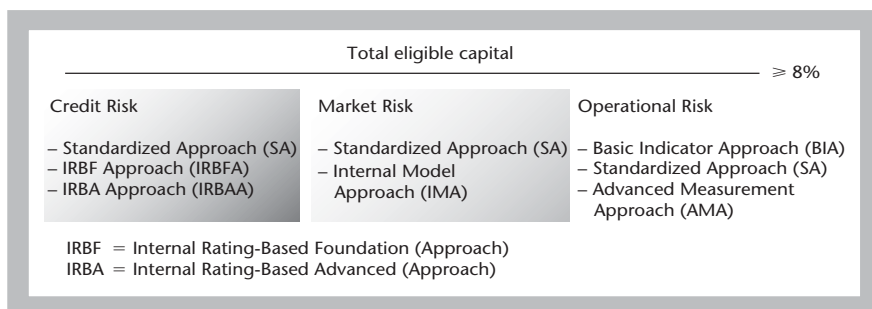


Figure 4.6 Solvency ratio

Pillar 2

The second axis of the regulatory framework is based on *internal controls* and *supervisory review*. It requires banks to have internal systems and models to evaluate their capital requirements in parallel to the regulatory framework and integrating the banks' particular risk profile. Banks must also integrate the types of risks not covered (or not fully) by the Accord, such as reputation risk and strategic risk, concentration credit risk, interest rate risk in the banking book (IRBBB) . . .

Under pillar 2, regulators are also expected to see that the requirements of pillar 1 are effectively respected, and evaluate the appropriateness of the internal models set up by the banks. If the regulators consider that capital is not sufficient, they can take various actions to remedy the situation. The most obvious are requiring the bank to increase its capital base, or restricting the amount of new credits that can be granted, but measures can also focus on increasing the quality of internal controls and policies.

The new Accord states explicitly that banks are expected to operate under a capital level higher than 8 percent, as pillar 2 has to capture additional risk sources.

Pillar 2 is very flexible because it is not very prescriptive (it represents 18 pages out of the 239 of the full Accord). Some have argued that this is a weakness, as regulators are left with too much subjectivity, which could undermine the level playing field objective. But it is at the same time the most interesting part of the framework, as it will oblige regulators and banks to cooperate closely on the evaluation of internal models. No doubt the regulators will use benchmarking as one of the tools to evaluate the banks' different approaches. This will create the dynamic necessary to standardize and better understand the heterogeneous ways credit risks are currently evaluated, and will ultimately pave the way to internal model recognition and its use as a basis for calculating capital requirements, as happened with market risk.

Pillar 3

This concerns *market-discipline*, and the requirements are related to disclosures. Banks are expected to build comprehensive reports on their internal risk management systems and on the way the Basel 2 Accord is being implemented. Those reports will have to be publicly disclosed to the market at least twice a year. This raises some confidentiality issues in the sector, since the list of elements to be published is impressive: description of risk management objectives and policies; internal loss experience, by risk grade; collateral management policies; exposures, by maturity, by industry,

and by geographical location; options chosen for Basel 2 . . . The goal is to let the market place an additional pressure on banks to improve their risk management practices. No doubt bank credit and equity analysts, bond investors, and other market participants will find the disclosed information very useful in evaluating a bank's soundness.

THE TIMETABLE

The timetable for implementation is year-end 2006 for Standardized and IRBF Approaches and year-end 2007 for the IRBA and the Advanced Measurement Approach (AMA) methods (it has been delayed several times since the Accord was first issued) (see Table 4.1). Before those dates, parallel calculations will be required (calculations of capital requirements under the Basel 1988 and the Basel 2 methods). In the early years after implementation, floors will be fixed that will prevent banks having new required capital levels below those calculated with the current approach multiplied by a scaling factor.

Table 4.1 The Basel 2 timetable

Approach	From year-end 2005	From year-end 2006 (%)	From year-end 2007 (%)	From year-end 2008 (%)
IRBF	Parallel run	95 floor	90 floor	80 floor
IRBA-AMA	Parallel run or impact studies	Parallel run	90 floor	80 floor

The floors applied could be extended, otherwise banks would be able to profit from the full reduction in capital requirements from 2010. In some cases, this will lead to impressive changes in reported solvency ratios for some specialized banks, as we shall see in Chapter 8.

SUMMARY

In summary, the six most noteworthy innovations of Basel 2 are the:

- Increased sensitivity of capital requirements to risk levels.
- Introduction of regulatory capital needs for operational risk.

- Important flexibility of the Accord, through several options being left at the discretion of the national regulators.
- Increased power of the national regulators, as they are expected under pillar 2 to evaluate a bank's capital adequacy considering its specific risk profile.
- Better recognition of risk reduction techniques.
- Detailed mandatory disclosures of risk exposures and risk policies.

Those measures should help the global industry to progress in its general understanding of credit risk management issues and constitute the intermediary step before full internal model recognition.

Pillar 1: The Solvency Ratio

INTRODUCTION

Our goal, of course, is not to review in details all 145 pages of the Accord that focus on pillar 1: it would be of limited interest to go into all the details and exceptions in the regulatory framework. Rather, we should like to provide to the reader with a “bird’s-eye” view of the general structure of pillar 1, highlighting the key points and issues. The use of the various options is subject to the constraint of a number of operational requirements that will not be reviewed in detail in this chapter. In Part III of the book, dealing with the implementation of Basel 2, we shall look more closely at the conditions linked to the main option of the Accord: the use of *internal rating systems*.

Pillar 1 options can be summarized as in Table 5.1.

Table 5.1 Pillar 1 options

+ Capital consumption	Credit Risk – unstructured exposures	Credit Risk – securitization	Operational risk	– Complexity
	Standardized Approach	Standardized Approach	BIA (Basic Indicator Approach)	
	IRBF (Internal Rating-Based Foundation) Approach	– RBA (Rating-Based Approach)	SA (Standardized Approach)	
	IRBA (Internal Rating Based-Advanced) Approach	– IAA (Internal Assessment Approach)	AMA (Advanced Measurement Approach)	
		– SF (Supervisory Formula)		

In principle, the various approaches are designed to produce lower capital requirements when moving from simple to more elaborated options (in fact, this is not always the case, depending on the particular risk profile of the bank). This is an incentive for banks to increase their risk management standards.

CREDIT RISK – UNSTRUCTURED EXPOSURES – STANDARDIZED APPROACH

Risk-weights

The Standardized Approach (SA) is the closest to the current approach. The main innovation is that the risk-weights are no longer a function only of the counterparties' types (banks, corporate ...) but also integrate their estimated risk level through the use of external ratings. A number of External Credit Assessment Institutions (ECAI) – companies that provide public risk assessment of borrowers through ratings – will be recognized if they meet the standard criteria of objectivity, independence, resources, transparency, and credibility. The regulators will then map those external ratings on the international rating scale of Standard & Poors (S&P). S&P ratings are finally converted into risk-weights (Table 5.2).

We detail the categories of RWA in turn in Box 5.1, with some considerations concerning implementation.

Table 5.2 RWA in the Standardized Approach

RWA	AAA to AA– (%)	A+ to A– (%)	BBB+ to BBB– (%)	BB+ to BB– (%)	B+ to B– (%)	Below B– (%)	Unrated (%)
Sovereign	0	20	50	100		150	100
Banks option 1	20	50		100		150	100
Banks option 2 (ST claims)	20 (20)	50 (20)		100 (50)		150 (150)	50 (20)
Corporate	20	50	100		150		100
Retail				75			
Residential property				35			
Commercial real estate				100			

Note: ST = Short-term.

Box 5.1 Categories of RWA

CATEGORIES OF RISK

- **Sovereign:** Exposures on countries are risk-weighted by function of their rating, and no longer on the rough criteria of their membership of OECD, as in Basel 1988. At national discretion, a lower risk-weight can be used for exposures to the country of incorporation of the bank denominated and funded in domestic currency. In addition to ECAI, the regulators can recognize scores given by Export Credit Agencies (ECA) that respect the OECD methodology.
- **Public Sector Entities (PSE):** Non-central government PSE can be weighted by regulators as banks or as sovereigns (in principle, it depends whether or not they have autonomous tax-raising power).
- **Multilateral Development Banks (MDB):** In principle, they are weighted as banks, except if they respect certain criteria that allow them to benefit from a 0 percent RWA (e.g. the European Bank for Reconstruction and Development (EBRD), the Asian Development Bank (ADB), the Nordic Investment Bank (NIB) ...).
- **Banks:** Under option 1, the regulators weight banks with a risk-weight one step higher than that given to claims on their country of incorporation. Under option 2, the risk-weight is a function of the bank rating, and a preferential treatment can be allowed for short-term claims with original maturity less than three months (not applicable to MDB and PSE assimilated to banks). Securities firms that are subject to the Basel 2 Accord are considered as banks for RWA, otherwise as corporate.
- **Corporate:** Includes insurance companies.
- **Retail:** The claim must be on an individual person or a small business; the credit must take the form of a retail product (revolving credit lines, personal-term loan and leases, or small business facilities and commitments); exposures must be sufficiently granular (no material concentration in the retail portfolio) and less than 1 million EUR (consolidated exposures on the economic group of counterparties – e.g. a mother company and subsidiaries).
- **Credits secured by residential property:** The claim must be fully secured and the borrower will be the one to occupy or to rent the property.
- **Credits secured by commercial real estate:** As such property has been at the heart of a number of past financial crises (see Chapter 1), the Basel Committee recommends not applying a lower risk-weight than 100 percent. However, exceptions are possible for mature and well-developed markets.

- **Past due loans:** Loans past due for more than 90 days will be risk-weighted by function of their level of provisioning (see Table 5.3).

Table 5.3 RWA of past due loans

Past due loan RWA (%)	Residential mortgage (%)	Other (%)
Provision <20 outstanding	100	150
Provision >20 outstanding	50	100

- **Other assets:** A 100 percent risk-weight will apply.
- **Off-balance sheet items:** Off-balance sheet items are converted into credit equivalent exposures through the use of a Credit Conversion Factor (CCF), as in Basel 1988 (see Table 5.4).

Table 5.4 CCF for the Standardized Approach

%	Item
0	– Commitments unconditionally cancellable without prior notice
20	– Short term self-liquidating trade-related contingencies (e.g. documentary credit collateralized by the underlying goods). – Undrawn commitments with an original maturity of max. 1 year
50	– Transaction-related contingencies (e.g. performance bonds) – Undrawn commitments with an original maturity > than 1 year
100	– Direct credit substitutes (e.g. general guarantees of indebtedness ...) – Sale and repurchase agreements – Forward purchased assets – Securities lending

IMPLEMENTATION CONSIDERATIONS

- If there is more than one external rating, banks should retain the lower of the two highest.
- If the bank invests in an issue that has a specific rating, it should retain it rather than the issuer rating.
- If there is no issuer rating but a specific issue is rated, a claim can get the issue rating only if it ranks at least *pari passu* with it.

- For banks and corporate, if the lending bank has a claim through a short-term issue that has an external rating, the risk-weights shown in Table 5.5 can be applied.

Table 5.5 RWA for short-term issues with external ratings

Credit assessment	A-1/P-1	A-2/P-2	A-3/P-3	Others
RWA (%)	20	50	100	150

Credit risk mitigation

Another important part of the Standardized Approach deals with Credit Risk Mitigation (CRM) techniques. Those are the tools that a bank can use to cover a part of its credit risk, and include requiring collateral (financial or other), guarantees, or using credit derivatives.

But if it reduces credit risk, the use of CRM creates other risks that the banks have to manage. As general requirements for the use of CRM, we can mention two points:

- *Legal certainty*: All the documentation used to set up the collateral, the guarantee, or the credit derivative must be legally binding on all parties, and legally enforceable in all relevant jurisdictions.
- The bank must have efficient procedures to *manage the collateral*. This means being able to liquidate it in a timely manner and to manage secondary risks (operational risks, liquidity risks, concentration risk, market risk, legal risk ...).

There are two approaches to integrate the use of collateral into the computation of RWA: the simple approach and the comprehensive approach. Their impact on RWA and the scope of eligible collateral are different, and are summarized in Table 5.6.

When using the comprehensive approach, banks have also to recognize that the current values of exposures and collateral may not be those that will prevail in case of default. The evolution of market parameters can have a material impact on the effectiveness of the hedge. Therefore, banks have to apply haircuts to take into account the fact that between the moment when the bank decides to sell the collateral because the counterparty is in default, and the moment when the position is effectively closed, the part of exposure that is covered may have decreased because: the market value of the collateral has decreased; the market value of the exposure has increased (in the case of securities lending, for instance); or the exposure and the

Table 5.6 Simple and comprehensive collateral approach

Collateral approach	Simple approach	Comprehensive approach
Impact on RWA	Covered exposure receives the risk-weight of the collateral with a minimum of 20%	Exposures are reduced by the value of collateral and the net result is risk-weighted as unsecured
Eligible collateral	<ul style="list-style-type: none"> ■ Cash on deposits at the issuing banks ■ Gold ■ Debt securities rated by ECAI at least: BB– for sovereigns (and assimilated PSE), BBB– for other; A–3/P–3 for short-term ■ Unrated debt securities if they are: issued by a bank, senior, liquid, listed on a recognized exchange ■ Equities (including convertibles bonds) included in a main index ■ Undertakings for Collective Investments in Transferable Securities (UCITS) and mutual funds if: quoted daily and invested only in the instruments mentioned above 	
		<ul style="list-style-type: none"> ■ Equities (including convertibles bonds) not included in a main index but listed on a recognized exchange ■ UCITS and mutual funds which include such equities

collateral are denominated in different currencies, and the exchange rate has moved against the bank.

The adjusted value of collateral in the comprehensive approach is calculated by (5.1):

$$AE = \max(0; [E \times (1 + He) - C \times (1 - Hc - Hfx)]) \quad (5.1)$$

where

- AE = Adjusted exposure
- E = Original exposure
- He = Haircut of the exposure (in case it is sensitive to market parameters)
- C = Collateral value
- Hc = Haircut for collateral type
- Hfx = Haircut for currency mismatch

To estimate the haircuts, there are two possibilities: using either supervisory haircuts or estimating the bank's own. Supervisory haircuts are shown in Table 5.7.

Reference values are given under the hypothesis of a ten-day holding period (the time between the decision to sell the collateral and the effective recovery). Then, as various types of collaterals on different markets can have

Table 5.7 Supervisory haircuts (ten-day holding period)

Collateral	Residual maturity	Sovereign (and assimilated) issuer (%)	Other issuer (%)
AAA to AA– and A1 securities	≤1 year	0.5	1.0
	>1 year, ≤5 years	2.0	4.0
	>5 years	4.0	8.0
A+ to BBB– and A2/A3/P–3 and unrated bank securities	≤1 year	1.0	2.0
	>1 year, ≤5 years	3.0	6.0
	>5 years	6.0	12.0
BB+ to BB–	All	15.0	Not eligible
Main index equities and gold			15.0
Other equities listed on a recognized exchange			25.0
UCITS/Mutual funds		Highest haircut applicable to any security in which the fund can invest	
Cash in the same currency			0.0
Collateral and exposures in different currencies			8.0

very different liquidation periods (depending on market liquidity and on the legal framework of the country where the collateral is located), supervisory haircuts have to be adapted.

In the Standardized Approach and the IRBF Approach, financial collateral is supposed to have the minimum holding period shown in Table 5.8.

Table 5.8 Minimum holding period

Transaction type	Minimum holding period (business days)	Condition
Repo-style transaction	5	Daily remarking
Other capital market transactions	10	Daily remarking
Secured lending	20	Daily revaluation

If there is no daily remarking or revaluation, the minimum holding period has to be adapted upward. To transform the supervisory haircuts for the ten-day holding period to haircuts adapted for the transaction-holding period, banks have to use the square root of time formula.

For instance: a bank has a three-year BBB bond as collateral to cover a three-year secured lending operation. The bond is MTM every week. The bond issuer is a corporate and the face value is 100 EUR. The haircut is calculated as in Box 5.2.

Box 5.2 Calculating a haircut for a three-year BBB bond

The supervisory haircut for a three-year BBB bond issued by a corporate is 6 percent (see Table 5.7).

The minimum holding period for secured lending is twenty business days.

As the bond is not revaluated daily but weekly (every five business days), the minimum holding period must be adapted to twenty-four (as there are five days instead of one between revaluations).

The supervisory haircut that is based on a ten-day holding period is scaled up using the square root of time formula:

$$\text{Haircut} = 6.0\% \times \sqrt{\frac{24}{10}} = 9.3\%$$

The value of the bond is then $100 \text{ EUR} \times (1 - 9.3\%) = 90.7 \text{ EUR}$

If the exposure is 200 EUR, for instance, the computation of RWA will be made on the basis of $200 \text{ EUR} - 90.7 \text{ EUR} = 109.3 \text{ EUR}$.

Another option, for the banks that do not want to use the supervisory haircut, is to estimate their own. To do so, they have to respect some qualitative and quantitative requirements summarized in Table 5.9.

Table 5.9 Criteria for internal haircut estimates

Qualitative	Quantitative
– Estimated haircuts must be used in day-to-day risk management	– Use of the 99th percentile, one-tailed confidence interval
– The risk measurement system must be documented and used in conjunction with internal exposures limits	– Use of minimum holding periods as for supervisory haircuts
– There must be at least annual review by the audit of the risk measurement framework	– Liquidity of the collateral taken into account when determining the minimum holding period
	– Minimum one year of historical data, updated at least every three months

At the national discretion, some collateral can receive zero haircuts when used in Repo-style transactions (if exposures and collaterals are cash or sovereign; in the same currency; there is a daily remargining; and the maximum liquidation period is four days) with core market participants (sovereigns, central banks, banks ...).

In the case of netting agreements, the adjusted exposure is calculated as shown in Box 5.3.

Box 5.3 Calculating adjusted exposure for netting agreements

The calculation is applied as in (5.2):

$$AE = \max [0; (\Sigma E - \Sigma C + \Sigma(Es \times Hs) + \Sigma(Efx \times Hfx))] \quad (5.2)$$

where AE = Adjusted exposure
 ΣE = Sum of exposures (positive and negative)
 ΣC = Sum of values of received collaterals
 Es = Absolute values of net positions in a given security
 Hs = Haircut appropriate to Es
 Efx = Absolute value of the net position in a currency different from the settlement currency
 Hfx = Haircut appropriate for currency mismatch

As an alternative to supervisory haircuts or own-estimated haircuts, banks can use VAR models to evaluate the adjusted exposures of Repo-style transactions. The validation criteria of these VAR models are the same as those of the 1996 Market Risk Amendment.

Guarantees and credit derivatives are also recognized as valuable CRM techniques subject to certain conditions. In this case, the RWA of the guarantor is substituted for the RWA of the counterparty (if it is lower). Eligible guarantors are sovereigns, PSE, banks and securities firms that have a better rating than the counterparty, and other types of counterparties with a minimum rating of A-. Where there is a currency mismatch between the exposure currency and the currency referred to in the guarantee contract, a haircut is applied as in (5.3):

$$\text{Adjusted guarantee} = \text{Nominal guarantee} \times (1 - Hfx) \quad (5.3)$$

Finally, banks have also to take into account possible maturity mismatches between exposures and CRM. The *maturity of the exposure* is defined as the longest possible remaining time before the counterparty is scheduled to fulfill its obligations, while the *maturity of the hedge* is defined as the shortest possible term of the CRM (e.g. taking into account embedded options which may reduce its initial maturity). CRM is considered as having no value in case of a maturity mismatch when the CRM has an original maturity of less than one year. Otherwise, (5.4) applies:

$$\text{Adjusted CRM value} = \text{Original CRM value} \times \frac{t - 0.25}{T - 0.25} \quad (5.4)$$

where $t = \min(T, \text{residual maturity of the CRM})$
 $T = \min(5, \text{residual maturity of the exposure})$

CREDIT RISK – UNSTRUCTURED EXPOSURES – IRB APPROACHES

In the IRB approaches, capital requirements are no longer global risk-weights based on external ratings, but are computed using formulas derived from advanced credit risk models that use risk parameters estimated by the bank itself. We shall present and discuss the derivation of the formulas later in this book (Chapter 15). The key risk parameters that are used in the approach are summarized in Table 5.10.

These variables are the key inputs of the supervisory formulas that are suited to various asset classes. The regulators give some parameters (ρ and CI in all cases); others have to be estimated internally by the banks, depending on the asset class and the chosen options. Table 5.11 summarizes this.

Table 5.10 Risk parameters

Symbol	Name	Comments
PD	Probability of default	The probability that the counterparty will not meet its financial obligations
LGD	Loss given default	The expected amount of loss that will be incurred on the exposure if the counterparty defaults
EAD	Exposure at default	The expected amount of exposure at the time when a counterparty defaults (the expected drawn-down amount for revolving lines or the off-balance sheet exposure \times its CCF)
M	Maturity	The average maturity of the exposure
ρ	Asset correlation	A measure of association between the evolution of assets' returns of the various counterparties (see Chapter 15 for details)
CI	Confidence interval	The degree of confidence used to compute the economic capital (see Chapter 15 for details)

Table 5.11 Source of risk estimations

Exposure type	IRBF		IRBA	
	Internal data	Regulators' data	Internal data	Regulators' data
Corporate, sovereigns, banks, eligible purchased receivables corporate	PD	LGD, EAD, M	PD, LGD, EAD, M	
Retail, eligible purchased receivables retail		Internal PD, LGD, EAD, M mandatory		
Equity	PD/LGD Approach or Market-Based Approach			

Note: ρ and CI are always given by the regulators.

Risk-weights

Exposures have to be classified in one of the six categories shown in Box 5.4.

Box 5.4 Classification of exposures

- Corporate:** This includes Small and Medium-Sized Enterprises (SMEs) and large corporate. Additionally it covers five sub-classes of Specialized Lending (SL) exposures that cover operations made generally on Special Purpose Vehicles (SPVs) that have no other assets than that financed whose cash flow constitutes the principal source of repayment. These sub-classes are: project finance (e.g. power plants, mines, transportation infrastructure ...); object finance (e.g. ships, aircrafts, satellites ...); commodities finance (e.g. crude oil, metals ...); income-producing real estate (e.g. office buildings, retail space, multifamily residential buildings ...), and high-volatility commercial real estate (HVCRE) (commercial real estate with high loss volatility). The risk-weighting function is shown in (5.5):

$$\rho = 0.12 \times \left(\frac{1 - \exp(-50 \times PD)}{1 - \exp(-50)} \right) + 0.24 \times \left(1 - \frac{1 - \exp(-50 \times PD)}{1 - \exp(-50)} \right) \quad (5.5)$$

$$K = LGD \times N \left(\frac{G(PD)}{\sqrt{1 - \rho}} + G(0.999) \sqrt{\frac{\rho}{1 - \rho}} \right) - PD \times LGD$$

$$\times \left(\frac{1}{(1 - 1.5 \times b)} \right) \times (1 + (M - 2.5) \times b)$$

$$b = (0.11852 - 0.05478 \times \ln(PD))^2$$

$$RWA = K \times 12.5 \times EAD$$

For SME with sales at the consolidated group level less than 50 million EUR, the correlation parameter is adapted as follows:

$$\rho_{SME} = \rho - 0.04 \times \left(1 - \frac{\max(\text{sales in million EUR}; 5) - 45}{45} \right)$$

For HVCRE, the correlation is:

$$\rho_{HVCRE} = \rho + 0.06 \times \left(1 - \frac{1 - \exp(-50 \times PD)}{1 - \exp(-50)} \right)$$

This may seem quite esoteric but we shall explain in detail how we can construct those functions later in the book (Chapter 15). N and G stand, respectively, for the cumulative and inverse cumulative normal standard distributions.

In principle, if the bank chooses to use the IRB approach, it has to do so for each type of exposure. However, an exception is SL. For these exposures, even if IRB is used for corporate exposures, the bank can classify operations in four rough supervisory risk bands and use a standardized approach (Table 5.12):

Table 5.12 RWA for Specialized Lending

SL	Strong (>BB+) (%)	Good (BB+/BB) (%)	Satisfactory (BB-/B+) (%)	Weak (B/C-) (%)	Default
RW (PF, OF, CF, IPRE)	70 (50)	90 (70)	115	250	0
RW (HVCRE)	95 (70)	120 (95)	140	250	0

Notes: RW for maturity <2.5 years at national discretion in parentheses.
PF = Project Finance; OF = Object Finance; CF = Commodities Finance;
IPRE = Income Producing Real Estate; HVCRE = High-Volatility Commercial
Real Estate.

- **Sovereign exposures:** Exposures that are treated as sovereign in the Standardized Approach (sovereigns, assimilated PSE, and MDB risk-weighted at 0 percent). The risk-weighting function is the same as for corporate.
- **Bank exposures:** Exposures to banks and assimilated securities firms (those subject to the same kind of regulation), assimilated domestic PSE, and MDB that are not risk-weighted at 0 percent in the Standardized Approach. The risk-weighting function is the same as for corporate.
- **Retail exposures:** These are exposures on individuals (without size limit), residential mortgages (without size limit), and loans extended to small businesses if the amount is less than 1 million EUR and if the counterparties are managed as retail exposures (which means assigned to pools of a large number of exposures that share the same risk characteristics). There are three sub-classes of retail exposures: residential mortgage; qualifying revolving exposures (exposures that are revolving, unsecured, uncommitted, on

individuals, less than 100,000 EUR, and that show low loss variance); and others. The risk-weighting functions are the same as for corporate, only the correlation parameters are adapted as follows (and maturity = 1):

$$\rho_{\text{Residential mortgage}} = 0.15$$

$$\rho_{\text{Qualifying Revolving Exposures}} = 0.04$$

$$\rho_{\text{Other}} = 0.03 \times \frac{1 - \exp(-35 \times PD)}{1 - \exp(-35)} + 0.16 \times \left(1 - \frac{1 - \exp(-35 \times PD)}{1 - \exp(-35)}\right)$$

■ **Equity exposures:** Exposures that represent a residual claim on the borrower's assets when all other debts have been repaid in the case of bankruptcy. They bear no obligation for the borrower (such as the obligation to pay interest). They include derivatives on equity exposures. There are three possible risk-weighting schemes:

- In the simple approach, listed equities get a 300 percent risk-weighting and unlisted 400 percent.
- In the internal model approach, the risk-weighting is 12.5 (1/8 percent) × a 99 percent VAR estimated between quarterly equity returns and a reference risk-free rate.
- In the PD/LGD approach, the corporate function is used, with a LGD of 90 percent and a maturity of five years.

■ **Purchased receivables exposures:** These are exposures not directly originated by the bank but that are purchased. They can be retail or corporate exposures. In principle, the PD of each corporate exposure should be evaluated separately, but a top-down approach (an approach where the bank evaluates the PD (and LGD for IRBA) parameters at the global-pool level) can be used if an individual borrower assessment would be too heavy to implement. The bank uses the appropriate risk-weighting function (corporate or retail) with the average estimated risk parameters, either internally or provided by external sources (generally, the vendor of the exposures). Additional capital requirements have also to be computed for dilution risk. "Dilution risk" refers to the possibility that the receivable amount is reduced through cash or non-cash credits to the receivable's obligor (examples include offsets or allowances arising from returns of good sold, disputes regarding product quality, promotional discounts offered by the borrower ...). The expected loss (which is the product of PD, LGD, and EAD) due to dilution risk has to be estimated by the bank and used in the corporate risk-weight function (even if it concerns retail exposures) as if it were the PD, and a 100 percent LGD should be used.

Credit risk mitigation

In IRBF for corporate, banks, and sovereign exposures, the standard values for LGD on the unsecured part of exposures are 45 percent for senior debts and 75 percent for subordinated debts. In IRBA and for retail exposures, the values have to be estimated internally.

As in the Standardized Approach, various collateral can be recognized and used to offset a part of the exposure before calculating the RWA. They are taken into account through the comprehensive approach (see Table 5.6, p. 54) as the simple approach is not allowed for IRB. In addition to the financial collateral recognized in the Standardized Approach, other types of CRM are recognized: Commercial Real Estate (CRE) and Residential Real Estate (RRE), receivables, and other physical collaterals. However, in IRBF, the recognition of the effect of those CRM is rather limited (Table 5.13).

Table 5.13 CRM in IRBF

Collateral type	Minimum collateralization (%)	Collateral haircut (%)	Final LGD (%)
Receivables	0	125	35
CRE/RRE	30	140	35
Other physical collateral	30	140	40

The collateral value is first compared to the covered exposure; if the coverage is less than the value in the column “Minimum collateralization,” it is not recognized. If it is greater, the value of the collateral is adjusted by dividing it by the value in the “Collateral haircut” column. The part of the exposure covered by the adjusted collateral value then receives the LGD level in the “Final LGD” column. For instance, an exposure of 100 EUR secured by a commercial real estate of 40 EUR would be valued as in Box 5.5.

Box 5.5 Calculating LGD

40 EUR/100 EUR = 40 percent which is greater than the 30 percent minimum collateralization level. The collateral value would then be haircutted by 140 percent, 40 EUR/140 percent = 28.6 EUR. The LGD applied on the part of the exposure corresponding to the haircutted value would then be 35 percent. The LGD on the 100 EUR exposure would then be 45 percent (assuming senior corporate exposure) on 71.4 EUR and 35 percent on 28.6 EUR.

In IRBA, the rules are less strict, as any kind of collateral can be recognized and deducted from the exposure to compute the capital requirements,

as long as the bank has historical data to support its valuation (at least seven years' data on average recovery value on the various types of collaterals it plans to use). Guarantees and credit derivatives in IRBF are treated broadly the same as in the Standardized Approach (the PD of the guarantor is substituted for the PD of the exposure if it is lower). In IRBA, the integration of the effect of the guarantee can be done at either the PD or at the LGD level.

Currency and maturity mismatches are treated as in the Standardized Approach.

EAD

EAD is defined as the estimated exposure at the time of default. In IRBF, it is estimated as in the Standardized Approach as the amount currently drawn on the line plus the undrawn amount \times the regulatory CCF (except for note issuance facilities (NIF) and revolving underwriting facilities (RUF), that receive a 75 percent CCF). In IRBA, the CCF can be estimated internally based on historical data.

Maturity

In IRBF, the average maturity is supposed to be 2.5 years, except for Repo-style transactions where it is six months. In IRBA, the bank has to compute the average maturity of each exposure through (5.6) (with a minimum of 1 and a maximum of 5):

$$\text{Maturity} = \frac{\sum tCF}{\sum CF} \quad (5.6)$$

where CF = Cash flows (interest and capital)
 t = Time of the cash flow (in years)

CREDIT RISK: SECURITIZATION

We saw in Chapter 3 what securitization is, and how banks have used it in order to perform capital arbitrage. In the new Accord, regulators paid special attention to setting strict rules for the treatment of such techniques in terms of capital requirements. However, securitization structures are often complex, different from one deal to the other, and the ways to evaluate the risks associated with such techniques are not straightforward. It was thus not easy for regulators to propose a flexible and (relatively) simple set of rules to determine capital requirements. The first propositions in CP 1 were rough approaches that provoked a lot of reaction from the industry. After

much debate, and some propositions for simplified analytical models (see, for instance, Gordy and Jones, 2003 or Pykhtin and Dev, 2003), regulators opted for a standard and two International Rating-Based (IRB) approaches. One of the two IRB approaches – the Supervisory Formula (SF) – is primarily model-based.

Basel 2 requirements

Basel 2 requirements cover both traditional securitizations and synthetic securitizations.

Traditional securitizations

Traditional securitizations are structures where the cash flows from an underlying pool are used to service at least two different tranches of a debt structure that bear different levels of credit risk (as the cash flows are used first to repay the more senior debt, then the second layer, and so on ...). The difference with classical senior and subordinated debts is that lower tranches of the debt structure can absorb losses while the others are still serviced, whereas classical senior and subordinated debt is an issue of priority only in the case of the liquidation of a company.

Synthetic securitizations

Synthetic securitizations are structures where the underlyings are not “physically” transferred out of the balance sheet of the originating bank, but only the credit risk is covered through the use of funded (e.g. credit-linked notes) or unfunded (e.g. credit default swaps) credit derivatives.

Originating and investing banks

Banks involved in a securitization structure can be either an originator or an investor.

Originating banks

Originating banks are those that originate, directly or indirectly, the securitized exposures, or that serve as a sponsor on an Asset-Backed Commercial Paper (ABCP) program (as a sponsor, the bank will usually manage or

advise on the program, place securities in the market, or provide liquidity and/or credit enhancements). Originating banks can exclude securitized exposures from the calculation of the RWA if they meet certain operational requirements.

For cash securitization, the assets have to be effectively transferred to an SPV and the bank must not have any direct or indirect control on the assets transferred.

For synthetic securitization (where assets are effectively not transferred to a third party but their credit risk is hedged through credit derivatives), the credit risk mitigants used to transfer the credit risk must fulfill the requirements of the Standardized Approach. Eligible collateral and guarantors are those of the Standardized Approach, and the instruments used to transfer the risk may not contain terms or conditions that limit the amount of risk effectively transferred (e.g. clauses that increase the banks' cost of credit protection in response to any deterioration in the pool's quality).

Originating banks that provide implicit support to the securitized exposures (they would buy them back if the structure was turning sour) in order to protect their reputation, must compute their capital requirements as if the underlying exposures were still in their balance sheet.

Clean-up calls (options that permit an originating bank to call the securitized exposures before they have been repaid when the remaining amount falls below some threshold) may be subject to regulatory capital requirements. To avoid this, they must not be mandatory (but at the discretion of originating banks), they must not be structured to provide credit enhancement, and they must be allowed only when less than 10 percent of the original portfolio value remains. If those conditions are not respected, exposures must be risk-weighted as if they were not securitized.

Investing banks

Investing banks are those that bear the economic risk of a securitization exposure. Those exposures can arise from the provision of credit risk mitigants to a securitization transaction, investment in asset-backed securities, retention of a subordinated tranche, and extension of a liquidity facility or credit enhancement.

The Standardized Approach

Banks that apply the Standardized Approach to credit risk for the type of underlying exposures securitized must use the Standardized Approach under the securitization framework. The RWA of the exposure is then a function of its external rating (Table 5.14).

Table 5.14 RWA for securitized exposures: Standardized Approach

LT rating (ST rating)	AAA to AA– (A–1/P–1)	A+ to A– (A–2/P–2)	BBB+ to BBB– (A–3/P–3)	BB+ to BB–	Other ratings and unrated
RWA (%)	20	50	100	350	Deducted

Note: ST = Short-term.

Banks that invest in exposures that they originate themselves that receive an external rating below BBB– must deduct them from their capital base.

For off-balance sheet exposures, CCF are used (if they are externally rated, the CCF is 100 percent). This is usually 100 percent except for *eligible liquidity facilities* (see p. 67).

There are three exceptions to the deduction of unrated securitization exposures. First, the most senior tranche can benefit from a “look-through” approach if the composition of the underlying pool is known at all times. This means that it receives the average risk-weight of the securitized assets (if it can be determined).

Secondly, second loss or better in ABCP programs that have an associated credit risk equivalent to investment grade, and when the *bank does not hold the first loss*, can receive the higher risk-weight assigned to any of the individual exposures (with a minimum of 100 percent).

Thirdly, *eligible liquidity facilities* can receive the higher risk-weight assigned to any of the individual exposures covered by the facility. Eligible liquidity facilities are off-balance sheet exposures that meet the following four requirements:

- Draws under the facility must be limited to the amount that is likely to be repaid fully from the liquidation of the underlying exposures: it must not be drawn to provide credit enhancement.
- The facility must not be drawn to cover defaulted assets, and funded exposures that are externally rated must be at least investment grade (at the time the facility is drawn).
- When all credit enhancements that benefit the liquidity line are exhausted, the facility cannot be drawn any longer.
- Repayment of draws on the facility must not be subordinated to any interest of any holder in the program or subject to deferral or waiver.

Eligible liquidity facilities can benefit from a 20 percent CCF if they have an original maturity less than one year and a 50 percent CCF if their original maturity is greater than one year (instead of the default 100 percent CCF).

In three other special cases, eligible liquidity facilities can receive a 0 percent CCF:

- When they are available only in case of market disruption (e.g. when more than one securitization vehicle cannot roll over maturing commercial paper for other reasons than credit-quality problems).
- When there are overlapping exposures: in some cases, the same bank can provide several facilities that cannot be drawn at the same time (when one is drawn the others cannot be used). In those cases, only the facility with the highest CCF is taken into account, the other not being risk-weighted.
- Certain servicer cash advance facilities can also receive a 0 percent CCF (subject to national discretion), if they are cancellable without prior notice and have senior rights on all the cash flows (until they are reimbursed).

CCF for securitization exposures can be summarized as in Table 5.15.

Table 5.15 CCF for off-balance securitization exposures

Eligible liquidity facilities					
Original maturity ≤1 year (%)	Original maturity > 1 year (%)	Cancellable servicer cash advances (%)	Overlapping exposures (%)	Available only in case of market disruption (%)	Other (%)
20	50	0	0	0	100

Credit risk mitigants can offset the risk of securitization exposures. Eligible collateral is limited to that recognized in the Standardized Approach.

The early amortization provision is an option that allows investors to be repaid before the original stated maturity of the securities issued. They can be controlled or not. They are considered as *controlled* when:

- The bank has a capital/liquidity plan to cover early amortization.
- Throughout the duration of the transaction, including the amortization period, there is the same *pro rata* sharing of interest, principal, expenses, losses, and recoveries based on the bank's and investors' relative shares of the receivables outstanding at the beginning of each month.
- The bank has set a period for amortization that would be sufficient for at least 90 percent of the total debt outstanding at the beginning of the early amortization period to have been repaid or recognized as in default.
- The pace of repayment should not be any more rapid than would be allowed by straight-line amortization over the period set out above.

Originating banks are required to hold capital against investors' interests when the structure contains an early amortization provision and when the exposures sold are of a revolving nature. Four exceptions are:

- *Replenishment structures*, where the underlying exposures do not revolve and the early amortization ends the ability of the bank to add new exposures.
- *Transactions of revolving assets* containing early amortization features that mimic term structures (i.e. where the risk on the underlying facilities does not return to the originating bank).
- *Structures where a bank securitizes one or more credit line(s)* and where investors remain fully exposed to future draws by borrowers even after an early amortization event has occurred.
- *The early amortization clause* is triggered solely by events not related to the performance of the securitized assets or the selling bank – such as material changes in tax laws or regulations.

In other cases, the capital requirement is equal to the product of the revolving part of the exposures, the appropriate risk-weight (as if it had not been securitized), and a CCF. The CCF depends upon whether the early amortization repays investors through a controlled or non-controlled mechanism, and upon the nature of the securitized credit lines (uncommitted retail lines or not). Its level is a function of the average three-months' excess spread (gross income of the structure minus certificate interest, servicing fees, charge-offs, and other expenses), and the excess spread trapping point (the point at which the bank is required to trap the excess spread as economically required by the structure, by default 4.5 percent). The CCF is then as shown in Table 5.16.

Table 5.16 CCF for early amortization features

Type of line	Three-month excess spread/trapping point (%)	Controlled early amortization (%)	Non-controlled early amortization (%)
<i>Retail credit lines</i>			
Uncommitted	≥ 133	0 CCF	0 CCF
	$100 \leq x < 133$	1 CCF	5 CCF
	$75 \leq x < 100$	2 CCF	15 CCF
	$50 \leq x < 75$	10 CCF	50 CCF
	$25 \leq x < 50$	20 CCF	100 CCF
	$x < 25$	40 CCF	100 CCF
Committed		90 CCF	100 CCF
<i>Other credit lines</i>		90 CCF	100 CCF

IRB approaches

Banks that have received approval to use the IRB Approach for the type of exposures securitized must use the IRB Approach to securitization. Under the IRB Approach, there are three sub-approaches:

- The Rating-Based Approach (RBA), that must be applied when the securitized tranche has external or internal ratings.
- The Supervisory Formula (SF), used when there are no available ratings.
- The Internal Assessment Approach (IAA), also used when there are no available ratings but only for exposures extended to ABCP programs.

The capital requirements are always limited to a maximum corresponding to the capital requirements had the exposures not been securitized.

In the *RBA*, a risk-weight is assigned by function of an external or internal inferred rating (that can be assigned with reference to an external rating already given to another tranche that is of equal seniority or more junior and of equal or shorter maturity), the granularity of the pool, and the seniority of the position. The granularity is determined by calculating the effective number of positions N , with the following formula:

$$N = \frac{(\sum EAD)^2}{\sum EAD^2} \quad (5.7)$$

The risk-weights can then be found as in Table 5.17.

Table 5.17 Risk-weights for securitization exposures under the RBA

RW	Rating	Senior tranche, N ≥ 6 (%)	Not senior tranches and N ≥ 6 (%)	N < 6 (%)	
Long-term ratings	AAA	7	12	20	
	AA	8	15	25	
	A+	10	18		
	A	12	20	35	
	A–	20	35		
	BBB+	35		50	
	BBB	60		75	
	BBB–		100		
	BB+		250		
	BB		425		
	BB–		650		
	Unrated and <BB–		Deduction		
Short-term ratings	A1/P – 1	7	12	20	
	A2/P – 2	12	20	35	
	A3/P – 3	60	75	75	
		Other and unrated		Deduction	

The *IAA* applies only to ABCP programs. Banks can use their internal ratings if they meet three operational requirements:

- The ABCP must be externally rated (the underlying, not the securitized tranche).
- The internal assessment of the tranche must be based on ECAI criteria and used in the bank's internal risk management systems.
- A credit analysis of the asset seller's risk profile must be performed.

The risk-weight associated with the internal rating is then the same as in the RBA (see Table 5.17).

The *SF* is used when there is no external rating, no inferred internal rating, and no internal rating given to an ABCP program. The capital requirement is a function of: the IRB capital charge had the underlying exposures not been securitized (K_{IRB}), the tranche's credit enhancement level (L) and thickness (T), the pool's effective number of exposures (N), and the pool's exposure-weighted average loss given default (LGD). The tranche's IRB capital charge is the greater of $0.0056 \times T$ or $S[L + T] - S[L]$. $S[L]$ is the SF, defined as:

$$S[L] \begin{cases} L & \text{when } L \leq K_{IRB} \\ K_{IRB} + K[L] - K[K_{IRB}] + (d * K_{IRB} / \omega)(1 - e^{\omega(K_{IRB} - L) / K_{IRB}}) & \text{when } K_{IRB} < L \end{cases} \quad (5.8)$$

where

$$\begin{aligned} h &= (1 - K_{IRB} / LGD)^N \\ c &= K_{IRB} / (1 - h) \\ v &= [(LGD - K_{IRB})K_{IRB} + 0.25(1 - LGD)K_{IRB}] / N \\ f &= [(v + K_{IRB}^2) / (1 - h) - c^2] + [(1 - K_{IRB})K_{IRB} - v] / (1 - h) \tau \\ g &= [(1 - c)c] / f - 1 \\ a &= g * c \\ b &= g * (1 - c) \\ d &= 1 - (1 - h) * (1 - \text{Beta}[K_{IRB}; a, b]) \\ K[L] &= (1 - h) * ((1 - \text{Beta}[L; a, b])L + \text{Beta}[L; a + 1, b]c) \end{aligned}$$

"Beta" refers to the cumulative Beta distribution. Parameters τ and ω equal, respectively, 1,000 and 20. K_{IRB} is the ratio of the IRB requirement including *EL* for the underlying exposures of the pool and the total exposure amount of the pool. L is the ratio of the amount of all securitization exposures subordinate to the tranche in question to the amount of exposures in the pool. T is measured as the ratio of the nominal size of the tranche of interest to the notional amount of exposures in the pool. N is calculated as in 5.7.

The formula is implemented in the worksheet file “Chapter 5 – supervisory formula.xls.” Until the sum of the subordinated tranches and tranche for which the capital is calculated is less than the regulatory capital had the exposures not been securitized, the capital rate is 100 percent. Then it decreases sharply until the marginal capital rate becomes close to zero, as illustrated in Figures 5.1 and 5.2 (in this example, the capital had

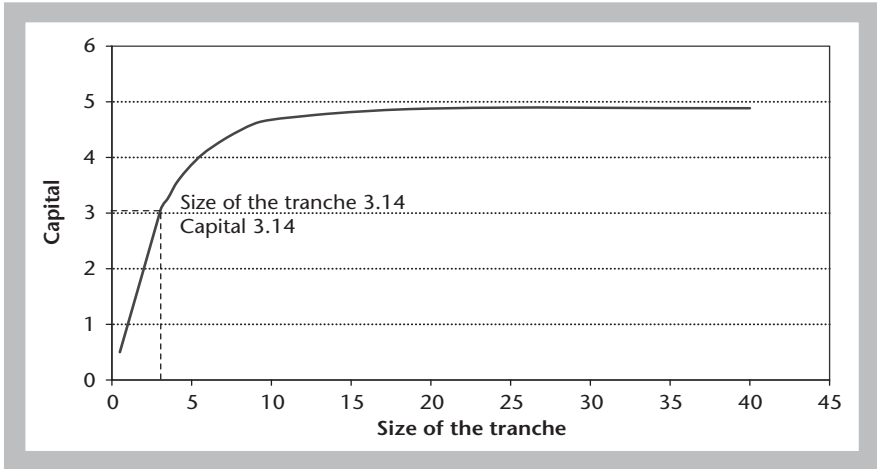


Figure 5.1 Capital using the SF

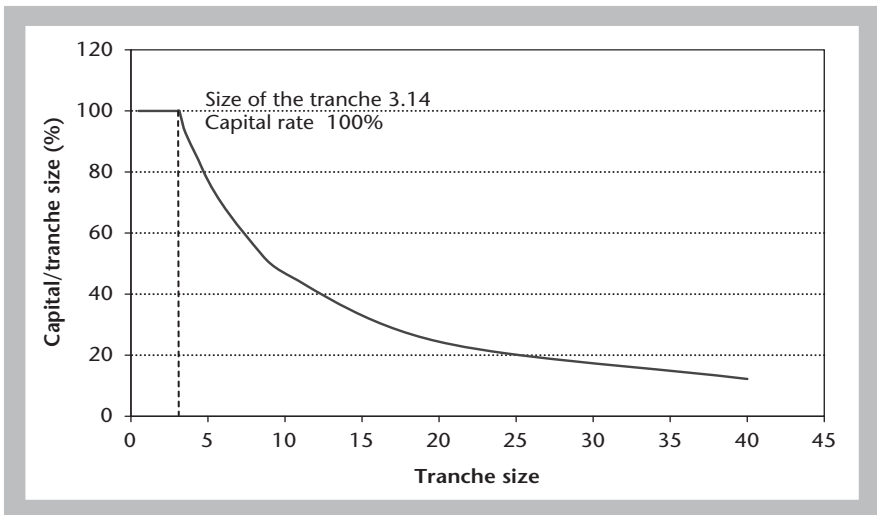


Figure 5.2 Capital rate using the SF

the exposures not been securitized would be 8.14 EUR, and the credit enhancement 5 EUR).

Liquidity facilities receive a 100 percent CCF. If they are externally rated, the bank may use the RBA. An eligible liquidity facility that is available only in the case of a general market disruption receives a 20 percent CCF (or, if it is externally rated, a 100 percent CCF and the RBA approach is used).

The securitization framework of Basel 2 is an important improvement over the current rules. This is a critical issue, as many capital arbitrage operations under the current Accord rules are done through securitization. Coming from simplified propositions at the beginning of the consultative process, the regulators ended with much more refined approaches in the final document thanks to an intense debate with the sector. This debate helped the sector itself to progress in its understanding of the main risk drivers of securitization. The SF is directly derived from a model proposed by Gordy (interested readers can consult Gordy and Jones, 2003; a detailed description of the model specifications is available on the BIS website). It integrates the underlying pool granularity, credit quality, asset correlation, and tranche thickness. Of course, each deal has its own specific structure and features that make it unique and it is very hard to find an analytical formula that captures precisely its risks; only a full-blown simulation approach (Monte Carlo simulations) can offer enough flexibility to be adapted to each operation. The formula chosen by the regulators tries to balance precision and simplicity (the latter being relative, when we look at (5.8)).

Even the RBA integrates the fact that a corporate bond AAA is not a securitized exposure AAA. It is widely recognized that a securitization tranche with a good rating is less risky than its corporate bond counterpart (except perhaps in leveraged structures), and that a securitization tranche with a low rating is much more risky than a corporate bond with the same rating. Looking at the risk-weighting given by the regulators we can see that it is integrated in the risk-weighting scheme (see Figure 5.3). Of course, not everybody agrees with the given weights (especially the 7 percent floor of a minimum RWA in both the RBA and SF approaches), but as we said the main risk drivers are incorporated in the formula and the approach is significantly improved compared to current rules. And before putting the new framework to the test the industry had to admit that there were still (even if the situation has improved over recent years) a lot of market participants, even among banks, that invest in securitization without having fully understood all the risks involved in such deals. The debate catalyzed by Basel 2 and the relative sophistication of the proposed formula will without any doubt help in the diffusion of a better understanding of these issues.

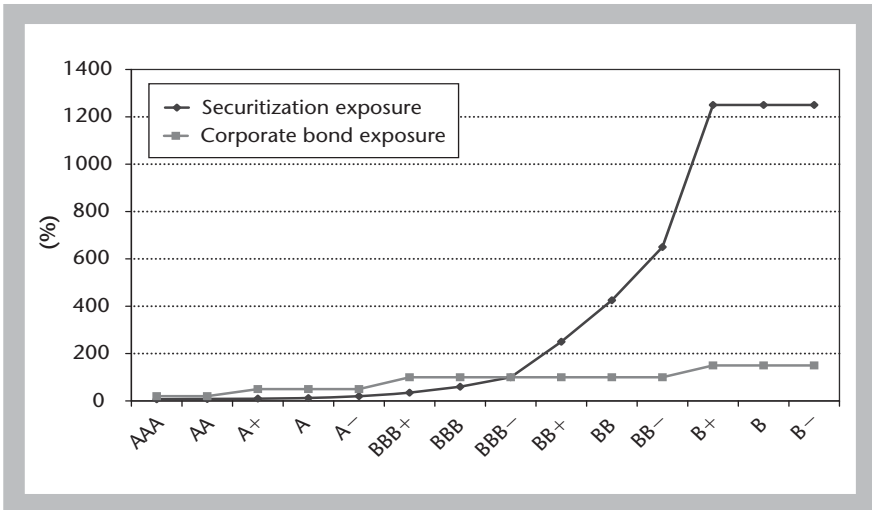


Figure 5.3 RWA for securitization and corporate exposures

OPERATIONAL RISK

“Operational risk” is defined as the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events. This definition includes legal risk, but excludes strategic and reputation risk. Capital requirements can be defined using three approaches, that have each their own specific quantitative and qualitative requirements.

Basic Indicator Approach (BIA)

The simplest method considers only that the amount of operational risk is proportional to the size of the bank’s activities, estimated through their gross income (net interest and commission income gross of provisions and operating expenses, and excluding profit/losses from the sale of securities in the banking book and extraordinary items).

The capital requirement is then the average positive gross income over the last three years multiplied by 15 percent. There are no specific requirements for banks to be allowed to use the BIA.

Standardized Approach (SA)

This is close to the BIA, except that banks’ activities are divided into eight business lines and each one has its own capital requirement as a function of its specific gross income. Again, the average gross income over the last

Table 5.18 The Standardized Approach to operational risk

Business line	Beta (%)	Description
Corporate finance	18	Mergers and acquisitions (M&A), underwriting, securitization, debt, equity, syndications, secondary private placements ...
Trading and sales	18	Fixed income, equity, foreign exchanges, commodities, proprietary positions, brokerage ...
Retail banking	12	Retail lending, deposits, merchant cards ...
Commercial banking	15	Project finance, real estate, export finance, trade finance, factoring, leasing, guarantees ...
Payment and settlement	18	Payments and collection, fund transfer, clearing and settlement ...
Agency services	15	Escrow, depository receipts, securities lending ...
Asset management	12	Pooled, segregated, retail, institutional, closed, open, private equity
Retail brokerage	12	Execution and full services

three years must be calculated. But this time the negative gross income of one business line can offset the capital requirements of another (as long as the sum of capital requirements over the year is positive). The formula is:

$$\text{Capital} = \sum_{j=1}^3 \frac{\max \sum_{i=1}^8 [(GI_{i,j} \times \beta_i); 0]}{3} \quad (5.9)$$

with $GI_{i,j}$ the gross income of business line i in year j and β_i the capital requirement for business line i . The Beta appropriated to the different business lines can be found in Table 5.18.

To be allowed to use the SA Approach, banks must fulfill a number of operational requirements:

- Board of directors and senior management must be actively involved in the supervision of the operational risk framework.
- Banks must have sufficient resources involved in Operational Risk Management (ORM) in each business line and in the audit department.
- There must be an independent ORM function, with clear responsibilities for tracking and monitoring operational risks.
- There must be a regular reporting of operational risk exposures and material losses.
- The banks ORM systems must be subject to regular review by external auditors and/or supervisors.

Advanced Measurement Approach (AMA)

As with VAR models for market risk and internal rating systems, the regulators offer the banks the opportunity with the AMA Approach to develop internal models for a self-assessment of the level of operational risk. There is no specific model recommended by the regulators. In addition to the qualitative requirements, that are close to those of the SA Approach, the models have to respect some quantitative requirements:

- The model must capture losses due to operational risk over a one-year period with a confidence interval of 99.9 percent (the expected loss is in principle not deducted).
- The model must be sufficiently granular to capture tail events i.e. events with very low probability of occurrence.
- The model can use a mix of internal (minimum five years) and external data and scenario analysis.
- The bank must have robust procedures to collect operational loss historical data, store them, and allocate them to the correct business line.

Regarding risk mitigation, banks can incorporate the effects of insurance to mitigate operational risk up to 20 percent of the operational risk capital requirements.

Operational risk is an innovation, as currently no capital is required to cover this type of risk, and it has been very controversial. For market risk, a lot of historical data are available to feed and back-test the models; for credit risk, data are already scarce; and for operational risk there are very few banks that have any efficient internal databases showing operational loss events. This is the more “qualitative” type of risk, as it is closely linked to procedures and control systems and depends significantly on experts’ opinions. Many people in the industry consider that it cannot be captured through quantitative requirements – the BIA and SA above all, requiring a fixed percentage of gross income as operational risk capital, are considered as very poor estimates of what should be the correct level of capital. The AMA is more interesting from a conceptual point of view, but as the major part of model parameters (loss frequencies and severities, correlation between loss types) cannot be inferred from historical data but have to be estimated by experts, it is hard to be sanguine as we work with such a high confidence level as 99.9 percent. But perhaps the regulators’ requirements are a necessary step to oblige banks to take a closer look at the operational risks associated with their businesses. We have to recognize that, even if the final amount of capital is open to discussion, many banks have gained a deeper understanding of the nature and the magnitude of such risks, and

as they involve the whole organization (and not only market and credit risk specialists) it is an opportunity to spread “risk consciousness” throughout all financial groups.

APPENDIX: PILLAR 1 TREATMENT OF DOUBLE DEFAULT AND TRADING ACTIVITIES

Introduction

In July 2005, the Basel Committee issued a complementary paper (“The application of Basel 2 to trading activities and the treatment of double default effects,” Basel Committee on Banking Supervision, 2005a) dealing with issues that were still being discussed at the time the core final Basel 2 text was published. The topics covered were some of the most debated in the industry, especially by securities firms. The Basel Committee on Banking Supervision has since had a permanent dialog with the International Organization of Securities Commissions (IOSCO). The paper proposes some updates, especially on the treatment of double default (since the substitution approach proposed in original paper was quite conservative) and on the treatment of trading activities.

Exposure at default for market-driven deals

Introduction

The computation of exposure at default (EAD) for transactions whose values are driven by market parameters (interest rates, exchange rates, equity prices ...) is as in Basel 1988 an MTM value plus an add-on related to the type of transaction and to the residual maturity (see Table 1.4, p. 20, for details). This is still the case with the update, but two other methods of increasing complexity have been added:

- Current Exposure Method (Basel 1988 method) (CEM)
- Standardized Method (SM)
- Internal Model Method (IMM)

EE, EPE, and PFE

The advanced approaches are based on three key concepts:

- Potential Future Exposure (PFE). This is the maximum exposure of the deal at a given high confidence interval (95 percent or 99 percent).

- Expected Exposure (EE). This is the probability-weighted average exposure at a given date in the future.
- Expected Positive Exposure (EPE). This is the time-weighted average EE over a given horizon.

Usually banks use PFE to set limits and EPE for computation of economic capital. The regulators consider that EPE is the appropriate measure for EAD.

A simplified example is given in Figures 5A.1–5A.3 (pp. 77, 79). Potential future interest rates have been simulated over a twelve-month-period, and the value of an amortizing swap has been estimated. By simulating 1,000 different possible paths of the floating-rate evolution, we can compute the value of the swap in each scenario and for each month. Then, by calculating the average value of positive exposures (negative exposures are set to zero as there are no compensating effects if a portfolio of swaps is made with different counterparties from a credit risk point of view), we can see the EE profile. The typical profile is an increase of the MTM value (because for longer horizons the volatility of the market parameters increases), and then a decrease (because of the amortization) (Figure 5A.1).

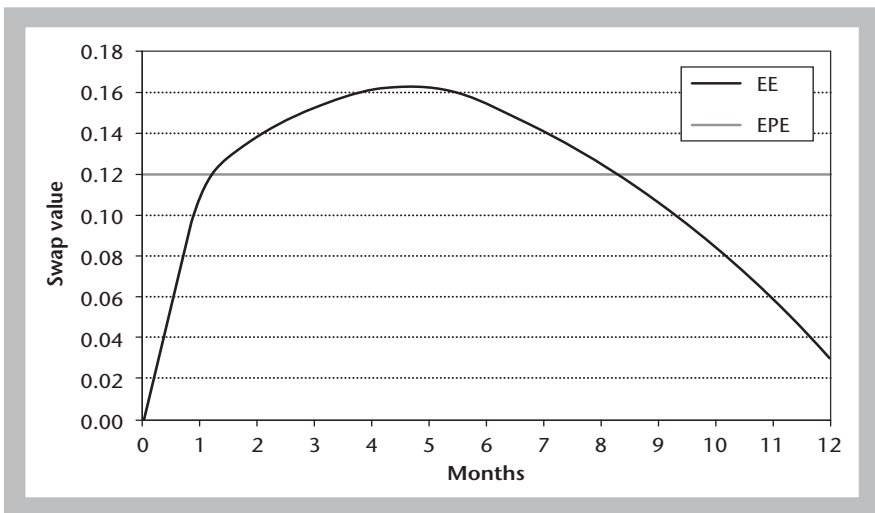


Figure 5A.1 EE and EPE

Looking at stressed exposures at 95 percent, we can also look at peak exposures (PFE) (Figure 5A.2).

The EPE is then an estimation of the average value at default for a portfolio of swaps on various counterparties over a one-year horizon.

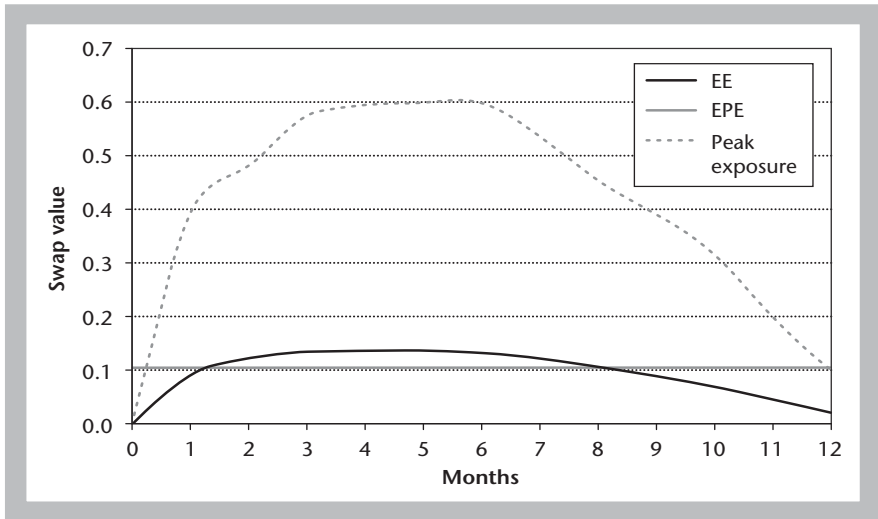


Figure 5A.2 EPE, EE, and PFE

The problem with this approach is that in many cases banks are doing short-term transactions that have exposures that rapidly go high but then quickly decrease. As the EPE is calculated over a one-year horizon, the average exposure will tend to be very low. But those transactions are usually rollover ones, and a new transaction is frequently made as soon as the first one comes to maturity. Taking only the first one into account would then underestimate the true risk.

To overcome this issue, the regulators have introduced the concept of *effective EE*. This is defined simply for a given time, t , as the maximum EE between $T = 0$ and $T = t$. EE is then never decreasing. With that concept, we can also calculate the effective EPE, which is considered by the regulators as being a good proxy for EAD estimation (see Figure 5A.3 opposite).

To take a conservative approach (because in a bad state of the economy the effective EPE might be higher than forecasted, to take into account the correlation between various products, the potential lack of granularity of the portfolio ...), the regulators impose a multiplicative factor of 1.4 to the effective EPE.

The rules

Banks can, as we have seen, then use three different approaches.

Current exposure method (CEM). The CEM can be applied only to OTC derivatives. It uses the add-on function proposed in Basel 1988 (p. 20).

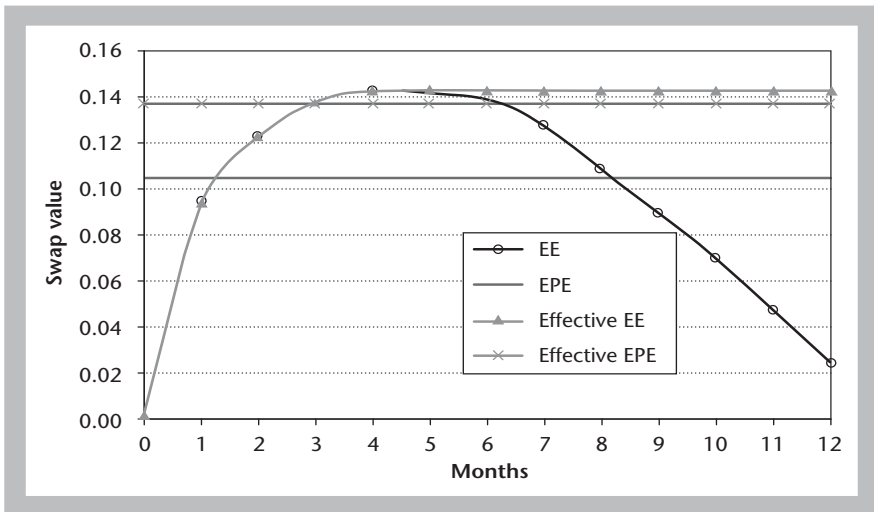


Figure 5A.3 EE, EPE, and effective EE and EPE

Standardized method (SM). The SM is based on methodologies already used for market risk. First, financial instruments are decomposed into their basic elements (for instance, a forex swap can be decomposed into a forex and an interest rate position). A net position is then calculated inside a *netting set* (a group of transactions with a counterparty that benefits from a netting accord). Positions are expressed in terms of a Delta equivalent (sensitivity of the change in value of the position to a one-unit change in the underlying risk parameters). Inside the netting sets, *hedging sets* (groups of positions inside a netting set that can be considered to offset each other as their value is driven by the same market parameters) are identified and net risk positions are calculated. For interest rates, there are six different dimensions to the hedging sets, depending on maturity (less than one year, from one to five years, more than five years) and on whether or not the reference rate is a government rate. The sum of these net positions are then calculated and multiplied by the CCFs given by the regulators. The CCFs have been calibrated by using effective EPE models (Tables 5A.1 and 5A.2).

“High” and “low” specific risks are defined in the 1996 Market Risk Amendment. Other OTCs benefit from a 10 percent CCF.

Table 5A.1 CCF for an underlying other than debt and forex instruments

Exchange rates (%)	Gold (%)	Equity (%)	Precious metals (%)	Electric power (%)	Other commodities (%)
2.5	5.0	7.0	8.5	4.0	10.0

Table 5A.2 CCF for an underlying that consists of debt instruments

High specific risk (%)	CDS or low specific risk (%)	Other (%)
0.6	0.3	0.2

The EAD then corresponds to:

$$EAD = \beta \times \max \left[CMV - CMC; \sum_j \left| \sum_i RPT_{ij} - \sum_l RPC_{lj} \right| \times CCF_j \right] \quad (5A.1)$$

where

β = Supervisory scaling factor

CMV = Current market value of transactions within the netting set

CMC = Current market value of the collateral assigned to the netting set

j = Index for the hedging set

l = Index for the collateral

i = Index for the transaction

RPT = Risk position for the transaction

RPC = Risk position for the collateral

CCF = CCF for the hedging set

Box 5A.1 gives an example.

Box 5A.1 Calculating the final exposure

As an example, suppose a US dollar-based bank, having two open swaps with the same counterparty, enters into a netting agreement. For each leg of the swap, we calculate the modified duration (as the Delta equivalent corresponds to the notional multiplied by the modified duration). Values are summarized in Table 5A.3.

Table 5A.3 Swap 1 and 2

Swap		Notional (million)	Modified duration	Delta equivalent
1	Paying	80	8	640
	Receiving		-0.25	-20
2	Paying	300	0.125	37.5
	Receiving		-6	-1,800

Each Delta equivalent is then grouped in a hedging set, the net value is calculated, and they are multiplied (the absolute amount) by corresponding CCF (0.2 percent in this case) (Table 5A.4).

Table 5A.4 CCF multiplication

Swap		Hedging set 1	Hedging set 2
		USD non-governmental <i>M</i> < 1y	USD non-governmental <i>M</i> > 5y
1	Paying		640
	Receiving	-20	
2	Paying	37.5	
	Receiving		-1,800
	Net positions	17.5	-1,160
	Absolute net positions	17.5	1,160
	CCF (%)	0.20	0.20
	Absolute net positions × CCF	0.035	2.32

In this case, the sum of net risk positions × CCF = 2.355. If we suppose a MTM value of -5 for swap 1, and +6 for swap 2, the net MTM (corresponding to CMV in (5A.1)) would be 1. The greater of the two is then is the sum or RPT that will be multiplied by the Beta factor (1.4).

The final exposure that will enter into the RWA computation will then be $2.355 * 1.4 = 3.297$.

If we had applied the Basel 1988 method (see Chapter 1, p. 20), the exposure would have been equal to:

$$NGR = 1/6 = 0.166$$

$$PFE \text{ (without netting)} = (80 + 300) \times 1.5 \text{ percent} \\ \times (\text{add-on for } + 5 \text{ years' interest position}) = 5.7$$

$$PFE \text{ (with netting)} = (0.4 + 0.6 \times 0.166) \times 5.7 = 2.85$$

The net exposure would then have been $1 + 2.85 = 3.85$, which is higher than the exposure calculated above. In this example, it is in the interest of the bank to choose the Standardized Method, as this will allow higher recognition of the offsetting effects of the two swaps.

Internal model method (IMM). Banks can finally use the IMM. In this approach, no particular model is prescribed and banks are free to develop their internal effective EPE measurement approach as long as they fulfill certain requirements and convince their regulators that their approach is

adequate (as in the AMA for operational risk). The effective EPE is then also multiplied by a regulatory factor Alpha(α) (in Principle, 1.4, but it can be changed by the regulator). Under specific conditions, banks can also estimate themselves the Alpha factor in their internal model (but there is a minimum of 1.2). To do this, banks should have a fully integrated credit and market risk model, and compare the economic capital allocated with a full simulation with the economic capital allocated on the basis of EPE (banks have to demonstrate that the potential correlation between credit and market risks has been captured).

The basic requirements for model approval are quite close to those for the VAR model under the Market Risk Amendment, but with some additional features (to work on a longer horizon, as one year is the reference, pricing models can be different from those used for short-term VAR, with regular back-testing, use tests, stress testing ...).

The IMM can also try to integrate the margin calls, but such modelizations are complicated, and will come under close scrutiny from the regulators.

If the CEM and SM are limited to OTC derivatives, the IMM can also be used for Securities Financing Transactions (SFT) such as repurchase/reverse-repurchase agreements, securities lending and borrowing, margin lending ...

The choice of one of the two more advanced approaches has additional impacts on pillar 2 (more internal controls, audit of the models by the regulators ...) and pillar 3 (specific disclosures on the selected framework) (see Chapter 7).

The IMM can be chosen just for OTC derivatives, just for SFT transactions, or for both. But, once selected, the bank cannot return to simpler approaches.

The two advanced approaches can also be chosen as if the bank is using an IRB or a Standardized Approach (SA).

Inside a financial group, some entities can use advanced approaches on a permanent basis and others the CEM. Inside an entity, all portfolios have to follow the same approach.

Double default

Introduction

The core principle in Basel 2 regarding the treatment of guarantees is the *substitution approach*, which means that the guaranteed exposure receives the PD and the LGD of the guarantor. The industry considered that this was too severe an approach, as to suffer a loss the bank has to face two defaults instead of one. For instance, with this approach, a single A-rated counterparty (on the S&P rating scale) benefiting from the guarantee of another A-rated company would not benefit from any capital relief compared to

an un-hedged exposure. On the other side, we cannot just multiply the PDs and LGDs because this would assume a null default correlation between the counterparty and the borrower. The regulators have proposed an update of the formula to take into account this “double default” effect, integrating some correlation between the two counterparties. This impacts on the PDs; for the LGDs no “double recovery” effect is recognized as the regulators consider that there are too many operational difficulties – both for the bank to benefit from this double recovery and for the regulators to set up rules to integrate it into their requirements.

Requirements

The scope of the eligible protection provider is quite limited. Only professional protection providers (banks, insurance companies ...) can be recognized. The reason is that the regulators want to make sure that the guarantee does not constitute too heavy a concentration for the guarantor. Professional providers are supposed to have diversified portfolios of the protections given. Regarding the rating, regulators require a minimum of A– at the time the guarantee is initiated. It still can be recognized if the rating of the guarantor is downgraded to a maximum of BBB–, to avoid too brutal changes in capital requirements. The exposure covered has to be a corporate exposure (excluding specialized lending if the bank uses the slotting criteria approach), a claim on a PSE (non-assimilated to a sovereign), or a claim on a retail SME. The bank has to demonstrate that it has procedures to detect possible too heavy correlations between guarantors and covered exposures. Only guarantees and credit derivatives (credit default swaps and total return swaps) that provide a protection comparable to guarantees are recognized. Multiple-name credit derivatives (other than *n*th to default eligible in the Basel 2 core text), synthetic securitization, covered bonds with external ratings, and funded credit derivatives are excluded from the scope of double default recognition.

Calculation of capital requirements

Those interested in the theoretical developments of the formula can read a White Paper from the FED (“Treatment of double default and double recovery effects for hedged exposures under pillar 1 of the proposed new Basel Capital Accord”, Heitfield and Barger, 2003). One has to make a hypothesis about the dependence of the guarantor on the systemic risk in the case of double default (the regulators used a correlation of 70 percent) and the pairwise correlation between the borrower and the guarantor (the regulators used 50 percent).

With some developments and simplifications, the regulators reached the following formula:

$$K_{DD} = K_o \times (0.15 + 160PD_g) \quad (5A.2)$$

with

$$K_o = LGD_g N \left[\frac{G(PD_o) + \sqrt{\rho_{os}} G(0.999)}{\sqrt{1 - \rho_{os}}} \right] - PD_o \frac{1 + (M - 2.5)b}{1 - 1.5b}$$

K_{DD} is the capital requirement in the case of a double default effect. We can see that it is a function of PD_g (the PD of the guarantor) and of K_o (the classical capital requirement formula). The only updates made to the computation of K_o are that we take LGD_g (the LGD of the guarantor) instead of the LGD of the borrower, and the maturity adjustment is calculated on the lower of the two PDs. PD_o and ρ_{os} represent the classical PD and correlation of the borrower. M is the maturity of the protection.

The formula is implemented in the worksheet file "Chapter 5 – double default effect.xls." We give some examples of application in Table 5A.5.

Table 5A.5 Application of the double default effect

	ex 1	ex 2	ex 3	ex 4
Exposure covered	100	100	100	100
PD borrower (%)	0.15	0.15	0.15	0.15
LGD borrower (%)	50	50	50	50
PD guarantor (%)	0.10	0.15	0.20	1.00
LGD guarantor (%)	40	50	50	50
Maturity protection	3	3	3	3
Regulatory capital (if not hedged)	3.70	3.70	3.70	3.70
Regulatory capital (substitution approach)	2.37	3.70	3.70	3.70
Regulatory capital (with double default effect)	0.97	1.44	1.74	6.48

We see in the first example that the capital consumption with double default effect is 0.97 against 2.37 for the substitution approach. The benefit is thus important.

In the second example, we show that even if the PD and LGD of borrower and guarantor are identical, there is still a capital relief (which is not the case with the substitution).

In the third example, we see also that even if the PD of the guarantor is higher than the PD of the borrower, there is also less capital consumed.

In the last example, we see that the capital relief has a limit, as for high PDs of the guarantor the capital consumption becomes higher with the guarantor than without. This is linked to the minimal rating requirement, as guarantors should be at least A– at the time the guarantee is issued. If we look at the first part of (5A.2) we see that the capital corresponds to the capital without

the guarantee effect (except for LGD and maturity adjustment) multiplied by $0.15 + 160 \text{ PD}$ of the guarantor. If we reverse the formula, we can easily see that if both LGD are equal, as soon as the PD of the guarantor was greater than $(1 - 0.15)/160 = 0.53$ percent, the formula would give a higher capital requirement than simply not recognizing the guarantee effect.

Short-term maturity adjustments in IRB

The industry has often complained about the fact that the capital requirements for short-term transactions have been too severe. The regulators were reluctant to authorize too heavy capital relief as they considered that such transactions were often rollovers and that they are in fact not really short-term transactions. After much debate and work to see if it was possible to develop a framework that would take into account the strategy of the bank regarding reinvestment of short-term transactions, the regulators concluded that a consensus was not achievable and that further work was needed. However, the regulators proposed some extended rules to facilitate the recognition of transactions eligible to break the minimum one-year floor for the maturity estimation in the July 2005 text (in the core Basel 2 text, the use of lower maturities is left at the national discretion).

The distinction is basically based on the idea that banks should separate relationship deals (where it is difficult not to renew deals without affecting the commercial relationship with the client) from non-relationship deals (where the bank can more easily stop dealing with a counterparty).

The rules

The regulators have decided that capital market transactions and Repo-style transactions, that are (nearly) fully collateralized, with an original maturity of less than one year, and with daily remargining clauses, will not be subject to the one-year minimum floor.

The regulators have also identified other transaction types that might be considered as non-relationship:

- Other capital market or Repo-style transactions not covered above.
- Some short-term self-liquidating letters of credit.
- Some exposures arising from settling securities purchases and sales.
- Some exposures arising from cash settlements by wire transfer.
- Some exposures arising from forex settlements.
- Some short-term loans and deposits.

These may not be subject to the one-year floor, but are still subject to national regulators' discretion.

Improvement of the current trading book regime

The 1996 Market Risk Amendment allows banks to use internal VAR models to compute their regulatory capital. But VAR models do not capture all risks (fat tails of distributions, intra-day risk, rapid increase of volatilities and correlations ...).

The results of the VAR model are then multiplied by 3 to arrive at the regulatory capital. In principle, specific risk linked to the credit quality of issuers should also be modeled. Otherwise, the multiplicative factor is 4.

Over recent years, credit risk in the trading book has increased, in part because of the increased use of new products (CDO, CDS ...). Liquidity risk has also risen with the use of ever more complex exotic products. Correctly capturing those increased risks in the trading book would generally result in higher capital requirements than simply using a multiplicative factor of 4 rather than 3. For that reason, the regulators have reviewed some requirements concerning the trading book to try to capture more efficiently the credit risks linked to it. For pillar 1, those requirements mainly cover four aspects:

- 1 Requirements linked to the *trading book/banking book border*. The trading book is currently not subject to capital requirements for credit risk. That is why some banks may try to perform capital arbitrage by classifying exposures in the trading book when they should be in the banking book. The July 2005 paper proposes a more narrow definition of "trading book" and requires the bank to have precise procedures to classify exposures. The trading book is limited to short-term positions taken in order to make quick profits, to perform arbitrage, or to hedge other trading book exposures. The procedures should clearly mention the definition of trading activities of the bank, its practices regarding MTM or marking to model, possible impairments to liquidity positions, and active risk management practices ...
- 2 *Prudent valuation guidance* is also stressed. The Basel 1996 text is already quite precise about the valuation rules but not always when dealing with the valuation of less liquid positions. The July 2005 text specifies that explicit valuation adjustments must be made to less liquid positions, taking into account the number of days necessary for liquidation, the volatility of the bid-ask spread, and the volatility of the trading volumes ...
- 3 The *trading book requirement for specific risk under the SA* is also updated (when no VAR model is used). The capital requirements for specific risk are currently linked to the RWA used in Basel 1988. The RWA are then

reviewed in light of the new Basel 2 approach. For instance, no capital charge is currently required for OECD government issuers, which corresponds to the 0 percent RWA in Basel 1988. This is modified to reflect the capital charge for sovereigns that will be a function of the rating in the Basel 2 SA.

- 4 Finally, the trading book requirements for banks using an Internal Model Approach (such as VAR) is also modified. The standards regarding model validation will be increased (for instance back-testing will have to be done at different percentile levels and not only at the 99th percentile). The multiplicative factor will be only 3, and no longer 4. But the regulators are concerned by the fact that a 99th percentile 10-day VAR may not capture the whole default risk of the position. Banks will be required to incorporate an *incremental credit risk measure* in their internal models, that captures risks not covered by existing approaches (such as the use of a credit spread VAR, for instance). Banks will have considerable freedom to develop their model and to try to avoid making a double count of the credit risk between this new requirement and the existing requirements relative to specific risks (double counts may be related to various forms of credit risk such as default risk, spread risk, migration risk ...). But if the bank does not succeed in developing such models and convincing its regulators that this approach is adequate, it will have to apply the IRB approach to the related positions! This will often result in much higher requirements than using a 4 rather than 3 multiplicative factor in the VAR. Additionally, banks will have to use the SA (instead of VAR) to measure specific risk. Banks that have already received an agreement to use an internal VAR model to quantify specific risk may defer until 2010 before bringing their model in line with the new standards.

Under pillar 2, the increased focus of the regulators on stress test is noticeable. Where they were already required under current regulation, the way their results should be explicitly incorporated into internal economic capital targets is now stressed.

Under pillar 3 (see Chapter 7), the requirements are linked to increased disclosures on the trading book valuation methods and on the way the internal economic capital for market risk is assessed.

Capital requirements for failed trades and non-Delivery Versus Payment transactions

The last part of the July 2005 paper deals with the capital requirements linked to exposures issued from failed trades. Currently, rules applied throughout the world (for instance in Europe and in the US) are different. A move to uniformity proposed.

The proposal applies to commodities, forex, and securities transactions (repurchase and reverse repurchase are excluded). For Delivery Versus Payment (DVP) transactions, the risk position equals the difference between the agreed settlement price and the current MTM. For non-DVP transactions, the risk position equals the full amount of cash or securities to be received.

For DVP transactions, the capital requirements are a function of the number of days of delay in payment (Table 5A.6).

Table 5A.6 Capital requirements for DVP transactions

Days of delay	Capital (%)
5–15	8
16–30	50
31–45	75
+45	100

For non-DVP transactions, the risk is first risk-weighted as a classical exposure in IRB. But if payment is still not received/delivery is still not made five business days after the second contractual date, the replacement cost of the first leg that was effectively paid/transferred by the bank will be deducted from the equity.

Pillar 2: The Supervisory Review Process

INTRODUCTION

Pillar 2 is the least significant of the three pillars in terms of number of pages devoted to it in the Accord, but is probably the most important. One could laconically summarize pillar 2 by the following commandment from the regulators:

Evaluate all your risks, cover them with capital, and we will check what you have done.

Pillar 2 principles are deliberately imprecise because what the regulators want is that banks identify all the risks not (or only partially) covered under pillar 1, and evaluate them. The regulators do not yet have a precise idea of the list of risks concerned (which could be different for each bank, as a function of its particular risk profile) and on the ways to evaluate the correct level of capital necessary to cover them. In a PriceWaterhouseCoopers study on pillar 2 issues in Europe (PriceWaterhouseCoopers, 2003), 37 percent of banks questioned considered that the regulators did not have the adequate skills and 75 percent that they did not have the adequate resources to implement pillar 2 effectively. This shows how the few pages in the Basel 2 Accord on pillar 2 hide a number of requirements regarding models and processes to manage the risk not treated under pillar 1 that can be as important and demanding as the whole of pillar 1 itself – perhaps even more so for large and complex banking groups.

In the next section we shall describe the main requirements of pillar 2 and in Part 4 of the book we shall give the reader some preliminary thoughts on

ways to handle some of the risk types that have to be covered under this part of the Accord.

PILLAR 2: THE SUPERVISORY REVIEW PROCESS IN ACTION

The goal of the SRP is to ensure that the bank has enough capital to cover its risks and to promote better risk management practices. The management of the bank is required to develop an Internal Capital Adequacy Assessment Process (ICAAP), and to fix a target capital level that is a function of the bank's risk profile. If the supervisors are not satisfied with the capital level, they can require the bank to increase its capital level or mitigate some of its risks. The three main areas that must be handled under pillar 2 are:

- Risks that are not fully captured by pillar 1 – such as concentration risk in credit risk.
- Risks that are not covered by pillar 1 – interest rate risk in the banking book, strategic risk, reputation risk ...
- Risks external to the bank – business cycle effects.

Under pillar 2, supervisors must also ensure that banks using the IRB and AMA Approaches meet their minimum qualitative and quantitative requirements.

The SRP is built upon four key principles:

Principle 1: Banks should have a process for assessing their overall capital adequacy in relation to their risk profile, and a strategy for maintaining their capital levels.

Banks have to demonstrate that their capital targets are consistent with their risk profile and integrate the current stage of the business cycle (capital targets must be forward-looking):

- The board of directors must determine the risk appetite, and the capital planning process must be integrated in the business plan.
- There must be clear policies and procedures to make sure that all material risks are identified and reported.
- All material risks must be covered. The minimum is: credit risk (including ratings, portfolio aggregation, securitization and concentration), market risk, operational risk, interest rate risk in the banking book, liquidity risk, reputation risk and strategic risk.

- A regular reporting system must be established to ensure that senior management can follow and evaluate the current risk level, as well as estimating future capital requirements.
- There must be a regular independent review of the ICAAP.

Principle 2: Supervisors should review and evaluate banks' internal capital adequacy assessments and strategies, as well as their ability to monitor and ensure their compliance with regulatory capital ratios. Supervisors should take appropriate action if they are not satisfied with the result of this process.

The goal is not for regulators to substitute themselves for the banks' risk management. Through a combination of on-site examinations, off-site reviews, discussions with senior management, review of external auditors' work, and periodic reporting, regulators must:

- Assess the degree to which internal targets and processes incorporate the full range of material risks faced by the bank.
- Assess the quality of the capital composition and the quality of senior management's oversight of the whole process.
- Assess the quality of reporting and of senior management response to changes in the bank's risk profile.
- Assess the impact of pillar 1 requirements.
- React if they are not satisfied by the bank's ICAAP (by requiring additional capital or risk-mitigating actions).

Principle 3: Supervisors should expect that banks will operate above the minimum regulatory capital ratios and should have the ability to require banks to hold capital in excess of the minimum.

As it is explicitly stated that pillar 1 does not cover all risks, the regulators also state explicitly that they expect banks to have capital ratios on RWA above the usual 8 percent requirement. Capital above the minimum level can be justified by:

- The desire of some banks to reach higher standards of creditworthiness (to maintain a high rating level, for instance).

- The need to be protected against any future unexpected shift in the business cycle.
- The fact that it can be costly to get some fresh capital; operating with a buffer can then be cheaper.

Principle 4: Supervisors should seek to intervene at an early stage to prevent capital from falling below the minimum level required to support the risk characteristics of a particular bank, and should require rapid remedial action if capital is not maintained or restored.

The range of actions that can be required by the regulators is wide: intensifying the monitoring of the bank; restricting the payment of dividends; requiring the bank to prepare and implement a satisfactory capital adequacy restoration plan; and requiring the bank immediately to raise additional capital. Supervisors will have the discretion to use the tools best suited to the circumstances of the bank and its operating environment.

Under the SRP, the regulators will ensure in particular that:

- *Interest rate risk* is correctly managed. A reference document was issued on the subject (“Principles for the management and supervision of interest rate risk,” Basel Committee on Banking Supervision, 2004b).
- Concerning *credit risk*, the definition of default, the stress tests for IRB required under pillar 1, the concentration risk, and the residual risk (the indirect risk associated with the use of credit risk mitigants) are all correctly applied and managed.
- *Operational risk* is correctly managed. A reference document was issued on the subject (“Sound practices for management of operational risk,” Basel Committee on Banking Supervision, 2003b).
- *Innovations on the securitization markets* are correctly covered by capital rules.
- The risks of a bank’s securitized assets are efficiently transferred to third parties and there is no implicit support from the originating bank.

As we can see, pillar 2 offers an important latitude to supervisors. There are some fears in the industry that it could lead to an unlevel playing field because some regulators could be more severe than others. In response to this, the Committee of European Banking Supervisors (CEBS) proposed a range of eleven “high-level principles” (CP03) that are designed to bring convergence in the regulators’ implementation of pillar 2 (CEBS, 2005). See Table 6.1.

Table 6.1 CEBS high-level principles for pillar 2

I	Every institution must have a process for assessing its capital adequacy in relation to its risk profile (an ICAAP)
II	The ICAAP is the responsibility of the institution itself
III	The ICAAP should be proportionate to the nature, size, risk profile, and complexity of the institution
IV	The ICAAP should be formal, the capital policy fully documented, and the management body's responsibility
V	The ICAAP should form an integral part of the management process and decision-making culture of the institution
VI	The ICAAP should be reviewed regularly
VII	The ICAAP should be risk-based
VIII	The ICAAP should be comprehensive
IX	The ICAAP should be forward-looking
X	The ICAAP should be based on adequate measurement and assessment processes
XI	The ICAAP should produce a reasonable outcome

INDUSTRY MISGIVINGS

The industry globally welcomed this initiative but some fears remain:

- The fact that it is still not yet clear at which level pillar 2 will have to be applied. The industry considers that, for a large banking group, most of the ICAAP makes sense only at the *group consolidated level*.
- The requirement that the bank will have to operate above the 8 percent minimum capital level for pillar 1 does not recognize the *potential diversification effect* as credit, market, and operational risks are not perfectly correlated (which is the underlying hypothesis in pillar 1 as capital requirements for those types of risks are simply added). The industry considers that sophisticated banks could have internal capital targets below the pillar 1 level.
- The SRP must remain a firm driven process and responsibility. There have been discussions between regulators about the use of a supervisory Risk Assessment System (RAS) that could be used to measure credit, market, interest rate, liquidity, and operational risks. This would be a kind of regulators' model that could be used to benchmark the results of various banks' own internal models. The sector is arguing that each bank has its own particular risk profile, and that such tools could cause a risk of *standardization of banks' risk models*, which could be a potential source of systemic risk.

- There are also fears about the quality of *cooperation* between various regulators when reviewing pillar 2 in large international groups. This is illustrated in the Basel 2 Accord by the numerous options left to national discretion, mostly resulting from the failure of the regulators to agree on a common methodology for complex items.

Pillar 2 will undoubtedly impose a heavy work-load on the banks. They have for the moment mainly focused on compliance with pillar 1. But pillar 2 is a strategic issue because the risks of an unlevel playing field may become more severe. For the moment, many banks are already operating above the minimum 8 percent BIS solvency ratio. But in most cases, this is to secure a desired credit rating, to align to peers, or to avoid the risk of falling below the 8 percent requirements; it is generally not to cover explicit risk types not dealt with in the current Accord. This could change in coming years as the integration of an economic capital culture, that seems to be generally accepted in the industry although not yet fully implemented, will probably be boosted by the need to meet pillar 2 requirements. With more transparent reporting of a banking group risk profiles and capital needs (which will be facilitated by pillar 3, see Chapter 7), and a more efficient dialog between banks' management, regulators, shareholders, and rating agencies, we shall probably see a major shift that will relate the total capital of a group to less subjective factors than today, which should lead to a more efficient use and allocation of capital that will benefit the sector as a whole.

To be efficient, capital management needs not only to be practiced by the more advanced credit institutions, but by a large part of the banking industry. This is a key issue if we want efficient secondary credit risk markets and even fair pricing competition. We shall discuss this in greater depth in Part IV of the book.

Pillar 3: Market Discipline

INTRODUCTION

With pillar 3, the third actor in the banking regulation framework enters the scene. Pillar 1 was focused on the banks' own risk-control systems, pillar 2 described how the regulators were supposed to control the banks' risk frameworks, and finally pillar 3 relies on market participants to actively monitor the banks in which they have an interest. Broadly, pillar 3 is a set of requirements regarding appropriate disclosures that will allow market participants to assess key information on the scope of application, capital, risk exposures, and risk assessment processes, and so the capital adequacy of the institution.

Investors such as equity or debt holders will then be able to react more efficiently when banks' financial health deteriorates, forcing banks' management to react to improve the situation.

PILLAR 3 DISCLOSURES

The exact nature of pillar 3 has yet to be determined, and national regulators should have an important freedom in designing the frameworks (although there is a desire to build a common skeleton framework across Europe). The regulators will have to decide which part of the disclosures will be addressed only to themselves and which part will be made public. The powers of the regulators concerning mandatory disclosures vary greatly

between various national contexts, and non-disclosure of some items should not automatically translate into additional capital requirements. However, some disclosures are directly linked to the pillar 1 options and their absence could consequently mean that the bank would not be authorized to use them.

The scope of required disclosures is very wide; we summarize the main elements in Table 7.1.

The disclosures set out in pillar 3 should be made on a semi-annual basis, subject to the following exceptions:

- Qualitative disclosures that provide a general summary of a bank's risk management objectives and policies, reporting system, and definitions may be published on an annual basis.
- In recognition of the increased risk sensitivity of the framework and the general trend towards more frequent reporting in capital markets, large internationally active banks and other significant banks (and their significant bank subsidiaries) must disclose their Tier 1 and total capital adequacy ratios, and their components, on a quarterly basis.

LINKS WITH ACCOUNTING DISCLOSURES

We cannot talk about pillar 3 without saying a word on accounting practices. Accounting rules differ between countries, and so can have a direct impact on the comparability of the RWA of different banks. Additionally, the International Financial Reporting Standards (IFRS) reform is bringing important changes in the way financial information is reported to the market. IFRS is based on the principles of Market Value Accounting (MVA), which means that all assets and liabilities should be valued at their market price (the price at which they could be exchanged on an efficient market). This will bring a dual accounting system to most countries: the local Generally Accepted Accounting Principles (GAAP) (at the national level) versus the IFRS GAAP (the standard for reporting on international financial markets). In Europe, local GAAP are mainly "historical cost"-oriented, rather than "market value"-based. The national regulators will have to decide on which set of figures the RWA will be based. IFRS rules generate much more volatility as they are linked to current market conditions, which is in opposition with some Basel 2 principles, such as the requirements to estimate ratings on a through-the-cycle (TTC) basis (we shall discuss this in Part III of the book) and PDs on a long-run average basis. MVA creates volatility in assets and liabilities valuation, which results in leveraged volatility of equity. As it is the numerator of the solvency ratio, we can understand the fears of regulators that it could increase the risks of procyclicality that are already inherent in the Basel 2 framework. (Procyclicality is the risk that

Table 7.1 Pillar 3 disclosures

Topic	Qualitative disclosures	Quantitative disclosures
Scope of application	<ul style="list-style-type: none"> – Name of top entity – Scope of consolidation – Restrictions on capital transfer – Description of various capital instruments 	<ul style="list-style-type: none"> – Surplus capital of insurance subsidiaries – Capital deficiencies in subsidiaries – Amount of interest in insurance subsidiaries not deducted from capital – Amount of Tier 1, Tier 2, and Tier 3 – Deductions from capital
Capital	<ul style="list-style-type: none"> – Summary of bank's approach to assessing the adequacy of its capital 	<ul style="list-style-type: none"> – Capital requirements for credit, market, and operational risks – Total and Tier 1 ratio
Capital adequacy	<ul style="list-style-type: none"> – Discussion of bank's credit risk management policy – Definitions of past due and impaired 	<ul style="list-style-type: none"> – Total gross credit risk exposures – Distribution of exposures by: country, type, maturity, industry and Basel 2 method (Standardized, IRB ...) – Amount of impaired loans
Credit risk – general disclosures	<ul style="list-style-type: none"> – Name of ECAI, type of exposures they cover – Alignment of scale of each agency used with risk buckets 	<ul style="list-style-type: none"> – Amount of a bank's outstandings in each risk bucket
Credit risk – SA	<ul style="list-style-type: none"> – Supervisor's acceptance of approach – Description of rating systems: structure, recognition of CRM, control mechanisms ... 	<ul style="list-style-type: none"> – EAD, LGD, and RWA by PDs – Losses of preceding period – Bank estimated versus realized losses over a long period
Credit risk – IRBA	<ul style="list-style-type: none"> – Policies and processes for collateral valuation and management – Main types of collateral and guarantors – Risk concentration within CRM 	<ul style="list-style-type: none"> – Exposures covered by: financial collateral, other collateral, guarantors
CRM		

Continued

Table 7.1 Continued

Topic	Qualitative disclosures	Quantitative disclosures
Securitization	<ul style="list-style-type: none"> – Bank's objectives in relation to securitization activity – Regulatory capital approaches – Bank's accounting policies for securitization activities 	<ul style="list-style-type: none"> – Total outstanding exposures securitized by the bank – Losses recognized by the bank during current period – Aggregate amount of securitization exposures retained or purchased
Market risk (internal models)	<ul style="list-style-type: none"> – General qualitative disclosure: strategies and processes, scope and nature of risk measurement system ... 	<ul style="list-style-type: none"> – High, mean, and low VAR values over the reporting period and period end – Comparison of VAR estimates with actual gains/losses
Operational risk	<ul style="list-style-type: none"> – Approach(es) for operational risk capital assessment for which the bank qualifies – Description of the AMA, if used by the bank 	
Equities	<ul style="list-style-type: none"> – Policies covering the valuation and accounting of equity holdings in banking book – Differentiation between strategic and other holdings 	<ul style="list-style-type: none"> – Book and fair value of investments – Publicly traded/private investments – Cumulative realized gains (losses) arising from sales and liquidations
Interest rate risk in banking book (IRRBB)	<ul style="list-style-type: none"> – Assumptions regarding loan pre-payments and behavior of non-maturity deposits, and frequency of IRRBB measurement 	<ul style="list-style-type: none"> – Increase (decline) in earnings or economic value for upward and downward rate shocks broken down by currency (as relevant)

all risk parameters will be stressed in an economic downturn, leading to a sharp decrease in the solvency ratio, which could cause the banks to turn off the credit tap, leading to a credit crunch.)

The regulators' decision is not yet clear; however, they seem to be opting rather for keeping the current accounting practices instead of encouraging MVA. This issue has been widely debated in the industry. Europeans tend to be more in favor of the historical cost method because European companies, especially banks, do not have the habit of communicating volatile results, as investors prefer predictable cash flows. In the US, the local GAAP accounting system is already more market-oriented, as large corporate companies represent a wider share of the global economy (there are fewer SME) and as the financial markets are more developed. Even if it brings more volatility in financial accounts, there are arguments in favor of MVA, even from a banking regulation point of view. A BIS Working Paper ("Bank failures in mature economies," Basel Committee on Banking Supervision, 2004a) pointed out that in 90 percent of recent banking failures, the reported solvency ratio was above the minimum. This shows that without a correct valuation of assets and an adequate provisioning policy, the solvency ratio is an inefficient tool to identify banks that are likely to run into trouble.

Proponents of the MVA argue that banks have interest in selling assets whose value has increased to show a profit, while maintaining assets whose value has decreased in their balance sheet at historical cost. Banks' balance sheets would then tend to be undervalued. They also argue that MVA would allow a quicker detection of problems and would then lead to a more efficient regulatory framework.

Opponents consider that, in addition to the problems caused by volatility and procyclicality, there are still too many assets and liabilities that do not have observable market prices, leading to too much subjectivity in valuing them with in-house models, opening the door to asset manipulation.

CONCLUSIONS

Pillar 3 is an integral part of the Basel 2 Capital Accord. It establishes an impressive list of required disclosures that should help investors to get a better picture of the banks' true risk profile. They should then be able to make more informed investment decisions and consequently create an additional pressure on banks' management teams to monitor their risks closely.

The choice of the accounting practices on which disclosures will be based (the basis for computing the solvency ratio) is still an open issue. Each approach – historical cost or MVA – has its advantages and drawbacks.

Our belief is that, even under a historical cost accounting system, the new Basel 2 framework will lead to a more efficient solvency ratio if rating systems are sufficiently sensitive (which means not too much TTC). MVA

is more appropriate for investment banks that have a significant portion of their assets in liquid instruments. The large commercial banks, despite the development of securitization markets, are still heavily dependent on short-term funding resources and have large illiquid loan portfolios. Reflecting any theoretical change in the value of these loans that will be, in principle, held to maturity, could result in more drawbacks than advantages.

However, over time there will be an increased amount of historical data on default, recoveries, and correlations of various banking assets. This will help the industry to build more efficient and standardized pricing models and will make secondary credit markets more liquid. At this stage, the MVA would make more sense as a reference for the whole industry.

The Potential Impact of Basel 2

INTRODUCTION

What are the most likely consequences of Basel 2? It is hard to give an answer without a crystal ball, as there are still many undecided issues and because the regulatory environment is not the only determinant of banks' capital level. But this need not prevent us from trying to draw broad conclusions.

During the consultative process, banks had to participate in several Quantitative Impact Studies (QIS) that were designed to assess the potential impacts of the new risk-weighting scheme. The initial goal of the regulators was to keep the global level of capital in the financial industry close to the current level, while changing only the allocation (more capital for riskier banks, and less for safer banks). The refined credit risk framework was clearly going to decrease global capital requirements, but this would be compensated for by a new operational risk framework.

The following results are based on the QIS 3 study ("Quantitative Impact Study 3 – overview of global results," Basel Committee on Banking Supervision, 2003a). At the time of writing, a QIS 5 is under way but the conclusions should broadly be the same.

RESULTS OF QIS 3

Table 8.1 presents the results of the QIS 3, by portfolio, in terms of contribution to the overall change in capital requirements, in comparison to the

Table 8.1 Results of QIS 3 for G10 banks

QIS 3 – G10 banks Portfolio	SA		IRBF approach		IRBA approach
	Group 1 (%)	Group 2 (%)	Group 1 (%)	Group 2 (%)	Group 1 (%)
Corporate	1	–1	–2	–4	–4
Sovereign	0	0	2	0	1
Bank	2	0	2	–1	0
Retail	–5	–10	–9	–17	–9
SME	–1	–2	–2	–4	–3
Securitized assets	1	0	0	–1	0
Other	2	1	4	3	2
Overall credit risk	0	–11	–7	–27	–13
Operational risk	10	15	10	7	11
Overall change	11	3	3	–19	–2

current Accord. The results are based on data provided by 188 banks of the G10 countries. Banks are classified into two groups:

- *Group 1:* These are large, diversified, and internationally active banks with a Tier 1 capital in excess of 3,000 million EUR.
- *Group 2:* These are smaller, and usually more specialized banks (results for the IRBA approach are not available for group 2).

The results show that the goal of regulators has been achieved, as the large internationally active banks, that are likely to opt for one of the IRB approaches, see their capital requirements unchanged (+3 percent IRBF, –2 percent IRBA). However, we can see that the impact is different for the various portfolios. Clearly, the winners are the retail portfolios, that see their average capital decreasing from –5 percent to –17 percent in the various approaches.

The relative stability of these global results hides an important variance if we look at individual banks. To see its magnitude, Table 8.2 shows the minimum and maximum change in the capital requirements for an individual bank.

The reason for such differences is the concentration of certain banks in particular portfolios. Table 8.1 shows the average contribution of each portfolio to the change in global capital requirements – it is a function of the current size of the portfolio in comparison to the global banking assets.

Table 8.2 Results of QIS 3 for G10 banks: maximum and minimum deviations

QIS 3 – G10 banks	SA		IRBF approach		IRBA approach
	Group 1 (%)	Group 2 (%)	Group 1 (%)	Group 2 (%)	Group 1 (%)
Maximum	84	81	55	41	46
Minimum	–15	–23	–32	–58	–36
Average	11	3	3	–19	–2

Table 8.3 Results of QIS 3 for G10 banks: individual portfolio results

QIS 3 – G10 banks	SA		IRBF approach		IRBA approach
	Group 1 (%)	Group 2 (%)	Group 1 (%)	Group 2 (%)	Group 1 (%)
Corporate	1	–10	–9	–27	–14
Sovereign	19	1	47	51	28
Bank	43	15	45	–5	16
Retail (total)	–21	–19	–47	–54	–50
– Mortgage	–20	–14	–56	–55	–60
– Non-Mortgage	–22	–19	–34	–27	–41
– Revolving	–14	–8	–3	–33	14
SME	–3	–5	–14	–17	–13
Specialized lending	2	2	n.a.	n.a.	n.a.
Equity	6	8	115	81	114
Trading book	12	4	5	4	2
Securitized assets	86	61	103	62	129

Note: n.a. = Not available.

If we want to make a more detailed analysis, it is interesting to look at the results portfolio by portfolio on a stand-alone basis, because the impact of Basel 2 could be a shift in the global allocation of banking assets to portfolios that consume less regulatory capital. Table 8.3 shows the relative change in regulatory capital consumption in comparison to the current method (Basel 1) for each portfolio.

Table 8.3 gives another picture of the possibly large impact that Basel 2 may have for banks that decide to focus on certain portfolios. Here we can see more clearly who are the winners and losers. As Table 8.1 showed, retail is the

great winner. But we can see here to what extent: in the IRB approaches there is a gain of 50 percent in capital consumption. Other winners are corporate and SME in the IRB approaches. European countries were concerned about the possible negative impact of the Basel 2 Accord on the credits made to SME, but after all the discussions and the new calibration of the SME risk-weighting curve, credit to SME will consume less capital than before. On the other side, the losers are sovereign and banks (OECD banks and sovereigns benefit from a low 0 percent and 20 percent RWA in the current Accord, whatever is their risk level), and especially equity and securitized assets portfolios. For securitized assets, as they were often used to make capital arbitrage (as we saw in Chapter 3), the increase in capital consumption gives a better image of the associated risks.

COMMENTS

The exact impact of those changes is hard to estimate. Three elements that we need to keep in mind when trying to figure out how the banking sector may evolve over the coming years are now considered:

- *Regulatory capital requirements* are not the only determinant of banks' capital level. Currently, most of the large internationally active banks are operating above the minimum 8 percent solvency ratio. There are pressures from the market and from rating agencies that will probably not disappear during the night between December 31, 2007 and January 1, 2008, even for banks that will see their solvency ratio double. The Basel 2 Accord will probably help in making the banks' true level of risk more transparent, but those that would be able to benefit from the lower capital level will have to take time to explain it to market participants. They will have to convince investors and rating agencies that a higher solvency ratio reflects a level of risk that may be currently over-estimated, and it will certainly take some years for them to get more confidence in the new framework.
- On the hypothesis that banks will really be able to *benefit from capital reductions*, it will not necessarily automatically result in additional profits (because of a lower cost of funding). The extent to which the benefits will be distributed between banks and their customers may vary from one country to another, and from one market to another. Where markets are efficient, with a true competition between banks and informed customers, most of the benefits may end in the clients' pockets as the pricing of the products will suffer from downward pressures. Only in niche markets, where customers are the captive of some banks, will true benefits be directed to financial institutions' shareholders.

- Some industry commentators believe that Basel 2 could be a catalyst for *consolidation* in the sector. For instance, banks that have large retail portfolios could use the liberated capital to buy competitors more concentrated in segments with higher capital requirements. Or banks that may qualify for the IRB approaches may want to buy competitors that are still using the SA that consumes more capital.

CONCLUSIONS

As we have seen, the global impact of Basel 2 is relatively neutral, as desired by the regulators. There are also some benefits in reaching the more advanced approaches, as the average difference with the current approach for group 1 banks (large international banks) is +11 percent in the SA, +3 percent in the IRBF; and -2 percent in the IRBA.

However, those results hide an important variability, with some banks seeing their capital requirements multiplied or halved. The more advantaged banks are those that have an important part of their assets in retail exposures.

How this will translate into effective capital reductions or increases, and what impact it may have on the banking sector, will also depend on market and rating agency reactions. But there will probably be a more intense competition in retail markets and shakeouts in emerging markets.

We should also bear in mind that the most important impact of Basel 2 will probably not be a direct reduction or increase in bank capital level, but an evolution of their *risk management capabilities*. With a little more work, what forms the basis of Basel 2's core requirements could be leveraged to meet state-of-the-art risk modeling techniques. Today's best practice will be tomorrow's minimum standard. A KPMG survey ("Ready for Basel 2 – how prepared are banks?," KPMG, 2003) showed that more than 70 percent of banks questioned considered that Basel 2 would improve current credit risk practices and would provide a better foundation for future developments in risk management.

From an organizational point of view, we can already see two main impacts of Basel 2. The first is, of course, an increasing importance given to risk managers in financial institutions that are more involved in the strategy development process and board-level communication than they were in the late 1990s. The second is an increasing overlap of responsibilities between the finance and risk functions. The risk inputs to Basel 2, and the resulting numbers, will need to be explained in some detail. This was usually done by finance but as those figures are risk-based, some risk management input will also be necessary. In some banks, we can see the creation of risk functions within finance, while in others a new hybrid function will be set up.

To be complete, we need to mention that results of the QIS 3 are based on the CP3 rules, which means that capital is calculated to cover both expected and unexpected losses. The Madrid Compromise has now led to a review of the supervisory formulas to make them better aligned with banking practices and financial theory. Capital levels calculated in the QIS 3 should be decreased by the expected loss amount on each portfolio ($= \text{exposures} \times \text{PD} \times \text{EAD} \times \text{LGD}$). However, the regulators have also announced their intention to use a scaling factor (around 1.06 – the reader may try to find the logic in the regulators' decisions ...) that will multiply the capital requirements derived from the formulas, and which will ultimately lead to a globally neutral impact.

PART III

IMPLEMENTING BASEL 2

Basel 2 and Information Technology Systems

INTRODUCTION

The challenges created by the Basel reform in the field of information technology (IT) systems are tremendous. Of course, the magnitude of the efforts and investments that will have to be made by banks will depend on their current developments in risk-measurement and risk-monitoring tools. But even more advanced banks will need to make significant adaptations because an important part of the data necessary for Basel 2 are not currently available in their systems. This can be seen, for instance, in the QIS 3 exercise, where even large banks have had problems in finding the required data on collateral values. Basel 2 imposes ways to value certain kinds of credit risk mitigants that are different from the methods currently in use.

The main IT challenge is in increasing the quality, consistency, auditability, and transparency of current data. There will also need to be a better sharing and reconciliation of information between a bank's finance and risk management functions.

SYSTEMS ARCHITECTURE

Traditionally, business units have developed their own databases without a global data management strategy at the bank level. This was not a problem in terms of regulatory reporting, as in Basel 1 there were few risk parameters: reporting was simply made on the basis of general ledger figures, and

small local databases were used for internal risk-based reporting applications. With Basel 2, the official information coming from the general ledger has to be enriched with risk management data, so banks have to reconcile both data sources. Of course, it is well known among bank practitioners that when you try to make a reconciliation of data on the same portfolio, but coming from two different sources, you should make some coffee, because you won't be home for a while ... This led banks to realize rapidly that continuing with independent and uncoordinated data stores was not sustainable in a Basel 2 environment. This explains why in studies made on Basel 2 implementation, banks usually considered that between 40 percent and 80 percent of the costs would be IT expenditures; in an IBM study ("Banks and Basel II: how prepared are they?," IBM Institute for Business Value, 2002) more than 90 percent of the banks cited data integration as one of their major challenges.

The first step in designing the target architecture is usually making a diagnosis of *current systems* and *data availability*. After a mapping of current data sources, banks have to evaluate the gaps in the data required for Basel 2, and the current degree of their data integration. The list of data that will enter in the new regulatory capital calculations is impressive (especially for banks targeting IRBA):

- *Credit data*: Exposures, internal and external ratings, current value of collateral, guarantees, netting agreements, maturities of exposures and collateral, type of client (corporate, bank ...), collateral revaluation frequency ...
- *Risk data*: Default rates, recovery rates on each collateral type, cost of recoveries, MTM values of financial collateral, macroeconomic data, transition matrixes, scenario data for stress tests, operational loss events ...
- *Scoring systems data*: Historical financial statements, qualitative factors, overrulings ...

All of these data will have to be consolidated across large banking groups. As a function of the first assessment results, banks can opt for two broad approaches: the *incremental* approach or the *integrated* approach.

A bank that already has a well-developed and integrated risk management system may decide to minimize its IT costs by adding the missing Basel 2 data in dedicated data marts that complement the existing heterogeneous systems. Figure 9.1 shows how individual enhancements can be implemented for credit, market, and operational risk systems.

This approach is cost-effective but creates several challenges: new developments need to be consistent with the existing framework, new risk data must continue to be comparable among the different business units and must be integrated easily in bank-wide regulatory risk systems.

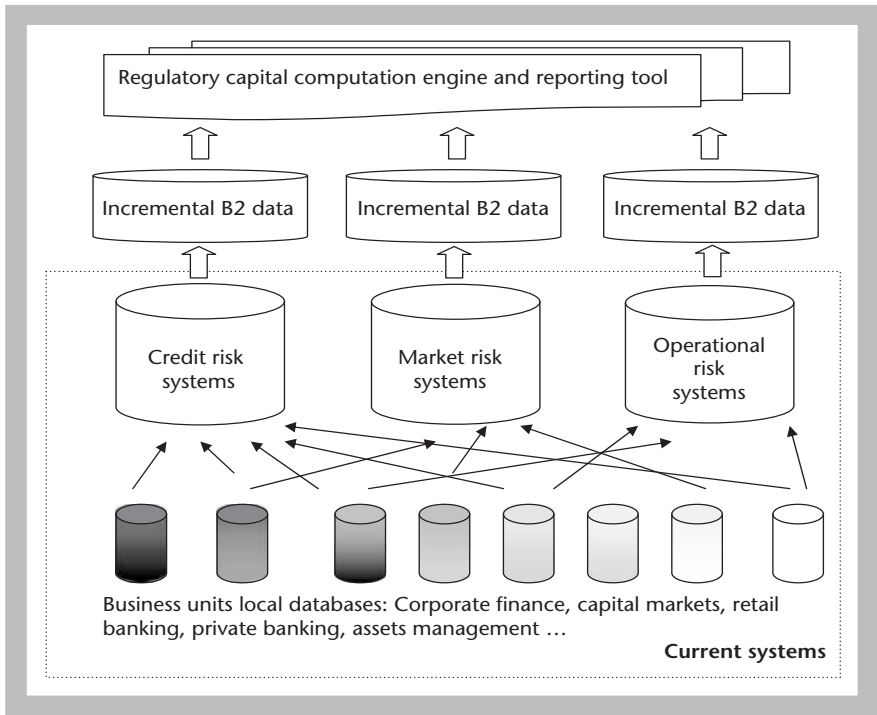


Figure 9.1 Incremental IT architecture

For banks that do not have a sufficient level of data integration and that need to bring more consistency and control across both data and systems, the incremental approach is not adequate. The other option is to create two additional layers. The first, the *Extracting and Transformation Layer* (ETL) is designed to extract data from the various local databases and to format them in a uniform and standardized way. The formatted data are then stored in a bank-wide risk-data warehouse that allows regulatory capital engines to have an easy access to information. This architecture is more costly to set up but ensures better data consistency, and future modifications to local databases can be made more easily as most components of the system are usually modular (Figure 9.2).

The main difference is that credit risk data, for instance, are stored in a bank-wide database i.e. the second layer, under a standardized format whatever its original source, which is not necessarily the case with the incremental approach, that builds on the current systems and uses them as direct inputs for the regulatory capital engine.

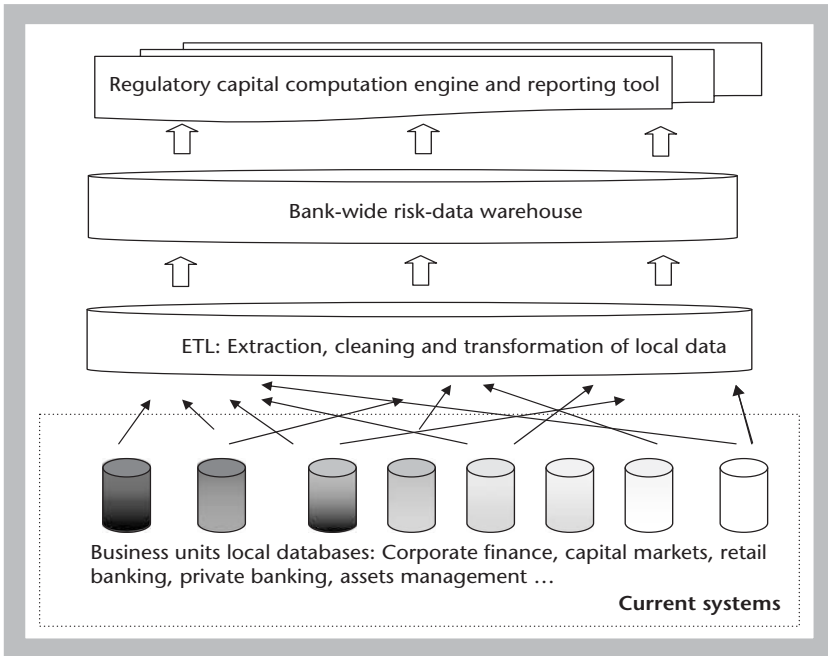


Figure 9.2 Integrated IT architecture

CONCLUSIONS

In this chapter, we have briefly examined the challenges associated with the IT implementation of Basel 2; they deserve a book to themselves, as they are as critical as the more purely methodological risk issues. We have explained why most banks – even those who currently have advanced risk management and risk-reporting capabilities – will need to invest substantially in IT expenditure. The two models we presented – the incremental and integrated architectures – are, of course, simplified views but they may help to understand what are the broad possible orientations.

One of the consequences of Basel 2 is that banks are now tending to develop integrated bank-wide data management strategies instead of small local current databases. This is another area where the reform is contributing to the “industrialization” of risk management. According to an Accenture/Mercer Oliver Wyman/SAP research project (“Reality check on Basel 2,” *The Banker*, 2004), 70 percent of banks have opted for centralized data management systems. There are four main benefits:

- More powerful data analysis capabilities.
- Increased accessibility for other users.

- Potential synergies with other projects (e.g. IFRS).
- Potential to reduce costs.

We think that when evaluating the cost–benefit trade-off between various alternatives, one should always keep in mind the fact that investments must be seen not only as a compliance cost but as an opportunity to gain more effective advanced risk management systems, which are the first step in any effective shareholder value management framework.

Scoring Systems: Theoretical Aspects

INTRODUCTION

We embark here on one of the two core aspects of this book. In this chapter, we shall explain what rating systems are, why they are key elements in meeting the Basel 2 requirements for the IRB approaches, how to select an appropriate approach to building a rating model, what data to use, the common pitfalls to avoid, and how to validate the system. We concentrate here on a theoretical discussion. In Chapter 11, we shall illustrate this concretely with a case study. We shall then discuss how the scoring model can be implemented and articulated in a bank organization. We concentrate on a rating model for SME and corporate portfolios, although the basic principles can be applied to others. Rather than remaining at the level of general description and mathematical formulas, we shall try to give to readers clear examples on how each step can be implemented, using the real-life datasets that are given on the accompanying website. Our goal is that, having read this chapter, the interested reader will be able to begin their own research even without being “quants” (quantitative specialists). Succeeding in setting up and implementing an efficient rating system is not a matter of applying cutting-edge statistical techniques; it relies more on qualities such as a good critical sense, a minimum knowledge of what financial analysis is, a capacity to lead changes in an environment that is most likely to be (at least initially) hostile to the project, and finally a capacity to be sensible.

THE BASEL 2 REQUIREMENTS

Rating systems are at the heart of the Basel 2 Accord. Efficient rating systems are the key requirements in reaching the IRB approaches (both IRBA and IRBF). But even without considering the regulatory capital reform, such ratings are at the center of the current risk management framework of most banks. The prediction of default risk is a field that has stimulated a lot of practitioners' and academics' research, mainly since the 1970s. The Basel reform simply acted as a catalyst to such developments, which have accelerated at a rapid pace since the late 1990s. As validated internal rating systems should allow a lot of banks to decrease their regulatory capital requirements, a strong incentive for investing in their development has been created.

Local banking regulators will do the final validation process: they will have an important role but also heavy responsibilities. If a bank runs into trouble because of deficiencies in its internal rating systems that were validated by its regulators, it will not carry the responsibility for the crisis alone ... Banks have to keep an important fact in mind when building their rating models: systems that are clear, transparent, and understandable at an acceptable level have far more chance of getting the regulators' agreements than "cutting-edge" black boxes. The clarity of the approach is so important that it is mentioned in the regulators' texts (see "The new Basel Capital Accord: an explanatory note," Article 248, Basel Committee on Banking Supervision, 2001). Keeping precise updated documentation of all the model's development steps is thus a critical point.

Summarizing the key requirements of Basel 2 for corporate, sovereigns, and banks' rating systems, we can note the sixteen matters discussed in Box 10.1.

Box 10.1 The key requirements of Basel 2: rating systems

- Rating systems must have two dimensions: one for estimating the PDs of counterparties (we treat this in this chapter) and one to estimate the LGD related to specific transactions.
- There must be clear policies to describe the risk associated with each internal grade and the criteria used to classify the different grades.
- There must be at least seven rating grades for non-defaulted companies (and one for defaulted).
- Banks must have processes and criteria that allow a consistent rating process: borrowers that have the same risk profile must be assigned the same rating across the various departments, businesses, and geographical locations of the banking group.

- The rating process must be transparent enough to allow third parties (auditors, regulators ...) to replicate it and to assess the appropriateness of the rating of a given counterparty.
- The bank must integrate all the available information. An external rating (given by a rating agency such as Moody's or S&P) can be the basis of the internal rating, but not the only factor.
- Although the PD used for regulatory capital computation is the average one-year PD, the rating must be given considering a longer horizon.
- The rating must integrate the solvency of the counterparty despite adverse economic conditions.
- A scoring model can be the primary basis of the rating assignment, but as such models are usually based only on a part of the available information, they must be supervised by humans to ensure that all the available information is correctly featured in the final rating. The bank has to prove that its scoring model has a good discriminatory power, and the way models and analysts interact to arrive at the final rating must be documented.
- The banks must have a regular cycle of model validation, including ongoing monitoring of its performance and stability.
- If a statistical model is part of the rating system, the bank must document the mathematical hypotheses that are used, establish a rigorous validation process (out-of-sample and out-of-time) and be precise as to the circumstances under which the model may under-perform (buying an external model does not exempt the bank from establishing detailed documentation).
- Overrides (cases where credit analysts give another rating than the one issued by a scoring model) must be documented, justified, and followed up individually.
- Banks must record all the data used to give a rating to allow back-testing. Internal default experience must also be recorded.
- All material aspects of the rating process must be clearly understood and endorsed by senior management.
- The bank must have an independent unit responsible for construction, implementation, and monitoring of the rating system. It must produce regular analyses of its quality and performances.
- At least annually, audit or a similar department must review the rating system and document its conclusions.

We are intentionally incomplete when listing these regulators' requirements, because our goal is not to duplicate the International Convergence of Capital Measurements and Capital Standards (ICCMS), the Basel 2 text; those mentioned in Box 10.1 are sufficient to demonstrate that the list is impressive. What is clear is that detailed model documentation is key because it is the bank that has the charge of the proof: it is the bank that has to convince its regulators that its rating systems are IRB-compliant, and not the regulators that have to prove that the bank rating systems do not meet the criteria.

CURRENT PRACTICES IN THE BANKING SECTOR

First, it is interesting to get an idea of what the industry current practices were before the Basel 2 reform. A task force of the Basel Committee interrogated several large banks to see how they were currently working and made a preliminary list of recommendations on what it considered to be sound practice ("Range of Practice in Bank's Internal Rating Systems," Basel Committee on Banking Supervision, 2000).

As a result, the task force categorized three main kinds of rating systems that could be seen as a continuum: statistical models, constrained expert models, and expert models. They mainly differed in respect to the weights given to the human and model results in the final rating. Most of the banks lay between the two extremes as a function of their portfolios. A large portfolio of small exposures (e.g. retail portfolios) tend to be managed with automatic scoring models while smaller portfolios of large exposures (e.g. large corporate portfolios) are usually monitored by qualitative individual analyses made by credit analysts (Figure 10.1).

Few banks rely only on statistical models to evaluate the risk of their borrowers, for three main reasons:

- Banks should develop several models for any asset type, and perhaps for their various geographical locations.
- The extensive datasets needed to construct those models are rarely available.
- The reliability of those models will be proved only after several years of use, exposing the bank to important risks in the meantime.

However, most of the banks use statistical models as one of the inputs in their rating process.

At one extreme, we have *statistical models*. Their main benefit is that the various risk factors are featured in the final rating in a systematic and consistent way, which is one of the requirements of the Basel 2 Accord. However,

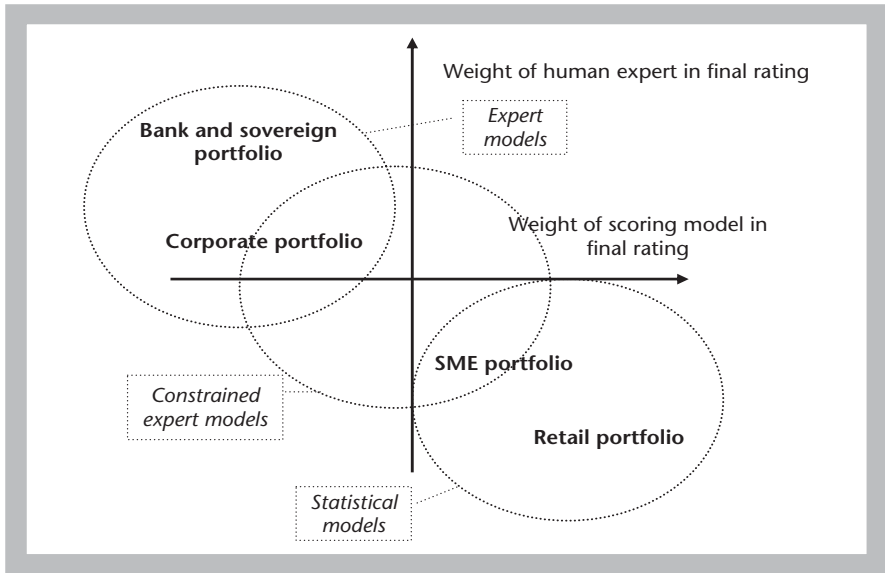


Figure 10.1 Current bank practices: rating systems

they are usually based only on part of the available information. At the other extreme, we have *expert rating systems*, where credit analysts have a complete freedom in coming to their final rating. The main benefit is that they are able to integrate all the available information in their final decision. The drawback is that studies of behavioral finance usually show that credit analysts are good at identifying what the main strengths and weaknesses of a borrower are, but integrating all the information into the final rating is not always done in a consistent way. Different analysts may have different views on the relative weight that should be given to the different factors: even a single analyst may not always be consistent. Studies tend to show that credit analysts put more weights on factors that drove defaults among counterparties that they had recently followed. For instance, if a company in an analyst's portfolio went bankrupt because of environmental problems, the analyst will usually shift its later rating practice to put more weight on environmental issues. This can be a good reaction if it reflects a fundamental change that may affect all counterparties, but not if it is a discrete factor.

In conclusion, as is often the case, the ideal model would be the one that reflected the best of both worlds. Most banks are currently working on constrained expert models that try to combine objectivity and comprehensiveness. The best mix is perhaps when a statistical model treats the basic financial information and when credit analysts spend more time where they have the most added-value: on the treatment of qualitative information, the quantitative information not already featured in the model, and especially

the detection of special cases that may not enter into the classical analysis framework.

We shall now begin to see how to develop and validate a statistical scoring model. Later, we shall discuss how its use can be related to the credit analyst's work.

OVERVIEW OF HISTORICAL RESEARCH

The construction of scoring models is a discipline of applied economic research that has led to a lot of papers and proposed models. Box 10.2 briefly presents some of the main references (the historical overview is based mainly on a paper of Falkenstein, Boral, and Carty, 2000). For some examples of the models presented, see the Excel workbook for Chapter 10.

Box 10.2 Overview of scoring models

- *Univariate analysis*: The pioneer of bankruptcy prediction models is probably Beaver (1966). Beaver studied the performance of various single financial ratios as default leading indicators on a dataset of 158 companies (79 defaulted and 79 non-defaulted). His conclusions were that “cash flows:equity” and “debts:equity” generally increased when approaching the default date.
- *Multivariate discriminant analysis (MDA)*: Altman (1968) proposed integrating several ratios in one model, in order to get better performance. He developed his famous *Z-score* using MDA. If his model remains a reference and is often cited as a benchmark in the literature, it is not (to the extent of our knowledge) used in practice by credit analysts. MDA was a technique developed in the 1930s, and was at that time mainly used in the fields of biology and behavioral sciences. It is used to classify observations into two groups on the basis of explanatory variables, mainly when the dependent variable is qualitative: good/bad, man/woman ... The classification is done through a linear function such as:

$$Z = w_1X_1 + w_2X_2 + \dots + w_nX_n \quad (10.1)$$

where Z is the discriminatory score, w_i ($i = 1, 2, \dots, n$) the weights of explanatory variables, and X_i ($i = 1, 2, \dots, n$) the explanatory variables (financial ratios, in this case). To find the optimal function, the model maximizes the ratio of the squared difference between the two groups' average scores divided by their variance.

- *Gamblers' ruin*: Developed by Wilcox (1971), this model is philosophically close to the well-known Merton Model (see below). The hypothesis is that

a company is a “tank” of liquid assets that is filled and emptied by its generated cash flows. The company starts with a capital level of K , and the generated cash flows, Z , have to be estimated from the historical average. The value of a company can then be estimated at any time, t :

$$t_1 : K_1 = K_0 + Z_1; \dots t_n : K_n = K_{n-1} + Z_n \quad (10.2)$$

The company is supposed to default when $K_{n-1} + Z_n < 0$. The problem in using this model in practice is to estimate the value of historical cash flows, and of their probability of realization.

- *The Merton model:* The Merton model (1974) was developed from the idea that the market value of a company can be considered as a *call option* for the shareholders, with a strike price equal to the net debts’ value. When the value of the company becomes less than its debt value, shareholders have more interest in liquidating it rather than reinvesting more funds. KMV developed a commercial application of this theory, after some modification to the initial formula, and some of the more advanced banks have developed internal models on this basis.

We can present the central concept for the discrete case in the following way: a company’s assets have a market value of A , an expected one-year return of r , an annual volatility of σ_A , and the market value of its debts in one year is expected to be L . We have to estimate what the probability is that in one year the market value of the assets will fall below L . To do this, we can calculate the normalized distance to default (DD):

$$DD_t = \frac{rA_{t=0} - L_{t=1}}{\sigma_A \sqrt{t}} \quad (10.3)$$

If we make a hypothesis of the normality of asset returns, we can use the cumulative standardized normal distribution (usually notated as ϕ) to estimate the default probability. A DD of 1 would correspond to a PD of $1 - \phi(1) = 15.9$ percent.

- *Probit/logit models:* Ohlson (1980) was the first to use the *logistic regression* for bankruptcy prediction. It is close to MDA in the sense that the goal of the approach is also to find an equation of financial ratios that can classify observations into two or more groups. The advantage over MDA is that MDA contains an implicit hypothesis of the normality of the distribution of financial ratios and of equality of the variance–covariance matrixes of the two groups, which is unlikely (see Ezzamel and Molinero, 1990). In addition, MDA does not allow us to perform significance tests on the weights of explanatory variables, which can be done using probit and logit models (we shall present logit models in more detail on p. 133).
- *Expert scoring systems:* We have seen that what are usually called “expert systems” are simply the traditional credit analyses where credit analysts have

a complete freedom in deriving a rating. But in the field of scoring models, the term “expert systems” is also used to refer to *scoring algorithms* that are designed to reproduce the reasoning of experts. Those techniques usually necessitate large databases constructed by discussion with the experts and an induction engine that will construct the model. As an example, we can mention decision trees. Problems are analyzed in a sequential way and each decision represents a “node” of the tree. In each node, the information from the previous node is analyzed and sent, by function of some pre-defined values, to the left or right branch of the tree. The operation is repeated until we arrive at the “leaves” that represent the output of the model. Schematically we can represent the process in the way shown in Figure 10.2.

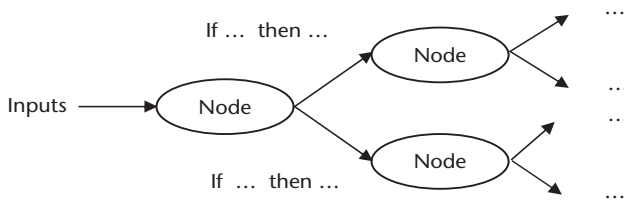


Figure 10.2 A decision tree

- *Neural networks*: Neural networks models are constructed by training them on large samples of data. They are inspired by the functioning of the human brain that is constituted of millions of interconnected neurons. In the model, each input is entered in the first layer. Each neuron makes the sum of the entries and passes the result to a threshold function. This function verifies that the value does not exceed a certain level (usually [0–1]) and transmits it to the following layer (Figure 10.3).

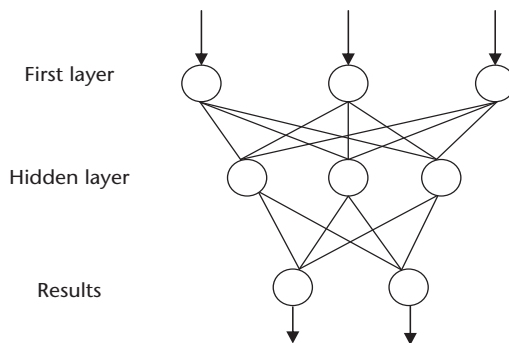


Figure 10.3 A neural network

The learning mechanism is as follows: each example is “shown” to the neural network, and then values are propagated to the output layer as

explained above. The first time, the predictions of the model are certainly false. Then, the errors made are “retro-propagated” back into the model by modifying each weight in proportion to its contribution to the final error: the model “learns” from its own mistakes. The advantage is that neural networks can emulate any function, linear or not. Additionally, they do not rely on statistical hypothesis that may not be as valid as the other approaches. The drawback is that they are “black boxes”: we do not know what happens between the inputs and the results (in the hidden layers). The models do not produce observable weights that we can interpret or test statistically. The only way to test the model is to apply it on a sample that was not used in the learning phase or to make sensitivity analyses. But those methods do not ensure that some cases not represented in the training sample will not result in absurd values. An important point that people should check when they have to evaluate the quality of a neural network model – proposed by some external vendor, for instance – is the way that the validation dataset has been used. In principle, the validation dataset should be used at the very final stage of the construction, to verify that the carefully constructed model is valid. However, what is sometimes seen is that people work in the following way: a first model is constructed on the training dataset, and then it is directly checked on the validation dataset. If the performance is poor, another model is constructed on the training dataset and then directly tested. And so on for hundreds of iterations ... By working in that way, the validation dataset is no longer really random, as hundreds of models have been tested until one works on both the training and the validation datasets. The risks of *over-fitting* (which means having a model that is too much calibrated on available data and that will not show performance on new data) may then become important, especially in the case of neural networks.

- *Genetic algorithms*: Finally, we mention genetic algorithms that belong, as do neural networks, to the artificial intelligence (AI) family. These algorithms are inspired by the Darwinian theory of evolution through natural selection, and their use remains marginal in the bankruptcy prediction field.

The techniques in Box 10.2 can be classified as in Table 10.1.

Table 10.1 Summary of bankruptcy prediction techniques

Non-structural models		
Classical statistical techniques	Inductive learning models	Structural models
<ul style="list-style-type: none"> ■ Univariate analysis ■ MDA ■ Probit/logit models 	<ul style="list-style-type: none"> ■ Expert scoring systems <ul style="list-style-type: none"> – decision trees ■ Neural networks ■ Genetic algorithms 	<ul style="list-style-type: none"> ■ Merton model ■ Gamblers’ ruin

Most studies that have compared MDA and probit/logit model techniques have shown that, although MDA is theoretically less robust, their performance is similar.

Few exhaustive studies have been made on a comparison of the Merton-style models with other techniques (it was often in the past tested against external ratings). The problems are how to incorporate volatile default risk information and the limitation of the model to listed companies. A version of the model was developed for unlisted companies that used Earnings Before Interest, Taxes, Depreciations, and Amortizations (EBITDA) multiples to emulate the market value of the company, but after Moody's bought KMV, a study showed that Moody's Riskcalc™ models that were based on logistic regression were superior to KMV for private companies (Stein, Kocagil, Bohn, and Akhavein, 2003).

Results of studies that compared classical statistical techniques to neural networks are mixed. Coats and Fant (1992), Wilson and Sharda (1994), and Charitou and Charalambour (1996) come down on the side of the superiority of neural networks while Barniv, Agarwal, and Leach (1997), Laitinen and Kankaanpaa (1999), Altman, Marco, and Varetto (1994) testify as the equality of performance. Generally speaking, we believe that neural networks offer a greater flexibility, as they are not subject to any statistical hypothesis. However, we also think that they necessitate a more extensive validation process because, inside the model, the information can follow a great number of different paths. It is impossible to verify them all to make sure that they all make sense. In addition, the ways to validate the models are more limited than with other techniques, as there is no observable weight given to the various inputs that can be interpreted and statistically tested. Over-fitting risks may prove to be important.

In Table 10.2, we summarize the main key selection criteria.

Taking into account the various issues, notably data availability, the possibility of validation, and widespread current market practice, we believe that classical statistical techniques offer the best trade-off.

In the following sections of this chapter, we shall show how to construct a scoring model using the logistic regression technique, which is used by Moody's in its Riskcalc™ model suite (see for instance Falkenstein Boral, and Carty, 2000). Probit and logit models usually lead to the same results.

THE DATA

An issue that is perhaps even more important than choosing the approach is *data availability*. In public bankruptcy prediction studies, the number of available defaults is usually small. The famous original Altman Z-score was constructed on a sample of thirty-three defaulted companies and thirty-three

Table 10.2 Key criteria for evaluating scoring techniques

Criteria	Statistical techniques	Inductive learning techniques	Structural models
Applicability	+	+	– (Limited to listed companies)
Empirical validation (out-of-sample and out-of-time tests)	+	+	+
Statistical validation	+	– (No weights that can be statistically tested)	n.a. (Parameters must not be statistically tested as they are derived from an underlying financial theory)
Economic validation	+(We can see if the weights of the various ratios correspond to the weight expected by specialists)	+(The impact of the ratios can be estimated using sensitivity analysis)	++ (Structural models are the only ones derived from a financial theory)
Market reference	++ (Riskcalc™ of Moodys, Fitch IBCA scoring models, various models used by central banks of France, Italy, the UK ...)	+(No model directly based on neural networks to our knowledge, but a model of S&P is based on Support Vector Machines that is derived from neural networks)	+ KMV model

Note: n.a. = Not available.

non-defaulted companies, which may give us serious cause to doubt its performance on other portfolios.

Three kinds of data may be used to construct bankruptcy prediction models. We present them in Box 10.3, in order of relevance.

Box 10.3 Data used in bankruptcy prediction models

- *Defaults*: The most reliable and objective source of data are the annual accounts of defaulted companies, simply because they are precisely what we want to modelize. Unfortunately, datasets of sufficient size are hard to find. If you have only thirty-three defaults, as in the Altman study,

you should choose another approach. It is hard to define the minimum number of defaults that are necessary as this depends on the type of portfolio, data homogeneity ... But from our experience, we would say that an absolute minimum is fifty defaults, and 100 non-defaulted companies are needed to mitigate sampling bias (while 200 defaults and 1,000 non-defaulted companies is a more comfortable size if you want to get the regulators' agreement).

- *External ratings:* Another possibility is to use the financial statements of companies that have external ratings. We can try to replicate them by using an ordered logistic regression that gives the probabilities of belonging to n categories (for the n ratings) and not only to two categories (default or not-default), as in the binomial logistic regression. Of course, by doing this we make the implied hypothesis that external ratings are good predictors of default risk. But as external ratings are used in the Standardized Approach of Basel 2 to calculate capital requirements, the regulators should accept models constructed on external ratings of the recognized agencies. As the model predicts a rating, we still have to associate it with a corresponding probability of default that can be derived from historical data published by rating agencies (however, we need to pay attention to the fact that the default definition of rating agencies is not that given in Basel 2, which means that some adjustments will be necessary).
- *Internal ratings:* Finally, if neither of those two possibilities is available, the last data we can use are internal ratings. We might wonder what the interest is in developing a model using internal ratings – what is its added-value? The answer is: to normalize the results. The main criticism usually made of human judgment is its lack of consistency: there may always be some ratings that are too generous or too severe because an analyst is not a robot and she can sometimes give too much weight on one factor or the other, or two different analysts may have different views on what are critical factors to assess, or an analyst can simply be perturbed by some external elements. But if we make the reasonable hypothesis that the processes and analysis schemes of the financial institution can ensure that, on average, the ratings are correct (at least in terms of ordinal ranking, we shall consider the calibration issue on p. 129), we can then work on this basis. In this case, the use of regression techniques allows us to reduce any possible bias associated with those values that are far from the general trend. A model would ensure that all the credit analysts started from a common base, with consistency in the weights given to the various risk factors, to derive their final rating. Of course, financial institutions that wanted to use this approach would have to demonstrate to their regulators the quality of their current rating systems. This can be done by: showing that the rating criteria currently used are close to those published by rating agencies, showing that on historical data there are more defaults on low ratings than on good ones, or by using some external vendor model to make a benchmarking study. If you want to work with an internal rating sample, pay attention to avoiding the survivor bias issue. The sample constituted should be representative

of those who have made credit requests to the bank, not those who have currently a credit at the bank, otherwise potential clients that have already been rejected by credit analysts will not be sufficiently represented in the sample.

HOW MANY MODELS TO CONSTRUCT?

How many different models should banks construct to cover their whole portfolio of counterparties? This depends on several factors. A study on banks' readiness for Basel 2 (KPMG, 2003) revealed important differences between the US and Europe: in the US there were on average five non-retail scoring models and three retail, while in Europe the average was ten non-retail models and eight retail. The optimal number should integrate two things:

- *The number of different types of counterparties.* Depending on the type of clients, we can have very different types of information, and we cannot use a single model to handle them all. As examples we can mention: retail customers, SME, large international corporate, banks, insurance companies, countries, public sector entities, non-profit sector companies, project finance ...
- *Data availability.* This is also a crucial issue. Regarding the SME and corporate portfolio for instance, one can imagine a lot of different models suited for different size types (very small companies, small companies, mid-sized companies, large international companies ...), for different sectors (services, utilities, trade, production ...), and for different geographical areas or countries (North America, Western Europe ...). If we use all those dimensions we shall already arrive at an impressive number of different models. In the real world, we have usually to group the data to reach a sufficient number of observations to perform construction and validation. For the SME and corporate portfolios, two or three different models are a reasonable number. We would like at this point to draw the reader's attention to a specific point: the more you construct different models, the more the risk of *over-fitting* becomes important. First, it decreases the amount of data for an objective validation. Secondly, there is a risk of calibrating too much on the past situation of specific counterparties. Imagine that you construct a specific model for the airline sector. It is rare that banks can get historical data that are available over a whole economic cycle (and we could discuss for a long time what is an "economic" or "business" cycle: five years, ten years, twenty years ...). If we have two or three years of financial statements and ratings, we can get a picture

of the relationship of ratios to risk for the airline sector over this specific time frame. There is always the risk that, over this period, the sector benefits from especially good or bad conditions. A model calibrated for this specific sector may show good performance on past available data but may lead to weak results over the coming years as sector-specific conditions are evolving. This kind of risk can be mitigated by constructing a single model for several sectors, as good and bad sector-specific issues will probably offset each other on average.

MODELIZATION STEPS

We can summarize the six main steps involved in the scoring model construction as in Box 10.4.

Box 10.4 Construction of the scoring model

- 1 *Data collection and cleaning*: The first step is, of course, to construct databases with financial statements and ratings or default information. The database can be composed of various sources: internal data, external databases sold by vendors, data pooling with other banks ... The first step is data cleaning and standardization. This means essentially: constructing a single database with the various sources to homogenize data definition (sometimes accounts' categories may have the same name but cover different things), and treating missing values by replacing them with median or average values (or by not using financial ratios that have too many missing values for the model's construction).
- 2 *Univariate analysis*: When the database is constructed, it is time to organize a first meeting with credit analysts to define what the possible candidate explanatory variables are. This is important, because since their acceptance is essential for a successful implementation of the model, they should feel included at the earliest stage of the project. Candidate variables are usually financial ratios, but there can be other parameters – such as the age of the company, its geographical location, its past default experience, if available ... When the candidates are constituted, they are submitted to a first examination. The univariate analysis consists of analyzing the discriminatory power of each variable on a stand-alone basis. This can conveniently be done using graphs. When we have a default/not-default dataset, we can classify it according to the tested variable, divide the sample into n groups and compute the average default rate for each group. The results can then be plotted on a graph to see the relationship between the ratio and the default risk (we usually have to eliminate very small and very large values of the ratios to get a readable graph). When we have a rating dataset, we

can replace ratings by numbers (e.g. AAA = 1, AA + = 2 ...) and compute the average rating instead of the average default rate. This allows us to see:

- If the relationship is *monotonic* (which means always decreasing or always increasing). If it is not the case, we may have to use an intermediary function to transform the ratio value before using it in the regression.
- If the relationship *makes sense*: if when the ratio is increasing, the risk is decreasing while in the financial theory it should be the contrary, the ratio should be rejected.
- If the ratio has any *explanatory power*. If the graph is flat, then the ratio is not discriminative and should be rejected (some will argue that a ratio that has no power on a stand-alone basis may become useful in a multivariate context, but from our experience this is rarely the case, and rejecting ratios without discriminatory power helps to make the model construction process more clear). The analysis of the graph is completed by the computation of some standard performance measure such as an accuracy ratio or cumulative notch difference (CND) (see Box 10.6).

3 *Ratio transformation*: In this step, we transform the ratios before using them in the regression. This can be done to treat non-monotonic ratios for instance, or in order to try to obtain higher performance. The simplest transformation is to put maximum and minimum values to each ratio. A classical technique consists of choosing some percentile of the ratio values (for instance the 5th and 95th percentile), but we prefer to use the graphs of the univariate study to put minimum and maximum values where the slope of the graphs becomes almost flat. By doing this, we try to isolate ratio values that have the greatest impact on the risk level, and to eliminate ratio values (by setting them all to a single minimum or maximum) that have a weak relationship with the risk level and that can "pollute" the results. A more profound transformation is to replace ratio values by other values derived from a regression (usually x^2 , x^3 , or logarithmic). This is the only way to treat non-monotonic relationships but for the other cases, from our experience, simply using maximum and minimum delivers the same performance level.

4 *Logistic regression*: Our ratios are then ready to be integrated in the logistic regression model. We have to find the best combination of the various candidates. One possibility is to use deterministic techniques such as:

- *Forward selection process*: In this approach, we start with a model that has only one ratio (the one that performs the best on a stand-alone basis). Then, we try a model with two ratios by adding successively all the others one by one and keeping the one that increases the model performance the most, and so on ... We stop adding ratios when adding a new one will not increase the performance of the model more than

by a predetermined value. Usually, the likelihood ratio test (*G*-test, see p. 136) is used. If adding a new ratio does not increase the likelihood by a confidence interval of 95 percent, we stop the selection process.

- *Backward selection process*: The principle is the same as in the forward selection process, except that we start with a model that contains all the candidates and eliminate them one by one, beginning with the least performing, until the performance decreases more than a certain pre-defined amount.
- *Stepwise selection process*: This is a mix of the two previous types. We use the forward selection process, but after each step we apply backward selection to see if adding a new ratio did not make one or the other redundant.
- *Best sub-set selection*: Here, the modeler defines how many variables she wants to have in her model, and the selection algorithm tests all possible combinations.

These approaches were very popular some years ago, but practitioners now tend to depart from those deterministic methods. The problem is that they tend often to select an important number of variables that are not really increasing a model's performance at all (they are, rather, "noise" in the model). From our experience, it is better to try some combinations of the variables manually. Of course, we cannot manually try all the possible combinations, but to select the best candidates we can base ourselves on some principles that we shall describe on p. 130. We also recommend appreciating the gain in the performance of a model by looking at an economic performance measure (such as accuracy ratios or cumulative notch differences) rather than relying on purely statistical tests that are more abstract and that usually lead simply to selecting more ratios.

- 5 *Model validation*: After model construction, the next step is model validation. This is a critical step, as this is the one that will be examined the most closely by the regulators. There are many model dimensions that have to be tested; we shall present various techniques in Box 10.6.
- 6 *Model calibration*: The final step is to associate a default probability with each score. When working on a default/not-default dataset, the output of the logistic regression is a probability of default. However, for many reasons, it may not be calibrated for the portfolio on which the model will be used: the default rate in the construction sample may not be representative of the default rate of the entire population or the default definition in the construction sample may not be the same as the Basel 2 default definition (which is usually more broad) ... Thus the PDs given by the model must be adjusted. This can be done by multiplying the entire model PDs by a constant to adjust them to the true expected default rate. The other possibility is to multiply the score not by a single constant but by different values because the broader default definition of Basel 2 may have more effect on good

scores than on bad scores: the proportion of Basel 2 default/bankruptcies (which usually constitutes the core of the defaults in the available datasets) may be more important for good companies (where “light” defaults are the main part of default events) than for risky companies (where “hard” defaults are more usual). High scores may then be multiplied by a higher number than low scores. However, one should pay attention to keeping the original ordinal ranking given by the model.

When working on a rating dataset, the calibration issue is less straightforward. A PD has to be associated with each rating given by the model. If the portfolio is close to the population rated by the rating agencies (the dataset is composed of S&P, Moody’s or Fitch IBCA ratings), we can use the historical default rates they publish as a basis (and make some adjustments to match the Basel 2 default definition). If the model is constructed on internal ratings and the bank has no internal default experience, it is more complicated. Calibration can be done by benchmarking with an external model. Or it is sometimes possible to find a broad estimate of the average default rate of the portfolio concerned; PDs may then be associated with each rating class to match the global average default rate.

PRINCIPLES FOR RATIO SELECTION

Starting with the same dataset, we can end with many different models that show globally equal performance, or with some that perform best on some criteria and others on other criteria, and with a different number of ratios (from three or four to twenty or more). It may then be useful before beginning the regression analysis to have some guidelines that will define a philosophy for the construction of the model. Of course, philosophy is like a club sandwich: everyone has their own recipe. And the philosophy should always be adapted to the discipline where the model is to be applied: regression analysis in hard science disciplines should not be governed by the same principles that govern regression analysis in soft sciences such as economics.

Basically, there are two broad decisions that have to be made: what should be the *ideal number of ratios* in the model and what is the main *performance measure* that will be used? These two decisions are linked.

The first possibility is to seek to incorporate a large number of ratios in the model. This is usually the result if we select purely statistical tests as the main performance measure (such as log-likelihood). Those in favor of this option use the following arguments:

- Statistical tests measure the fit between predicted and observed values and are thus an objective performance measure.
- Using a large number of ratios allows us to incorporate more risk information.

- A model with more ratios will lead to a better acceptance by credit analysts, as it will be more credible than a model with only a few ratios.

The second possibility is to seek to retain the minimum number of ratios that still gives a high performance. This is usually done when we focus on economic performance measures such as accuracy ratios or cumulative notch differences. The arguments in favor of this approach are:

- Avoiding the classical trap of regression analysis: *over-fitting*. With the classical linear regression, for instance, adding a variable always increases the R^2 (or leaves it unchanged), but will never decrease it. Over-fitting is calibrating the model too much on the available data. It will show high performance on them, but results may be unstable on other data or in other time frames. The fewer variables a model has, the more easily it will be generalized.
- *Model transparency* is also a key factor. A model with only a few parameterized ratios will allow users to have a critical view of it, and to identify more easily cases where it will not deliver good results. A model with an important number of correlated ratios (several profitability ratios, several leverage ratios ...) will be less transparent and harder to interpret.

Our personal point of view is that the second approach is better adapted to constructing bankruptcy prediction models. To illustrate our position, we shall summarize an interesting study made by Ooghe, Claus, Sierens, and Camerlynck (1999). They compare the performances of seven bankruptcy prediction models on a Belgian dataset. The models' main characteristics are summarized in Table 10.3.

Table 10.3 Bankruptcy models: main characteristics

Model	Altman	Bilderbeek	Ooghe– Verbaere	Zavgren	Gloubos– Grammatikos	Keasy– McGuines	Ooghe– Joos– Devos
Country	US	Netherlands	Belgium	US	Greece	UK	Belgium
Year	1968	1972	1982	1985	1988	1990	1991
Number of defaults in sample	33	83	663	45	54	58	486
Technique	MDA	MDA	MDA	Logistic	Logistic	Logistic	Logistic
Number of variables	5	5	5	10	3	10	11

Table 10.4 Accuracy ratios

Model	Altman	Bilderbeek	Ooghe– Verbaere	Zavgren	Gloubos– Grammatikos	Keasy– McGuines	Ooghe– Joos– Devos
1 year	–7.9	59.7	68.7	17.4	68.6	33.5	61.3
2 years	–7.3	46.8	51.7	6.0	56.3	37.2	n.a.
3 years	–8.3	38.3	44	24.5	43.9	28.0	44.9

Note: n.a. = Not available.

The study was conducted on Belgian companies that defaulted between 1995 and 1996 (5,821 defaults). The financial statements one year, two years, and three years before bankruptcy were used. The comparison is not really objective as models that have been developed on a Belgian dataset (Ooghe–Verbaere and Ooghe–Joos–Devos) have an advantage. The authors of the study made several hypotheses on what the elements could be that led the various performances of the tested models:

- The *age of the model*: a more recent model should deliver higher performance.
- The *modelization technique*: logistic regression is more recent and conceptually sounder than MDA, so it should deliver better results.
- The *number and complexity* of the variables: the more variables a model contains, the more it should perform.

Accuracy ratios were then computed for each model. This gave the results in Table 10.4.

We can see that the models that show the higher performance at 1 year are Ooghe–Verbaere and Gloubos–Grammatikos. This latter is also the best at 2 years. It is normal to find the Belgian models among the best performers. But for Gloubos–Grammatikos it is more astonishing. This was developed fifteen years ago on only fifty-four defaults and has only three basic ratios (net working capital:assets, debt:assets, EBIT:assets).

It seems, then, that the age of the model and the technique used are not clearly linked to the models' performances out-of-sample and out-of-time. The number of variables seems to have a relationship to performance that is the contrary of the one expected by the authors of the study: fewer ratios deliver higher performance when the dataset is clearly different for the construction sample.

The results of this study comfort us in the belief that higher model stability is obtained when using fewer ratios. This is an important advantage,

for two reasons. First, when the construction sample is not completely representative of the portfolio on which the scoring system will be applied (for instance, when geographical areas or sectors of the construction sample do not match those of the target portfolio), a more generic model would then ensure more consistent performance between the two datasets. Secondly, the stability of the model can make us more confident in the risks associated with a shift in the composition of the reference portfolio (due to a new lending policy, for instance) or to a more systemic shift in some sectors (deregulation, for instance). A model that is too “well” calibrated to a certain construction sample that usually covers a relatively small sample of counterparties over a small time frame (usually a few years, at best) creates a risk that its performance will decrease as soon as the rated population does not any longer exactly match the reference population. In principle, it is the role of the credit analysts to react, and to say that the model should be reviewed. But when you have a model that works correctly for some time, the analysts tend to rely more and more on its results and can sometimes be slow to respond to these kinds of situations.

In conclusion, there is no one optimal number of ratios, but we recommend being parsimonious in their selection because this decreases the risks of over-fitting and increases stability across different sectors, among geographical locations, and over time. Four–eight ratios are usually sufficient to obtain optimal performance.

THE LOGISTIC REGRESSION

Binary logistic regression

The use of logistic regression has exploded since the mid-1990s. Used initially in epidemiological research, it is currently used in various fields such as biomedical research, finance, criminology, ecology, and engineering ... In parallel to the growth of its users, additional efforts have been pursued to acquire a better knowledge and a deeper understanding.

The goal of any modelization process is to find the model that best mirrors the relationship between the explanatory variables and a dependent variable, as long as the relationship between inputs and outputs makes sense (economic sense concerning bankruptcy prediction). The main difference between the classical linear model and the logistic model is that in the latter the dependent variable is binary. The output of the model is, then, not a $y_{estimated}$ that must be as close as possible to the $y_{observed}$, but a probability π that the observation belongs to one class or the other.

The central equation of the model is:

$$\pi = \frac{1}{1 + \exp[-(b_1x_1 + b_2x_2 + \dots + c)]} \quad (10.4)$$

where x_i are the variables, b_i their coefficients, and c a constant. Each observation will then have a probability of default of $\pi(x)$ and a probability of survival of $1 - \pi(x)$. The optimal vector of weights that we note $B = \{b_1, b_2, \dots, b_n\}$ will then be the one that will maximize the likelihood function l :

$$l(B) = \prod \pi(x_i)^{y_i} [1 - \pi(x_i)]^{1-y_i} \quad (10.5)$$

where $y_i = 1$ in case of defaults, 0 if not. If the observation is a default, the right-hand side of (10.5) will then be 1 (because of $1 - y_i$) and the likelihood function will be incremented by $\pi(x_i)$, which is the predicted PD. If the observation is not a default, the left-hand side of (10.5) will =1 (because of y_i) and the likelihood function will be incremented by the probability of survival ($1 - \pi(x_i)$). Mathematically it is more convenient to work with the log of the equation that we notate $L(B)$:

$$L(B) = \ln[l(B)] = \sum (y_i \ln[\pi(x_i)] + (1 - y_i) \ln[1 - \pi(x_i)]) \quad (10.6)$$

The optimal solution can be found by deriving the equation for each of its variables. As the results are non-linear on the coefficients, we have to proceed by iterations. Fortunately, most of the available statistical software will easily do the job.

Ordinal logistic regression

If we want to develop a model on a dataset composed of internal or external ratings, the problem is no longer binary (default/not-default) but becomes a multi-class problem (the various ratings levels). In this case, the binary logistic model can easily be extended. Intuitively, what the model will do is to construct $(n - 1)$ equations for n rating classes, taking each time a different cutoff value. A problem with an n class can then be decomposed in $(n - 1)$ binary problems. The model will impose that all coefficients b_i have to be the same, only the constant will change.

Say that p_{ij} is the probability that the observation i belongs to the class j (here, the rating). The j classes are supposed to be arranged in ordered sequence $j = 1, 2, \dots, J$. F_{ij} is then the cumulative probability of an observation i belonging to the rating class j or to an inferior class:

$$F_{ij} = \sum_{m=1}^j p_{im} \quad (10.7)$$

The specified model will then have $J - 1$ equations:

$$\begin{aligned}
 F_{i,1} &= \frac{1}{(1 + \exp(Bx_i + c_1))} \\
 &\dots \\
 F_{i,n} &= \frac{1}{(1 + \exp(Bx_i + c_n))}
 \end{aligned}
 \tag{10.8}$$

with $Bx_i = b_1x_{i1} + \dots + b_kx_{ik}$

As in the binary case, optimal coefficients are estimated using a log-likelihood function. Then, for n ratings, the model will give $n - 1$ probabilities of belonging to a rating class or to an inferior one (e.g. probability 1 = probability of being AAA, probability 2 = probability of being AA+ or better, probability 3 = probability of being AA or better ...). From those binary probabilities (e.g. better or equal to AA/worse than AA), we can deduce the probability of belonging to each rating class by making a simple difference (e.g. the probability of being AAA is given by the model, the probability of being AA+ is the probability of being AA+ or better minus the probability of being AAA ...). We can then see that the ordinal model is a simple extension of the binary model.

The ordered logistic model can be seen as if it were constructed on a continuous dependent variable (in our case, the default risk of the company) that has been discretized in several categories. Suppose we notate Z_i this continuous unobserved variable that is explained by the linear model:

$$Z_i = \frac{1}{(1 + \exp(Bx_i + c + \sigma\varepsilon_i))}
 \tag{10.9}$$

We do not observe directly Z but rather a set of intervals t_1, t_2, \dots, t_{J-1} that are used to transform Z into n discrete observations (the rating classes) with the following rules: $Y = 1$ if $t_1 < Z$; $Y = 2$ if $t_2 < Z < t_1$; ...

The advantage of the logistic approach is that the model does not depend on where the cutoff points t_i are placed. There is no implicit hypothesis of distance between the various values used for the Y s (as is the case in the linear regression, for instance, which is the reason why it is theoretically not well adapted for performing this kind of analysis).

This short presentation of the logistic models was designed to allow the reader to get a general understanding of the basic mechanics of the approach. The use of logistic regression does not necessitate mastering all the formulas, as this is done by most standard statistical analysis software (for a more detailed review of logistic regression see Hosmer and Lemeshow, 2000).

PERFORMANCE MEASURES

As we have performed a regression analysis and selected a combination of ratios, it is time to run several performance tests. We have classified these into two categories. *Statistical tests* are designed to see if each ratio in the model can be considered as significant and if the logistic model is adapted for those data. *Economic performance measures* are designed to evaluate the discriminatory power of the model, which means its ability to discriminate correctly good-quality counterparties from low-quality counterparties.

Statistical tests

Box 10.5 outlines five commonly used statistical tests.

Box 10.5 Five statistical tests

- *G-test*: A first significance test is called the G-test. When a model is designed, we have to test if all the ratios, and the model globally, are significant. This means that we can conclude with reasonable certainty that the results have not been obtained by chance. As for the classical linear regression, we shall compare the $y_{predicted}$ with those of a saturated model (which is a model with as many variables as observations). The comparison will be done with the likelihood function:

$$D = -2 \ln \left[\frac{l(Mt)}{l(Ms)} \right] \quad (10.10)$$

With $l(Mt)$ the likelihood of the tested model and $l(Ms)$ the likelihood of the saturated model. D is called the likelihood ratio. $-2 \ln$ is used because it allows us to link the results to a known distribution. By definition, the likelihood of the saturated model equals 1. The equation can then be simplified as:

$$D = -2 \ln [l(Mt)] \quad (10.11)$$

To assess the pertinence of a variable, D will be calculated for the model with and without it:

$$G = D(\text{model without the variable}) - D(\text{model with the variable})$$

$$G = -2 \ln \left[\frac{l(Mt_{k-1})}{l(Mt_k)} \right] \quad (10.12)$$

Where $l(Mt_{k-1})$ is the likelihood of the model with $k - 1$ variables and $l(Mt_k)$ is the likelihood of the model with k variables. G follows a Chi-squared (χ^2) distribution with two degrees of freedom (df). Then, if the result of (10.12) used in a χ^2 with 2df gives a result inferior to some pre-defined confidence interval (e.g. 99 percent), we can reasonably suppose that the tested variable does not add performance to the model. It should then be rejected.

- *Score test*: A second significance test is the score test. It allows us to verify that the model is significantly better performing than a naïve model. It is based on the conditional distribution of the derivatives of the log-likelihood function (the notation \bar{x} or \bar{y} is used to design average values):

$$ST = \frac{\sum x_i(y_i - \bar{y})}{\sqrt{\bar{y}(1 - \bar{y}) \sum (x_i - \bar{x})^2}} \sim N(0, 1) \quad (10.13)$$

- *Wald-test*: Another test often used is the Wald-test. It allows us to construct a confidence interval for the weights of the ratios, as their standard deviation is supposed to follow a normal distribution:

$$W = \frac{b_i}{\sigma(b_i)} \sim N(0, 1) \quad (10.14)$$

- R^2 : The R^2 -test is no longer a significance test, it is a correlation test. Various correlation measures are frequently used in statistics. The most popular in classical linear regression is the determination coefficient R^2 (which is the square of the correlation coefficient ρ). For the logistic regression, one of the similar measures frequently used is called the generalized R^2 . It is based on the likelihood ratio L :

$$R^2 = 1 - \exp\left[-\frac{L^2}{n}\right] \quad (10.15)$$

It is, however, more frequent to see the “max rescaled R^2 ,” as the maximum value of the R^2 of (10.15) is less than 1. To adapt it in a similar scale as the R^2 of linear regression, it is usually divided by its maximum potential value. The values observed for the logistic regression are usually much lower than those observed for the linear regression (as the two measures are not directly comparable). This is then a measure of association between observed and predicted values.

- *Goodness-of-fit-test*: A final type of test that we find interesting is the goodness-of-fit-test. It is used to verify the correspondence between the real observed y and those predicted by the model, \hat{y} . The test that is the most frequently used when the explanatory variables are continuous is the Hosmer–Lemeshow-test. It consists in dividing predicted values, classified

in ascending order, into $2 \times g$ groups (usually 2×10 groups), and to compare the number of observations $y = 1$ and $y = 0$ in each of the twenty intervals to what is expected by the model:

$$\hat{C} = \sum_{k=1}^g \frac{(O_k - n_k \bar{\pi}_k)^2}{n_k \bar{\pi}_k (1 - \bar{\pi}_k)} \quad (10.16)$$

where n_k is the number of observations in the group k , O_k the sum of the observations y in the interval k : $O_k = \sum_{j=1}^{n_k} y_j$, and $\bar{\pi}_k$ the average probability of occurrence of $y = 1$ or $y = 0$ in the group k . Hosmer and Lemeshow have showed that under the conditions of a correct model specification, \hat{C} follows a Chi-squared distribution with $(g - 2)$ degrees of freedom.

To simplify, what this test basically does is to group data in several intervals and to compare the observed default and survival rates with those predicted by the model (which is the average probability of the observations in the interval).

Economic performance measures

Box 10.6 outlines five commonly used economic performance measures.

Box 10.6 Five measures of economic performance

- *The cost function*: The model classifies companies from the riskiest to the safest. It is then possible to determine a cutoff point that will isolate the bad companies from the good ones. By doing this, two kinds of errors can be made. *Type I* errors consist of classifying a bad company (a company that defaulted) in the group of good companies (companies that did not default). There is then the risk of lending money to a borrower that will default. *Type II* errors are those where a good company is classified in the group of the bad ones. The risk here is to reject the credit request of a good client, which is an opportunity cost.

If we define *Type I* and *Type II* as being the number of errors of each type, and *CI* and *CII* the costs associated with each type of error, the cost function can be defined as:

$$C = (\textit{Type I} \times \textit{CI}) + (\textit{Type II} \times \textit{CII}) \quad (10.17)$$

This function has then to be minimized. Of course, the costs associated with the two types of errors may not be the same (the cost of lending to a bad client is usually much higher than the opportunity cost of missing a good client). However, the costs are very hard to assess and we usually

see the same weight given to the two errors in the literature. This is a performance measure that is easy to construct and to interpret; however, its binary nature is not very well suited to current bank practices, where credit decisions are much more complicated than a simple automatic “yes” or “no” as a function of the rating of the counterparty.

■ *The graphical approach:* We have already spoken about the graphical approach in the univariate study (p. 127). There are four main steps:

- Ordering the dataset as a function of the tested ratio or model.
- Representing those values on the X -axis of a graph.
- On the Y -axis we put either the average default rate, or the median rating (after a transformation such as AAA = 1; AA+ = 2...), observed on companies that have an X -value close to the one represented.
- The results are smoothed and outliers (extreme ratios values) are eliminated, capped to minimum and maximum values.

The graphical approach has the advantage of being simple and intuitive. It also allows us to check that the tested ratio has the expected relationship with the default risk (either increasing or decreasing). But we need to keep in mind that only a part of the distribution is represented (as outliers are eliminated). This usually eliminates 10–30 percent of the available data. The graphical approach may also constitute a good basis for ratio transformation (e.g. deciding what are the optimal minimum and maximum to use).

■ *Spearman rank correlation:* This is a modified version of the classical correlation coefficient used in the classical linear regression approach. The advantage is that it constitutes a non-parametric test of the degree of association between two variables. It is not constructed directly on the values of the two variables, but rather on their rank in the sample. For each pair of observations (x_i, y_i) we replace them with their rank R_i and S_i (1, 2... N). The correlation coefficient is then calculated as:

$$\theta = \frac{\sum (R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum (R_i - \bar{R})^2(S_i - \bar{S})^2}} \quad (10.18)$$

■ *Cumulative notch difference (CND):* When we work with a dataset of internal or external ratings, a convenient and simple performance measure is the cumulative notch difference. When comparing predicted and observed ratings, it is simply the percentage of observations that receive the correct rating (CND at zero notch), the percentage of companies that have a predicted rating equal or at the maximum one step (one step being, for instance, the difference between AA and AA–) away from the observed rating (CND at one notch), and so on ...

- *Receiver Operating Characteristic (ROC) and Cumulative Accuracy Profile (CAP):* We present these two performance measures at the same time, as they are very similar.

– CAP

CAP is one of the most popular performance measures for scoring models. It allows us to represent graphically the discriminatory power of a model or a variable.

The graph is constructed in the following way: on the X-axis we classify all the companies from the riskiest to the safest as a function of the tested score or ratio value, and on the Y-axis we plot the cumulative percentage of defaults isolated for the corresponding X-value. If the model has no discriminatory power at all, we will have a 45° straight line: in 20 percent of the population, we will have 20 percent of the defaults, in 50 percent of the population, we will have 50 percent of the defaults, and so on ... The ideal model would isolate directly all the defaults: if the default rate of the sample is 25 percent, the 25 percent lowest scores would be those that defaulted. A true model will usually lie between those two extremes (Figure 10.4).

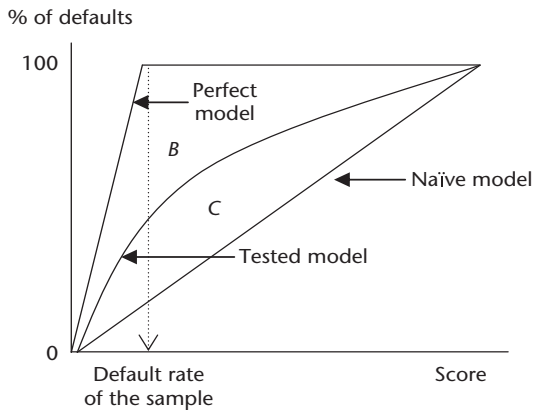


Figure 10.4 A CAP curve

The graph allows us to have a visual representation of the model's performance. However, to be more precise and to have a quantified value that permits easier comparisons between several models, we can calculate the accuracy ratio (AR). This is the surface covered by the tested model (above, the naïve model) divided by the surface covered by the perfect model, in our graph:

$$AR = \frac{C}{B + C} \quad (10.19)$$

– ROC

ROC is an older test, used originally in psychology and medicine. The principle is as follows: any model/ratio value can be considered as a cutoff point between good and bad debtors. For each cutoff, C , we can calculate a performance measure:

$$HR(C) = \frac{H(C)}{N_D} \quad (10.20)$$

where $HR(C)$ is the hit rate for the cutoff C , $H(C)$ the number of defaults correctly predicted, and N_D the total number of defaults in the sample. We can also calculate an error measure:

$$FAR(C) = \frac{F(C)}{N_{ND}} \quad (10.21)$$

where $FAR(C)$ is the false alarm rate for the cutoff C , $F(C)$ the number of non-defaulted companies that are classified in the bad companies, and N_{ND} the total number of non-defaulted companies in the sample.

If we calculate those values for each value of the tested ratio/model, we can represent the relationship, graphically (Figure 10.5).

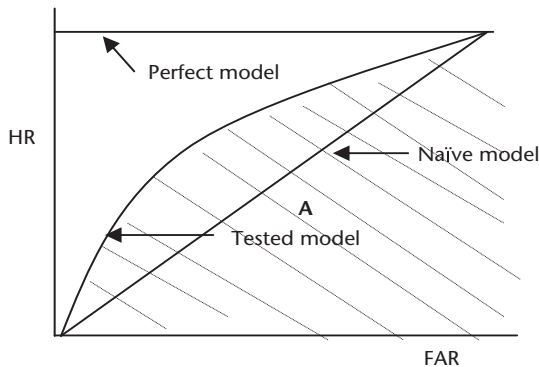


Figure 10.5 A ROC curve

A naïve model (with no discriminatory power) will have always equivalent values of HR and FAR . A perfect model will always have an HR of 100 percent (it will never classify a defaulted counterparty in the non-defaulted group). A true model will lie between those two extremes. As for the accuracy ratio, the area under the curve (shaded in Figure 10.5) will summarize the results in one number:

$$A = \int HR(FAR) d(FAR) \quad (10.22)$$

For the perfect model, $A = 1$. For the naïve model $A = 0.5$.

Link between ROC and CAP and reference values

We presented both ROC and CAP in Box 10.6 because they are very similar. In fact, there is a linear relationship between these two values (as shown, for instance, by Engelmann, Hayden, and Tasche, 2002):

$$AR = 2 \times (A - 0.5) \quad (10.23)$$

Although there are no absolute rules (CAP and ROC can allow us to compare models only on the same dataset, as their value depends on its underlying characteristics), we can find the following reference values in the literature (see Hosmer and Lemeshow, 2000) (see Table 10.5).

Table 10.5 ROC and AR: indicative values

AR (%)	ROC (%)	Comments
0	50	No discriminatory power
40–60	70–80	Acceptable discriminatory power
60–80	80–90	Excellent discriminatory power
+80	+90	Exceptional discriminatory power

Extending the ROC concept to the multi-class case

When the dependent variable is not binary but can have several values (as in ratings), the ROC concept can be extended (we shall use the notation ROC*). To calculate the ROC* in this case, we consider each possible pair of observations. In a dataset of n observations, there are $(n * (n - 1))/2$ pairs. We look to see if the observation that is predicted as being the riskiest is effectively the riskiest. If it is the case, this pair is said to be “concordant.” If both the predicted and the observed values are equal, this pair is said to be “even.” Finally, if the prediction is wrong, the pair is said to be “discordant.” If we notate, respectively, the number of each pair by n_c , n_e , and n_d , the ROC* can be defined as:

$$ROC^* = \frac{(n_c + 0.5n_e)}{n} \quad (10.24)$$

We have briefly reviewed some tests; readers that want to go into more detail should consult standard statistical textbooks on logistic regressions (e.g. *Applied Logistic Regression*, by Hosmer and Lemeshow, 2000, or *Logistic Regression using the SAS System* by Allison, 2001).

POINT-IN-TIME VERSUS THROUGH-THE-CYCLE-RATINGS

There is a classical debate to be considered when constructing a rating system. Should it deliver a point-in-time (PIT) or a through-the-cycle (TTC) rating?

A PIT rating is usually said to be a rating that integrates the last available information on the borrower, and that expresses its risk level over a short period of time – usually one year or less. Those kinds of ratings would be volatile, as they would rapidly react to a change in the financial health of the counterparty. They can result in ratings that can rapidly move while default rates by rating grade would be rather stable.

A TTC rating, on the contrary, is a rating supposed to represent the average risk of the counterparty over a whole business cycle. It also incorporates the last available information, the history of the company, and its long-term prospects over the coming years. The ratings produced are more stable, but the default rates are more volatile.

There are often debates on what is the best approach – or should both be used in conjunction? Scoring models tend to be PIT, as they are usually based on the last available year of financial statements, while external rating agencies usually say that their ratings are TTC (they usually say that their rating estimates the default risk over the next three–five years). The Basel text seems to be more in favor of the TTC approach, one of the reasons being that the regulators wanted to avoid the volatility that might produce the PIT approach. In economic downturns, downgrades would be more rapid and the required regulatory capital could increase significantly, eventually leading to a credit crunch (which means that because of the solvency ratio constraint, the banks would decrease their credit exposures and companies would have problems in finding fresh funds). It is also considered more prudent to give a rating that reflects a company's financial health under adverse conditions.

We think that this debate is very largely theoretical, and that none of those approaches reflects the real practice. First of all, it is impossible to give a rating TTC. An economic or business cycle is not covered only because you assess the risk over the three–five following years (as is said by rating agencies). A business cycle may differ from one sector to the other, but if we consider a cycle as the time between the start of an above-average growth phase, a decreasing-speed phase, and then a recession, we would say that it might last for ten–twenty years rather than three–five (the famous Kondratief cycles in the macroeconomy lasted for twenty-five years).

Then, on which horizon is a rating based? This depends on many factors. The ideal maturity is the maturity of the borrower's credit. It is clear that if the only exposure of a bank on a counterparty is a 364-day liquidity line, the credit analyst has few incentives to try to estimate the company's situation in five years. A credit analyst who has to analyze a project finance deal with an amortizing plan over fifteen years will be more prudent and try to integrate a long-term worst-case scenario in the rating. The rating maturity also depends on the available information, of course. If there are clear indices that the sector where the analyzed company is active will go through a turbulent phase, the analyst will integrate this in the rating. If the company

is in a sector that is in very good health and there are no signs of imminent downturn, the analyst will not wonder what the company financials would be in ten years' time.

The TTC approach offers greater stability in the ratings, but this can also be a risk. Rating agencies have been highly criticized because in the name of the TTC approach they were sometimes slow to decrease the rating of companies they followed when they began to deteriorate. More recently, they published papers stating that they were going to be more reactive.

From a risk-modeling perspective, TTC ratings may not be the optimal solution. Expected losses or economic capital are usually calculated over a one-year horizon. PIT ratings would in principle deliver more accurate estimates, as they are more reactive and as the default rate by rating class tends to be less volatile (and thus more predictable). Opponents of PIT ratings say that the TTC approach allows us to integrate a buffer when calculating the required capital, which is positive as capital requirements that show sharp increases or decreases each year are hard to manage. But is it perhaps preferable to have explicit capital buffers than to integrate them indirectly through the ratings given? Or would the optimal solution be to work with both short-term and long-term ratings (as suggested by Aguais, Forest, Wong, and Diaz-Ledezma, 2004)?

CONCLUSIONS

In this chapter, we examined some of the main Basel 2 requirements regarding internal rating systems. After a review of the current practices, we concluded that the best internal rating system was the one that integrated, as one of its components, the use of a scoring model (that ensured consistency in the approach and that allowed regulators' validation). Of course, a scoring model is only one piece of the global rating system architecture, that we shall discuss in more detail in Chapter 13.

We made a brief review of historical studies regarding bankruptcy prediction models, and discussed the data that we could use, how many models and ratios should be used, and the various steps in model construction. We then presented the logistic regression model, which is one possible approach. Frequently used performance measures were described, and we ended with a discussion on PIT versus TTC ratings.

The approach presented here is one possibility. But practical views, although partial, may be more beneficial to readers who want to start their own research on scoring models than neutral detached discussions that briefly review a range of possibilities. Chapter 11 focuses on a concrete case study. We invite readers that wish to go deeper into the field to read other papers (see the Bibliography) so that they can form their personal view on the many issues, options, and hypotheses that make the construction of scoring models such an open, creative, and exciting discipline.

Scoring Systems: Case Study

INTRODUCTION

In this chapter, we shall construct scoring models on real-life datasets that are furnished on the accompanying website. There are two datasets, one composed of defaulted and non-defaulted companies, and one composed of external ratings so that readers can gain experience on both type of approaches. To perform the tests, you may download an excellent free statistical software that is called Easyreg, that allows us, among other things, to perform binary and ordered logistic regression (this software was developed by J. Biersen; see his website www.easyreg.com).

The goal is to show concretely how we can proceed to perform the different steps and some of the tests described in Chapter 10. We shall also try to give some practical tips to avoid the common pitfalls encountered when constructing scoring models.

To get the best from this chapter, we advise the reader to go through it with the related Excel workbook files opened on a PC.

THE DATA

We shall begin to work with the workbook file named “Chapter 11 – 1 datasets.xls.” When constructing a dataset we should try to collect data on companies that are similar to those in the bank’s portfolio. This means that

geographical locations or sectors should globally match the bank's exposures characteristics. There should at least be specific performance tests on the parts of the datasets where the bank is more exposed.

The rating dataset

On the workbook file "rating dataset," you will find a sample of financial statements of 351 companies that have external ratings. The ratings were converted on a scale between 1 (the best) and 16 (the worst). The rating distribution is that shown in Figure 11.1.

The ratings used need to be coherent with the date of the financial statements. If you work, for instance, with the financial statements of 2000, you should not use the ratings available in January, February, or March 2001 as between the closing date and the availability of the accounts there can be a delay that can range from some months to a year. You should then always choose default or rating information that is in a time frame coherent with the delay necessary to get the corresponding financial information. In the case of external ratings, the companies covered are usually large international companies that publish quarterly results. In addition, rating agencies usually have access to unaudited financial statements before their official publication date. Ratings available from three months after the financial statement date should therefore be adequate.

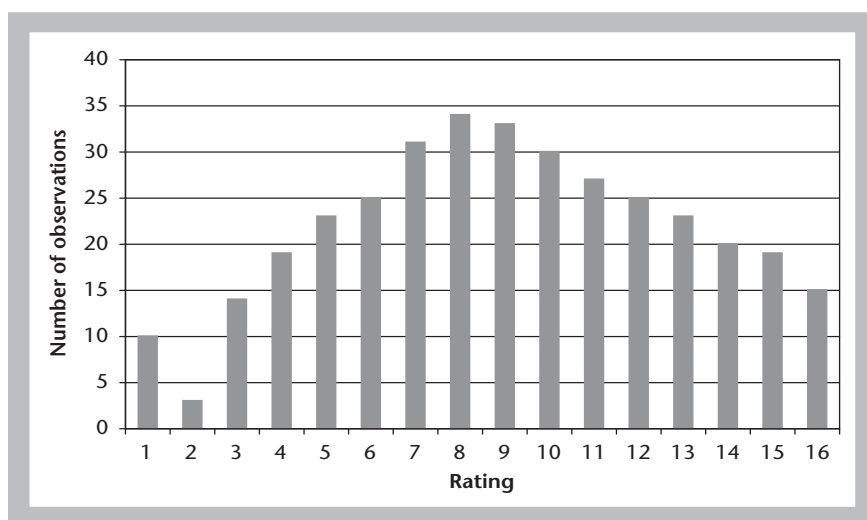


Figure 11.1 Rating distribution

The distribution of the available ratings is also an issue. We have to remember that the model is trying to minimize an error function. Thus, the model will usually show the highest performance on the zones where there are more observations. It is then important that the rating distribution in the sample matches the rating distribution of the bank portfolio on which the model will be used (as already discussed (p. 125), we have to pay attention to survivor bias). Most frequently, the distributions of the exposures of a bank are “bell-shaped”: this means that there are few exposures on the very good and very bad companies and more on the average-quality companies. One could wish to use a sample that has an equal number of observations in each rating class to have a model that produces the same average error over all the ratings. Or one could use a rating distribution with a higher number of observations on low ratings because it is considered to be more important to have a good performance on low-quality borrowers. All this can be discussed, but we recommend using a classical distribution with the highest concentration on average-quality borrowers where most of the exposures usually lie.

The default dataset

On the workbook file “default dataset” you will find a sample of 1,557 companies (150 defaulted and 1,407 safe). When selecting the data for defaulted companies, we have to pay attention to three things:

- The *default date*: As for ratings, we have to be coherent by selecting default events that occurred after the financial statements used became available. Availability of financial statements can depend on local regulation and practices and publication can sometimes take a year (which means, for instance, that financial statements of year-end 1998 are available only at the beginning of 2000). Credit analysts, as we have seen, may have access to unaudited financial statements before they are officially published. In our dataset, the first defaults occurred three months after the closing date of the financial statements.
- The *time horizon*: Another question is – how far do we go from the closing date of financial statements? Do we take defaults only of the following year, or all the defaults that occurred the next two years, five years ...? There is no single answer to this problem. The ideal is to take a time period that corresponds to the *average maturity* of the credits. Of course, the more you consider a long period, the less the model will show a high discriminatory power as predicting a default that will occur in one year is easier than in five years. In our dataset, we have financial statements of year N and defaults on three cumulative years, $N + 1$, $N + 2$, and $N + 3$.

- The *default type*: What is a default? Ideally, we should work with default events that match the Basel 2 definition. However, the definition used in Basel 2 is so broad (“unlikely to pay” is already considered as a default) that it is hard to get such data. The most current default events that can be found are real bankruptcies – Chapter 11 in the US, and so on ... – or at best 90-day delays on interest payments. After having constructed the model, a further step will be to calibrate it to match the *average default probability* (in a Basel 2 sense) that is expected in the sample. This step is usually called “calibration,” and we shall discuss it more deeply on p. 178.

CANDIDATE EXPLANATORY VARIABLES

We shall now define the potential explanatory variables. As we work in the field of bankruptcy prediction, explanatory variables will usually be financial ratios, as they are often used by credit analysts to assess a company’s financial health. However, other variables may be used: sector of the company, date of creation, past default experience... In fact, there is no limit except that the variable should make economic sense (which means that economic theory can link it to the default risk) and that it proves to be statistically significant. For retail counterparties, for instance, the most popular scoring models at the moment are behavioral scoring models. This means that the explanatory variables are mainly linked to the behavior of the customer: average use of its facilities, movements on its accounts ...

Using only truly explanatory variables

However, we have to pay attention to some particular kinds of variables. Sectors, for instance, can be incorporated through the use of binary variables (coding 1 or 0 if the company belongs, or does not belong, to a certain specific sector), which avoids having to construct several different models for different sectors (which divides the number of available data). But we should like to recall an issue already discussed in Chapter 10: the dangers of integrating specific temporary situations. There is a golden rule that a scoring modeler should always keep in mind: the goal of the exercise is to construct a *performing default-prediction model*, not to show the highest performance on the available dataset. Those are two different things. The objective is not to show how well we can explain, afterwards, past events. It is to have a model sufficiently general to react in a timely fashion to changes in some of the characteristics of the reference population. We achieve this by asking ourselves the crucial question in regression analysis: are the variables really explanatory variables or are they observations explained by other hidden explanatory factors? To take an example. Imagine that ten years

ago we constructed a model that incorporated a specific binary variable indicating that the company belonged, or did not belong, to the utility sector. The variable proved to be statistically significant on the reference sample, leading on average to a higher rating for utilities companies. What would be the performance of such a model in the many countries where utilities firms over previous years had gone through a heavy deregulation phase, losing implicit state support? This could be a dangerous situation if credit analysts did not launch a warning signal, because people would rely too heavily on the model. The error here is that belonging to the utilities sector was not in itself the explanatory variable making utilities firms safer: it was the *implicit state support* that was the real issue. This should have been integrated into the model in another way (either in a second part of the rating model which could be a qualitative assessment, or in the financial score part by using a binary variable that was the analyst's answer to the question about potential state support). Belonging to the utilities sector in itself was not the issue, and a lot of companies became riskier because of deregulation while still belonging to this sector. The same kind of danger can arise when we use binary data to code the country as an explanatory variable: the situation of the country can improve or deteriorate and the model will not react. We recommend, for instance, using the external rating of a country as a possible explanatory variable, rather than the single fact of belonging to the country.

The conclusion is that the first focus is not always performance on the available dataset, but the possible generalization of the model. *Reactivity* is more important than performance on past data. This is especially an issue when we consider that when credit analysts work for several years with scoring models and that they deliver relatively good results, they tend to rely more and more on them ...

Defining ratios

Financial ratios are correlated to default risk, but they are not the only explanatory variables. Many other elements can influence the probability of default. Additionally, ratios are not observable natural quantities but are artificial constructions, so we can expect to find some extreme ratio values without defaults. Selecting and transforming ratios are thus key steps in the modeling process.

The first step is to test the performance of individual ratios. This allows us to have a first look at their respective stand-alone discriminatory power. Some of them will be rejected if they have no link at all with default risk, or if they have a relationship that does not make sense in light of economic theory (e.g. higher profitability linked to higher default risk). However, we have to be prudent before eliminating ratios, as some ratios that have

a weak discriminatory power in an univariate context can perform better when integrated in a multivariate model.

The problem with financial ratios is that they are too numerous. Chen and Shimerda (1981) made a list of a hundred financial ratios that could potentially have some discriminatory power. It would be time-consuming and unproductive to test them all, and as we want to develop stable and discriminatory models we have to use generic ratios that are not too specialized and that have an interest only for very specific types of companies (the size of the available dataset has to be taken into account). The best way to proceed is thus to meet expert credit analysts and to establish with them a list of potential ratios that they consider as relevant (a performing ratio from a statistical point of view but that would not be considered as meaningful by analysts should be avoided, as model acceptance is crucial).

In our dataset, we selected a short list of ratios, as our goal was simply to explain the mechanics of model construction. They are listed in Table 11.1.

Table 11.1 Explanatory variables

Category	Ratio	Midcorp definition	Corporate definition
Profitability	ROA	= $\text{sum}(16 \text{ to } 24)/8^a$	= $\text{sum}(20 \text{ to } 30)/12$
	ROA bef. exc. and tax	= $\text{sum}(16 \text{ to } 20)/8$	= $\text{sum}(20 \text{ to } 27)/12$
	ROE	= $\text{sum}(16 \text{ to } 20)/(9 + 10)$	= $\text{sum}(20 \text{ to } 30)/$ $(18 + 19)$
	EBITDA/Assets	= $(16 + 17)/8$	= $\text{sum}(20 \text{ to } 23)/12$
Liquidity	Cash/ST Debt	= $7/\text{sum}(13 \text{ to } 15)$	= $4/\text{sum}(13 \text{ to } 15)$
	(Cash and ST assets)/ ST debt	= $\text{sum}(4 \text{ to } 7)/$ $\text{sum}(13 \text{ to } 15)$	= $\text{sum}(1 \text{ to } 4)/$ $\text{sum}(13 \text{ to } 15)$
Leverage	Equity/Assets	= $(9 + 10)/8$	= $(18 + 19)/12$
	(Equity – goodwill)/ Assets	= $(9 + 10 - 1)/8$	= $(18 + 19 - 7)/12$
	Equity/LT fin. debts	= $(9 + 10)/11$	= $(18 + 19)/16$
Coverage	EBIT/interest	= $\text{sum}(16 \text{ to } 20)/22$	= $\text{sum}(20 \text{ to } 24)/26$
	EBITDA/interest	= $\text{sum}(16 \text{ to } 17)/22$	= $\text{sum}(20 \text{ to } 23)/26$
	EBITDA/ST fin. debt	= $\text{sum}(16 \text{ to } 17)/13$	= $\text{sum}(20 \text{ to } 23)/$ $\text{sum}(13 \text{ to } 15)$
Size	Assets	= $\ln(8)$	= $\ln(12)$
	Turnover	= $\ln(16)$	= $\ln(20)$

Notes: ROA = Return on assets.

ROE = Return on equities.

ST = Short-term.

^a See the codes given to the financial statements in the Excel workbook file.

Transforming ratios

Having defined the ratios, we have to treat them before beginning the univariate analysis. A number of operations of data cleaning, transformation, and standardization need to be done. Box 11.1 considers four key issues.

Box 11.1 Steps in transforming ratios

- For *size ratios*, we use a classical logarithmic transformation. This is useful as we get better performance with the logit model if the ratios have a distribution close to the normal. If we take the original distribution of total assets on the default dataset, for instance, we get the graph in Figure 11.2.

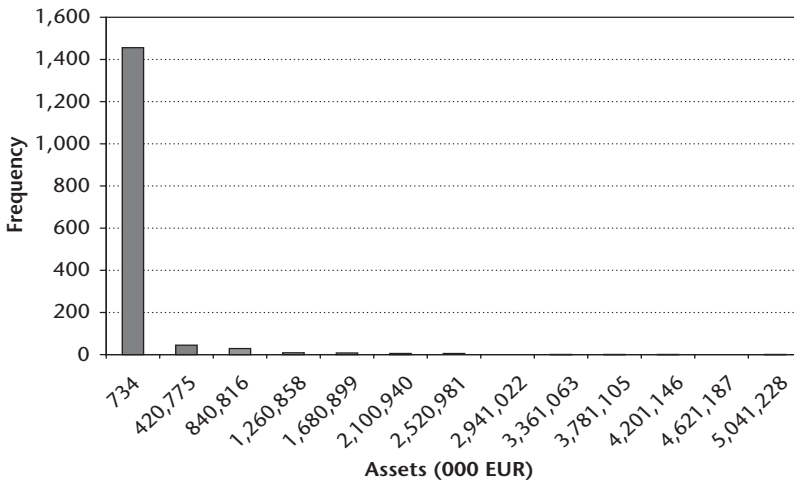


Figure 11.2 Frequency of total assets

We can see that the distribution is very concentrated on a certain zone and that there are some extreme values. Using the logarithmic form in Figure 11.3 we get a graph with a more equilibrated distribution.

Transforming total assets is straightforward, but for some other size variables we have to take care. Equity, for instance, can be equal to zero, or even have negative values. Then, before using the logarithm, we have to transform zero and negative values into small positive ones, by replacing them by 1, for instance (or by adding a large enough constant).

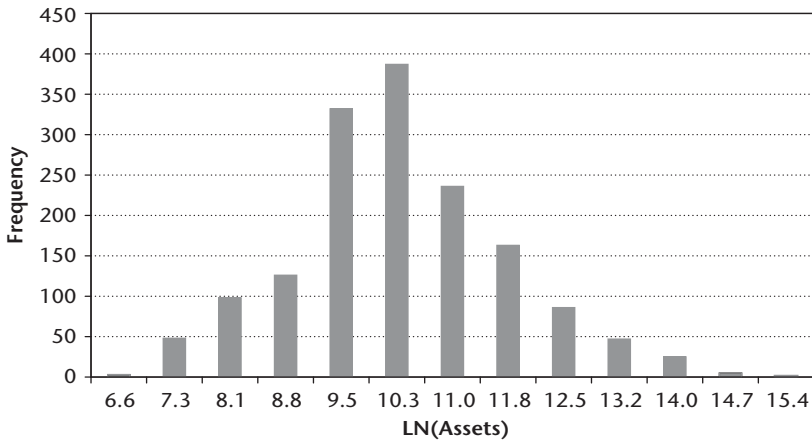


Figure 11.3 Frequency of LN(Assets)

- *Missing values:* When we have missing values, we have first to investigate the database to see if it means that it equals zero. If it is not the case, we have to evaluate the number of missing values per financial variable. If the percentage of such values is too high, we should consider excluding financial ratios that use this variable in order to keep objective results. If the percentage of such values is small, a classical technique consists of replacing them by sample median values for this type of data.
- *Extreme values:* As ratios are artificial constructions and not natural quantities, they can reach some extreme values that do not make sense. For instance, (EBITDA/Interest) is often used to measure the debt payback ability. Values between -10 and $+35$ are a reasonable range. However, a company can have almost no financial debt and could pay, for instance, 1,000 EUR of financial charges. If its EBITDA is 1 million EUR, its (EBITDA/Interest) would be 1,000. A similar company but of a different size may pay the same charges but have an EBITDA of 100,000 EUR. Its ratio would be 100 (10 times smaller). However, the difference in the financial health of those two companies is much less significant than between two companies that have ratio values of 1 and 3. We can see that when we face a very high or very low ratio level, the differences between two values lose significance (companies are both very good or very bad). It is common in econometrics to limit maximum and minimum values. This is usually done by constructing an interval corresponding to certain percentiles of the distribution (5th and 95th percentiles, for instance) or corresponding to the average value plus and minus a certain number of standard deviations (3, for instance). In our dataset, we have capped values between percentiles 5 and 95.

- *Fraction issues:* When constructing the ratios, we have to check that they keep all their sense whatever the numerator or denominator values may be. Let us take the situations in Table 11.2.

Table 11.2 Ratio calculation

Profit/Equity			Equity/LT fin. debt		
Profit	Equity	Result (%)	Equity	LT fin. debt	Result (%)
10	100	10	-10	100	-10
-10	-100	10	-10	10	-100
			-100	10	-1000

In Table 11.2, we have computed two ratios. The first is Profit/Equity. We can see that as both numerator and denominator can take negative values, we can have polluted results as one company having positive profits and equity can get the same ratio as another having negative profits and equity, which means that its financial health is much weaker. When computing the ratio, a first test could be to see if equity is negative, and if it is the case forcing the ratio value to zero.

Another example is Equity/LT fin. debt. It is interesting to note that, in this case, only the numerator can take negative values. However, we may still have some problems. The first company has a negative equity of -10 and 100 of financial debt; its ratio is then -10 percent. The second company has also a negative equity of -10 but has fewer debts, 10; its ratio is then -100 percent. The second company has a lower ratio than the first and has a better financial structure. The third company has the same amount of debt than the second, but has more negative equity (-100 against -10). Its ratio is -1000 percent. It then has a lower value than the ratio of the second company, while its risk is greater, which is the converse of the situation between the first and second company. We can now see that there is no rationale in the ordering of the companies (we cannot say that a greater ratio or a lower ratio means better or a worse financial health). This kind of phenomenon can be observed when the numerator can take a negative value and when a higher denominator means more risk. To overcome this problem, we can set ratios with a negative numerator at a common negative ratio value, -100 percent for example.

A last point of attention is ratios where the denominator can have a zero value, which makes the computation impossible. This can be corrected by adding a small amount to the denominator. For instance, if there are no LT fin. debts, we suppose an amount of 1 EUR so that our ratio can be computed. This will give a very high value, but as we limit ratios between the 5th and 95th percentiles, this is not a problem.

We have implemented such treatments in the excel workbook file, in the computation of the following ratios: ROE, Equity/LT fin. debt and EBITDA/interest.

SAMPLE SELECTION

Having collected the gross data (as said in Chapter 10, this can be external databases, internal default data, or even internal ratings), having defined the potential explanatory variables, and having treated them (missing values, extreme values, size variables, fraction issues), we have now to *select the sample* that we shall use.

If the available data are not really representative of the target portfolio, we can select *sub-samples* that meet the geographical or sector-specific concentrations. However, limiting the sample is always dependent on the number of available data, as there is a trade-off between sample size and its correspondence to the reference portfolio, both being important.

Another issue when dealing with the rating dataset is to pay attention to the *sovereign ceiling effect*. Available ratings are usually ratings after the sovereign ceiling, which means the transfer risk of countries (if a country runs into default, it will usually prevent local companies from making international payments in a foreign currency). The ratings of companies in a given country are then limited to a maximum that equals the rating of the country. These companies should be removed from the dataset as in these cases (for companies that may have higher ratings before the application of the sovereign ceiling) the financial ratios are no longer related to the rating, and could pollute the sample. This is usually an issue for companies located in countries that have low ratings. Of course, if we want to develop a scoring model for emerging countries in particular, this could be a problem. We have then to find country-specific datasets, or at least to group financial statements of companies in countries that have the same rating and to develop a specific model for them.

Another point of attention is *groups of companies*. When several companies belong to the same group in the dataset, we should work only with the top mother companies (those that usually have consolidated financial statements) because the risks of subsidiaries are often intimately linked to the financial health of the mother companies that would support them in case of trouble. Ratings or observed default events on such companies may also be less linked to financial ratios, as a weak company (low profitability, high leverage, for instance) but that is owned by a strong company, will usually be given a good rating by rating agencies (if support is expected). Subsidiaries should be removed from the sample.

Financial companies may also be removed from the sample if we want to develop scoring models for corporate counterparties. Banks, finance

companies, or even holdings may be removed as their balance sheets and P & L statements have a different nature from classical corporate ones.

Start-up companies (those created over the year preceding the rating or the default event date) may also be removed as their financial statements may not have the quality of established companies and may not reflect their following-year target financial structure.

Studying outliers

When the above filters and sorting have been used, a useful step to clean the data is to study outliers. To perform this, the modeler can construct a “quick and dirty” first version of the model. Taking two or three ratios that should perform well according to financial theory, we can by using a simple linear regression – for instance, ordinary least squares, OLS – calibrate a first simple model. The goal is to identify the *outliers*: companies that get a very high predicted rating (PD) while the true rating is very low (the company did not default), or the reverse. This allows us to isolate companies that have a risk level that is not correctly predicted by the model. We can then look at each one to see if there is a reason. If we cannot identify the cause, we have to leave the company in the sample, but in some cases we can remove it. For instance, if we find a company that has a very bad predicted rating (because of bad financial statements) while its true rating is very good, we could discover that the rating was given after that the company had announced that it was to be taken over by another big healthy company. The good rating is in this case clearly explained by external factors, and is not linked to financial ratios. We can increase the sample quality by removing the observation: however, we need always to have an objective justification before eliminating a company, because the modelization process must stay objective.

UNIVARIATE ANALYSIS

We now have a clean sample. The next step is to study the univariate discriminatory power of each candidate ratio. To do this, we shall use some of the performance measures presented in Chapter 10. We shall work with the graphical approach, the CND, the Spearman rank correlation (for the rating dataset only), and the ROC curve.

Profitability ratios

The first kind of ratios that we test are *profitability ratios*. The expected relationship is a positive one: a higher profitability should lead to a lower

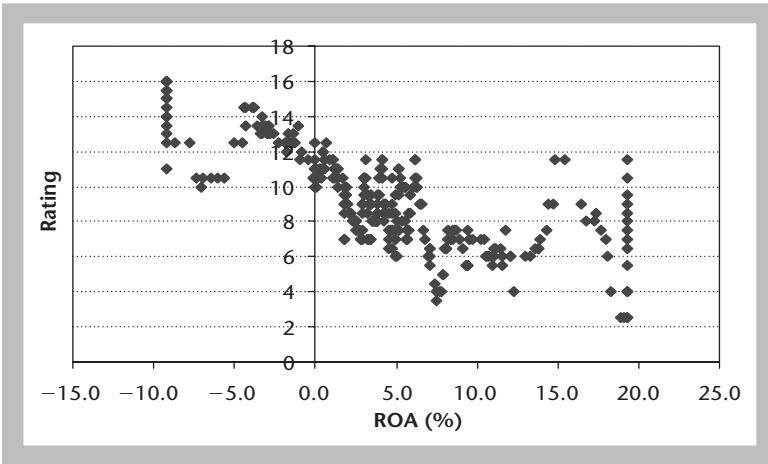


Figure 11.4 ROA:rating dataset

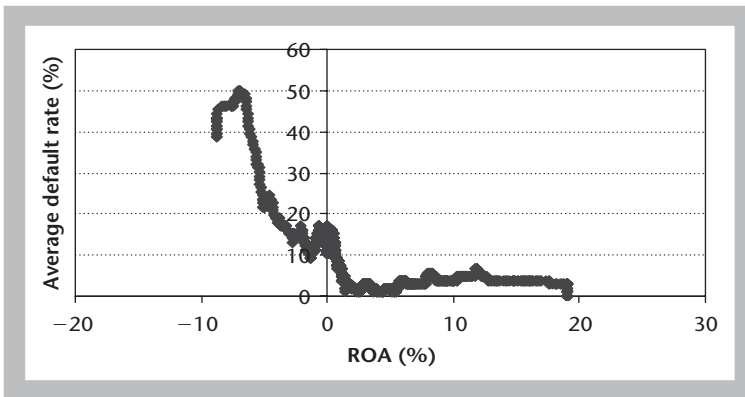


Figure 11.5 ROA:default dataset

default probability or a higher rating. Readers can use the Excel workbook file “Chapter 11 – 2 profitability ratios.xls” to see how the various tests are constructed. Figures 11.4–11.11 show how the datasets are graphed.

We can see from Figures 11.4–11.11 that the graphical approach is a useful tool as it gives us a first intuitive look at the relationship between the ratios and the default risk. We can check that the global relationship between the ratio value and risk makes economical sense – for instance, higher ROA leads effectively to a lower average default rate and a better rating. Secondly, as

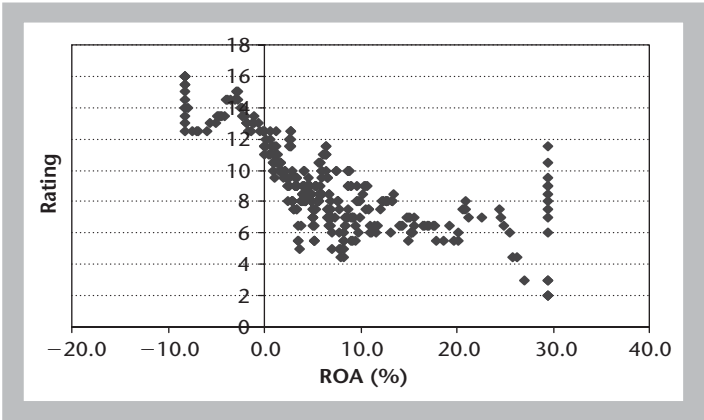


Figure 11.6 ROA before exceptional items and taxes:rating dataset

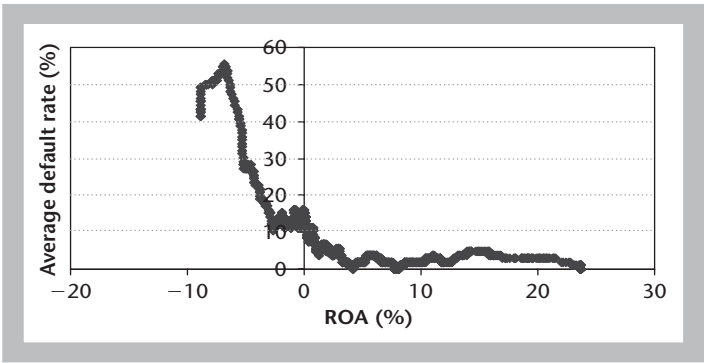


Figure 11.7 ROA before exceptional items and taxes:default dataset

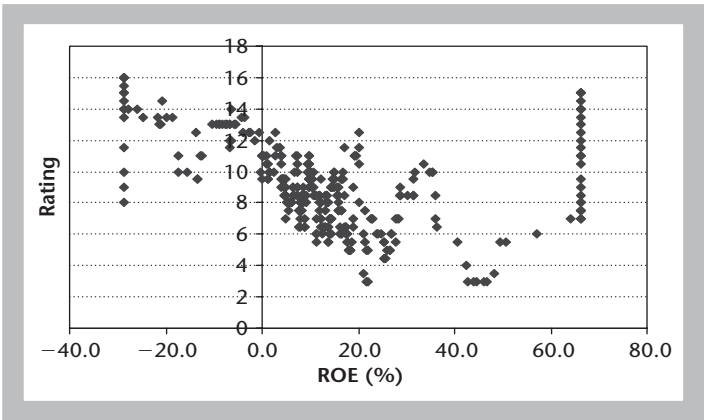


Figure 11.8 ROE:rating dataset

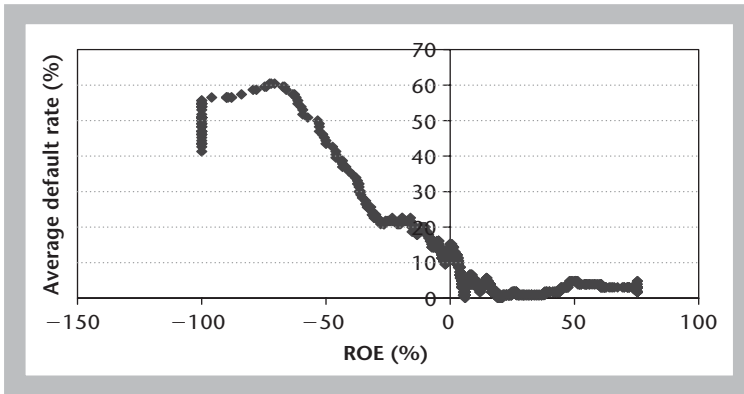


Figure 11.9 ROE:default dataset

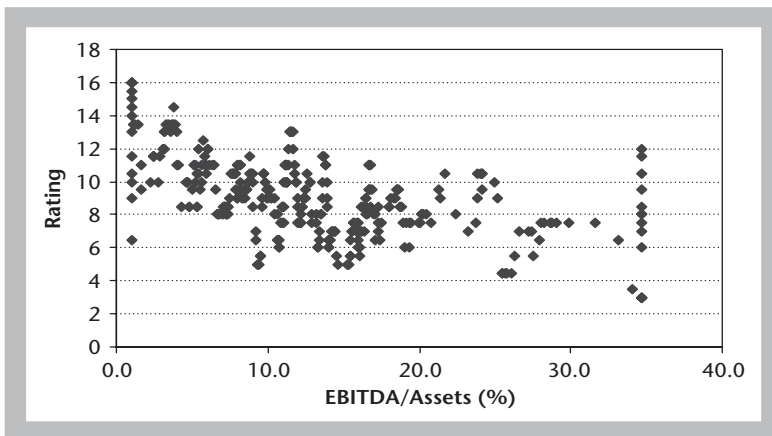


Figure 11.10 EBITDA/Assets:rating dataset

explained in Chapter 10, the third step of model construction (after data collection and cleaning, and univariate analysis) is ratio transformation. In this step, we set maximum and minimum ratio values on the basis of the graphical analysis where the curves of average ratings or average default rates seem to become flat (which means that in this zone the discriminatory power of the ratio becomes close to zero). There is no absolute rule to fix the optimal level of the interval, it is a mix between the analysis of the graphs, financial analysis theory, intuition, and trial and error. For instance, if we return to Figure 11.4, repeated here as Figure 11.4A, we can see that below -3 percent and above $+13$ percent the relationship between the ratio and

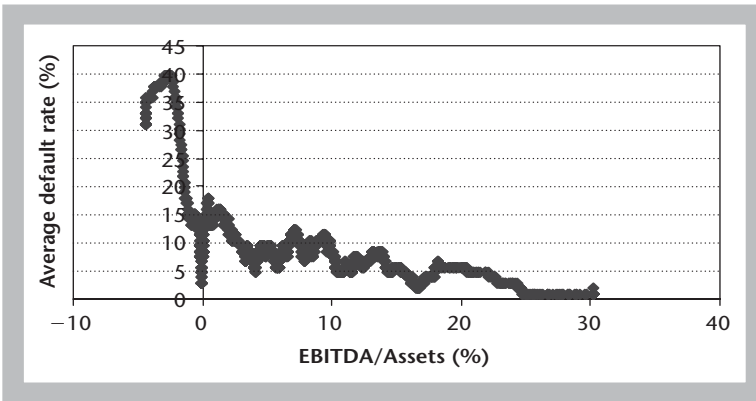


Figure 11.11 EBITDA/Assets:default dataset

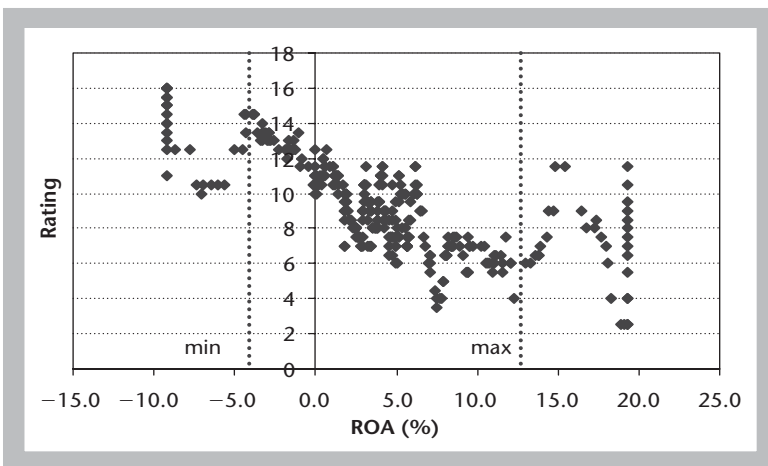


Figure 11.4A ROA:rating dataset

the average rating becomes less clear. These could thus be good reference values to limit the ratio as we do not want to “pollute” the model with false signals.

We can see that all candidate ratios seems to have some discriminatory power. To complement the analysis, some numbers could help us to compare their performance. We can use all the performance measures we described in Chapter 10; however, we limit ourselves here to two key indicators (Table 11.3).

ROA excluding exceptional items and taxes seems to show the highest performance on both datasets. ROE has weaker results, which is an expected

Table 11.3 Profitability ratios: performance measures

Profitability ratios	Rating dataset		Default dataset	
	Performance (Spearman rank correl.) (%)	Proposed* limits (%)	Performance (AR) (%)	Proposed* limits (%)
ROA	-41	-3; 13	52	-10; 5
ROA bef. exc. and taxes	-46	-5; 13	57	-10; 5
ROE	-24	-10; 40	40	-50; 25
EBITDA/Assets	-27	1; 30	34	-5; 30

* Except for EBITDA/Assets.

conclusion as high-ROE companies can be very profitable companies or companies with average earnings but very little equity (high leverage), which is not a sign of financial health.

Liquidity ratios

The second kind of ratios we test are *liquidity ratios*. The expected relationship is also a positive one: a higher liquidity should lead to a lower default probability or a higher rating. Readers can use the Excel workbook file "Chapter 11 – 3 liquidity ratios.xls" to see how the various tests are constructed (Figures 11.12–11.15).

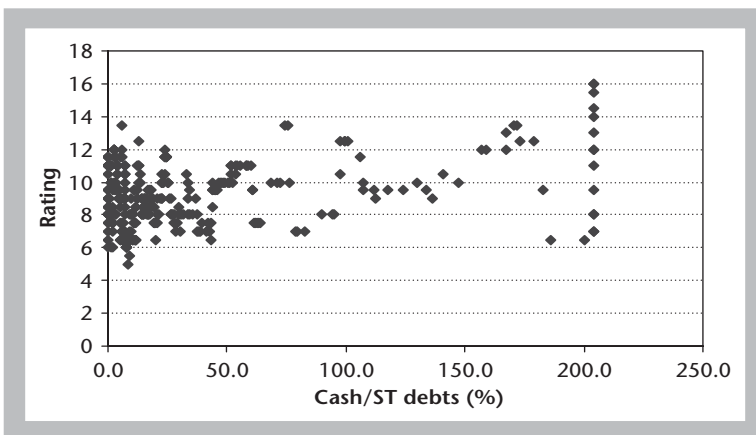


Figure 11.12 Cash/ST debts:rating dataset

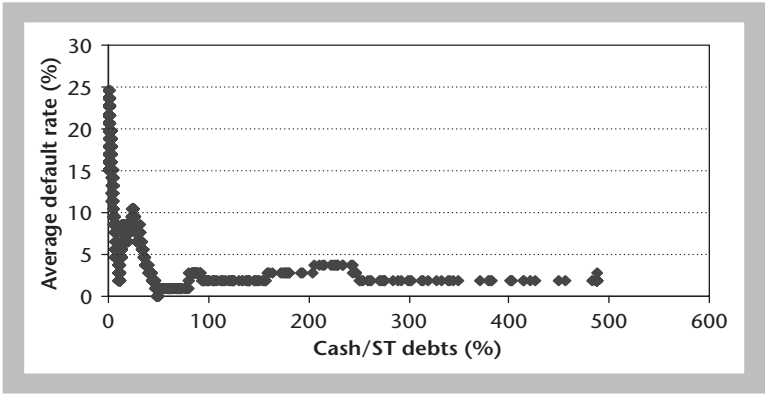


Figure 11.13 Cash/ST debts:default dataset

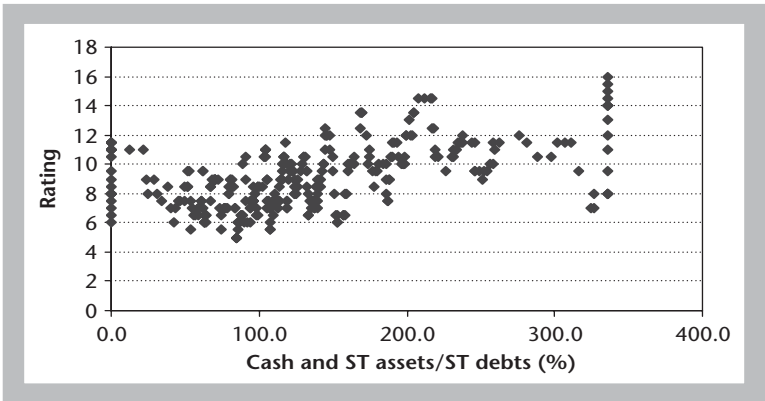


Figure 11.14 Cash and ST assets/ST debts:rating dataset

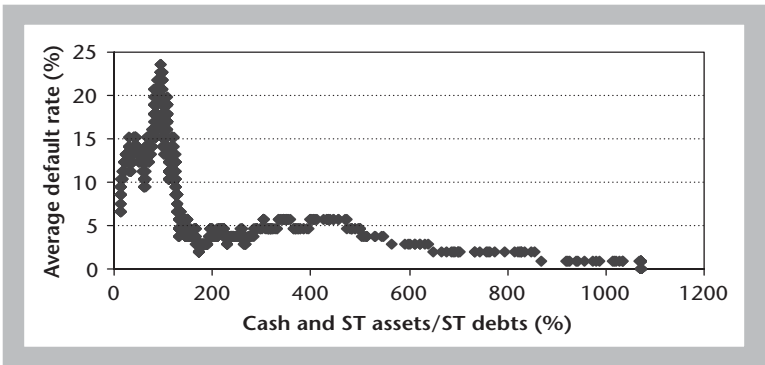


Figure 11.15 Cash and ST assets/ST debts:default dataset

The case of liquidity ratios is an interesting one. One point should strike the readers looking attentively at Figures 11.12 and 11.14: the sense of the relationship. The graphs are increasing with the liquidity ratio values, which means that higher liquidity leads to lower ratings. We have here an example of ratios that have a relationship to default risk that does not make sense. This surprising result was also an observation that can be found in Moody's research (see Falkenstein, Boral, and Carty, 2000). The reason is that, for large corporate, good companies tend to have low liquidity reserves as they have easy access to funds (through good public ratings, by raising funds on capital markets when they are listed, or through the issue of commercial paper programs), while low-quality companies have to maintain important liquidity reserves as they may have difficulty getting cash in time of troubles. Referring to the section in this chapter on "Using only truly explanatory variables," we have an example of a variable that is not an explanatory one but rather a consequence of *credit quality*. We should therefore exclude it.

In the case of the default dataset (Figures 11.13 and 11.15), we don't find this problem. There are two reasons. The first is that this dataset is mainly constituted of smaller companies that are not listed and that do not have external ratings, which means that even good companies have to keep adequate liquidity reserves. The second, and more fundamental, is that we are working here on companies that have defaulted, not on external ratings. If for the large corporate dataset we had default observations, we would not have encountered such problems, as most defaulted companies would effectively be found to have a liquidity shortage. Companies with good external ratings do not need to have a liquidity surplus, until they run into trouble ... This is an illustration of the fact that when we have a choice, it is always better to work directly on default observations.

Performance measures for the rating and default datasets are presented in Table 11.4.

Table 11.4 Liquidity ratios: performance measures

Liquidity ratios	Rating dataset		Default dataset	
	Performance (Spearman rank correl.)(%)	Proposed limits	Performance (AR)(%)	Proposed limits (%)
Cash/ST debts	Rejected (12)	n.a.	39	0; 50
Cash and ST assets/ST debts	Rejected (26)	n.a.	28	50; 200

Note: n.a. = Not available.

Leverage ratios

The third kind of ratios that we test are *leverage ratios*. A company that finances its assets through a higher proportion of equity should have a lower default probability or a higher rating. Readers can use the Excel workbook file “Chapter 11 – 4 leverage ratios.xls” to see how the various tests are constructed (Figures 11.16–11.21).

The relationships seem to make sense in all cases. The vertical lines that we can see at the beginning and at the end of the graphs are due to the limits at the 5th and 95th percentiles. For the rating dataset (Figure 11.20),

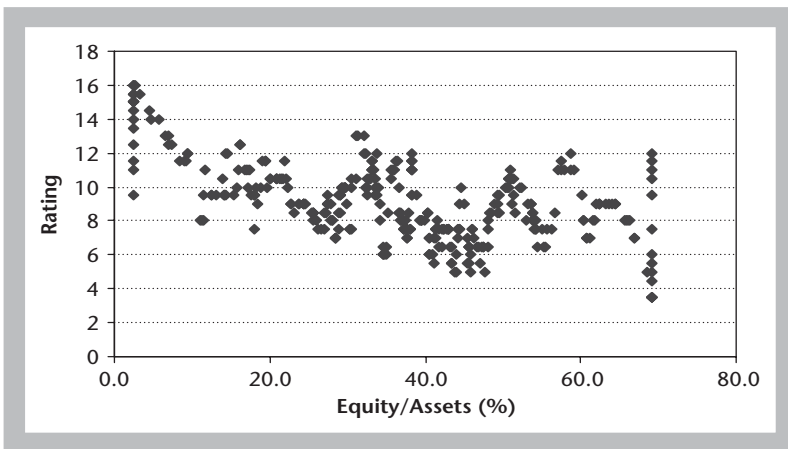


Figure 11.16 Equity/Assets:rating dataset

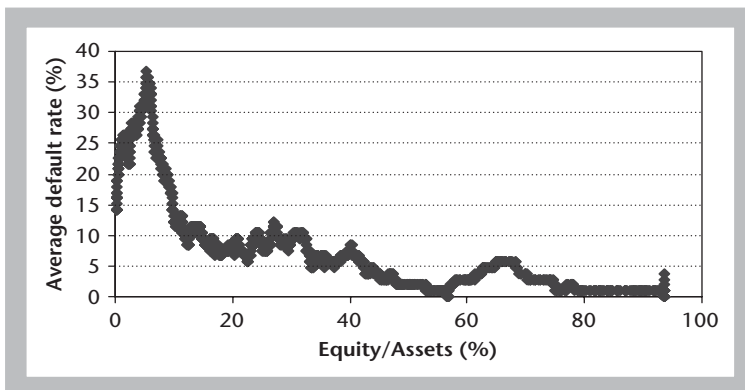


Figure 11.17 Equity/Assets:default dataset

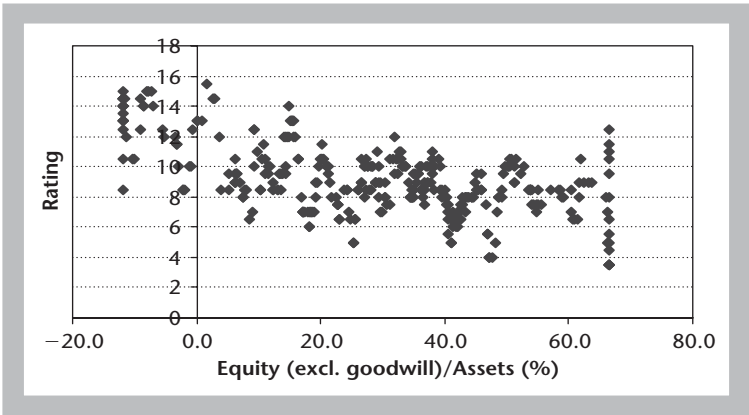


Figure 11.18 Equity (excl. goodwill)/Assets:rating dataset

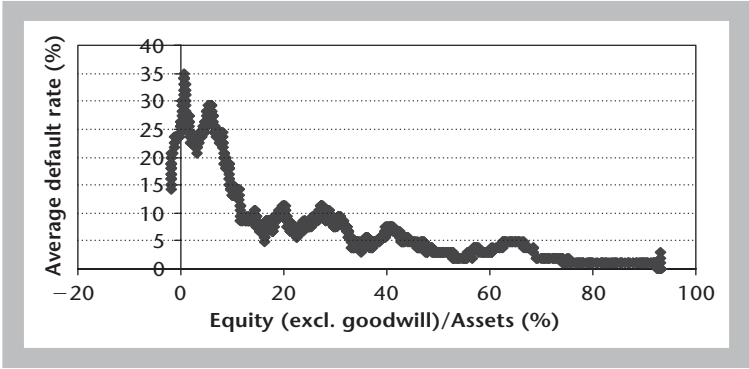


Figure 11.19 Equity (excl. goodwill)/Assets:default dataset

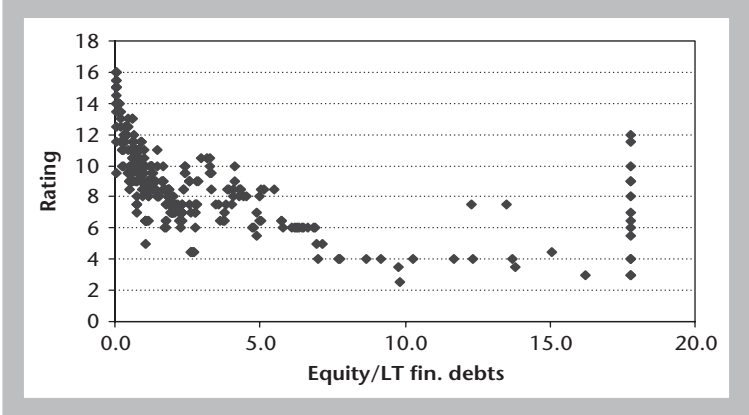


Figure 11.20 Equity/LT fin. debts:rating dataset

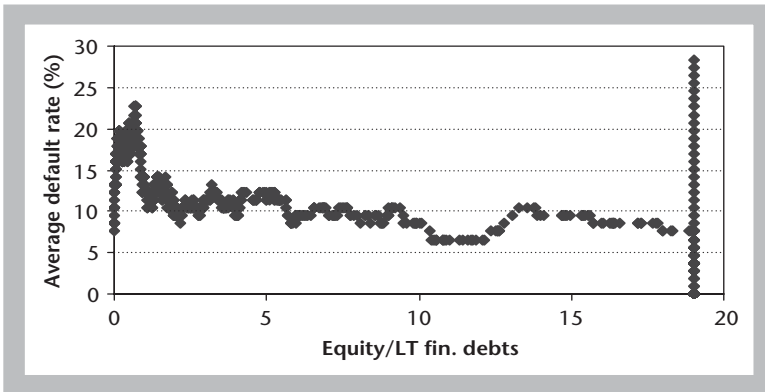


Figure 11.21 Equity/LT fin. debts:default dataset

Table 11.5 Leverage ratios: performance measures

Leverage ratios	Rating dataset		Default dataset	
	Performance (Spearman rank correl.) (%)	Proposed* limits (%)	Performance (AR) (%)	Proposed* limits (%)
Equity/Assets	-24	0; 40	41	0; 60
Equity (excl. goodwill)/Assets	-25	-10; 40	43	0; 60
Equity/LT fin. debts	-40	0; 10	17	0; 10

* Not in % for equity/LT fin. debts.

we can see that the ratio of equity/LT fin. debts seems to offer the best discriminatory power, as there are a lot of points grouped on a straight descending line between 0 and 3.5. For the default dataset (Figure 11.21), both Equity/Assets and Equity (excluding goodwill)/Assets (Figure 11.19) seem to be the best performers. The analysis can be complemented with Table 11.5.

Coverage ratios

The fourth kind of ratio is *coverage ratios*. A company that produces cash flows that cover many times its financial debt service should have a lower default probability or a higher rating. Readers can use the Excel workbook file “Chapter 11 – 5 coverage ratios.xls” to see how the various tests are constructed (Figures 11.22–11.27).

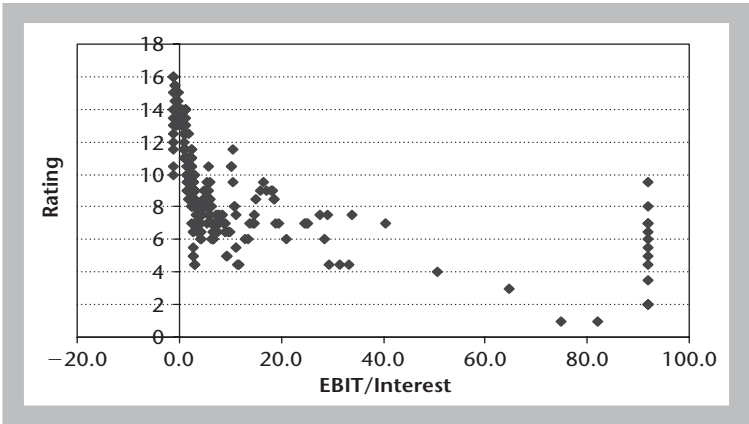


Figure 11.22 EBIT/Interest:rating dataset

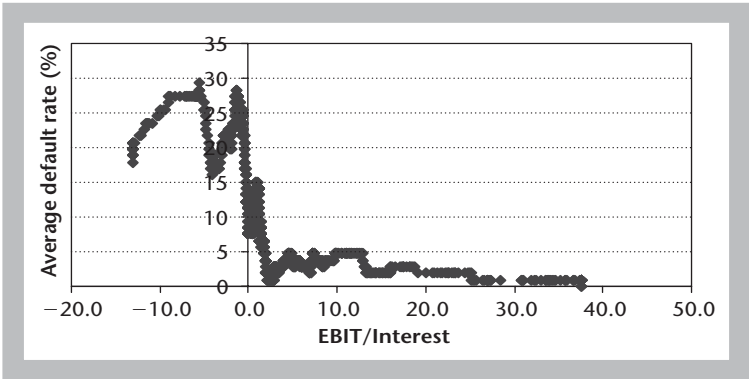


Figure 11.23 EBIT/Interest:default dataset

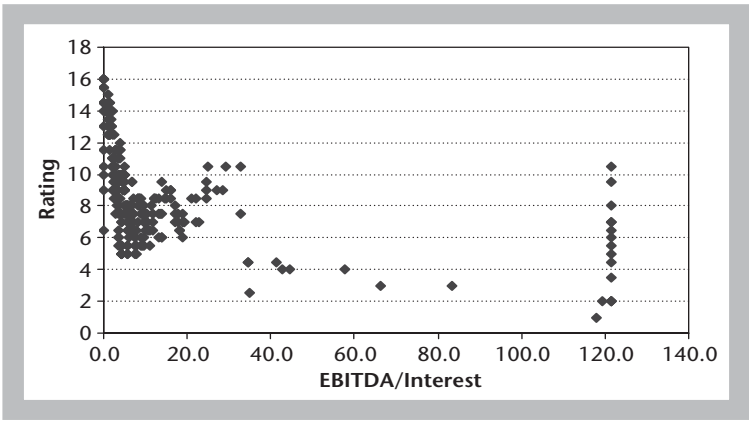


Figure 11.24 EBITDA/Interest:rating dataset

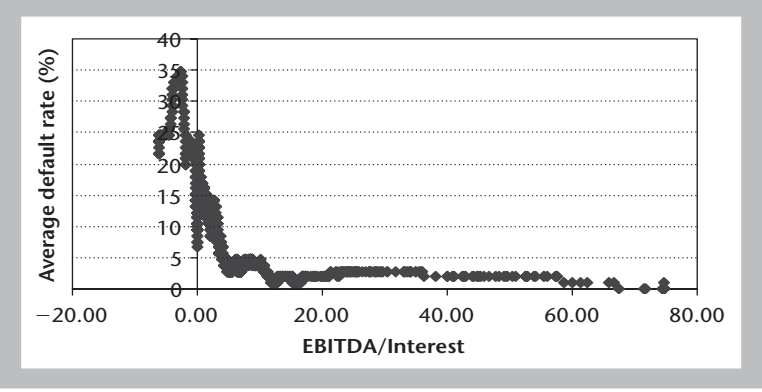


Figure 11.25 EBITDA/Interest:default dataset

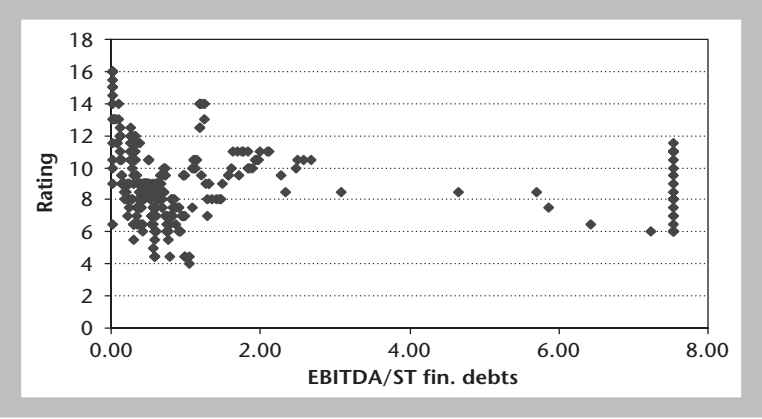


Figure 11.26 EBITDA/ST fin. debts:rating dataset

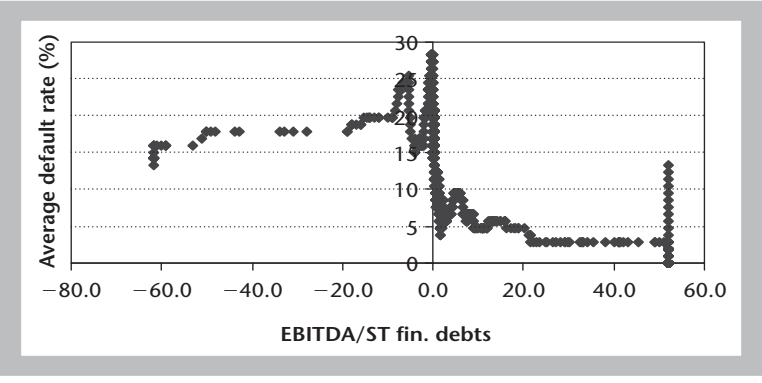


Figure 11.27 EBITDA/ST fin. debts:default dataset

Table 11.6 Coverage ratios: performance measures

Coverage ratios	Rating dataset		Default dataset	
	Performance (Spearman rank correl.) (%)	Proposed limits	Performance (AR) (%)	Proposed limits
EBIT/Interests	-47	-1; 15	43	-1; 20
EBITDA/Interests	-45	0; 10	43	-2; 15
EBITDA/ST fin. Debts	-15	0; 1	37	0; 20

For EBITDA/ST financial debts (Figures 11.26, 11.27), lower percentiles were used (below the 95th) to get an upper bound that can be represented on a graph (for instance the 95th percentile on the default dataset was 2,355). However, for this ratio and for the other coverage ratios, the limits are very wide (Table 11.6). For instance, an EBITDA/Interest above 20 has little meaning. It just shows that the company this year probably had almost no financial charges, it does not mean that the EBITDA was exceptionally high. A ratio of 100 instead of 20 is not representative of the difference in the credit quality of the two companies. The limits we shall set will be narrower, which means that usually for this kind of ratio only half to two-thirds of the values are not outside the limits and allows us to differentiate the various companies.

The performance of EBITDA/ST fin. debts on the rating dataset is very weak (15 percent of the Spearman rank correlation).

Size variables

The last kind of variables are *size indicators*. Large companies may be supposed to have a lower default probability or a higher rating.

However, we have to be particularly careful when working with size variables, as they are especially sensitive to *selection bias*. Unlike ratios that are the result of a division, size indicators are *absolute values*. For various reasons, the collected databases may also be subjective, in the sense that the observations concerning large companies are of different kind to those concerning small companies.

For instance, one bias we can often meet when working on a default dataset is that default events related to large companies are usually more notorious, more striking, and are more carefully recorded in the database than defaults on very small companies. This can give an erroneous image of the relationship between default risk and size (this bias is less an issue when working with ratios, as ratios of large companies are in principle not fundamentally different from those of small companies).

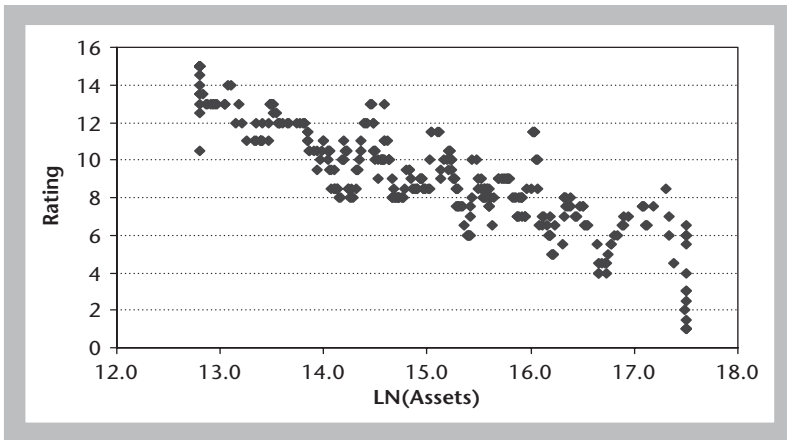


Figure 11.28 LN(Assets):rating dataset

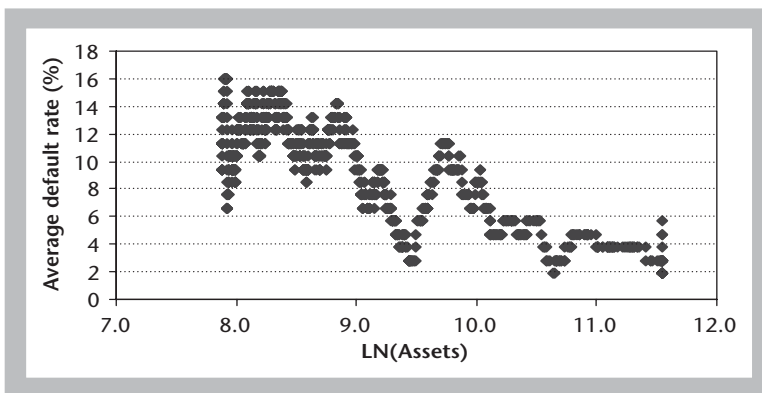


Figure 11.29 LN(Assets):default dataset

A possible bias in working on an external ratings dataset is that we can suppose that most of the very large international companies have an external rating as they often issue public debt, while smaller companies that issue public debt may be those that have an aggressive growth strategy (the others can finance themselves through bank loans). This could induce a bias, as small companies with external ratings could be the riskier ones (the “over-” importance of the size factor in the rating given by international agencies has been debated many times in the industry). If the scoring model is to be also used on small companies without an external rating, great care should be provided to verify that the size factor has not been over-weighted.

Readers can use the Excel workbook file “Chapter 11 – 6 Size variables.xls” to see how the various tests are constructed (Figures 11.28–11.31; Table 11.7).

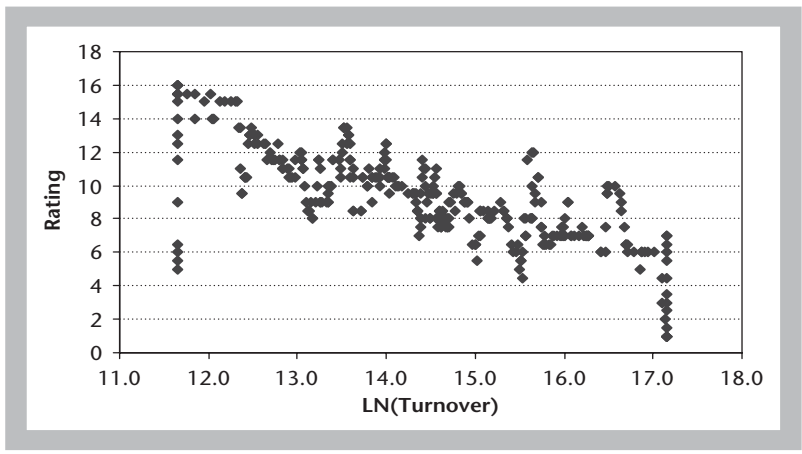


Figure 11.30 LN(Turnover):rating dataset

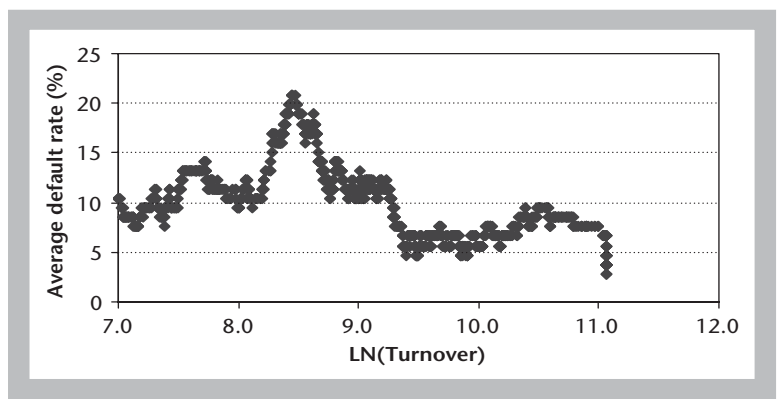


Figure 11.31 LN(Turnover):default dataset

Table 11.7 Size variables: performance measures

Size variables	Rating dataset		Default dataset	
	Performance (Spearman rank correl.) (%)	Proposed limits	Performance (AR) (%)	Proposed limits
LN(Assets)	-48	13; 17.5	14	8; 11
LN(Turnover)	-42	11.5; 17	3	n.a.

Note: n.a. = Not available.

We can see that Turnover has no discriminatory power on the default dataset, so it can then be rejected.

The performance of Assets on the default dataset (Figure 11.29) looked good on the graph but is weak when looking at the AR, which shows that those measures are useful indicators (the construction of the graphs is somewhat arbitrary).

Correlation analysis

Now that we have gained an initial idea of the performance of individual ratios, verified that their relationship to risk made economic sense, and determined what could be at a first sight the interval where the ratios really add value in terms of discrimination, we shall perform a final step before beginning the regression itself. This step is *correlation analysis*. Two ratios can show good performance individually, but integrating them both into the model may lead to perverse results if they are too correlated. For instance, both ROA and ROA before exceptional items and taxes seem to be performing. But they are bringing basically the same information to the model. If we try to integrate both, we shall usually end with one of them with a good sign, and the other with an opposite sign (opposed to what is expected from financial theory) as it will not add information. Not integrating ratios that are too correlated is thus a constraint.

In Tables 11.8–11.9, we check the correlation of the various ratios. Readers can see the details in the Excel workbook file “Chapter 11 – 1 datasets.xls.”

We can see from Tables 11.8 and 11.9 that ratios in the same categories tend to be correlated. There is no absolute rule regarding the level above which this becomes a problem, but as a rule of thumb we often find in the literature that we should take care when correlation is above 70 percent and that no ratios that are more than 90 percent correlated should be integrated in the same model.

MODEL CONSTRUCTION

Our goal here is not to be exhaustive. We could have constructed more ratios, we could have used (if data were available) average ratios for the last two years, or trends ... We could also have built in more complex transformations of ratio values (instead of just determining a maximum and a minimum). Classical transformations consist of creating a *polynomial function* that transforms the ratio into the average default rate or the median rating. This is the only way to proceed if we want to treat non-monotonic variables. For instance, if we test turnover growth, we could find that slow growth and high growth means more risk than moderate growth.

But our goal here is to be illustrative, so we want to keep it simple. Simple models also lead to easier generalization (see our discussion of this in Chapter 10).

Table 11.8 Correlation matrix: rating dataset

Correlation matrix: rating dataset		ROA (%)	ROA bef. exc. and tax (%)	ROE (%)	EBITDA/Assets (%)	Equity/Assets (%)	(Equity-goodwill)/Assets (%)	Equity/LT fin. debts (%)	EBIT/Interest (%)	EBITDA/Interest (%)	EBITDA/ST fin. debt (%)	Assets (%)	Turnover (%)
ROA	100	88	68	73	34	37	38	73	68	48	4	16	
ROA bef. exc. and tax	88	100	62	78	32	33	33	75	74	53	6	22	
ROE	68	62	100	59	-10	-1	10	52	45	29	1	16	
EBITDA/Assets	73	78	59	100	11	12	20	69	66	59	-9	18	
Equity/Assets	34	32	-10	11	100	79	47	26	33	25	7	0	
(Equity-goodwill)/Assets	37	33	-1	12	79	100	46	30	33	30	1	-9	
Equity/LT fin. debts	38	33	10	20	47	46	100	51	49	7	9	11	
EBIT/Interest	73	75	52	69	26	30	51	100	85	41	5	19	
EBITDA/Interest	68	74	45	66	33	33	49	85	100	38	10	29	
EBITDA/ST fin. debt	48	53	29	59	25	30	7	41	38	100	-12	-14	
Assets	4	6	1	-9	7	1	9	5	10	-12	100	77	
Turnover	16	22	16	18	0	-9	11	19	29	-14	77	100	

Table 11.9 Correlation matrix: default dataset

Correlation matrix: default dataset													
	ROA (%)	ROA bef. exc. and tax (%)	ROE (%)	EBITDA/Assets (%)	Cash/ST Debt (%)	(Cash and ST assets)/ST debt (%)	Equity/Assets (%)	(Equity-goodwill)/Assets (%)	Equity/LT fin. debts (%)	EBIT/Interest (%)	EBITDA/Interest (%)	EBITDA/ST fin. debt (%)	Assets (%)
ROA	100	90	86	48	27	25	31	32	23	50	50	33	3
ROA bef. exc. and tax	90	100	79	51	29	25	31	32	23	53	56	37	2
ROE	86	79	100	43	21	22	27	28	22	42	42	25	4
EBITDA/Assets	48	51	43	100	14	10	6	6	-2	59	69	39	-9
Cash/ST Debt	27	29	21	14	100	54	41	41	25	28	25	36	-2
(Cash and ST assets)/ST debt	25	25	22	10	54	100	43	43	21	24	20	21	-3
Equity/Assets	31	31	27	6	41	43	100	99	51	24	23	18	-1
(Equity-goodwill)/Assets	32	32	28	6	41	43	99	100	50	24	22	18	-1
Equity/LT fin. debts	23	23	22	-2	25	21	51	50	100	28	20	5	2
EBIT/Interest	50	53	42	59	28	24	24	24	28	100	81	44	-4
EBITDA/Interest	50	56	42	69	25	20	23	22	20	81	100	54	-7
EBITDA/ST fin. debt	33	37	25	39	36	21	18	18	5	44	54	100	-5
Assets	3	2	4	-9	-2	-3	-1	-1	2	-4	-7	-5	100

Now that we have our candidate variables, we shall construct our scoring models. As mentioned in Chapter 10, there are various deterministic techniques to select the best sub-set of ratios (a forward or backward selection process, for instance); however, we prefer to work by trial and error. We shall try to incorporate a ratio of each kind (profitability, leverage ...), avoid ratios that are too correlated, and keep a low number of ratios while achieving good performance.

To be objective, we have to divide our samples in two: a *construction* sample and a *back-testing* sample. The construction sample will be used to calibrate the model while the back-testing sample will help us to verify that the model is not subject to over-fitting (which means that it would be too greatly calibrated on the specific sample and would show low performance outside it). We propose to use two-thirds of the samples for construction and one-third for back-testing. The data are segmented at each class level (which means that the selection is done randomly inside each rating class for the rating dataset, and separately in the defaulted and in the safe companies for the default dataset). The goal is that we do not have an over-representation of a specific rating class or a higher proportion of defaulted companies in one of the two samples. The samples can be found in the Excel workbook file "Chapter 11 – 7 samples.xls." We shall use the software Easyreg to perform the analysis, but most classical statistical software performs binary or ordered logistic regression.

Use of Easyreg

The first step is to save the data on your PC (you can do this from Excel) in csv format, with the first line being the name of the ratio (symbols such as % should be avoided). The file must be placed directly on the "C:\". Then in the Easyreg File Menu, choose "Choose an input file" and then "Choose an Excel file in csv format." Follow the instructions, and when you are asked to choose the data type select "cross-section data." If you get an error message saying that the file contains text, you should change your settings concerning the decimal symbols (selecting "." instead of ",", or the reverse), reopen the file so that changes are applied, and save it again in csv.

When the data are loaded, select "single equation model" then "discrete dependent variable model." Then follow the instructions until you have to select the kind of model. Select "logit" if you are working with a default dataset, or "ordered logit" if you are working with a rating dataset.

Results

We constructed two simple models. They are certainly not the best we could get from the data, but they are designed for illustration purposes.

Interested readers may try to do all the former steps to end up with better performing ones.

From the rating dataset, we retained three ratios: ROA excluding taxes and exceptional items, Equity/LT fin. debts, and Assets. The output from Easyreg is given in an annex on the website “Ordered Logit Model_corp model.wrd.” The model is implemented in the Excel workbook file “Chapter 11 – 8 Models.xls.”

From the default dataset, we retained three ratios: ROA excluding taxes and exceptional items, Equity/Assets, and Cash/ST debts. The output from Easyreg is given in an annex on the website “Binary Logit Model_Midcorp model.wrd.” The model is implemented in the Excel workbook file “Chapter 11 – 8 Models.xls.”

MODEL VALIDATION

Now that we have constructed our models by trying different combinations of ratios and testing various possibilities (mainly through key performance measures such as the CND and Spearman rank correlation for the rating dataset, and the AR for the default dataset), we shall try to validate them. Validation can have many different definitions, the ultimate being the agreement of the regulator to use the scoring system in an IRB framework. At this stage, by “validation” we mean gaining confidence, through different performance measures, that our models perform better than naïve ones, and that they are correctly specified.

The first thing that we have to do when a model is constructed is to check the p -values of the various coefficients. These represent the probability that the true values of the coefficients (those that would apply if we had the entire population and not just a sample) would be zero. They are usually given by most statistical software (they can be found in blue in the word file containing a copy of the output of Easyreg). There are no absolute rules about which values to accept or to reject but classically we use the 1 percent or 5 percent level (corresponding to 99 percent and 95 percent CIs). However, we have to use our own judgment rather than rely on given values. For instance, if in one model you end up with a p -value of 10 percent for one ratio that is considered as very important for financial analysts and that would be useful to integrate for model acceptance, the modeler might decide to keep it. A 10 percent value still means that there are 90 percent chances that the ratio is significantly different from zero. So people decide, not exogenous rules. In the case of our models, all the p -values are below the 1 percent level.

We can also look at some key performance measures and compare them with simpler models. The simplest model we can use as a benchmark is to take the single ratio that has the best stand-alone discriminatory power.

Table 11.10 Performance of the Corporate model

Performance measures CND (%)	Benchmark: Assets Construction sample	Corporate model	
		Construction sample	Back-testing sample
0	13	16	23
1	36	42	50
2	53	61	72
3	68	76	86
Spearman correl.	75.30%	80.40%	88.90%

However, other publicly available models may be used to compare the results (e.g. the Altman Z-score; see Chapter 10).

From Table 11.10, we can see that the Corporate model performs better than the stand-alone best ratio (total assets). At two notches from the true rating, we have 61 percent of the companies in the construction sample and 72 percent in the back-testing sample while only 53 percent for the single ratio. The Spearman rank correlation goes from 75 percent to 80 percent and 89 percent.

The results look better on the back-testing sample than on the construction sample. Such a disparity (if we exclude a bias that might have occurred when selecting the two samples) can be attributed to the small size of the sample: 238 companies in the construction sample are not very many. One solution in these cases is to use all the available data (351 companies) to build the model. Validation can then be performed using the “leave-one-out” process. This means that we construct a model on the entire sample but one company. We then test the model on this single company. We record the results and then calibrate the model again on all companies but one (a different company, of course). We do this as many times as there are companies in the sample so that each company is left out of the construction sample once. At the end, we can calculate the performance measures such as CND as usual as all companies were tested (they were left out of the construction sample and then given a predicted rating). Then we have to look at the distribution of the various coefficients of the ratios (we have as many coefficients as constructed models). If they are concentrated around the same values, we can conclude that the model is stable.

The “leave-one-out” process has been criticized by some statisticians. The risk of not detecting cases of over-fitting is indeed greater with this kind of method, but there is a trade-off to be made when samples are small. Those kinds of techniques may be indeed useful, but more classical tests should be done as the available databases become larger over time.

From Table 11.11, we can see that the Midcorp model performs better than the best stand-alone ratio (ROA before exceptional items and taxes).

Table 11.11 Performance of the Midcorp model

Performance measures	Benchmark: ROA bef. exc. and taxes		Midcorp model	
	Construction sample	Back-testing sample	Construction sample	Back-testing sample
AR (%)	58	55	69	63

Conclusions

We have made a quick and (over-)simple first validation of the models we have developed. Looking at the p -values, we made sure that all the selected ratios had some explanatory power, and by benchmarking performances with single ratios we could conclude that the models were adding performance.

Again, our goal here is to be pedagogic and to give non-specialist readers a first insight into model construction and validation. The development of scoring models deserves an entire book to itself; we limited ourselves to two chapters. Extensive validation of the scoring models would include, among other things, additional tests on:

- *The correlation between the selected ratios.* The correlation matrix we constructed is a first approach but there may be multivariate correlation (one of the ratios is correlated to several others). Additional tests usually consisted of regressing each ratio against all the others to see if we obtained a high correlation value. The Variance Inflation Factor (VIF) is then computed.
- *The transformation of the inputs* (where do we set the limits, do we use polynomial transformations ...?) might be further investigated to see if we can get better performance.
- *The median errors* can be checked on each rating zone to see if there are systematic errors in a certain zone.
- *Performance tests* may be run on many sub-sets of the data: by sectors, by countries ...
- *The weights* of the various ratios may be calculated through sensitivity analysis and discussed with financial analysts to see if they look reasonable.
- *Outliers* (companies whose ratings are very far from the model's predictions) may be analyzed further ...

Interested readers can download from the BIS website a paper on validation techniques (“Studies on the validation of internal rating systems,” Basel Committee on Banking Supervision, 2005b, www.bis.org).

MODEL CALIBRATION

Calibration was discussed in Chapter 10. We have to associate a PD to each class of the rating dataset, and to group the scores given to the default dataset into homogeneous classes and also associate a PD with them. Except for the special cases where a scoring model is directly constructed on a default dataset that is representative of the expected default rate of the population, and that meets the Basel 2 definition of default (in this case, the output of a logistic model is directly the PD associated to the company), PDs have to be estimated in an indirect way.

Box 11.2 shows that there are basically three means to estimate a PD.

Box 11.2 Estimating a PD

- The *historical method* uses the average default rate observed on the various rating classes over earlier years. It may be suitable when the number of companies in the portfolio and the length of the default history are sufficient to be meaningful.
- The *statistical method* uses some theoretical model to derive expected probabilities of default. Examples are the “Merton-like” models that use equity prices or asset-pricing models that may use market spreads to derive implied expected PDs. These estimates will be good only if the underlying models are robust and if markets are efficient (equity prices or bond spreads are determined efficiently by the market). These approaches have thus to be used carefully.
- *Mapping* is the last possibility. It consists of linking model rating with external benchmarks for which historical default rates are available (mainly rating agencies’ ratings). To be valuable, not only should the current mapping be done carefully but the underlying rating processes should be similar. For instance, if a bank mainly uses a statistical model to determine its internal ratings, results will tend to be volatile if they closely follow the evolution of the borrowers’ creditworthiness (a PIT rating model). Conversely, external ratings from leading agencies tend to integrate a stress scenario (a TTC rating model), and will be more stable. The evolution of observed default rates will be different in both approaches (the default rate for each class will be more stable in a PIT approach while rating migration is more stable in a TTC approach).

In some cases, none of those approaches will be possible. For mid-sized companies, for instance, there may not be enough internal data due to the good quality of the portfolio and its small size; there are no observable market prices; and those companies cannot be mapped to rating agencies' scales as they are of a different nature. All that is left here is good sense, expert opinions, and conservatism.

The validation of the PD estimates is also a problem. There are some standard methods in the industry to measure scoring models' discriminatory power (such as ARs), but the techniques to validate PD estimates are less developed. The problem is that due to correlation of default risk, the variability of the observed default rate is expected to be very large. It is then difficult to determine a level above which estimates should be questioned. However, we have tried to develop an approach that is consistent with the regulators' models and that gives results of a reasonable magnitude. This method was published in *Risk* magazine and is implemented in a VBA program that is included on the website. The article is reproduced in Appendix 1 (p. 182) (readers who want to fully understand it may wish first to read Chapter 15 explaining the Basel 2 model).

QUALITATIVE ASSESSMENT

Automated statistical models may be suited for retail counterparties, where margins are small and volumes are high so that banks cannot devote too much time to the analysis of single counterparties (for obvious profitability reasons). But for other client types, such as other banks, large international corporate, large SME ..., the amounts lent justify a more detailed analysis of each borrower. Scoring models may then be an interesting tool, a first good approximation of the quality of the company, but are clearly not sufficient. Their performance will always be limited, for the simple reason that they use only financial statements or other available quantitative information as input. But default risk is a complex issue that cannot be summarized simply in some financial ratios or in the current level of equity prices. A good rating process has to integrate *qualitative* aspects, as all the available information should be used to give a rating. Qualitative information may consist of an opinion from expert credit officers about the quality of the management of a company, about the trend of the sector where the company is active, about the history of the banking relationship ... In fact, it may cover all the information that is not available in a uniform and quantitative format (otherwise it will be incorporated in the scoring model).

Some banks may consider that the qualitative assessment of a company should be left to the judgment of credit officers and may be undermined by any overruling (a change to the rating given by the scoring model) made by them. Another option is to try to formalize the qualitative assessment

Table 11.12 Typical rating sheet

Name of borrower:	XYZ Company			
Name of credit analyst:	Joe Peanuts			
Country rating:	2			
Date:	01/01/2006			
Scoring module				
Ratio 1	2%			
Ratio 2	30%			
Ratio 3	2.5			
Ratio 4	15			
Implied financial rating	4			
Qualitative scorecard				
Category 1	Yes	No	NA	Results
Question 1	X			+2
Question 2		X		-1
...	X			+3
	Score category 1			+4
Category 2	Yes	No	NA	Results
Question 1			X	0
Question 2	X			+2
...	X		...	-3
	Score category 2			-1
Implied qualitative score	2			
Final result	Model score:	3		

and integrate it in a systematic way in the rating process. The advantage is that this gives more confidence to the banking regulators because the ratings will not vary for the same kinds of counterparties, depending on each credit officer's personal view. Many banks have developed what we could call "qualitative scorecards" that are formalized checklists of the qualitative elements that should be integrated in the rating. Credit officers answer a set of questions that have different weights and that finally produce a qualitative score for each company. The process can be based on closed questions (with "yes" or "no" answers) or on open evaluations (credit officers are, for

Table 11.13 Impact on qualitative score on the financial rating

Impact in steps		Qualitative score				
		Very good	Good	Neutral	Bad	Very Bad
Financial score	AAA	0	0	0	-6	-7
	AA	1	0	0	-5	-6
	A	2	1	0	-4	-5
	BBB	3	2	0	-3	-4
	BB	4	3	0	-2	-3
	B	5	4	0	-1	-2

instance, asked to give a score between 1 and 10 to the quality of the management). When a sufficient number of companies has received a qualitative score, it can be combined with the rating given by the scoring model to give a final rating that integrates both quantitative and qualitative aspects.

The efficiency of the qualitative part can be checked with the same tools as those used to verify the discriminatory power of the scoring models.

A typical rating sheet may look like that in Table 11.12.

From our experience, a matrix is a good way to integrate the qualitative score and the financial rating. Both tend to be correlated, which means that companies with good (bad) financial scores will usually have also good (bad) qualitative scores, so the latter will have a limited impact on the final rating. In the cases when companies with good (bad) financial scores get bad (good) qualitative scores, the impact will be important. Stylized interaction could look like the matrix in Table 11.13.

We can see, for instance, that a bad qualitative assessment leads to a downgrade of five steps in an AA rating, while it downgrades a BB by only two steps, because the bad health of the company is already partially integrated in its financials.

CONCLUSIONS

We have now come to the end of our case study. We had to limit ourselves to what we considered as the basic foundation of the development and testing of scoring models. We tried to incorporate what we considered the most relevant tools and techniques, as making a complete overview of the available literature on model types, statistical techniques, discriminatory power, calibration validation techniques, and other rating systems-related issues would have deserved a book in itself. We hope that the practical case

and the accompanying files on the website will help non-expert readers to start their own researches and investigations in this rapidly evolving and creative discipline.

Chapter 12 deals with the measurement of LGDs.

APPENDIX 1: HYPOTHESIS TEST FOR PD ESTIMATES

Introduction

The Basel 2 reform has completely changed the way banks have to compute their regulatory capital requirements. The new regulation is much more risk-sensitive than the former one as capital will become a function of (among other things) the risk that a counterparty does not meet its financial obligations. In the Standard Approach, risk is evaluated through external ratings given by recognized rating agencies. In the IRB approach, banks will have to estimate a PD for each of their clients. Of course, to qualify for the IRB, banks will have to demonstrate that the PDs they use to compute their RWA are correct. One of the tests required by regulators will be to compare the estimated PDs with observed DRs. This will be a tough exercise, as DRs are usually very low and highly volatile.

The goal of this Appendix is to show how we can develop *hypothesis tests* that can help to make our comparison. Credit risk models and default-generating processes are still topics that are subject to a lot of debate in the industry, as there is far from being any consensus on what is the best approach. We have chosen to build the tests starting only from the simplified Basel 2 framework – even if it has been criticized, it will be mandatory for the major US banks and almost all the European ones. Even if many find it overly simplistic, the banks will have to use parameters (PDs and others) that give results consistent with the observed data, even if they think that bias may arise from model misspecification. Our goal is to propose simple tools that can be among those used as a basis for discussion between the banks and the regulators during the validation process.

PD estimates

The banks will be required to estimate a one-year PD for each obligor. Of course, “true” PDs can be assumed to follow a continuous process and may thus be different for each counterparty. But, in practice, true PDs are unknown and can be estimated only through rating systems. Rating systems can be statistical models or expert-based approaches (most of the time, they are a combination of both) that classify obligors into different rating categories. The number of categories varies, but tends to lie mostly between

5 and 20 (see “Studies on the validation of internal rating systems,” Basel Committee on Banking Supervision, 2005b). Companies in each rating category are supposed to have relatively homogeneous PDs (at least, the bank is not able to discriminate further). Estimated PDs can sometimes be inferred from equity prices or bonds spreads, but in the vast majority of cases historical default experience will be used as the most reasonable estimate. The banks will have groups of counterparties that are in the same rating class (and then have the same estimated PD derived from historical data) and will have to check if the DRs they observe each year are consistent with their estimation of the long-run average one-year PD.

The Basel 2 Framework

The new Basel 2 capital requirements have been established using a simplified portfolio credit risk model (see Chapter 15). The philosophy is similar to the market standards of KMV and CreditMetrics, but in a less sophisticated form. In fact, it is based on the Vasicek one-factor model (Vasicek, 1987), which builds upon Merton’s value of the firm framework (Merton, 1974). In this approach, the asset returns of a company are supposed to follow a normal distribution. We shall not expand on the presentation of the model here, since it has already been extensively documented (see, for instance, Finger, 2001).

If we do not consider all the Basel formula but look only at the part related to PD, we need to consider (11A.1): for a probability of default PD , and an asset correlation ρ , the required capital is:

$$\text{Regulatory capital}^1 = \Phi\left(\frac{\Phi^{-1}(PD) + \sqrt{\rho} \times \Phi^{-1}(0.999)}{\sqrt{1 - \rho}}\right) \quad (11A.1)$$

Φ and Φ^{-1} stand, respectively, for the normal and inverse normal standard cumulative distributions. The formula is calibrated to compute the maximum default rate at the 99.9th percentile. With elementary transformations, we can construct a CI at the α level (note that the formula for capital at the 99.9th percentile is based on a one-tailed test while the constructed CI is based on a two-tailed test):

$$\left[\Phi\left(\frac{\Phi^{-1}(PD) - \sqrt{\rho} \times \Phi^{-1}(1 - \alpha/2)}{\sqrt{1 - \rho}}\right); \Phi\left(\frac{\Phi^{-1}(PD) - \sqrt{\rho} \times \Phi^{-1}(\alpha/2)}{\sqrt{1 - \rho}}\right) \right] \quad (11A.2)$$

The formula in (11A.1) and (11A.2) gives us a CI for a given level of PD if we rely on the Basel 2 framework. For instance, if we expect a 0.15 percent DR

on one rating class, using the implied asset correlation in the Basel 2 formula (23.13 percent if we assume that we test a portfolio of corporate), and a CI at the 99 percent level ($\alpha = 1$ percent), we get the following: [0.00 percent; 2.43 percent]. This means that if we observe a DR that is beyond those values we can conclude that there are 99 percent chances that there is a problem with the estimated PD.

As already discussed on p. 182, one could argue that the problem does not come from the estimated PD but has other causes: wrong asset correlation level, wrong asset correlation structure (a one-factor model should be replaced by a multi-factor model), the rating class is not homogeneous in terms of PDs, there is bias from small sample size (we shall see how to relax this possible criticism in the next section), wrong assumption of normality of asset returns ... The formula will have to be applied, however, so a bias due to too weak correlation implied by the Basel 2 formula, for instance, should be compensated by higher estimated PDs (or by the additional capital required by the regulators under pillar 2 of the Accord).

Correction for finite sample size

One of the problems that the banks and the regulators will often have to face is the small sample of counterparties that will constitute some rating classes. The Basel 2 formula is constructed to estimate stress PDs on infinitely granular portfolios (the number of observations tends to infinity). If an estimated PD of 0.15 percent applies only to a group of 150 counterparties, we can imagine that the variance of observed DR could be higher than that forecast by the model.

Fortunately, this bias can easily be incorporated in our construction of CI by using Monte Carlo simulations. Implementing the Basel 2 framework can be done through a well-known algorithm:

- 1 Generate a random variable $X \sim N(0,1)$. This represents a common factor to all asset returns
- 2 Generate a vector of nY random variable (n being the number of observations a bank has on its historical data) with $Y \sim N(0,1)$. This represents the idiosyncratic part of the asset returns
- 3 Compute the firms' standardized returns as

$$\begin{bmatrix} Z_1 \\ \dots \\ Z_n \end{bmatrix} = \sqrt{\rho}X + \sqrt{1-\rho} \begin{bmatrix} Y_1 \\ \dots \\ Y_n \end{bmatrix}$$

- 4 Define the returns thresholds that lead to default as $T = \Phi^{-1}(PD)$

5 Compute the number of defaults in the sample as

$$\sum D_i \begin{cases} D_i = 1 & \text{if } Z_i < T \\ D_i = 0 & \text{if } Z_i \geq T \end{cases}$$

- 6 We can then compute the average DR in the simulated sample
- 7 We repeat steps 1–6, say, 100,000 times we will get a distribution of simulated DR with the correlation we assumed and incorporating the variability due to our sample size. Then, we have only to select the desired α level.

Extending the framework

Up to this point, we are still facing an important problem: the CI is too wide. For instance, for a 50 bp PD, a CI at 99 percent would be [0.00 percent; 5.91 percent]. So, if a bank estimates 50 bp of PD on one rating class and observes a DR of 5 percent the following year it still cannot reject the hypothesis that its estimated PD is too weak. But we can intuitively understand that if over the next five years the bank observes 5 percent of DR each year, its 50 bp initial estimates should certainly be reviewed. So, if our conclusions on the correct evaluation of the PD associated with a rating class are hard to check with one year of data, several years of history should allow us to draw better conclusions (Basel 2 requires that banks have at least three years of data before qualifying for the IRB).

In the simplest case, one could suppose that the realizations of the systematic factor are independent from one year to another. Then, extending the MC framework to simulate cumulative DR is easy, as we have after the 7th step only to go back to step 1 and make an additional simulation for the companies that have not defaulted. We do this t times for a cohort of t years and we can then compute the cumulative default rate of the simulated cohort. We follow this process several thousands of times so that we can generate a whole distribution, and we can then compute our CI.

As an example, we have run the tests with the following parameters: number of companies = 300, PD = 1 percent, correlation = 19.3 percent, number of years = 5. This gave us the following results for the 99 percent CI:

1 year	2 years	3 years	4 years	5 years
[0.0%; 9.7%]	[0.0%; 12.7%]	[0.0%; 15.7%]	[0.0%; 17.7%]	[0.3%; 19.3%]

To see clearly how the effect of the cohort approach allows us to narrow our CI, we have transformed those cumulative CI into yearly CI using the Basel 2 proposed formula:

$$PD_{1year} = 1 - (1 - PD_{tyears})^{(1/t)}$$

1 year	2 years	3 years	4 years	5 years
[0.0%; 9.7%]	[0.0%; 6.5%]	[0.0%; 5.4%]	[0.0%; 4.6%]	[0.06%; 4.2%]

We can see that the upper bound of annual CI decreases from 9.7 percent for one year of data to 4.2 percent for five years of data. This shows that the precision of our hypothesis tests can be significantly improved once we have several years of data.

Of course, those estimates could be under-valued because one could reasonably suppose that the realizations of systematic factors are correlated from one year to another. This would result in a wider CI. This could be an area of further research that is beyond the scope of this Appendix, as modifying the framework could be done in many ways and cannot be directly constructed from the Basel 2 formula.

We can, however, conclude that to make a conservative use of this test the regulators should not allow a bank to lower its estimated PD too quickly if the lower bound is broken, while they could require a higher estimated PD on the rating class if the observed DR is above the upper limit.

Conclusions

In the FED's draft paper on supervisory guidance for IRB of the Federal Reserve (FED, 2003) we can find the following:

Banks must establish internal tolerance limits for differences between expected and actual outcomes ... At this time, there is no generally agreed-upon statistical test of the accuracy of IRB systems. Banks must develop statistical tests to back-test their IRB rating systems.

In this Appendix, we have tried to answer the following question: what level of observed default rate on one rating class should lead us to have doubts about the estimated PD we use to compute our regulatory capital requirements in the Basel 2 context?

As many approaches can be used to describe the default process, we decided to focus on the Basel 2 proposed framework which will be imposed on banks. The parameters used should deliver results consistent with the regulators' model.

We first showed how to construct a hypothesis test using a CI derived directly from the formula in CP3. Then we explained how we can build a simple simulation model that gives us results that integrate variance due to the size of the sample (while the original formula is for the infinitely granular case). Finally, we explained how to extend the simulation framework to generate a cumulative default rate under the simplifying assumption of independence of systematic risk from one year to another. This last step is necessary if we want to have a CI of a reasonable magnitude.

This approach could be one of the many used by banks and regulators to discuss the quality of the estimated PDs. The model has been implemented in a VBA program, and is available from the author upon request.

Note

Without taking into account the maturity adjustment (the formula is for the one-year horizon) and for LGD and EAD equal to 100 percent.

APPENDIX 2: COMMENTS ON LOW-DEFAULT PORTFOLIOS

One of the most frequent problems when none of the three methods of doing the calibration exercise we have considered may be used is to determine expected PDs on a portfolio where almost no default has been recorded over the preceding years. It is clear that an almost null PD will not be accepted by the regulators without a very strong argument.

The method we propose, however, can be used to derive conservative estimates of the average PD of a portfolio even without any default.

Suppose that we have a portfolio with 500 counterparties and that over the last five years, no default was recorded. We can run simulations and increase the sequentially estimated average PD of the portfolio until the lower bound of the CI at a reasonable level (say, 90 percent or 95 percent) becomes higher than zero. At this moment, we know that taking the PD we have used in the model as the average expected PD of the portfolio is conservative, as if it were higher we should have observed at least some default on the historical data.

In our examples we got intervals of cumulative defaults at 90 percent of (2;34) for a 0.5 percent PD and (1;28) for a 0.4 percent PD. This means that if the unknown underlying PD was at least 0.4 percent there are nine chances out of ten that we should at least have observed one default over five years for a portfolio of 500 counterparties. If we then use an estimated PD of 0.4 percent, it is a conservative estimate.

When the average PD of the portfolio is estimated this way, we can use an expert approach to associate a PD with each rating class so that it matches our portfolio average.

Loss Given Default

INTRODUCTION

Loss given default (LGD) is not an issue for the standardized and IRBF approaches of Basel 2. The Standardized Approach gives us rough weights for the various asset classes that does not explicitly integrate LGD in the way they are formulated. The IRBF approach relies on values furnished by the regulators, and the recognition of collateral (except for financial collateral) is done only to a limited extent.

The IRBA approach is much more challenging regarding LGD estimations. Basically, banks have to estimate an LGD reflecting the loss it would incur on each facility in the case of economic downturn. This at first sight straightforward requirement hides an important complexity that appears only when we try to apply it to all the numerous cases that we can meet in real life.

An additional complexity is that LGD has until recently received little attention from the industry, as it was considered a second-order risk. It has been often modeled as a fixed parameter, independent from the PD, and the integration of collateral value was rarely deeply discussed (one of the reasons is that collateral valuation is often dependent on national practices and regulations and cannot easily be compared internationally).

In this chapter, we try to give readers an initial overview of the various aspects that have to be investigated to develop an LGD framework.

LGD MEASURES

Theoretically, there are various kinds of measures that can be used to estimate LGDs:

- *Market LGD*: For listed bonds, LGD can be estimated in a quick and simple way by looking at secondary market prices a few days after a default. It

is then an objective measure of the price at which those assets might have been sold.

- *Implied LGD*: Using an asset-pricing model, one can theoretically infer market expected LGD for listed bonds using information on the spreads.
- *Workout LGD*: This is the observed loss at the end of a workout process when the bank has tried to be paid back and when it decides to close the file.

Market LGD might be an interesting measure, but it has some drawbacks. First, it is limited to listed bonds, that are unsecured most of the time. The results cannot then be easily extrapolated to the commercial loans portfolios often backed by various forms of collateral. Secondly, secondary market prices are a good measure for banks that have the policy of effectively selling their defaulted bonds quickly. For those that prefer to keep them and to go through the workout process, the results may be quite different. The reason is that secondary market prices are influenced by current market conditions: the bid–ask for these kind of investments (junk bonds), liquidity surplus, market actors' (sometimes irrational) expectations ... The final recovery may then be quite different from what the secondary prices indicate. The observed secondary market prices are dependent on the interest rate conditions prevailing at that time, which may not be appropriate (see the discussion on p. 193).

Implied LGD is theoretically elegant, but hard to use in practice. The reason is that there are many different asset-pricing models with no clear market standards and there is no obvious market reference. Also, if LGD can theoretically be inferred from such a model, there is not (to the limited extent of our knowledge) any extensive empirical study that shows that this approach makes a good job at predicting actual recoveries. One of the main difficulties with such approaches is that market spreads contain many things. We can reasonably think that one part is influenced by risk parameters (PD, LGD, Maturity), but they also contain a liquidity premium, some researchers consider that they are influenced by the general level of interest rates, and they are of course subject to the market conditions (demand and supply) ... It is hard to isolate only the LGD component.

Workout LGD will probably be for most banks, completed by the use of external data (unfortunately most of the time secondary market prices of large US corporate bonds), the main means of LGD estimation.

DEFINITION OF WORKOUT LGD

LGD is the economic loss in the case of default, which can be very different from the accounting one. "Economic" means that all related costs have to

be included, and that the discounting effects have to be integrated. A basic equation might be:

$$LGD = 1 - \frac{\sum \frac{Recoveries_t - Costs_t}{(1+r)^t}}{EAD} \quad (12.1)$$

This is then 1 – all the recoveries (costs deducted) discounted back at the time of default divided by the EAD. Box 12.1 gives an example.

Box 12.1 Example of calculating workout LGD

- A default occurs on a facility of 1 million EUR
- At the time of default, the facility is used for 500,000 EUR
- There is a cost for a legal procedure of 1,000 EUR one year after the default
- After two years the bankruptcy is pronounced and the bank is paid back 200,000 EUR
- The discount rate is 5 percent.

The workout LGD would be:

$$LGD = 1 - \frac{\frac{-1000}{1.05} + \frac{200.000}{1.05^2}}{500.000} = 64\%$$

Recoveries gained from the selling of collateral have also to be included in the computation of the effective LGD on the facility.

PRACTICAL COMPUTATION OF WORKOUT LGD

Starting from the theoretical framework in Box 12.1, many issues have to be dealt with when trying to apply it. We discuss some of the main ones.

Costs

As we have seen, all the costs (direct and indirect) related to the workout process have to be integrated. The first thing for banks to do is to determine which costs might be considered as *linked to the recovery procedure*. The banks will usually integrate a part of the legal department costs and of the credit risk department costs (credit analyst, risk monitoring) ... Some costs will be easy to allocate to a specific defaulted exposure, others will be global costs,

and the bank will have to decide how to allocate them. Will it be proportional to exposure amounts, or a fixed amount per exposure, or depending on the workout duration ...? The choice is not neutral as, even if it does not impact the average LGD at the portfolio level, it may have a material impact on the estimated LGD of individual exposures.

Null LGD

Some LGD may be null or negative. The reason is that all recoveries have to be included, which includes even penalties forecast in the contracts. Contracts are often structured so that in case of late payment, additional fees or penalty interest are dues that are usually much higher than the reference interest rate. As the Basel 2 definition of “default” (unlikely to pay) is very broad, a part of defaults will be linked to temporary liquidity problems from companies that will regularize their situation within a few months and will pay the forecast penalties. Discounting all the cash flows back to the time of default will then lead to a negative LGD.

Other cases may be linked to situations where the default is settled by the company giving some kind of physical collateral so that the bank abandons its claim. If the collateral is not sold immediately, we may face a situation where the final actual selling price is higher than the claim value.

The question that arises then is: how do we deal with negative LGD when defining our expected LGD on non-defaulted facilities? The first and simplest solution is to integrate them in the computation of the reference LGD on one facility type, as it is a real economic gain for the bank that effectively offsets losses on other credits. A second solution, usually referred to as “censoring the data,” might consist of setting a minimum 0 percent LGD on the available historical data in order to adopt a prudent bias (which might be the solution preferred by the regulators). A final solution is to go to the end of the censoring reasoning, and in addition to set a limit at 0 percent for LGD, also bearing in mind that those default cases should be censored for the PD computation. This is the only way to get a correct estimation of the true economic loss on a reference portfolio. However, in this case we change the reference definition of default, which might have other consequences ... The first solution is the one we advocate, except in the very special case where a bank may have observed a negative LGD due to exceptional conditions that should not occur again in the future, on a credit of a high amount that could materially influence the final result (if LGD computations are weighted by the EAD).

Default duration

When a company runs into default and the repayment of credits is demanded by the bank shortly afterwards, the position is clear. Credit utilization and

credit lines are frozen and the recovery process starts. But after a default a bank may often consider that it has more chance to recover its money when it accepts some payment delays, restructures the credit, or even gives new credit facilities. It can sometimes need a year or two of intensive follow-up before either the company returns to a safe situation or definitively falls into bankruptcy. The regulators expect the banks to discount back recoveries and costs at the time of default (the first 90-day payment delay, for instance):

- What will be the treatment of the credit lines that existed at the time of default but not at the end of the workout process? Sometimes lines are restructured in such a way that they are reimbursed by a new credit facility (and the company is still in default). Do banks have to consider that the credit is paid back, or must they track the new credit and impact the recoveries on the old one?
- What will be the treatment of the additional drawn down amount on credit lines that were not fully used at the time of default? In theory, this could be incorporated in either the LGD or the EAD estimations. But even if this gives in principle identical final results (concerning the loss expectations), this will result in materially different estimates on the same dataset, which will be complicated to manage for the regulators if various banks in the same countries select different options. If banks choose to incorporate it in LGD, it might have some LGD well above 100 percent. (For instance, a borrower has a credit line of 100 EUR but uses only 10 EUR at the time of default. Some months later, the attempts of the bank to restructure the credit fail and the company falls into bankruptcy while its credit line use is 50 EUR; the LGD might be 500 percent if nothing is recovered.)

Discount rate

One of the more fundamental and material questions is: what is the appropriate discount rate that should be used for recoveries? The Basel 2 text is not clear on the issue.

If we look at the first draft implementation paper of the UK and US regulators (FSA and FED) we read:

Firms should use the same rate as that used for an asset of similar risk. They should not use the risk free rate or the firm's hurdle rate. (FSA, 2003) [and] A bank must establish a discount rate that reflects the time value of money and the opportunity cost of funds to apply to recoveries and costs. The discount rate must be no less than the contract interest rate on new originations of a type similar to the transaction in question, for the lowest-quality grade in which a bank originates such transactions. Where possible, the rate should reflect the fixed rate on newly

originated exposures with term corresponding to the average resolution period of defaulting assets. (FED, 2003)

We can see that what should be used is what the market rate would be for a given asset class, and it should then be a risk-adjusted interest rate. But this raises four questions:

- How to *estimate these rates*? The only means would be to compare the secondary market prices of defaulted bonds with actual cash flows from recoveries and to infer the implied market discount rate. This is, of course, difficult as the recovery process may last several years and bond prices fluctuate.
- How to deal with *asset classes without secondary market prices*? What is the rate the market would use for a defaulted mortgage loan, for instance? As banks rarely give new credits to defaulted counterparties, a possible proxy (as suggested by the FED) would be to use the rate that the bank applies to its lowest-quality borrowers.
- If such approaches (use of junk bond market rates) are valid for true defaults, are they appropriate for “*soft*” defaults? For instance, the bank may know that a client has temporary liquidity problems and that the next payment will be made with a delay of 120 days. As the default is automatic after 90 days past due, does the bank have to discount the cash flow using a junk bond rate, which can be three times the contract reference rate?
- Has the bank to use *historic rates*, or *forward-looking* ones? A lot of default occurred in the 1970s, for instance, at a time when interest rates were 10 percent or more. Are these data valid to estimate recoveries for the 2000s now that interest rates are lower than 5 percent? Certainly not. One solution may be to split the historical rate between credit spreads and risk-free components. Historic spreads should then be applied to current market conditions, using forward interest rates for the expected average duration of the recovery process.

As we can see, choosing the appropriate rate is not straightforward, and it can have a material impact on the final results. Moral and Garcia (2002) estimated LGD on a portfolio of Spanish mortgages. They applied three different scenarios: a rate specific to each facility (the last rate before the default event), an average discount rate for all facilities (ranging from 2 percent to 6 percent), and finally the rates that were prevailing at the time the LGD was estimated (forward-looking rates instead of historic ones). They concluded that, on their sample, increasing the discount rate by 1 percent (e.g. using 5 percent instead of 4 percent) increased the LGD by 8 percent. They also showed that using different forward-looking rates on

a period of 900 days (a new LGD estimation was made each day on the basis of current market conditions) may give a maximum difference between best- and worst-case discounted recoveries of 20 percent.

PUBLIC STUDIES

As internal data will be hard to obtain for many banks, they will have to rely on pooled or public data. Public data are mostly based on secondary market prices and are related to US corporate unsecured bonds. As defaults are rare events, it is difficult to get reliable estimates for a lot of counterparties (banks, countries, insurance companies ...). Studies published by external rating agencies are one of the classic references (see Table 12.1). This will not be sufficient for a validation (banks have to have seven years' internal data before the implementation date), but it is a starting point that allows us to have an initial look at the characteristics of the LGD statistics.

We present here some of the results of the studies that contains the greatest number of observations. The reader that desires a comprehensive set of references of available studies may find them in "Studies on the validation of internal rating systems" (Basel Committee on Banking Supervision, 2005b).

What are the main characteristics of the LGD values:

- First, we can see that recovery rates exhibit a high degree of variability. The standard deviation is high compared to the average values.
- Secondly, the distributions of the LGD values are far from being normal. All researchers conclude that the distributions have fat tails and are skewed towards low LGD values (the average is always less than the median). Some observe bimodal distributions, others consider that a Beta distribution is the better fit.

Of course, those conclusions about the high dispersion of observed LGD and their skewed distributions hold as the analysis is made on global data. If we could make a segmentation of the bonds and loans and group them in classes that shared the same characteristics, we would probably get more precise estimated LGD values, with lower standard deviations and distributions closer to the normal. If we could identify the main parameters that explain the recovery values, we could develop a *predictive model*. The uncertainty, and the risk, would then be considerably reduced.

That is an area of research that will surely be one of the hottest topics in the industry over the coming years (as was the case for scoring models over the last few years), as internal historical data are being collected in banks to meet Basel 2 requirements (for banks that want to go for IRBA). Moody's has launched a first product called LossCalcTM (see their website

Table 12.1 LGD public studies

Author	Period	Sample	LGD type	Statistics
Altman, Brady, Resti, and Sironi (2003)	1982–2001	1,300 corporate bonds	Market	<ul style="list-style-type: none"> – Average 62.8% – PD and LGD correlated
Araten, Michael, and Peeyush (2004)	1982–99	3,761 large corporate loans of JP Morgan	Workout	<ul style="list-style-type: none"> – Average 39.8% – St. dev. 35.4% – Min/Max (on single loan) – 10%/173%
Ciochetti (1997)	1986–95	2,013 commercial mortgages	Workout	<ul style="list-style-type: none"> – Average 30.6% – Min/Max (annual) 20%/38%
Eales and Edmund (1998)	1992–95	5,782 customers (large consumer loans and small business loans) from Westpac Banking Corp. (Australia), 94% secured loans	Workout	<ul style="list-style-type: none"> – Average business loan 31%, Median 22% – Average consumer loans 27%, Median 20% – Distribution of LGD on secured loans is unimodal and skewed towards low LGD – Distribution of LGD on unsecured loans is bimodal
Gupton and Stein (2002)	1981–2002	1,800 defaulted loans, bonds, and preferred stocks	Market	<ul style="list-style-type: none"> – Beta distribution fits recovery – Small number of LGD < 0
Hamilton, Parveen, Sharon, and Cantor (2003)	1982–2002	2,678 bonds and loans (310 secured)	Market	<ul style="list-style-type: none"> – Beta distribution skewed toward high recoveries – Average LGD 62.8%, Median 70% – Average LGD secured 38.4%, Median 33% – PD and LGD correlated

www.moodyskmv.com) that tries to predict LGD using a set of explanatory variables. But the quest for LGD forecasting will be harder than for PD as data are more scarce, more country-specific (especially for collateral valuation), and depend significantly on bank practices.

The important question then is: what are the main factors that influence recovery values? Some are obvious, other emerge in some studies and not in others:

- The *seniority of the credit* is an obvious criterion. Senior credits have clearly lower LGD than subordinated or junior subordinated credits, as in the case of bankruptcy they are paid first.
- The fact that the credit is *secured or unsecured* is another factor that emerges from all the studies. Unfortunately, the studies usually mention only the fact that the credit is secured, but do not say precisely by what form of collateral, or what is its market value ... For Basel 2, each collateral is evaluated individually and the simple fact that the credit is secured is not a criterion that has enough precision to be exploited.

Those two elements are clear and objective factors that influence recovery. The following three are common to several studies, although not used by everyone:

- The *rating of the counterparty*. Several studies, mainly from S&P and Moody's, showed higher recoveries on credits that were granted to companies that were investment grade one year before default than on credits granted to non-investment grade companies. We might then think that riskier companies have riskier assets that will lose more value in case of a distressed sale.
- The *country* may also have an impact as local regulations may treat bankruptcies in a different way concerning who has the priority on the assets (the state, senior and junior creditors, suppliers, shareholders, workers, local authorities ...). Moody's and S&P studies on large corporates tend to show that recoveries are higher in the US than in Europe.
- The *industry* may be important as some industries traditionally have more liquid assets while other may have more specific (and so less easily sold) ones.

There are many possibilities, but due to limited datasets and highly skewed distributions, one may quickly have a problem in finding statistically significant explanatory variables when using more than two or three.

PD and LGD correlation

One of the more crucial and controversial questions is the following: are PDs and LGDs correlated? Most recent studies tend to show that this is the case (see Table 12.1 for some examples). This is a vital issue as currently most credit risk models, and the Basel 2 formula itself, presume independence (however, the regulators tried to correct this in the last version of their proposal, see the discussion of stressed LGD on p. 198). An interesting study (Altman, Resti, and Sironi, 2001), tried to quantify losses on a portfolio where PDs and LGDs were correlated to a reasonable extent. The conclusion was that for an average portfolio of unsecured bonds, the base case (independence) could lead to an under-estimation of roughly 30 percent of the necessary capital (for the 99.9 percent CI, which is the one chosen by the regulators).

The rationale is that some common factors may affect PDs and LGDs: the general state of the economy, some sector-specific conditions, financial market conditions ...

However, the conclusion of correlation is mostly based on LGD measured with secondary market prices and not on workout LGD. In Altman, Brady, Resti, and Sironi (2003) the researchers also found a positive correlation between LGDs and PDs; however, they concluded that the general state of the economy was not as predictive as expected. They concluded rather that the supply and demand of defaulted bonds explained much of the difference. We could then think about the following process:

- For some years, we have observed an important number of defaults, well above the average. The general economic climate has tended to be bad.
- As there is an unusual quantity of distressed bonds on the markets, specialized investors (those that target junk bonds) face an offer that is well above demand.
- As the economic climate is bad, investors will also tend to require a higher risk premium.

Then, with a supply above the demand, and a higher discount rate applied to expected cash flows, the secondary market prices of defaulted bonds will tend to fall. We shall effectively observe a correlation between the years of high default rates and high market LGDs. But market LGDs are measured by the secondary prices shortly after default (usually one month). Workout LGDs, on the contrary, tend to be measured on longer horizons as the workout period may last two or three years. The correlation is then less evident.

In conclusion, we think that banks that want to modelize their credit risk for their commercial loan portfolio should wait before introducing such an important stress into their loss estimates.

STRESSED LGD

This brings us to our final point, the notion of stressed LGD. In the early consultative papers, regulators were basing their LGD estimates on average values. In the final text, they clearly stated (see Article 468, of ICCMCS, Basel Committee on Banking Supervision, 2004d) that:

A bank must estimate an LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks ... In addition, a bank must take into account the potential for the LGD of the facility to be higher than the default-weighted average during a period when credit losses are substantially higher than average ... For this purpose, banks may use averages of loss severities observed during periods of high credit losses, forecasts based on appropriately conservative assumptions, or other similar methods.

This clearly states that LGD should not only be based on average values but should incorporate a *stress factor*. Banks should then use average LGD measured during economic downturns. This new requirement is clearly related to the fear of the regulators that they may observe a positive correlation between PDs and LGDs (and to a lesser extent to the fact that LGD distributions are highly skewed, which makes their average value a poor estimator).

The way to stress the LGD is not clear. There was a discussion among the regulators to decide if the best solution would not be to incorporate the stress in the formula. It seems that the regulators will finally let the responsibility to show that their LGD estimates are sufficiently conservative lie with the banks.

Should banks use a certain percentile of the LGD historic data instead of a simple average (certainly not the 99.9th percentile as in the formula to stress the PDs, as it would assume a perfect correlation between them). The sector was in fact very reluctant to put in an additional stress. The regulators already required banks to be conservative in all other estimates (PDs, CCFs ...). We have to remember that they will also use an add-on following the Madrid Compromise (where it was decided to base requirements on unexpected losses only and not include expected losses, as was first proposed) that will multiply the required regulatory capital to keep the global level of capital in the industry relatively unchanged (+6 percent?). The systematic risk level embedded in the regulators' formula (see Chapter 15 of this book for details) is also relatively high compared to industry standards. The treatment of double default (Chapter 5) is also very strict and does not

recognize the full risk mitigation effect of guarantors (except, in a limited way, for professional protection providers).

Additionally to the conservatism that banks must already use in most risk parameters, there are also some arguments that we should consider before rejecting the use of average LGDs:

- Available data on LGDs are often based on *unsecured measures*. The integration of the collateral may change the view we have. In the IRB, financial collateral, for instance, is evaluated with a lot of conservatism (banks that want to use internal measures to define haircuts must use a 99 percent CI).
- LGD statistics are also measured mainly on *US data*. A bank that has credit exposures spread over Europe, the US, Asia ... may reasonably expect some diversification effects as the bottoms of economic cycles will not be perfectly correlated.
- Also, *public LGD statistics* are usually based on only a few types of products (mainly bonds and some on loans). A diversified commercial bank that has credit exposures in many different asset classes (corporate, banks, mortgages, ABS, credit cards ...) may also expect that stressed LGDs will not be observed in the same year on each part of the portfolio.

CONCLUSIONS

In conclusion, there is still a lot of work to do to get a better and deeper understanding of LGD modeling. Available public data are scarce and often concentrated on US bonds. How LGD at the bank-wide level should be quantified, and integrating the various asset classes, markets, and forms of collateral, will surely be the stimulating debate in the industry and with the regulators. The first step, today's priority, should be to build robust databases to support our researches.

Implementation of the Accord

INTRODUCTION

In this chapter, we shall discuss some of the key issues regarding implementation of the Basel 2 Accord. (The main topics we present are based on drafts for supervisory guidance published by the FED and the FSA.)

Developing PD and LGD models is an important step, but the organization, the management, and the ongoing monitoring of all Basel 2 processes is an even more crucial task.

The full implementation of the IRB approaches may be considered to rely on four interdependent components:

- An *internal ratings system* (for PD and for LGD in the case of IRBA) and a validation of its accuracy.
- A *quantification process* that associate IRB parameters with the ratings.
- A *data management system*.
- *Oversight and controls* mechanisms.

The regulators do not intend to impose a standard organizational structure on banks. But the latter have to be able to demonstrate that non-compliance and any potential weaknesses of their systems can be correctly identified and reported to senior management.

INTERNAL RATINGS SYSTEMS

Banks must use a *two-dimensional rating system* in their day-to-day risk management practices. One dimension has to assess the creditworthiness of borrowers to derive PD estimates, the other must integrate collateral and other relevant parameters that permit the assignment of estimated LGD to each credit facility.

The discriminatory power of the rating system has to be tested, documented, and validated by independent third parties. This can be done by external consultants, by the audit, or by an internal validation unit. Detailed validation should be performed first after the model development phase, and then each time there is a material adaptation.

Additionally, the rating systems must be frequently monitored and back-tested. Banks should have specified statistical tests to monitor discriminatory power and correct calibration. They should also have pre-defined thresholds concerning the comparison of actual versus predicted outcomes, and clear policies regarding actions that should be taken if those thresholds are violated.

Because internal data will often be limited, banks should when possible perform *benchmarking exercises*. Benchmarking the ratings, for instance, may be performed by comparing them with those given by other models, with external ratings, or with ratings given by independent experts on some reference datasets.

THE QUANTIFICATION PROCESS

Quantification techniques are those that permit us to assign values to the four key risk parameters: PD, LGD, EAD, and Maturity.

The quantification process consists of four stages:

- *Collecting reference data* (e.g. our rating datasets for scoring). Such data can be constituted by internal data, external data, or pooled data. They must be representative of the bank's portfolio, should include a period of stress, and be based on an adequate definition of default.
- Estimating the reference data's relationship to the explanatory parameters (e.g. developing the *score function*).
- Mapping the *correspondence* between the parameters and the bank's portfolio data (e.g. comparing the bank's credit portfolio and the reference dataset to make sure that inference can be done). If the reference dataset and the current portfolio do not perfectly match, the mapping must be justified and well documented.

- *Applying* the identified relationship to the bank's portfolio (e.g. rating the bank's borrowers with the developed score function). In this step, adjustments may be made to default frequencies or the loss rate to account for reference dataset specificities.

All the quantification process should be submitted to an independent review and validation (internal or external).

Where there are uncertainties, a prudent bias should be adopted.

THE DATA MANAGEMENT SYSTEM

It is also important that the models are supported by a good IT architecture, as one of the important Basel 2 requirements is that all the parameters used to give the rating have to be recorded. This means that all financial statements, but also qualitative evaluations, detailed recoveries, lines usage at default ..., have to be stored so that in case of any amendment to the model direct back-testing can be carried out. Central databases have then to be set up to collect all the information, including any overruling and default events.

The collected data must permit us to:

- *Validate and refine IRB systems and parameters:* We need to be able to verify that rating guidelines have been respected, and to compare estimates and outcomes. One of the key issues here is that systems must be able to identify all the overrulings that have been made, and their justification.
- *Apply improvements historically:* If some parameters are changed in a model, the bank should have all the basic inputs in its databases to retroactively apply the new approach to its historical data. It will then be able to do efficient back-testing and will not have breaks in its historical time series.
- *Calculate capital ratios:* Data collected by banks will be essential in solvency ratio computation and for external disclosures (pillar 3; see p. 95). Their integrity should then be ensured and verified by internal and external auditors.
- *Produce internal and public reports.*
- *Support risk management:* The so-called "use tests" will require that IRB parameters – such as credit approval, limit-setting, risk-based pricing, economic capital computation ... – are effectively used in daily risk management.

Institutions must then document the process for delivering, retaining, and updating inputs to the data warehouse and ensuring data integrity. They

must also develop a data dictionary containing precise definitions of the data elements used in each model.

OVERSIGHT AND CONTROL MECHANISMS

Building the model is an important first step, but integrating it operationally in procedures and in the firm's risk management culture is a further challenge. Introducing the use of models in environments where credit analysts are completely free to give the rating they want is a cultural revolution. They will probably in the first instance argue that models should be used only as an indicative tool and that the final ratings should be left entirely at the analysts' discretion.

But working that way will be of little help in meeting the Basel 2 requirements. Nevertheless, it is true that even models that integrate both quantitative and qualitative elements will never be right in 100 percent of cases. There are always elements that cannot be incorporated in the model: the financial statements used may not be representative (because the last year was especially good or bad and is then not representative of the company's prospects, for instance), the interaction between all variables cannot be perfectly replicated by a statistical model, the weight of various items may be more relevant for a certain period of time or for a certain sector ... There should be limited possibilities left to credit officers to modify the rating given by the model if they do not agree with it: one could leave a limited freedom to the analyst to incorporate her view and her experience in the final rating, and overrulings beyond that level of freedom could be reviewed by an independent department (independent from both credit analysts and model developers). This third party could then give an objective and independent opinion on the overrulings and discuss the rating with the analysts if they did not agree with it, or discuss them with the model developer if they consider that the overrule is justified.

Schematically, the organization may look like that in Figure 13.1.

The role of the independent third party is critical. In the absence of external ratings and of sufficient internal default data (which is often the case), it is very hard to say who is right when model results and analysts' opinions diverge significantly. The third party may then discuss with the analysts when they think the overruling is not appropriate and eventually organize a rating committee when they cannot reach an agreement. This role is also essential in the constant monitoring, back-testing, and follow-up of the model. All the cases of justified overrulings are an important source of information to identify model weaknesses and possible improvements (especially in the qualitative part of the model).

Besides the follow-up of the overruling, which is important, oversight and control mechanisms have a broader scope. They should help to

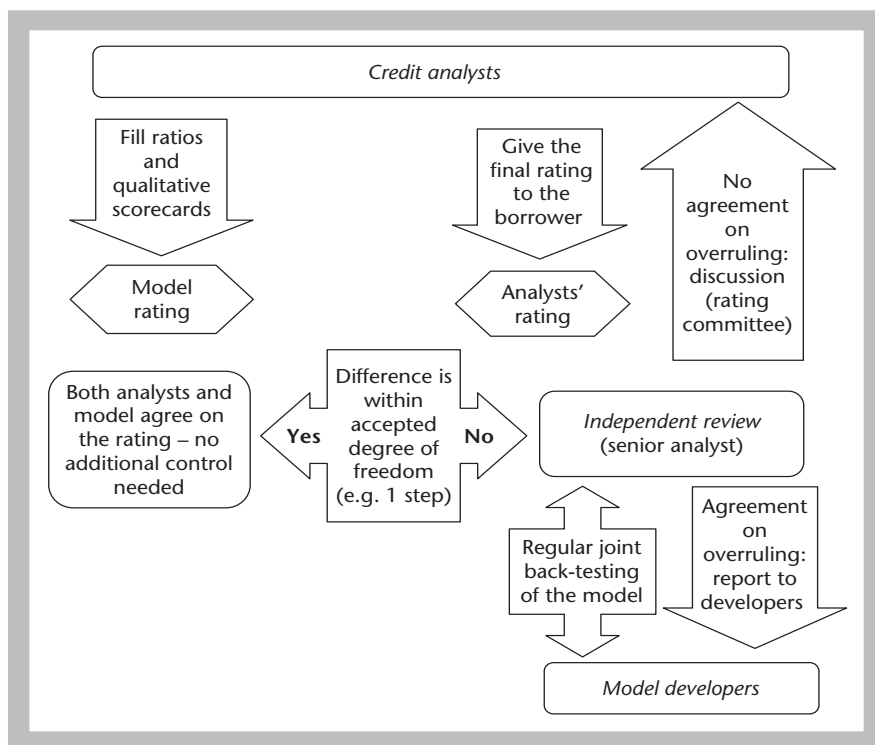


Figure 13.1 Rating model implementation

monitor: the design of the rating system, the compliance with internal guidelines and policies, the consistency of the ratings across different geographical locations, the quantification process, the benchmarking exercises ... These responsibilities could be assumed by a central unit or spread across different departments: modelers, a validation unit, audit, a quality control department ... depending on the bank's organizational structures, and on various available competencies. A report of the various controls should be regularly sent to senior management.

CONCLUSIONS

Implementation of the Accord is a real challenge. There is no single good answer about the optimal organizational structure: it depends on each bank's culture, available competencies, and business mix.

In an ideal world (perhaps the world dreamed of by the regulators), there would be plenty of controls on each IRB process. Each parameter for

each portfolio would be back-tested, benchmarked, cross-checked ... We start from the current situation where credit analysts control the risks that commercial people would like to take and we add five more controls:

- Modelers who develop rating tools to verify that credit analysts give accurate estimates.
- Independent reviewers who check both analysts' and model results.
- Internal audit that checks modelers', analysts', and reviewers' work.
- Validation experts who check the statistical work.
- Senior management and board of directors who monitor the whole process.

There is currently an inflation of control and supervision mechanisms while bank revenues stay the same. So, the principles we list here are taken from the regulators' proposed requirements, but no doubt in 2007 and 2008 we shall probably observe more flexible application of this theoretical framework.

However, this trend towards quantification and a more formalized and challenging organization is inevitable and, if implemented smartly, may deliver real benefits.

PART IV

Pillar 2: An Open Road to Basel 3

From Basel 1 to Basel 3

INTRODUCTION

What is the future of banking regulation? What will be the next evolution of the fast-moving regulatory framework? Those questions are central for top management as more advanced banks will clearly have a key competitive advantage. With the progressive integration of risk-modeling best practices into the regulation framework, banks that have the best-performing risk management policies, and that can convince regulators that their internal models satisfy basic regulatory criteria, will be those that will be able to fully leverage their risk management capabilities as the double burden of economic and regulatory capital management progressively becomes a unified task.

HISTORY

The future is (hopefully) full of surprises; however looking at history is one of the most rational ways to build a first guess at how things may go. We shall not review banking regulation developments in detail as they were considered in Part 1, but we may reprise the three most significant steps:

- The first major international regulation was the *Basel 1 Accord*. It focused on the credit risk which was the industry's main risk at the time. Regulators proposed a simple rough weighting scheme that linked capital to the (supposed) risk level of the assets.

- Some years later, with the boom in derivatives in the 1980s and the greater volatility of financial markets, the industry became conscious that market risk was also an issue. The *1996 Market Risk Amendment* proposed a set of rules to link capital requirements with interest, currency, commodities, and equity risk.
- The proposed *Basel 2 framework* was a reaction to the critics of the increasing inefficiency of the Basel 1 Accord and of the capital arbitrage opportunities that recent product developments had facilitated. Besides a refined credit risk measurement approach, it also recognized the need to set capital reserves to cover a new type of risk – *operational risks*.

From those three major steps in banking regulation, we can already draw four broad conclusions:

- First, there is a clear evolution towards *more and more complexity*, necessary to manage the sophistication of today's financial products. Today, fulfilling regulatory requirements is a task reserved for highly skilled specialists and this trend is unlikely to reverse.
- Secondly, we can see that regulators tend to follow *market best practices* concerning risk management. They are obliged to do so if they want their requirements to have any credibility. The Basel 1 framework was very basic. The market Risk Amendment was already much more sophisticated with the recognition of internal VAR models, a major catalyst to their widespread use today. The credit risk requirements in Basel 2 were also based, as we shall see in Chapter 15, on state-of-the-art techniques. No doubt future regulations will continue to integrate the latest developments in risk modeling.
- The *scope of the risk types* that are being integrated is becoming wider. The 1988 Accord focused on credit risk, then market risk was introduced, and in Basel 2 operational risk appeared. We can reasonably expect that future developments will keep on broadening the risk types covered as the industry becomes more and more conscious of them and devotes efforts to quantifying them (see chapter 17 for an overview).
- Recognition of VAR internal models, and our comments on Basel 2 also show that regulators have come to acknowledge that simplified "one-size-fits-all" models are not a solution for efficient oversight of the financial sector. No doubt future trends will involve working in partnership with banks to validate *their internal models* rather than to impose external regulations.

PILLAR 2

A review of history can give us some insights, but we can go further if we look in greater detail at pillar 2. The introduction of Basel 2 says that:

The Committee also seeks to continue to engage the banking industry in a discussion of prevailing risk management practices, including those practices aiming to produce quantified measures of risk and economic capital. (Basel Committee on Banking Supervision, 2004d).

The future is thus the increasing use of economic capital frameworks that will integrate quantified measures of the various types of risk.

What is “economic capital”? Enter those words in an Internet search engine and you will quickly see that it is a hot topic in the financial industry. Economic capital is similar to regulatory capital, except that it does not have its (over-)conservative bias, and it is adapted to each particular bank risk profile. Economic capital stands for the necessary capital to cover a banking group’s risk level, taking into account its risk appetite, and measured with its own internal models. It is clearly a response to an important aspect of pillar 2.

Pillar 2 is short and vague, because neither the regulators nor the industry could agree on a unified set of rules to manage it; but it is the seed that will grow to become Basel 3.

Basically, pillar 2 requires that banks:

- Set capital to cover all their material risks, including those not covered by pillar 1
- As a function of the bank’s particular risk profile;
- The regulators will evaluate the bank’s pillar 2 framework, and
- Top management will be required to approve and follow the ICAAP.

This simply means that banks will be encouraged to set up integrated economic capital frameworks, and that the regulators will evaluate them.

BASEL 3

What will be the next move? Pillar 2 is a strong incentive for both academics and the industry to work on integrated risk measurement and risk management processes. This movement began in the mid-1990s, but the regulatory framework will act as a catalyst, as was the case for market risk models.

Internal models will be checked by national regulators, who can compare them between banks and begin to share their experiences in international forums such as the Basel Committee. This will probably lead to some

standardization, not only of some particular models, but also of the main regulatory principles.

Basel 3 should then simply be the authorization of regulators for banks to rely on internal models to compute their regulatory capital requirements under a set of basic rules, supported by internal controls. Most advanced banks will then clearly have a competitive advantage, especially those whose strategy is to have a low risk profile. Currently, most AA-rated banks have to keep capital levels above what is really needed as a function of their risk level. That is why many have engaged in regulatory capital arbitrage operations. When their internal models are fully recognized, and when standardization permits the market to gain confidence in them, banks will be able to leverage their economic capital approach to fully benefit from the advantages offered by such frameworks:

- Efficient risk-based pricing to target profitable customers.
- Capital management capabilities to lower the costs linked to over-large capital buffers.
- Support for strategic decisions when allocating limited existing capital resources to various development opportunities.

CONCLUSIONS

In conclusion, we think that those banks that devote sufficient effort to Basel 2 issues will be the first to be ready for Basel 3. Although pillar 2 is still imprecise and incomplete, we consider that it was a very positive element in the Basel 2 package, as it will force both the industry and the regulators to engage in a debate on integrated capital measurement approaches. A variety of approaches is necessary as risk profiles, and the ways to manage risk differ from one bank to another. Too tightly standardized a framework would be a source of systemic risk, which is certainly not the goal of the regulators; an open debate on a common set of principles and an industry-wide diffusion of the various models is therefore necessary. Banks opposed to this idea have failed to see an important fact – until now, economic capital approaches have not been widely accepted by the markets. Most advanced banks have communicated for several years on their internal approach (see Chapter 17 for a benchmark study), but it has not yet become a central element for rating agencies and equity analysts. What is the point of internal models that come to the conclusion that the bank needs 5 billion EUR of capital if its regulators require it to have 6 billion and rating agencies require 7 billion for it to maintain its rating? What is the point of a bank coming to the conclusion that it should securitize a bond portfolio and sell it on the market with a 20 basis points (Bp) spread, which is the fair price as a

function of the economic capital consumed, if it cannot find a counterparty because half of the banks are still thinking in terms of regulatory capital, and the other half have internal models that deliver completely different results regarding the estimation of the portfolio's fair price? The integration of these approaches in a set of regulatory constraints is the necessary step to reach efficient secondary risk markets, and should be seen by the industry as an opportunity rather than as a threat, whose success is conditional on the industry's ability to engage in an open and constructive debate with the regulatory bodies.

The Basel 2 Model

INTRODUCTION

In this chapter, we shall try to give readers a deeper understanding of the Basel 2 formula. Gaining full comprehension is important, as it may affect the way we consider the quantification of the key variables (PD, LGD, Maturity, and EAD). It is also interesting to appreciate what choices were made by regulators, as the base case model can be extended to fulfill some requirements of pillar 2.

We shall begin by discussing the context of the portfolio approach, and then introduce the Merton theory that is at the basis of model construction, and shall end by discussing the way the regulators have parameterized it.

A PORTFOLIO APPROACH

The probability of default

How can we quantify the adequate capital needed to protect a bank against severe losses on its credit portfolios? That is the basic question that we have to answer. Let us start with the most basic risk parameter we have, the PD.

Not so long ago, the quantitative approach to credit risk was quite simple and could be reduced to a binary problem: do I lend or not? Credit requests were analyzed and commented on by credit analysts and submitted to a committee that decided to grant the credit or to refuse the request. Credit risk was essentially a *qualitative issue*.

In the early 1970s, international rating agencies such as S&P and Moody's, began to give ratings to borrowers that issued public debt. These ratings were not binary but were organized in seven risk classes that were designed to provide an ordinal ranking of the borrower's creditworthiness. In the

1980s, the number of rating classes was increased to seventeen (with the introduction of rating modifiers). The use of rating scales was becoming more common in the banking industry, though even in the early 1990s many banks still had no internal ratings on many of their asset classes.

When the use of rating scales became generalized, an initial risk parameter could be used: the PD. Just by looking historically at what was the average default rate in the various rating classes, banks could get an initial idea of what could be the default rates for coming years.

But for the sake of simplicity, we can forget the rating issues and consider that the whole credit portfolio belongs to the same rating class. Under the hypothesis of a stable structure of the portfolio (the same proportion of good and bad borrowers), which could be the case for a hypothetical bank that had a monopoly and lent to most of the companies in a given country, we can consider the past default rate of the portfolio as a good estimate of the future. The next basic question for this hypothetical bank is: are the default risks of the various companies correlated? If it is not the case, which means that there is independence between the default risk of all the firms, the risk-management strategy will be simple: the bank can just increase the size of its portfolio. In the case of independent events, the next year's default rate will tend to the average historical default rate related to the portfolio size (the greater the size, the more precise the estimate). We have illustrated this in Figure 15.1. We simulated the default rate over ten consecutive years for

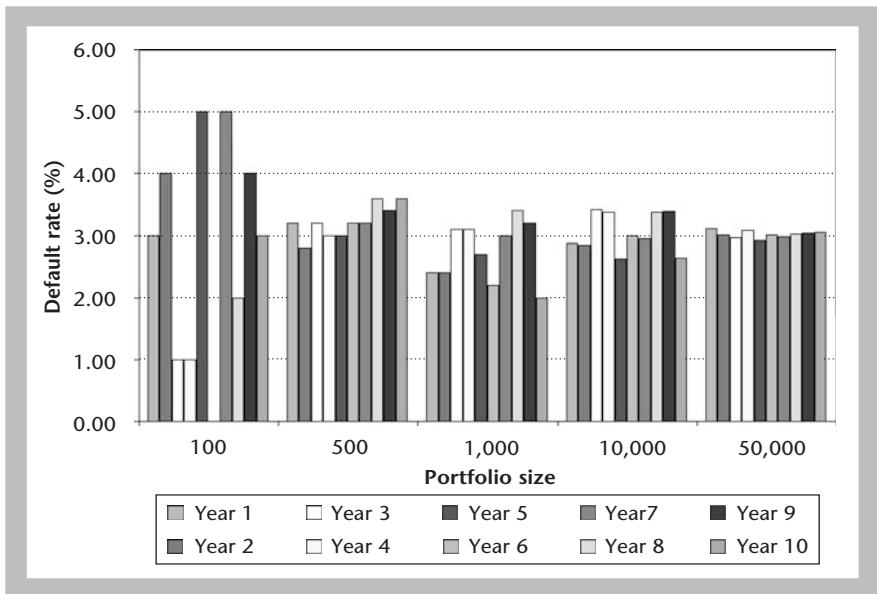


Figure 15.1 Simulated default rate

portfolios of various sizes, with all the companies having a 3 percent PD (the graph can be found in the workbook file “Chapter 15 – 1 portfolio default rate simulation.xls”).

We can see that for a small portfolio of 100 borrowers, there is a huge variability of observed default rates (the standard deviation equals 1 percent). As we increase the size of the portfolio, the variability of the losses falls (the standard deviation for a portfolio of 1,000 borrowers is 0.5 percent), and finally disappears as the losses of a 50,000 borrowers’ portfolio are nearly equal to 3 percent each year (the standard deviation is 0.05 percent). If all our borrowers were independent, the best risk management strategy would be growth, as if the following year’s default rate is known, it is no longer a risk (it is a cost). But can we make such a presumption?

Correlation

If we look at the public statistics of default rates, we can see that they show a huge variability. Figure 15.2 shows the historical default rate of borrowers rated in the S&P universe.

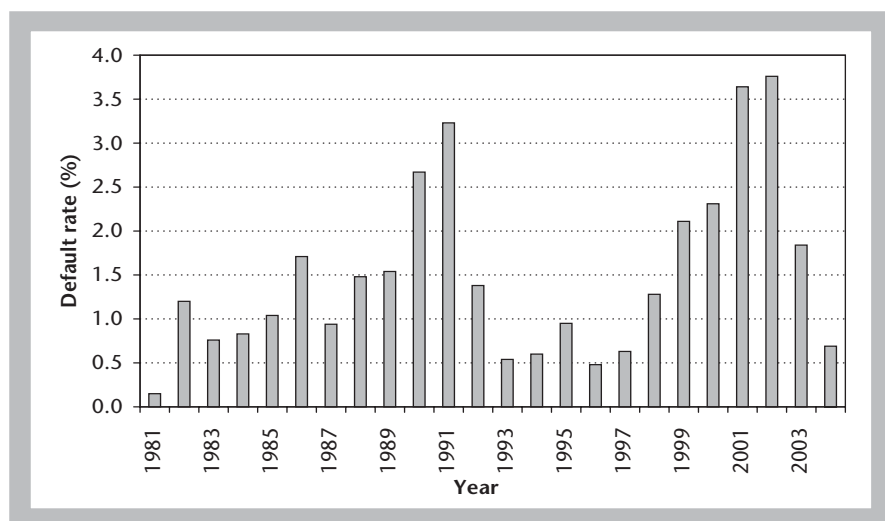


Figure 15.2 S&P historical default rates, 1981–2003

The average is 1.5 percent and the standard deviation is 1.0 percent. The size of the portfolio that has a public rating has increased with time, but a rough estimation of the average may be 3,000 counterparties (it increases each year, so 3,000 is a rough and conservative guess). We can then build a simple statistical test: we can simulate the standard deviation of the observed default rates on a twenty-four-year history if we suppose

independence and compare it with those observed on the S&P data. Making several different simulations, we can build a distribution of the observed default rate under the independence assumption. The test can be found in the workbook file “Chapter 15 – 2 Standard deviation of DR simulation.xls.” The results are summarized in Table 15.1.

Table 15.1 Simulated standard deviation of DR

Statistic	Result (%)
Average simulated	0.23
95th percentile simulated	0.28
99th percentile simulated	0.31
S&P observed	1.0

We can see that the worst simulated standard deviation (on twenty-four years of history, 3,000 borrowers, average PD of 1.5 percent, and independence) at the 99th percentile is 0.31 percent while that observed on S&P historical data is 1.0 percent. We can then reasonably conclude that there is correlation between the various borrowers, which increases the variance of the default rates.

THE MERTON MODEL

Now that we have concluded that there is some correlation of default risk in our portfolio, we need a way to modelize it to meet our goal of computing the necessary capital. The model chosen by the regulators is based on one of the theories of the Nobel Prize winner, Robert Merton, that was used by Vasicek (1984) to build an analytical model of portfolio default risk.

First, Merton considered the following default-generating process:

- A company has assets whose market value is A . Basic financial theory suggests that the correct market value of an asset is the present value (PV) of the future cash flows it will produce (discounted at an appropriated rate).
- On the liabilities side, a company is funded through debts that will have to be paid back to lenders, and through equity that represents the current value of the funds belonging to shareholders.
- If at a given time, t , the market value of the assets becomes less than the value of the debts, it means that the value of equity is negative and that shareholders have an interest in letting the company fall into bankruptcy rather than bringing in new funds (by raising new capital) that would be used only to pay back debts.

This approach, which is quite theoretical, proved to be successful in predicting defaults, as it is the basis of the well-known Moody's KMV model for listed companies. Using Merton's theory, all the additional variables we need are an estimation of the assets' returns and of their volatility. Supposing a normal distribution of asset's returns we can then compute the estimated probability of default in a straightforward way.

For instance, suppose we have a company whose asset value $A = 100$, the expected return of those assets is $E(Ra) = 10$ percent, the volatility of those returns is $\text{Stdev}(Ra) = 20$ percent, and the value of the debts in one year will be $D = 80$. As the normal distribution is defined by its average and its standard deviation, we can estimate the distribution of asset values in one year and then the probability that it will be lower than the debt values. The following graph can be found in the workbook file "Chapter 15 – 3 the Merton model.xls" (Figure 15.3).

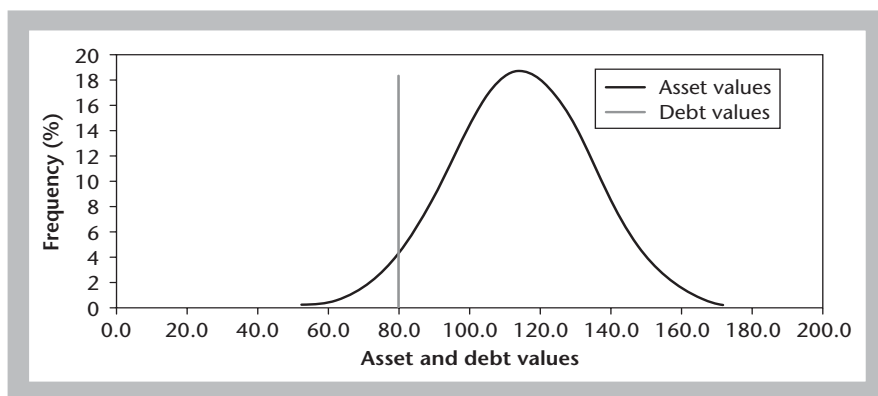


Figure 15.3 Distribution of asset values

Figure 15.3 represents the possible values of the assets in one year, and the vertical line represents the value of the debt. The company will default for an asset's value below 80. The probability of occurrence can easily be computed:

- First, we compute expected asset value, $E(A)$:

$$A \times (1 + E(Ra)) = 100 \times (1 + 10\%) = 110 \quad (15.1)$$

- Then, we can measure what is the distance to default (DD) as the difference between expected asset values and debt values:

$$E(A) - D = 110 - 80 = 30 \quad (15.2)$$

- Finally, we normalize the result by dividing it by the standard deviation:

$$(-DD)/\text{Stdev}(Ra) \times A = 30/(20\% \times 100) = 1.5 \quad (15.3)$$

- This means that the company will default if the observed asset returns are below 1.5 standard deviations of their expected value. The probability of occurrence of such an event, which is the PD (graphically, it is the area under the curve in Figure 15.3 from the origin up to the vertical line), can be computed using the standard normal cumulative distribution (the NORMSDIST function in Excel):

$$\phi(-1.5) = PD = 6.7\% \quad (15.4)$$

Of course, this model is a theoretical one. We have also presented a very simple version of it, as we may introduce many further refinements: we could work in the continuous case instead of the discrete one, we could introduce a volatility of the debts' value, integrate the fact that various debts have various maturities, that asset returns' volatilities might not be constant . . . But the goal here is not to develop a PD prediction model, but rather to explain the default-generating process that is the basis of the Basel 2 formula construction. We can then for the sake of simplicity use elementary statistics.

THE BASEL 2 FORMULA

The default component

Now that we have defined a default-generating process, we have to see how we can introduce a *correlation factor*, as we have seen that, in a portfolio context, defaults cannot be reasonably assumed to be independent. In the Merton framework, correlation can occur if the returns of the assets of various companies are linked. From that, Vasicek (1984) developed a closed-form solution to the estimation of a portfolio credit/loss distribution making some hypotheses and simplifications.

First, we suppose that the asset returns of various companies can be divided in two parts. The first is the part of the returns that is common to all companies – it can be seen as the influence of global macroeconomic conditions. In case of growth, it influences all companies positively, as it creates a good environment for business development. In the case of a severe recession, conversely, bad economic conditions have a negative impact on all companies. The second part of the asset returns is specific to each company. The global environment clearly has an influence, but local factors, the

quality of the management, clients, and many other variables are company-specific and are not shared in common (they are supposed independent for each company). Asset returns can then be written as:

$$\begin{aligned} Ra &= \alpha_a Re + \beta_a Rsa \\ Rb &= \alpha_b Re + \beta_b Rsb \end{aligned} \tag{15.5}$$

The asset returns of company A (Ra) are a weighted sum of α_a times the global return of the economy (Re), and β_a times the company-specific return (Rsa). As we see, the returns for company B share a common term with those of company A : Re . Within this model, asset returns are correlated through the use of a common factor whose dependence is expressed by the coefficient α . As asset returns are a key parameter in the Merton default-generating process, the asset correlation induces default correlation, which is needed to explain the observed variance of historical default rates. The common part of the returns is called *systematic risk*, while the independent part is called *idiosyncratic risk*.

Now that correlation has been introduced, we still have to find a formula to estimate our stress default rate. We have to remember what the goal of those developments is: the estimation of the capital amount that is needed to cover a credit portfolio against high losses for a given degree of confidence. If we want to cover the highest losses possible, the capital should be equal to the credit exposures, which means that banks could be financed only through equity. This would create a very safe financial system, but profitability would be quite low . . .

Suppose that we have an infinitely granular portfolio, which means that we have an infinite number of exposures with no concentration on a particular borrower. We also assume that all borrowers have the same probability of default. To use the Merton default-generating process, we should estimate expected returns and variances on the assets of each borrower. To simplify this, we assume that we standardize all asset returns, which means that instead of defining an asset return as having an average of μ and a variance of σ and following a normal law $\sim N(\mu, \sigma)$, we consider the *normalized returns* ("normalized" means that the expected returns are deducted from the observed returns, and that they are divided by the standard deviation) that follow the standardized normal distribution with an average of zero and a variance of one $\sim N(0, 1)$.

What interests us here is not the estimation of individual default probabilities. We suppose that that is given to us (which can be done by looking at any rating system and historical data on past default rates, for instance). Then, for each borrower in the credit portfolio, we have an estimation of its PD. As we said, we assume that all borrowers are of the same quality and so share the same PD. As we have the PD, we can infer the value of the standardized asset return that will lead to default, which in fact represents

the “standardized” DD. If we return to our example above of company *A* with 100 of assets, an average return of 10, and a standard deviation of 20, the PD we calculated was 6.7 percent. Taking the inverse normal cumulative distribution of the PD we have:

$$\phi^{-1}(6.7\%) = \text{normalized } DD = -1.5 \tag{15.6}$$

This means that if the standardized return is below -1.5 , the company will default. If we return to (15.5) and impose that company returns, as well as the idiosyncratic and systematic parts of the return, follow a standard normal distribution (for notation we use sRa for the standardized return of company *A*); we can redefine α and β as:

$$sRa = \alpha sRe + \beta sRsa \tag{15.7}$$

by definition

$$VAR(sRa) = \alpha^2 VAR(sRe) + \beta^2 VAR(sRsa)$$

as

$$VAR(sRa) = VAR(sRe) = VAR(sRsa) = 1$$

then

$$1 = \alpha^2 + \beta^2$$

$$\beta = \sqrt{1 - \alpha^2}$$

Putting all this together, we have:

- A company will default if its standardized return is below the standardized DD:

$$sRa < \phi^{-1}(PD) \tag{15.8}$$

$$\alpha sRe + \sqrt{1 - \alpha^2} sRsa < \phi^{-1}(PD)$$

$$\sqrt{1 - \alpha^2} sRsa < \phi^{-1}(PD) - \alpha sRe$$

$$sRsa < \frac{\phi^{-1}(PD) - \alpha sRe}{\sqrt{1 - \alpha^2}}$$

- Default will then occur if the company-specific (idiosyncratic) part of the return is below the threshold defined by the right-hand term of (15.8). As the stand-alone part of the returns follows a standard normal distribution and is supposed to be independent of other companies’ returns, we can say that:

$$\text{Prob } \{sRsa < x\} = \phi(x) \tag{15.9}$$

Then

$$PD = \text{Prob} \left\{ sRsa < \frac{\phi^{-1}(PD) - \alpha sRe}{\sqrt{1 - \alpha^2}} \right\} = \phi \left(\frac{\phi^{-1}(PD) - \alpha sRe}{\sqrt{1 - \alpha^2}} \right)$$

We are close to the final expression of the regulators' formula. We can see that the probability of default in a given year (which we call the "conditional default probability") is a function of the realization of the economy standardized return (sRe) and of the unconditional long-run average probability of default (PD). It is interesting to see that the company-specific return is no longer a variable of the equation, as in fact with the hypothesis of our infinitely granular portfolio, the idiosyncratic part of the risk is supposed to be diversified away.

The last thing we have to do is to define our desired *confidence interval*. As we have said, if we want to have sufficient capital to cover all the cases, 100 EUR of credit should be covered by 100 EUR of equity. As that is not realistic, the regulators decided to use a conservative confidence interval: 99.9 percent. In the formula, we have seen that the only random variable is sRe , as both α and PD are given parameters. Then, to estimate our portfolio stressed PD at this confidence level, we have simply to replace the random variable by its realization at the 99.9th percentile. The worst return for the global economy would be:

$$-\phi^{-1}(99.9\%) = -3.09 \quad (15.10)$$

But the regulators preferred to replace sRe by the left-hand term (15.10) rather than by the result. The Basel formulation of default risk for a given portfolio at the 99.9th percentile is then:

$$\phi \left(\frac{\phi^{-1}(PD) + \alpha \phi^{-1}(0.999)}{\sqrt{1 - \alpha^2}} \right) \quad (15.11)$$

The correlation between the asset returns of the various companies in the portfolio can be defined from (15.5), knowing that the company-specific part of the return is independent ($\rho = 0$), as:

$$\rho(Ra, Rb) = \alpha_a \alpha_b \rho(Re, Re) \quad (15.12)$$

By definition, $\rho(Re, Re) = 1$ and we suppose that the share of the returns explained by the systemic factor is the same for all companies; then $\alpha_a = \alpha_b$:

$$\rho(Ra, Rb) = \alpha^2 \quad (15.13)$$

which can be written as:

$$\alpha = \sqrt{\rho(Ra, Rb)} \quad (15.14)$$

If we use this notation in the regulatory formula to express clearly the impact of the estimated asset correlation, we have:

$$\phi \left(\frac{\phi^{-1}(PD) + \sqrt{\rho}\phi^{-1}(0.999)}{\sqrt{1-\rho}} \right) \tag{15.15}$$

The formula is implemented in the workbook file “Chapter 15 – 4 Basel 2 formula.xls.” For instance, using a 1 percent PD and an asset correlation of 20 percent, we arrive at a stressed default rate of 14.6 percent. The formula can be used to derive the whole loss distribution (Figure 15.4).

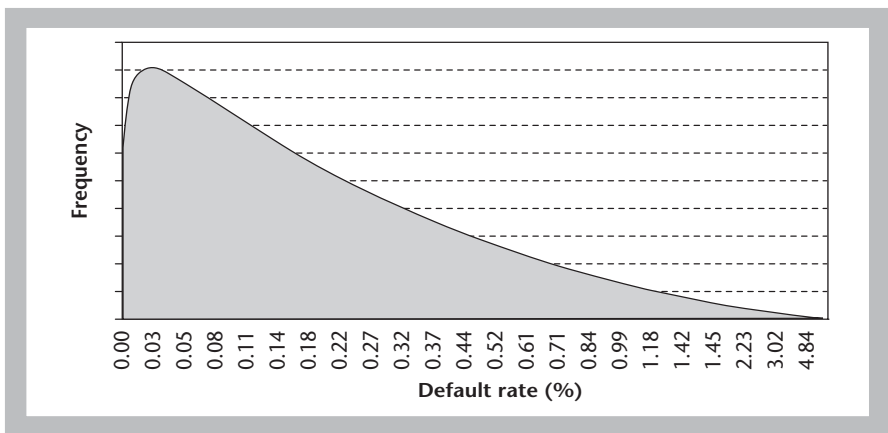


Figure 15.4 Loss distribution

We can see that the loss distribution is far from being normal, and has a high frequency below the average and fat tails on the right.

Estimating asset correlation

We began by choosing a default-generating process, the Merton approach. We have showed that under the hypothesis of uniform PD and granularity of the portfolio it is possible to derive an analytical formulation of the loss distribution function (as shown by Vasicek, 1984). Now, we have to estimate the value of its parameters. The PD has to be given by the bank and is derived from its rating system. The confidence interval is given by the regulators (99.9 percent). The next step is then to calibrate the *asset correlation*.

There are various ways to estimate the asset correlation. The only valid one would be to observe the historical data on the borrowers’ financial statements to measure their asset returns and derive an asset correlation.

Of course, this would be unrealistic, and all the necessary data would not always be available.

A proxy often used in the industry is instead to measure the correlation between *equity returns* through stock market prices. Equity returns are linked to asset returns, but they also depend on other factors: the cost of the debt, the debt structure (maturity, seniority . . .), the leverage of the company . . . Measuring correlation on historical equity prices supposes that the liabilities structures of the companies is rather stable. Equity prices can then give us a rough idea of asset returns correlations, but there are significant differences. S&P have shown that the link between the two is quite low (see de Servigny and Renault, 2002).

Another possibility is to infer asset correlation from the *volatility of historical default rates*. It is important to make a clear distinction between default correlation and asset correlation. Default correlation is the degree of association of the PDs of several companies, which means the risk that if one defaults the other will be more likely to do so also. Asset correlation is the degree of association of the asset returns of several companies. If we suppose a Merton-type default-generating process, default correlation is produced by asset correlation. Asset correlation is then only an indirect way to estimate default correlation. Its interest is that a data series of equity values (used as a proxy for asset values) is easier to collect and more numerous than the data series of default events, which are scarce data.

We try now to estimate asset correlation. By definition, the correlation between two random variables is equal to their covariance divided by the product of their standard deviation (see any elementary statistical textbook):

$$\rho = \frac{\sigma_{x,y}}{\sigma_x \sigma_y} \quad (15.16)$$

The covariance can often be simplified by the following formula:

$$\sigma_{x,y} = E(XY) - \mu_x \mu_y \quad (15.17)$$

Covariance is equal to the probability of observing X and Y jointly minus the probability of observing X times the probability of observing Y . If we apply these definitions to the PDs of two companies, A and B , we have:

$$\rho_{\text{default}} = \frac{JDP(A,B) - PD(A) \times PD(B)}{\sqrt{PD(A) \times [1 - PD(A)] \times PD(B) \times [1 - PD(B)]}} \quad (15.18)$$

The default correlation is equal to the probability of both companies defaulting at the same time minus the product of their PD divided by the standard deviation of their PD (as the default is a binomial event, its variance is by definition equal to $[PD \times (1 - PD)]$).

As we said before, defaults are rare events, so it is difficult to get reliable estimates of their correlation (to measure correlation between various

economic sectors, for instance, we would need to divide available default data by however many different sectors there are). But correlation can be approximated through the following developments (see Gupton, Finger and Bhatia, 1997).

If we consider the default event associated with a company, X_i ($X_i = 1$ if default, $X_i = 0$ if no-default). The average default rate for a given rating class is:

$$\mu_{rating} = \mu(X_i) \quad (15.19)$$

The volatility of the default event is, as we have seen for the binomial law:

$$\sigma(X_i) = \sqrt{\mu_{rating} \times (1 - \mu_{rating})} = \sqrt{\mu_{rating} - \mu_{rating}^2} \quad (15.20)$$

D is the number of defaults in a rating class:

$$D_{rating} = \sum (X_i) \quad (15.21)$$

The variance of D is then the sum of the variance of the default events in the rating class multiplied by the correlation coefficient:

$$\sigma^2(D_{rating}) = \sum_i^N \sum_j^N \rho_{i,j} \sigma(X_i) \sigma(X_j) \quad (15.22)$$

If we consider all the companies in a given rating class, they are all supposed to have the same standard deviation; the formula can then be simplified to:

$$\sigma^2(D_{rating}) = \sum_i^N \sum_j^N \rho_{i,j} \sigma(X_i)^2 \quad (15.23)$$

The variance of default events can be written, using (15.20), as:

$$\sigma^2(D_{rating}) = \sum_i^N \sum_j^N \rho_{i,j} (\mu_{rating} - \mu_{rating}^2) \quad (15.24)$$

Instead of looking at the correlation between each counterparty of the rating class, we shall focus on the *average correlation* of the rating class. If we have N counterparties, we will have $N \times (N - 1)$ correlations (as we have N correlations of a counterparty with itself, which equals 1). The average correlation, $\bar{\rho}$ is then:

$$\bar{\rho} = \frac{\sum_i^N \sum_j^N \rho_{i,j} - N}{N \times (N - 1)} \quad (15.25)$$

Then:

$$\sum_i^N \sum_j^N \rho_{i,j} = \bar{\rho} \times (N^2 - N) + N \quad (15.26)$$

We then have:

$$\sigma^2(D_{rating}) = [\bar{\rho} \times (N^2 - N) + N] \times [(\mu_{rating} - \mu_{rating}^2)] \quad (15.27)$$

$$\bar{\rho} = \frac{\sigma^2(D_{rating})}{[(\mu_{rating} - \mu_{rating}^2)]} - N \quad (15.28)$$

The variance of the default rate of a given rating class is equal to the variance of the default events divided by the number of counterparties:

$$\sigma^2(DR_{rating}) = \sigma^2(D_{rating}/N) = \sigma^2(D_{rating})/N^2 \quad (15.29)$$

If we plug this result in (15.28), we have:

$$\bar{\rho} = \frac{\sigma^2(DR_{rating}) \times N^2}{[(\mu_{rating} - \mu_{rating}^2)]} - N \quad (15.30)$$

$$\bar{\rho} = \frac{\sigma^2(DR_{rating}) \times N}{[(\mu_{rating} - \mu_{rating}^2)]} - 1 \quad (15.31)$$

If N is sufficiently large, we can approximate by:

$$\bar{\rho} = \frac{\sigma^2(DR_{rating})}{[(\mu_{rating} - \mu_{rating}^2)]} \quad (15.32)$$

Formula (15.32) is the end result we wanted to have. It shows that the default correlation can be approximated by the observed variance of the default rate divided by the theoretical variance of a default event (see (15.20)). This test is implemented in the workbook file “Chapter 15 – 5 correlation estimation.xls.” We used Moody’s historical default rates between 1970 and 2001. The results are shown in Table 15.2.

Of course, there are many implied hypotheses in this estimation procedure: the number of counterparties in the sample should be large enough, correlation is supposed constant over time, rating methods should be stable over the years, cohorts should be homogeneous . . . This all means that results should be treated with care, but it can give us some rough insight on the general level of correlation. Many references usually estimate the level of default correlation between 0.5 percent and 5 percent, which is in line

Table 15.2 Estimated default correlation

Moody's data (1970–2001)	μ Average DR (%)	σ Observed st. dev. of DR (%)	$SQRT(\mu^*(1-\mu))$ Theoretical st. dev. of default event (%)	ρ Implied default correlation (%)
Aaa	0.00	0.00	0.00	n.a.
Aa	0.02	0.12	1.47	0.69
A	0.01	0.06	1.17	0.22
Baa	0.15	0.28	3.91	0.52
Ba	1.21	1.33	10.91	1.48
B	6.53	4.66	24.70	3.55
Caa-C	24.73	21.79	43.15	25.50
Investment grade	0.06	0.10	2.44	0.16
Speculative grade	3.77	2.87	19.04	2.27

Note: n.a. = Not available.

with our results (the number of observations in the Caa–C rating class is too small to be significant). We can also see that default correlation increases with PDs, which is logical.

Now that we have an estimation of the default correlation, we can infer an estimation of asset correlation from (15.18). In this formula, the only unknown parameter is now the joint default probability (JDP). As we have seen, Basel 2 uses a Merton-type default-generating process. The question is, then, what is the probability of both companies *A* and *B* defaulting at the same time? This is equivalent to wondering what the probability is of both their asset returns falling below the default point. As their asset returns are supposed to follow a standard normal distribution, with a given correlation, the answer is given by the bivariate normal distribution:

$$JDP = \frac{1}{2\pi\sqrt{1-\rho^2}} \int_{-\infty}^{N^{-1}[PD_A]} \int_{-\infty}^{N^{-1}[PD_B]} \exp\left[-\frac{x_i^2 - 2\rho x_i x_j + x_j^2}{2(1-\rho^2)}\right] dx_i dx_j \tag{15.33}$$

This function is implemented in the workbook file “Chapter 15–5 correlation estimation.xls” in the worksheet “bivariate.” Figure 15.5 shows the bivariate distribution for a level of asset correlation of 20 percent.

Figure 15.5 shows the probability (Z-axis) of both returns being below some threshold. For instance, for two companies having a 1 percent PD, the return threshold, as we saw earlier, would be $\phi^{-1}(1 \text{ percent}) = -2.3$. With a 20 percent asset correlation, the JDP would be 0.034 percent. This means

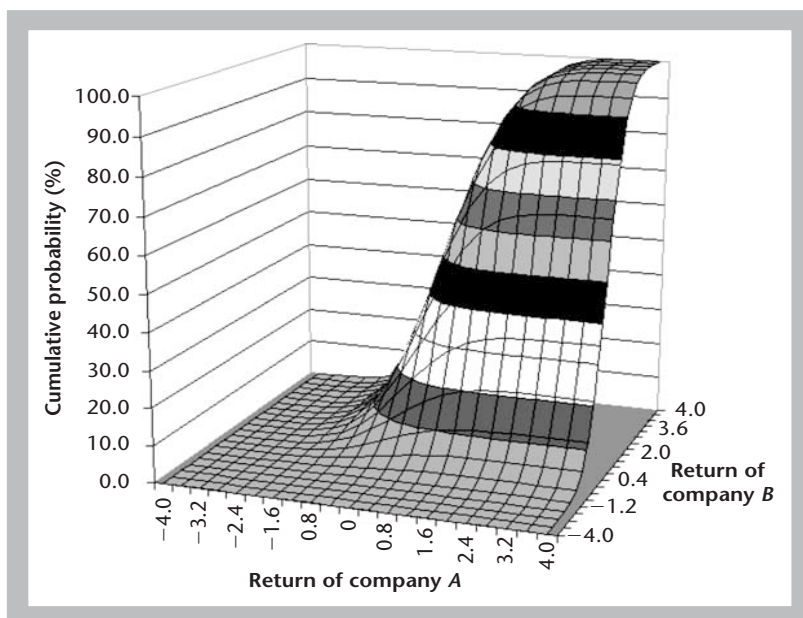


Figure 15.5 Cumulative bivariate normal distribution

that there are 0.034 percent chances that both returns will be below -2.3 at the same time (in the same year).

So, we have all the elements of (15.18) except JDP, and for JDP we know all the variables except the asset correlation. We can then solve the equations to infer the asset correlation from the PDs and the default correlations. This procedure is implemented in the workbook file “solver.” The results are shown in Table 15.3.

Table 15.3 Implied asset correlation

Ratings	Default correlation (%)	Implied asset correlation (%)
Aa	0.69	31.5
A	0.22	22.9
Baa	0.52	15.9
Ba	1.48	13.0
B	3.55	11.7
Investment grade	0.16	11.9
Speculative grade	2.27	10.3

We can see that the asset correlation is of a much larger magnitude than the default correlation. Again, there are so many implied hypotheses in this estimation procedure (we shall discuss this further in the section dealing with the critics of the Basel 2 model, p. 235) that the results should be treated with care and considered as only a rough initial guess.

Using those kinds of estimation procedures and datasets from the G10 supervisors, the Basel Committee calibrated a correlation function for each asset class. For corporate and SME (= companies with less than 50 million EUR turnover), the correlation function is:

$$\begin{aligned} \rho_{corporate} &= 0.12 \times \frac{1 - \exp(-50 \times PD)}{1 - \exp(-50)} + 0.24 \\ &\times \left(1 - \frac{1 - \exp(-50 \times PD)}{1 - \exp(-50)} \right) \tag{15.34} \\ \rho_{SME} &= \rho_{corporate} - 0.04 \times \left(1 - \frac{\max(\text{sales in million EUR}; 5) - 45}{45} \right) \end{aligned}$$

For large corporate, we see that asset correlation is a function of the PDs and is estimated between 12 percent and 24 percent (see the workbook file “Corporate Correl” for illustration) (Figure 15.6).

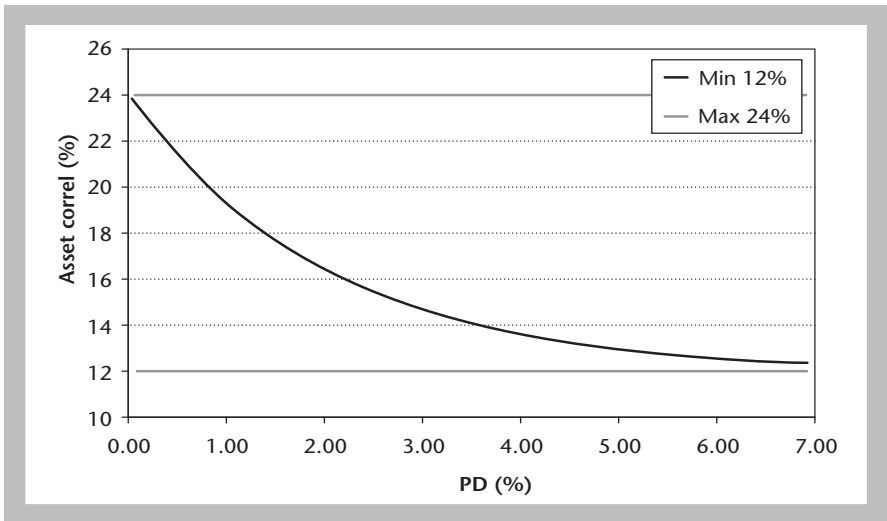


Figure 15.6 Asset correlation for corporate portfolios

The results are quite close to what we found in Table 15.3, as *B*’s asset correlation was 11.9 percent (and the minimum is set at 12 percent) and *A*’s asset correlation was 22.9 percent (and the maximum is set at 24 percent;

the asset correlation on AA was 31.5 percent but as we have a very limited number of observations we should be careful with this number).

For SME, we start from the asset correlation for corporate but decrease it by a number that is a function of turnover (for turnovers between 5 and 50 million EUR). The range of correlation for SME then goes from 20.4 percent to 4.4 percent.

There is a debate in the industry about the asset correlation structure. Its dependence on size and PDs is sometimes questioned, and some studies find different results. The size factor is easily understood and acceptable from a theoretical point of view. It is normal that larger companies – that have assets and activities spread over a larger client base and geographical area – are more dependent on the global economy (the systematic risk) than smaller companies that are more influenced by local and firm-specific factors (their clients, customers, region . . .). But the calibration may be questioned (the 50 million EUR turnover limit is quite low).

The dependence of asset correlation on PDs is more questionable. What is the rational economic reasoning behind it? Imagine a global company such as Microsoft. It is certainly dependent on the global world software market's economic health. Imagine that tomorrow Microsoft changes its funding structure and carries a higher debt:equity ratio. Being more leveraged, it will be more risky, and will probably see its rating downgraded. Does this mean that the return on its assets will be less correlated than before to global factors? Some think that riskier firms bear more idiosyncratic risk, but it is hard to get conclusive results with the few data we have. In Table 15.3, we seem to get the same result. But we have to take into account the fact that rating agencies are sometimes criticized for their over-emphasis on the size factor to determine their rating. In Chapter 11 on scoring models, we saw that the size factor was the most predictive variable. Then, to get an objective picture, the test on default-rate volatilities should be done on the groups segmented on both rating and size criteria. We should test whether for companies of different ratings, but belonging to the same asset size class, we also find a negative correlation between PD and asset correlation.

For High-Volatility Commercial Real Estate (HVCRE), the correlation depends on the PD but not on the size (see Chapter 5, p. 60, for the formula).

For retail exposures, the correlations are fixed for residential mortgages (15 percent) and qualifying revolving exposures (4 percent). For other retail, the correlation is a function of the PD. The correlation for retail asset classes was calibrated by the regulator with G10 databases using historical default data and with information on internal economic capital figures of large internationally active banks (the regulators calibrated the correlation to get a similar capital level). Interested readers should look at "An explanatory note on the Basel 2 IRB risk weight functions" (Basel Committee on Banking Supervision, 2004c).

Maturity adjustment

Up to this point, we have seen how to quantify the regulatory capital necessary to cover stressed losses at a given confidence level. But this was only a “default-mode” approach. A default-mode approach is a model where we look only at default events and consider them as the only risk that requires capital.

But even using a default-mode approach, we made an implicit hypothesis about the time span of the model results. The PDs required by Basel 2 are one-year PDs, and the correlation estimation is also based on yearly data. This means that if we stop now, the model will deliver only regulatory capital to protect us against the risk of default on a one-year horizon. We can intuitively understand that making a loan for five years is more risky than making a one-year loan to the same counterparty. For the moment, this is not reflected in the framework.

But why one year? Why not use the maturity of the loan, for instance (by using a cumulative PD corresponding to the average life of the loan, for example)? The maturity we choose is an arbitrary one. In fact, the maturity should depend on the time necessary for the bank to identify severe losses and to react to cut them. A bank may react by cutting short-term lines, selling some bonds, securitizing some loans, buying credit derivatives, or raising fresh capital. People usually consider that a one-year period is a reasonable time span. But there are arguments for both longer and shorter maturities. The one-year period is typically found in most credit risk models and industry practice.

Does this mean that we don't care with what happens after this horizon? Of course not. The risk associated with longer maturities is taken into account through the *maturity adjustment*.

Imagine that a bank has granted only five years' bullet (non-amortizing) loans to a group of AA counterparties that are highly correlated. After six months, there begin to be significant losses on the portfolio. The model says that the stressed default rate for the year could reach 3.0 percent (so that the bank has 3 percent of the loan amount in regulatory capital). But it is clear that if the bank has to face a 3 percent loss the first year, it will no longer have capital, and there are high risks that in later years there will continue to be major losses on this portfolio, as the companies are highly correlated. By just looking at the losses for the first year, in fact, we make a hypothesis that the bank could close its portfolio if it has no longer any capital by selling all the loans at the end of year 1. So the bank on the asset side had 100 EUR of loans, and on the liabilities side 3 EUR of capital and 97 EUR of debt. If the bank loses the 3 EUR of capital because of the credit losses, it can sell the 97 EUR remaining loans and reimburse its debt. The bank does thus not go into bankruptcy, even if we look only at the first year. The problem with this reasoning is that we will probably not be able to sell the remaining 97 EUR

of credit for its book value. If we want to sell it, we will get a market value that has fallen. For instance, suppose that an AA bond pays a spread of 5 Bp above the risk-free rate of 5 percent. At the end of the year, there was a bad economic climate and the bank lost a lot on its credit portfolio. The AA bond did not default, but there is a strong chance that it will be downgraded. Let us say that its new rating is BBB. At that time, the market pays a spread for BBB counterparties of 35 bp, and the risk-free rate is still 5 percent. The market value of the bond will then be:

$$MTM = \frac{5.05}{1.0535} + \frac{5.05}{1.0535^2} + \frac{5.05}{1.0535^3} + \frac{105.05}{1.0535^4} = 98.94$$

This means that it has lost $100 - 98.94 = 1.06$ EUR of its market value. This loss should be covered with capital.

To take this into account, the regulators used credit VAR simulation models (we shall see these in Chapter 16). In those approaches, we simulate the migration of one rating to another by the same process as we simulate defaults in the Merton framework. Instead of using the probability of default in the model, we use the probability of making a transition to another rating. We simulate an asset return, and as a function of it, the borrower is classified in one of the rating categories (including default), and the value of the credit is recomputed: it corresponds to the LGD in the case of default, it is the discounted value of the future cash flows with the new interest rate curve in the case of migration to another rating. With this method, the value of the portfolio at each simulation is no longer only a function of the default but also of migrations: this is called a “MTM model.” Of course, bonds with longer maturities are more sensitive to a downgrade because there are more cash flows to be discounted at a higher rate. The regulators then compared the stressed losses for a portfolio of one-year maturity (only the default matters in this case) with the losses on portfolios of longer maturities. They then expressed the additional capital due to longer maturities as a percentage of the capital necessary for the one-year case:

$$K = LGD \times N \left(\frac{G(PD)}{\sqrt{1-\rho}} + G(0.999) \sqrt{\frac{\rho}{1-\rho}} \right) - PD \times LGD \\ \times \underbrace{\frac{1}{(1 - 1.5 \times b)} \times (1 + (M - 2.5) \times b)}_{\text{maturity adjustment}}$$

with $b = (0.11852 - 0.05478 \times \ln(PD))^2$

The right-hand side of the regulatory formula is this multiplicative factor, the *maturity adjustment*. It integrates the potential fall in value of the portfolio over one year due to both defaults and the fall in MTM values due to migrations. The results obtained by the regulators were smoothed with a regression. The regulators capped the maturity adjustment to a maximum

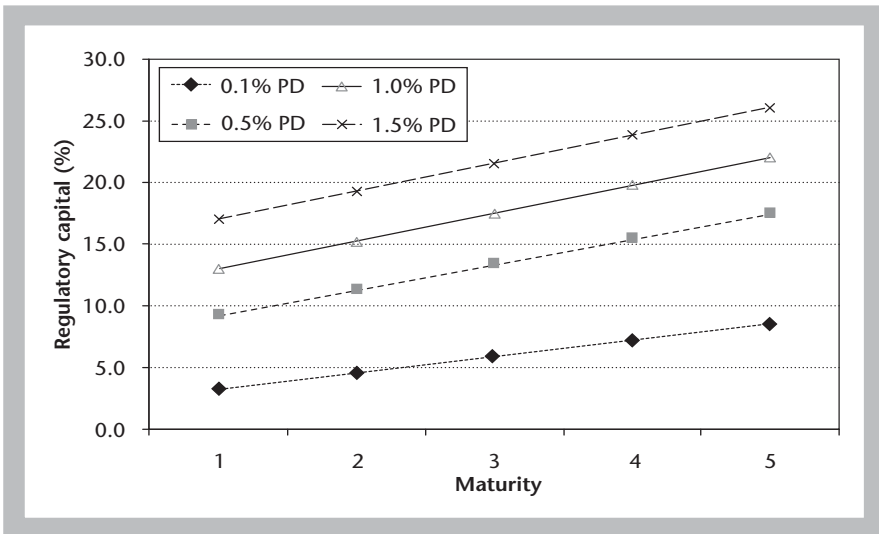


Figure 15.7 Maturity effect

of five years (longer credits are no longer penalized). This is illustrated in Figure 15.7 (see the workbook file “Chapter 15 – 6 Maturity effect.xls”).

We can see that the regression used was a linear one.

It is important to notice that the maturity adjustment applies only to the corporate risk-weighting function, and not the retail one. This is not explained through differences between the two asset classes, but through the data available for the regulators. The data they used to estimate the asset correlation for retail counterparties were aggregated figures that did not allow them to make a distinction between the various maturities. Additionally, there are no standard rating scales and easily available spread data for retail markets, so the regulators could not modelize the MTM adjustments. They therefore decided to calibrate the correlations for retail classes so that they would also implicitly include migration risk. This explains why, for instance, the correlation for mortgages is so high: 15 percent. It also includes the risk linked to the maturity of these loans, that are usually quite long.

Unexpected versus expected losses

The last point we need to highlight in the regulatory formula is that it is calibrated to cover the losses for *unexpected losses* (UL) only. This was not the case in CP1, and the industry had to lobby to achieve the so-called “Madrid Compromise,” in which expected loss was removed from the capital formula. “Expected loss” (EL) is the average loss we expect to have in the long

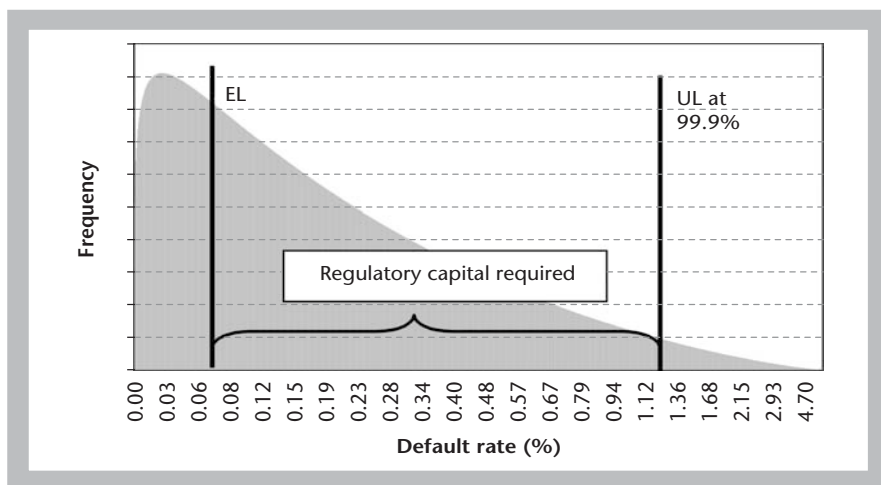


Figure 15.8 Loss distribution

term in the credit portfolio. It corresponds to the $EAD \times \text{the PD} \times \text{the LGD}$. EL is in fact not a risk, as we now realize that we will lose this amount as we grant credits. Banks then usually have a policy to charge the expected loss in the spread required to clients, or to cover it by an adequate provisioning policy. Requiring capital to cover it would then mean covering twice the same risk. If we look again at the regulator's formula:

$$K = LGD \times N \left(\frac{G(PD)}{\sqrt{1-\rho}} + G(0.999) \sqrt{\frac{\rho}{1-\rho}} \right) - \underbrace{PD \times LGD}_{\text{EL}} \\ \times \frac{1}{(1 - 1.5 \times b)} \times (1 + (M - 2.5) \times b)$$

We can then see the expected loss-deduction component (Figure 15.8).

Critics of the model

The Basel 2 formula is without any doubt a significant improvement over the current risk-weighting framework. The regulators have done a great job in integrating state-of-the-art risk modeling techniques into the Basel 2 text. However, there are some critics in the industry. Ironically, these critics come from both sides: small banks think that it is too complex and elaborate a framework, giving too much advantage to larger and more sophisticated institutions; large international banks complain about the fact that the framework is over-simplistic and regret that the regulators did not

recognize internal model fully. Most advanced banks usually highlight six points:

- The *correlation structure is too simplistic*. The use of a one-factor model (all companies are sensitive to the same global macroeconomic factors) was necessary to derive a closed-form solution to the Merton default-generating process for a credit portfolio. Advanced banks usually use a multi-factor model where the systematic risk is not explained only by a single common factor but by a set of correlated factors that may represent various industries or various countries, for instance. It is true that with the current formula, bank *A* (having its exposures spread across all economic sectors) and bank *B* (having all its exposures in the automobile sector) will get the same capital requirement if they have the same risk parameters (under pillar 1, this issue has to be treated under pillar 2). The formula does not recognize fully *diversification effects* and *concentration risk*.
- The cap at a maximum of five years for the *maturity adjustment* has no real economic justification.
- The *confidence interval* chosen is unique: 99.9 percent, which corresponds on average to the capital necessary for an A rated bank. Other banks may have different strategies and may want to be BBB or AA rated.
- The implied hypothesis of *granularity* of the portfolio fails to recognize the concentration risk on single counterparties.
- The LGD in the formula is considered as fixed, while in reality it shows some volatility.
- Finally, some people consider that imposing a *single approach* (the Merton–Vasicek-type one) is not a good thing for the stimulation of future research on other approaches to credit-risk modeling.

Despite those criticisms, the Basel 2 formula is a clear improvement over the current situation and should be seen as an intermediate step before further progresses.

CONCLUSIONS

In this chapter, we have seen that defaults are correlated events. To take this into account, and to calibrate the regulatory formula, we saw that the regulators started from the Merton framework that considers a default-generating process using the asset returns of the companies. The default correlation is then linked to the asset correlation, and we saw that with some simplifying assumptions (granularity, one-factor model . . .) we could get a closed-form solution to quantify the stressed default rate at a given confidence interval

for a credit portfolio. We have seen an estimation procedure to estimate asset correlation from default rates' volatilities, and studied the correlation structure in Basel 2 (dependence on size and rating). We then discussed the maturity adjustment that integrates the risk of a rating downgrade over the one-year horizon. Finally, the main critics of the formula were noted.

Our goal in this chapter was to give the reader a better understanding of the Basel 2 formula, and its components. Readers will get an even more valuable understanding of it in Chapter 16, when we will discuss the credit VAR models that are based on the same principles as the regulatory formula.

Extending the Model

INTRODUCTION

Pillar 2 requires that banks set up capital against all material risks, including those not covered by pillar 1. One of the most important risks is *concentration risk*, the risk linked to the fact of having too many credit exposures on a single counterparty, a correlated group of counterparties, a given economical sector, or a specific region. In this chapter, we shall show how to extend the regulatory formula in a simulation framework that allows us to measure concentration effects, and then helps to meet some of the pillar 2 requirements.

THE EFFECT OF CONCENTRATION

To understand clearly what impact concentration may have, we will first run a simple experiment that is implemented in the work book file “Chapter 16 – 1 concentration effect.xls.” In this test, we simulate the losses on two different portfolios, assuming a zero correlation, and having different granularities. All PDs are equal to 2 percent. The first portfolio is perfectly granular with 1,000 exposures of 1 EUR. The second has the exposures in Table 16.1.

We ran 5,000 simulations and looked at the loss at 99.95 percent. The results are shown in Table 16.2.

We can see that concentration increases the loss by 316 percent. It is clear that the banks will have to show the regulators how they measure and manage concentration.

Traditionally, banks manage concentration through *limits systems*. There is a maximum credit exposure amount allowed to a group of linked

Table 16.1 A non-granular portfolio

Number of exposures	Size (EUR)
10	50
10	25
68	1
908	0.2
4	0.1
<i>Total 1,000 exposures</i>	<i>1,000</i>

Table 16.2 The concentration effect

Losses on 1,000 exposures for a total of 1,000 EUR, PD 2%, no correlation	Loss at 99.95%
Granular portfolio (EUR)	37
Not granular portfolio (EUR)	154
<i>Difference (%)</i>	<i>316</i>

counterparties that is a function of the rating of the counterparty and of the collateral received. Consolidated exposures on a sector or on a country are also monitored to see if they remain in an acceptable range. But concentration management has traditionally been a rather qualitative issue. With the development of credit risk quantification methodologies, it is now possible to have a more precise idea of the effect of concentration on a credit risk portfolio. However, there is no longer a possibility of getting a simple formula, as in Basel 2, to achieve our estimates, we have to build simulation models.

EXTENDING THE BASEL 2 FRAMEWORK

The one-factor, default-mode case

We shall see how we can extend the regulatory formula to build a simple one-factor simulation model. The goal is to simulate losses on a credit portfolio an important number of times to get an estimate of the loss distribution.

We have seen in Chapter 15 that we may use a Merton-type default-generating process. For each credit in our portfolio, we will then simulate an asset return that follows a normal distribution. We will also simulate a return

for the global economy and compute the final return for each company, with the formula:

$$Ra = \alpha sRe + \sqrt{1 - \alpha^2} sRsa \quad (16.1)$$

With sRe being the standardized return for the economy, $sRsa$ being the standardized stand-alone return for the company A , Ra the total return of company A , and α the asset correlation.

The generated return will then be compared to the company default threshold (the return that is the boundary between survival and default):

$$Ra < \phi^{-1}(PD) \quad (16.2)$$

In the case of default, the loss will be equal to the expected LGD. The losses on all credits of the portfolio are then summed. The worst simulation at the 99.9th percentile is finally selected.

We implemented the formula in the workbook file “Chapter 16 – 2 one factor simulation.xls.” This worksheet is designed so that readers can follow the simulation step by step to get a good understanding of the process.

Of course, this workbook is limited to five counterparties and 500 simulations. In real life, we have to handle thousands of credit exposures and to make thousands of simulations to get reliable estimates.

We have developed a simple Excel function that performs quick Monte Carlo simulations and implements a one-factor credit VAR model. It can be found in the workbook file “Chapter 16 – 3 simulation tool.xls.”

We returned to our portfolios used in Table 16.2 and ran the same test, but this time integrated a 20 percent asset correlation (still at 99.95 percent). The results are synthesized in Table 16.3 (20,000 simulations).

Table 16.3 The credit VAR-test

Credit VAR-test	Independent case	Credit VAR function	Basel 2 formula
Granular portfolio (EUR)	37	245	258
Not-granular portfolio (EUR)	154	306	258
Delta (%)	316	25	0

The first striking point is the impact of correlation. In this case, it multiplies the loss at 99.95 percent by more than six for the granular portfolio. For this portfolio, we also see that the Basel 2 formula (258 EUR) gives a good approximation of the simulation approach (245 EUR) as the difference is only 5 percent. Finally, we see that the non-granular portfolio is underestimated by Basel 2 (by 19 percent) and produces losses 25 percent higher than the granular one (at 99.95 percent).

The one-factor, MTM case

The next step in the refinement of credit VAR models is to integrate the MTM issue. We have seen that the maturity adjustment in Basel 2 was designed to quantify the capital necessary to protect the bank against a decrease in the market value of the credit due to a migration of the borrower towards a lower rating. From rating agencies' statistics, for instance, we may know the probability of migration from historical data. For example, Table 16.4 reproduces an average one-year transition matrix for Moody's between 1970 and 2001.

Table 16.4 An average one-year migration matrix

In %	Aaa	Aa	A	Baa	Ba	B	Caa-C	Default
Aaa	91.79	7.37	0.81	0.00	0.02	0.00	0.00	0.00
Aa	1.21	90.73	7.67	0.28	0.08	0.01	0.00	0.02
A	0.05	2.49	91.96	4.84	0.51	0.12	0.01	0.01
Baa	0.05	0.26	5.45	88.54	4.72	0.72	0.09	0.16
Ba	0.02	0.04	0.51	5.57	85.42	6.71	0.45	1.28
B	0.01	0.02	0.14	0.41	6.69	83.38	2.57	6.79
Caa-C	0.00	0.00	0.00	0.62	1.59	4.12	68.04	25.63

This means, for instance, that a BBB rating has 88.54 percent chances to remain BBB at the end of the year, 0.16 percent chances to default, 0.26 percent chances to become AA, and so on.

To integrate this in the simulation framework, we just use several boundaries instead of one. For the default mode, we use one limit between the default and the non-default state; now we shall use as many limits as there are rating classes. This is illustrated in Figure 16.1.

The return thresholds are defined as follows:

- The PD is 0.16 percent. The company will then default for its 0.16 percent worst returns, which corresponds to $\phi^{-1}(0.16 \text{ percent}) = -2.95$.
- The probability of being downgraded to CCC is 0.09 percent. This will correspond to the 0.25 percent worst returns (as we have to add also the returns corresponding to the default state). The limit will then be $\phi^{-1}(0.16 \text{ percent} + 0.09 \text{ percent}) = -2.81 \dots$

At each simulation, the credits are repriced using the interest rate curve corresponding to the new rating. We then need to have an estimate of the spread level for each rating and for each maturity. The loss can roughly

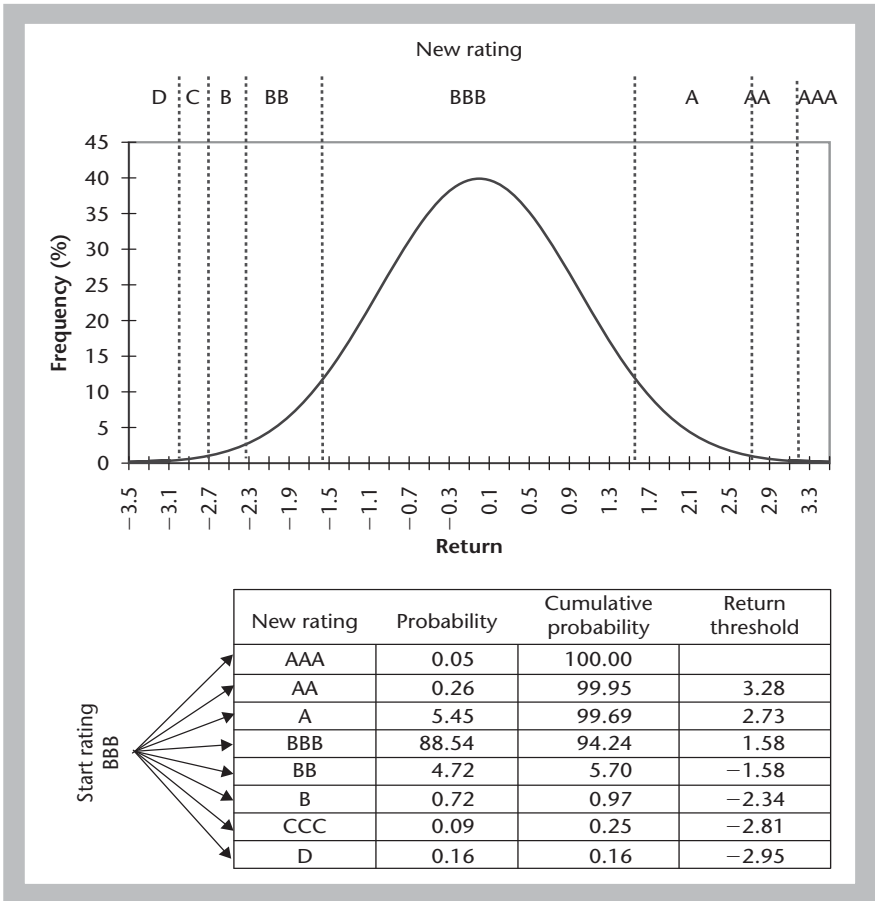


Figure 16.1 Potential asset return of a BBB counterparty

be estimated if we have the average life of the credit as the product of the average life with the interest rate differential:

$$\Delta MTM = \left(\frac{\sum tCF}{\sum CF} - 1 \right) \times \Delta rate \tag{16.3}$$

The first part of (16.3) is the computation of the *average life*, that is also used by Basel 2 (see Chapter 5). One year is deducted because we are interested in the value of the loans one year later, at the end of the period. We implemented the MTM simulation framework in a worksheet called “Chapter 16 – 4 MTM

simulation tool.xls.” The inputs are the credit amounts, the average life, the spread curves, and the migration matrix:

- We made a test by setting the migration matrix at 0 percent in all cases except for default, where the probability was 2 percent. Running the simulation with the granular portfolio of earlier examples, we got a loss of 259 EUR (compared to 245 EUR in the default-mode test, and 258 in the Basel 2 formula without maturity adjustment). The results are then close (the difference is due to simulation noise).
- The second test we ran was to keep a 2 percent PD but also a 98 percent probability of migration to another rating with a higher (+1 percent) spread. The maturity of the loans was six years. We could then expect results corresponding to the loss we got in the first test plus a loss corresponding to the decrease in market value of the surviving credits. This loss can be roughly approximated as five (years remaining) \times 1 percent (increase of spread) \times 741 EUR (the non-defaulting credits), which equals 37 EUR. The loss we got was 289 EUR, which is 30 EUR higher than the default-mode test. The results are thus close to expectations.

Those two tests were made to verify that the model seems to work correctly and to get a better illustration of the default and MTM components. Now we shall use true market data to see if we can get results of a similar magnitude as those of Basel 2 with the maturity adjustment. We need a complete migration matrix (with rating modifiers) and spread curves. Those data can be found over the Internet. Migration matrixes can be found on rating agencies websites (www.standardandpoors.com or www.moodyskmv.com) and spread data can be found on the website of “bonds online,” for instance (http://www.bondsonline.com/Todays_Market/Corporate_Bond_Spreads.php). In Tables 16.5–16.6 we show the sample data we used for the test.

We need to pay attention to the fact that market data may sometimes be incoherent. For instance, for good ratings, we often see default rates for a given rating higher than those for a lower one. Similarly, if we look at spread data, we can see, for instance, that BBB+ three-year spread (90 bp) is superior to a BBB three-year spread (88 bp), which is not logical. Before using our data, we may want to make some corrections.

The tests we ran to investigate the maturity adjustments were to play with a granular portfolio of 1,000 exposures of 1 EUR and to increase its maturity from one year to five years (with different PDs, correlation assumptions similar to the Basel 2 formula, and a 45 percent LGD).

The results of the test are shown in Table 16.7 on page 245 (figures are at 99.9 percent, gross of EL).

We can see that the results are of a comparable magnitude. To get data more close to the Basel 2 ones, we would need to know which transition

Table 16.5 Corporate spreads

Rating	1 year	2 year	3 year	5 year	7 year	10 year	30 year
Aaa/AAA	5	10	15	22	27	30	55
Aa1/AA+	10	15	20	32	37	40	60
Aa2/AA	15	25	30	37	44	50	65
Aa3/AA-	20	30	35	45	53	55	70
A1/A+	30	40	45	58	62	65	79
A2/A	40	50	57	65	71	75	90
A3/A-	50	65	79	85	82	88	108
Baa1/BBB+	60	75	90	97	100	107	127
Baa2/BBB	65	80	88	95	126	149	175
Baa3/BBB-	75	90	105	112	116	121	146
Ba1/BB+	85	100	115	124	130	133	168
Ba2/BB	290	290	265	240	265	210	235
Ba3/BB-	320	395	420	370	320	290	300
B1/B+	500	525	600	425	425	375	450
B2/B	525	550	600	500	450	450	725
B3/B-	725	800	775	800	750	775	850
Caa/CCC	1,500	1,600	1,550	1,400	1,300	1,375	1,500

matrix and which spreads they used. However, the mechanics of the default and MTM views of capital needed are correctly illustrated.

The multi-factor, MTM case

One additional possible refinement is to use a multi-factor VAR model. Up to now, companies were supposed to be sensitive to a single common factor representing the global economy. As we saw in Chapter 15, critics from the industry felt that this did not recognize fully diversification and concentration. Using a credit VAR model instead of the formula allows us to take into account concentrations on single counterparties. But we should also integrate concentrations on specific industries or countries. The models used by the banks are usually multi-factor models where we do not have a single return for systemic risk, but a return for each specific sector, for instance (automobile, construction ...). Correlation for companies belonging to the same industry occurs as before (the total return is composed for one part of the industry return and the other part is company-specific). Correlation between companies in different industries occurs because the returns generated for each sector are correlated. One may use stock returns of different industries to get an estimate of the intensity of the correlation. For three

Table 16.6 A stylized transition matrix

(%)	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa	D
Aaa	88.8	5.8	3.3	0.7	0.8	0.4	0.2	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.01
Aa1	2.6	76.9	9.0	8.2	2.7	0.2	0.0	0.2	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.02
Aa2	0.6	2.6	80.3	9.5	4.5	1.2	0.8	0.2	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.03
Aa3	0.1	0.4	3.0	80.1	10.7	4.0	0.9	0.1	0.3	0.2	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.04
A1	0.0	0.1	0.7	4.6	81.8	7.5	3.0	0.7	0.2	0.2	0.4	0.4	0.1	0.2	0.0	0.0	0.0	0.05
A2	0.0	0.0	0.2	0.7	5.7	80.9	7.6	3.2	0.8	0.3	0.2	0.1	0.1	0.0	0.1	0.0	0.0	0.06
A3	0.0	0.1	0.0	0.2	1.6	9.0	75.4	6.8	3.9	1.5	0.5	0.2	0.3	0.4	0.0	0.0	0.0	0.07
Baa1	0.1	0.0	0.1	0.1	0.2	3.3	8.9	73.4	8.0	3.2	1.0	0.4	0.5	0.6	0.1	0.0	0.0	0.18
Baa2	0.0	0.1	0.2	0.2	0.1	1.0	3.8	8.0	74.0	7.9	2.0	0.4	0.7	0.4	0.5	0.3	0.0	0.34
Baa3	0.0	0.0	0.0	0.1	0.3	0.6	0.5	4.4	10.6	69.3	7.0	3.1	2.0	0.9	0.3	0.1	0.1	0.72
Ba1	0.1	0.0	0.0	0.0	0.2	0.1	0.7	0.9	3.0	6.7	75.0	4.9	4.1	0.8	1.4	1.0	0.1	0.91
Ba2	0.0	0.0	0.0	0.0	0.0	0.2	0.1	0.3	0.5	2.4	8.0	73.5	6.2	1.4	4.2	1.8	0.3	1.15
Ba3	0.0	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.2	0.8	2.5	5.0	76.0	2.7	6.2	2.6	0.5	2.68
B1	0.0	0.0	0.0	0.0	0.1	0.1	0.2	0.1	0.3	0.4	0.4	2.7	6.5	77.4	1.6	5.4	1.0	3.95
B2	0.0	0.0	0.1	0.0	0.2	0.0	0.1	0.2	0.1	0.0	0.3	2.1	3.7	5.8	67.7	8.0	2.8	9.07
B3	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.2	0.2	0.2	0.3	1.5	5.0	2.5	71.7	4.3	13.84
Caa	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.7	0.9	0.0	2.4	2.4	1.5	2.9	57.6	30.87

Table 16.7 Comparison between the Basel 2 formula and the credit VAR MTM results

Rating	PD	Method	1 year (%)	3 years (%)	5 years (%)
A	0.06	Basel 2	1.06	2.02	2.99
		Credit VAR	0.95	2.08	3.17
		Δ	-11.6	2.9	5.7
BBB	0.34	Basel 2	3.50	5.21	6.93
		Credit VAR	3.69	5.97	7.67
		Δ	5.1	12.7	9.6
BB	1.15	Basel 2	6.74	8.78	10.83
		Credit VAR	6.35	10.06	13.18
		Δ	-6.1	12.7	17.8

companies *A*, *B*, and *C*, *A*, and *B* belonging to sector 1 and *C* belongs to sector 2; the returns will be modelled as follows:

$$\begin{aligned}
 Ra &= \alpha_a s R_{sector1} + \sqrt{1 - \alpha_a^2} s Rsa \\
 Rb &= \alpha_b s R_{sector1} + \sqrt{1 - \alpha_b^2} s Rsb \\
 Rc &= \alpha_c s R_{sector2} + \sqrt{1 - \alpha_c^2} s Rsc
 \end{aligned}
 \tag{16.4}$$

The correlation between the two companies will then be:

$$\rho_{A,B} = \rho_{sector\ 1,sector\ 2} \alpha_a \alpha_b
 \tag{16.5}$$

For companies belonging to the same sector, this will simplify to $\alpha_a \alpha_b$. The generation of correlated random numbers is usually done through the Cholesky decomposition (see, for instance J.P. Morgan/Reuters, 1996 for description).

The hardest issue with MTM multi-factor models is to estimate correctly the correlation between the various sectors ($\rho_{sector\ i,sector\ j}$ in (16.5)) and the so-called "loading factor," which means the dependence on the sector returns (α in (16.5)). The estimation of the volatility of the default rates is hard to perform because we need to have enough default data for each sector. The correlation is then usually estimated through equity returns used as a proxy for asset returns. Some banks even decompose asset returns into more than two parts. International companies that are diversified in several sectors may be modeled as having one part of the return explained by the return on the automobile sector, one part explained by the computer sector, and one part specific to the company. The problem as we decompose returns into more than two parts is again to estimate which weight-setting to use on each part (one can use the percentage of turnover in each sector, for instance). Evaluating the correlation between two companies if the returns of each are spread over three different sectors is not straightforward.

The multi-factor MTM model is implemented in the workbook file “Chapter 16 – 5 multifactor MTM simulation tool.xls.”

To illustrate the effect of sector concentration, we used a correlation matrix set at 30 percent for inter-sector correlation, and a loading factor of 50 percent. The PD was 0.34 percent, the LGD 45 percent, and the average life three years. We tested two portfolios, one with 1,000 counterparties belonging to 10 sectors in equal proportions (10 sectors of 100 companies) and the other portfolio with 300 companies in a single sector and 700 others over seven other sectors (7×100). The results are shown in Table 16.8.

Table 16.8 VAR comparison between various sector concentrations

Portfolio of 100,000 EUR, 0.34% PD, LGD 45%, 3 years, loading 50%	VAR 99.9 (%)
100 exposures \times 10 sectors	2.78
300 exposures in 1 sector and 700 exposures in 7 sectors (7×100)	3.20
Δ	15.1

We can see that, in this example, the concentration on one specific sector increases capital requirements by 15.1 percent.

Other developments

We will leave the development of our credit VAR model here. However, several additional refinements may be added to get closer to reality:

- LGD could be modeled as *stochastic* (we would then have to choose the correct distribution: normal, beta, gamma ...).
- In addition to *volatility*, LGD may be correlated to the default rates generated in each scenario (which seems to be shown by some empirical studies – that are, however, contested by part of the industry). That is the reason why regulators require that the LGDs used for Basel 2 must be stressed LGDs reflecting economic downturn conditions.
- The *link between the group of companies* may be modeled: when a mother company defaults in a simulation, the probability that its subsidiary also defaults could be higher.
- *Country risk* may be incorporated by simulating the potential defaults of countries that could be affected by transfer risk (see Chapter 17, p. 249).

- *Collateral* may be integrated separately from LGDs, and its value modeled as stochastic and correlated between the various types (real estate, financial collateral ...).
- *Guarantees* may be added and double default may be simulated in a more objective way than simply by replacing the PD of the borrower by the PD of the guarantor (the substitution approach of Basel 2) ...

Of course, each additional refinement is made at the expense of clarity, and challenges the calibration issue. We have to admit that a model integrating all those features would be hard to interpret (in terms of identifying which of the many variables were the main risk drivers that needed to be managed).

CONCLUSIONS

In this chapter, we have seen that the Basel 2 formula can be extended in a simulation framework to take concentration into account. A single-factor, default-mode model takes into account the increased default risk due to concentration. A single-factor MTM model integrates the risk due to rating migrations and can be used with an asset correlation consistent with the Basel 2 formula, which can then be a basis for discussion with the regulators as it integrates the concentration risk on single counterparties while remaining completely coherent with the Basel 2 formula and its parameters. Finally, a multi-factor MTM model helped us to see how concentration in some industries could be quantified.

Of course, credit VAR models rely on several hard-to-prove estimations, and key parameters such as correlation and PDs are only a best guess. Results of such models should thus be interpreted with care and should be considered only as “help decision tools,” and not decision tools. It is, for instance, so hazardous to calibrate an MTM multi-factor model correctly that it should be used only to detect material concentrations. For instance, one should not try to optimize the risk of the portfolio by rebalancing it from a sector that has an average correlation with the rest of the portfolio of 33 percent to a sector having an average correlation of 25 percent, as the margin of error on those results may be quite important.

Integrating Other Kinds of Risk

INTRODUCTION

In this chapter, we discuss the integration of other kinds of risks in capital measurement.

Integrating all the material risks that face a bank in a coherent and well-articulated framework is the basic idea behind pillar 2, it is also the practice of most advanced banks in the industry for several years, where it is called “economic capital” (EC) frameworks. We introduced the concept of economic capital earlier (pp. 211–12), and defined it as the capital that a bank considers as necessary to protect it against what it has identified as its material risks using its in-house measurement systems.

Of course, the first and most important way to manage risks is to have a set of efficient procedures and guidelines to drive the risk-taking, risk-identification, risk-measurement, and risk-reporting processes. But in this chapter we shall focus mainly on the quantification of risks.

We shall not see in this chapter how to build an extended economic capital model, as that would need a whole book in itself (the credit VAR models described in Chapters 15 and 16 are often a part of an economic capital model to measure credit risk), but we shall discuss briefly the different kinds of risks and possible measurement and aggregation techniques.

IDENTIFYING MATERIAL RISKS

The first step in building an economic capital framework is then to identify what may be the *most relevant risks*. We can gain an initial idea by: looking at

risk taken in Basel 2, and looking at risks mentioned in the annual reports of large banks that have an economic capital approach. We have made a small benchmarking study on ten banks using annual reports from 2004, and we present the results for each risk type here.

Credit risk

Credit risk is, of course, the main risk for most banks, and was the first one treated in the Basel 1 Accord.

Credit risk is usually divided into three kinds:

- *Counterparty risk*: the risk associated with the decrease in quality of a counterparty on which the bank has exposures.
- *Country risk*: the risk linked to direct exposures on countries and the transfer risk (the risk that if a country defaults, local companies may be prevented from making international payments in foreign currencies).
- *Settlement risk*: the risk linked to transactions that are not made Delivery Versus Payment (DVP), which means that the bank may pay a counterparty and fail to receive the corresponding settlement in return.

The foundation of credit-risk quantification is to have well-articulated *rating* and *scoring* processes. Classifying borrowers in ratings grades to assess their PD, and evaluating the collateral and guarantees that may mitigate the risks, provide the basic inputs for portfolio credit risk measurement. Evaluating exposure at default is also a delicate issue, especially for market-driven exposures. At the time a deal is concluded (for instance, an interest rate swap), the market value is always zero. Of course, it may increase significantly over the following years as market rates fluctuate. Advanced banks then usually have simulation models that evaluate the maximum potential exposures and expected exposures, taking into account the correlation between all their positions.

The current state-of-the-art techniques to measure and manage credit risk involve the use of credit portfolio models. We have seen credit VAR models congruent with the Basel 2 formula, but there are also other approaches. In fact, there are four leading types of models: the Moody's KMV model, the Creditmetrics model, the Credit Risk+ model and the McKinsey model. KMV and Creditmetrics are based on the Merton principles and are the market leaders (see Smithson *et al.*, 2002). CreditRisk+ was created by Credit Suisse First Boston (CSFB) and is derived from actuarial science (it is thus used more by insurance companies). The McKinsey integrates explicitly macroeconomic variables and tries to measure their influence on default risk.

The next challenge for the regulators is to determine the basic principles that a model should follow to be recognized for computing regulatory capital, which will be one of the main issues for Basel 3. Table 17.1 shows some leading companies' benchmarking results for measuring credit risk with different methodologies.

We can see that credit risk usually consumes more than the half of the economic capital and is measured through unexpected loss quantification at a given confidence interval and over a one-year horizon (typically with the use of credit VAR models).

Market risk

Table 17.2 shows some leading companies' benchmarking results for measuring market risk with different methodologies.

We can see that market risk management is applied on both the trading book (which was the scope of the 1996 Market Risk Amendment) and on the banking book (see interest rate risk below).

Market risk for the trading book is usually measured with market VAR systems that are regularly back-tested. However, all banks recognize that VAR models can identify risks only under normal market conditions, and then usually complement them with stress scenarios analysis. Scenarios can be hypothetical, building on managers' views of plausible events, or historical (e.g. the stock market crash of 1987, the bond market crash of 1994, the emerging markets' crises of 1997, the financial markets' crisis of 1998, the WTC attacks of 2001 ...).

Economic capital is measured by transforming 99 percent one-day VAR figures into annual and at the desired confidence interval numbers (which is straightforward if we suppose normality of the distribution).

Economic capital for market risk usually covers, in addition to the traditional market risk of the trading book, the interest rate risk of the banking book, behavioral risk (pre-payment on mortgages and withdrawals of deposits), liquidity risk, and sometimes the risks linked to pension schemes (as market rate movements may impact the value of pension schemes, which could force the bank to inject additional funds: this will be an issue of growing importance with the IAS 19 accounting norm).

Interest rate risk

The Basel Committee have issued a paper on interest rate risk ("Principles for the management and supervision of interest rate risk", Basel Committee on Banking Supervision, 2004b). This paper is inspired by earlier ones, but the new items discuss somewhat more deeply the management

Table 17.1 Benchmarking results: credit risk

Bank	Definition	Economic capital (%)	Measurement methodology
Commerzbank	Credit risk is the risk of losses or lost profits due to defaults (default or deterioration in creditworthiness) of counterparties and also the change in this risk ... Credit risk also covers country and issuer risk as well as counterparty risk and settlement risk	55	Credit VAR at 99.95% one year (target A+ rating)
JP Morgan Chase	Credit risk is the risk of loss from obligor or counterparty default	47	Unexpected loss drives the allocation of credit risk capital by portfolio segments ... Capital allocations are differentiated by risk rating, loss severity, maturity, correlations and assumed exposures at default ... The new approach employs estimates of default likelihood that are derived from market parameters and intended to capture the impact of both defaults and declines in market value due to credit deterioration
ING	Credit risk is the risk of loss from the default by debtors or counterparties	49	Internal rating methodologies, RAROC systems EC is the loss at 99.95% over a one-year horizon (Target rating AA)
Barclays	Credit risk is the risk that the Group's customers, clients, or counterparties will not be able or willing to pay interest, repay capital or otherwise to fulfill their contractual obligations under a loan agreement or other credit facilities ... Furthermore credit risk is manifested as country risk ... Settlement risk is another special form of credit risk.	62 (33 wholesale, 29 retail)	Internal rating system (12 rating levels) to assign PDs Measure of earnings volatility for portfolio unexpected loss at 99.95%

Continued

Table 17.1 Continued

Bank	Definition	Economic capital (%)	Measurement methodology
Fortis	Credit risk is the risk arising when a borrower or counterparty is no longer able to repay their debt This may be the result of inability to pay (insolvency) or of government restrictions on capital transfer... Three main potential sources of credit risk are: the counterparty risk, the transfer risk, and the settlement risk	51	VAR at 99.97%, one year
RBC Financial Group	Credit risk is the risk of loss due to a counterparty's inability to fulfill its payment obligations It also refers to a loss in market value due to the deterioration of a counterparty's financial position A counterparty may be an issuer, debtor, borrower, policy holder, reinsurer, or guarantor	34	Credit-scoring models (applicant scoring, behavioral scoring, internal rating approach) Economic capital (EC): retail capital rates are applied on exposures Loan Book, KMV portfolio model Trading book, CARMA portfolio model 99.95% for target AA rating (<i>Source</i> = presentation at a CIA seminar)
CSFB	Credit risk – the risk of loss from adverse changes in the creditworthiness of counterparties	n.a.	The position's economic risk capital (ERC) estimates and measures the unexpected loss, in economic value on the groups portfolio positions that is exceeded with a small probability: 0.03% for capital allocation (99.97% confidence for AA target rating), and 1% for risk management purposes

ABN Amro	<p>Credit risk relates to the risk of losses incurred when a counterparty that owes the bank money does not pay the interest, principal ...</p> <p>This also covers losses in value resulting from an increased probability of default</p> <p>Transfer and convertibility risk is also included</p>	61	<p>Extensive rating systems and rating tools</p> <p>Economic capital (EC) is the amount of capital that the bank should possess to be able to sustain larger than expected losses with a high degree of certainty</p>
CIBC	<p>Credit risk is defined as the risk of loss due to borrower or counterparty default</p>	n.a.	<p>Market-based techniques are used in the management of the credit risk component of EC</p> <p>It applies enhanced credit models to the analysis of the large corporate credit portfolios</p>
Citigroup	<p>Credit risk losses primarily result from a borrower's or counterparty's inability to meet its obligations</p>	58	<p>Credit exposures of derivative contracts are measured in terms of potential future exposures based on stressed simulations of market rates</p> <p>PDs are estimated through the use of statistical models, external ratings, or judgmental methodologies</p> <p>EC unexpected losses at 99.97% over a one-year horizon</p>

Note: n.a. = Not available.

Table 17.2 Benchmarking results: market risk

Bank	Definition	Economic capital (%)	Measurement methodology
Commerzbank	Market risk covers the potential negative change in value of the bank's positions as a result of changes in market prices – for instance, interest rates, currency and equity prices, or parameters which influence prices (volatilities, correlations)	27 (17 Equity holdings; 6 market risk banking book; 4 trading book)	VAR (historical VAR using 255 trading days data for general market risk, variance–covariance method for specific market risk, stress test of 200 bp parallel shift of interest rate for interest rate risk)
JP Morgan Chase	Market risk represents the potential loss in value of portfolios and financial instruments caused by adverse market movements in market variables, such as interest and foreign exchange rates, credit spreads, and equity and commodity prices	21	Statistical measures: VAR and Risk Identification For Large Exposures (RIFLE) = worst-case analysis Non-statistical measures: economic value stress tests, earnings at risk stress tests, sensitivity analysis
ING	Market risk arises from trading and non-trading activities: market-making, proprietary trading in fixed income, equities and foreign exchange ... Banking book products of which future cash flows depend on client behavior ...	27	Trading risk is measured with VAR and stress testing Non-trading interest rate risk is measured with an earnings at risk approach for a 200 bp interest rate shock
Barclays	Market risk is the risk that the group's earnings or capital, or its ability to meet business objectives, will be adversely affected by changes in the level of volatility of market rates or prices such as interest rates, credit spreads, foreign exchange rates, equity prices, and commodity prices Barclays also includes the risks associated with its pension scheme	5	Daily VAR (at 98%, historical simulation with two years' data), stress tests, annual earnings at risk (shock at 99%, one year as recommended in Basel 2) and EC

Fortis	Market risk is the risk of losses due to sharp fluctuations on the financial markets – in share prices, interest rates, exchange rates, or property prices	41 (3.3 trading risk; 37.4 ALM risk)	ALM risk is monitored through basis-point sensitivity, duration, earnings at risk, and VAR 99% (for calculation of EC, VAR figures are reworked because of a more severe interval, 99.97%)
RBC Financial Group	Market risk is the risk of loss that results from changes in interest rates, foreign exchange rates, equity prices, and commodity prices	13 (3 trading risk; 10 non trading risk)	Trading risk is measured with VAR 99% one-day VAR, sensitivity analysis and stress testing
CSFB	Market risk is the risk of loss arising from adverse changes in interest rates, foreign currency exchange rates, and other relevant market rates and prices such as commodity prices and volatilities	n.a.	VAR, scenario analysis, EC measurement
ABN Amro	Market risk is the risk that movements in financial market prices – such as foreign exchange interest rates, credit spreads, equities, and commodities – will change the value of the bank's portfolios	10	VAR (historical simulation using four years' of equally weighted historical data, 99%, one-day) complemented with stress tests and scenario analysis for trading risk ALM risk monitored through scenario analysis, interest rate gap analysis, and market value limits
CIBC	Market risk is defined as the potential for financial loss from adverse changes in underlying market factors, including interest and foreign exchange rates, credit spreads, and equity and commodity prices	n.a.	99% VAR with historical correlations and volatilities complemented with stress testing and scenario analysis Interest rate risk in the banking book includes embedded optionality in retail products (e.g. pre-payment risk)

Continued

Table 17.2 Continued

Bank	Definition	Economic capital (%)	Measurement methodology
Citigroup	Market risk losses arise from fluctuations in the market value of trading and non-trading positions, including changes in value resulting from fluctuations in rates	28	<p>Trading risk is measured with VAR, sensitivities analysis, and stress testing</p> <p>Citigroup VAR is based on volatilities and correlation of 250,000 market risk factors</p> <p>Risk capital is based on an annualised VAR with adjustments for intra-day trading activity</p> <p>Non-trading risk is measured with stress scenarios as 200 bp shock of interest rates, non-linear interest rate movements, analysis of portfolio duration, basis risk, spread risk, volatility risk, and close-to-close</p>

Note: n.a. = Not available.

of interest rate risk in the banking book. If we read between the lines, we can see that the Committee is also considering some sort of standard approach for quantifying capital due to interest rate risk in the coming years:

Even though the Committee is not currently proposing mandatory capital charges specifically for interest rate risk in the banking book, all banks must have enough capital to support the risk they incur, including those arising from interest rate risk ... The Committee will continue to review the possible desirability of more standardised measures and may, at a later stage, revisit its approach in this area ... As part of a sound management, banks translate the level of interest rate risk they undertake, whether as part of their trading or non-trading activities, into their overall evaluation of capital adequacy, although there is no general agreement on the methodologies to be used in this process. In cases where banks undertake significant interest rate risk in the course of their business strategy, a substantial amount of capital should be allocated specifically to support this risk.

The Committee identifies four main kinds of interest rate risk that need to be identified and managed:

- *Repricing risk*: This arises from the difference in maturities between assets, liabilities, and off-balance sheet items. For instance, if a five-year fixed-rate loan is funded through a short-term deposit, the evolution of short-term rates represents a risk for the bank margin.
- *Yield curve risk*: This concerns risks linked to changes in the slope and the shape of the yield curve. Changes in interest rates rarely consist of parallel shifts (the same shifts for all maturities). The curve may become steeper, or we may even have an inverse curve (short-term rates higher than long-term ones).
- *Basis risk*: This arises from imperfect correlation in the adjustment of rates earned and paid on different instruments with otherwise similar repricing characteristics. For instance, a one-year loan repriced monthly as a function of the short-term US treasury bill rate, funded through a one-year deposit repriced monthly on the basis of the one-month LIBOR exposes the bank to the risk that the spread between those two indexes may change.
- *Optionality*: This risk is becoming more and more important. It is the risk linked to the implied options given in many products. For instance, in several countries, mortgages can be pre-paid without penalties. This leaves the bank vulnerable to unexpected interest rate positions. Non-maturing liabilities such as current accounts and deposits are also carrying options, as their holders have the right to withdraw funds at any time.

The effects of interest rate risks are often considered from two points of view: their impact on *earnings*, and their impact on *economic value*. The earnings perspective looks at the impact that a shift of rate curves may have on short-term reported earnings. The economic value perspective is more comprehensive, as it tries to assess the impact of new rates on all assets, liabilities, and off-balance sheet items, even if this impact is not directly translated into the Profit & Loss account (P&L).

Interest rate risk is usually managed through the setting of limits on risk positions, and reports are made frequently to senior management up to the board of directors so that they can verify that the bank policies and procedures regarding interest rate risk management are being respected.

Although there is no standard method to measure interest risk, the common techniques can be classified into three groups:

- *Gap analysis*: One of the first methods developed, and still in use in many banks. It basically consists of classifying risk-sensitive assets and liabilities in various time bands to calculate a net position (assets minus liabilities), called the *gap*. This gap can be multiplied by the estimated change in interest rates to assess roughly the impact it may have on net income.
- *Duration*: This is similar to gap analysis, but is more refined, as the sensitivity of the change in economic value is estimated through the duration of each asset and liability.
- *Simulation approach*: This is used in large banks as it can handle more complex products and is more comprehensive (gap and duration techniques focus mainly on repricing risk). These simulations typically involve detailed assessments of the potential effects of changes in interest rates on earnings and economic value by simulating the future path of interest rates and their impact on cash flows. These can be static simulations, where cash flows are estimated only as a function of the current on- and off-balance sheet positions, or dynamic simulations that integrate hypotheses about the changes in bank activity as a function of any new rates.

As we have seen in Table 17.2, the interest rate risk of the banking book is usually treated within the global market risk framework. Banks usually report that they manage this risk through VAR, scenario analysis, gap analysis, and earning at risk methodologies. One of the main requirements of the regulators is that a parallel shift of the interest rate curve representing a standard shock (for instance, 200 bp) should not translate into a decline of economic value of more than 20 percent of Tier 1 and Tier 2 capital (for instance, Commerzbank reports that a 200 bp shock would translate in a 7.4 percent fall in its capital base).

Operational risk

This is covered by Basel 2. Operational risk is identified and quantified by most banks having an economic capital approach. They tend to use internal simulation approaches, but the scarcity of data is still an issue. The Basel 2 Accord is undoubtedly encouraging many banks to set up internal operational loss databases to collect operational loss events, and in the near future data pooling initiatives will make the advanced approaches more easy to reach (Table 17.3).

We can see from Table 17.3 that most of the large banks want to use the AMA approach proposed for Basel 2, and will then base their economic capital quantification on VAR simulations using historical data (internal and external), complemented by self-assessment and scorecard approaches.

Strategic risk

We mention this risk as it was listed in a Consultative Paper of the Committee of European Banking Supervisors (CEBS) (see CEBS, 2005) as one of the risks that should be covered in pillar 2. It is defined as the

current or prospective risk to earnings and capital arising from changes in the business environment and from adverse business decisions, improper implementation of decisions or lack of responsiveness to changes in the business environment.

From our experience, and as we can see in our benchmarking study, we did not encounter banks specifically quantifying such a risk. However, strategic risk was clearly mentioned by some banks (Table 17.4).

We can see that three out of the ten banks mention strategic or strategy risk, and it remains mainly a qualitative issue. The problem is that, with such a definition, strategic risk seems to be a risk linked to wrong strategic decisions (or the absence of timely decisions) of top management. Most banks would consider that sufficient support and attention was already being given to strategic issues, as these are the more important decisions a bank must take.

Reputation risk

This is also extracted from the CEBS paper (2005) and is defined thus:

Reputation risk is the current or prospective risk to earnings and capital arising from adverse perception of the image of the financial institution by customers, counterparties, shareholders/investors, or regulators (Table 17.5).

Table 17.3 Benchmarking results: operational risk

Bank	Definition	Economic capital (%)	Measurement methodology
Commerzbank	Operational risk is the risk of losses through inadequate or defective systems and processes, human or technical failures, or external events (such as systems breakdowns or fire damage) It also includes legal risk	13	Advanced Measurement Approach (AMA) at 99.95% (= operational VAR) based on internal data (operational losses above 5,000 EUR recorded) and external loss data from the Operational Riskdata eXchange (ORX) association + SA for benchmarking
JP Morgan Chase	Operational risk is the risk of loss resulting from inadequate or failed processes or systems, human factors, or external events	13	Capital is allocated to the business lines on a bottom-up basis The model is based on actual losses and potential scenario based stress losses, with adjustments to the capital calculation to reflect changes in the quality of the control environment and with a potential offset for the use of risk-transfer products
ING	The risk of direct or indirect loss resulting from inadequate or failed internal processes, people, and systems, or from external events	12	EC for operational risk consists of two parts The first is a probabilistic model in which a general capital-per-business unit is calculated based on an incident loss database and the relative size and inherent risk of the business units The second part is the scorecard adjustment, which reflects the business unit-specific level of ORM implementation

Barclays	Operational risks and losses can result from fraud, errors by employees, failure to properly document transactions, or to obtain proper internal authorization, failure to comply with regulatory requirements and Conduct of Business rules, equipment failures, natural disasters or the failure of external systems	7	The AMA approach targeted at Basel 2 Scenario analysis and self-assessments are currently used An external database of public risk events is used to assist in risk identification and assessment
Fortis	Operational risk covers both business risk (losses due to changes in the structural and/or competitive environment) and event risk (losses due to non-recurring events such as errors or omissions, system failures, crime, legal proceedings, or damage to building or equipment	8.7 (operational + business + insurance risk)	The AMA approach targeted at Basel 2 Fortis is a co-founder of ORX
RBC Financial Group	Operational risk is the risk of direct or indirect loss resulting from inadequate or failed processes, technology, and human performance, or from external events	13	Risk and control self-assessment (RCSA), Loss event database (LED) and key risk indicators (KRIs)
CSFB	Operational risk is the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events	n.a.	Loss over a one-year horizon that is exceeded by a 0.03% probability Determined using a combination of quantitative tools and senior management judgment

Continued

Table 17.3 Continued

Bank	Definition	Economic capital (%)	Measurement methodology
ABN Amro	Risk of losses resulting from inadequate or failed internal processes, human behavior and systems, or from external events This risk includes operational risk events such as IT problems, shortcomings in organizational structure, lapses in internal controls, human errors, fraud, and external threats	17	Risk self-assessments, corporate loss database, external loss database (ORX), KRIs ... The AMA approach targeted at Basel 2
CIBC	Operational risk is the risk resulting from inadequate or failed processes or systems, human factors, or external events	n.a.	The AMA approach targeted at Basel 2: it uses historical loss information, supplemented by scenario analysis, to produce loss events frequencies, and severities
Citigroup	Operational risk results from inadequate or failed internal processes, people, systems, or from external events It includes reputation and franchise risk	14	Risk capital is calculated based on an estimate of the operational loss potential for each major line of business, adjusted for the quality of its control environment

Note: n.a. = Not available.

Table 17.4 Benchmarking results: strategic risk

Bank	Definition	Economic capital (%)	Monitoring methodology
Commerzbank	Risk of negative developments in results stemming from previous or future fundamental business policy decisions	Not explicitly quantified	As it is not possible to model these risks with the aid of mathematical–statistical methods, this type of risk is subject to qualitative control Responsibility for the strategic steering of Commerzbank lies with the board of managing directors ... constant observation of German and international competitors ... appropriate measures for ensuring competitiveness
JP Morgan Chase	Not mentioned	Not explicitly quantified	Not mentioned
ING	Not mentioned	Not explicitly quantified	Not mentioned
Barclays	The group devotes substantial management and planning resources to the development of strategic plans for organic growth and identification of possible acquisitions, supported by substantial expenditures to generate growth in customer business If these strategic plans do not meet with success, the group's earnings could grow more slowly or even decline	Not explicitly quantified	Not mentioned
Fortis	Not mentioned	Not explicitly quantified	Not mentioned

Continued

Table 17.4 Continued

Bank	Definition	Economic capital (%)	Monitoring methodology
RBC Financial Group	Mentioned but not among the "controllable risks"	Not explicitly quantified	Not mentioned
CSFB	Strategy risk is the risk that the business activities are not responsive to changes in industry trends	Not explicitly quantified	At CSFB, strategic risk management is an independent function headed by business units' chief risk officers with responsibility for assessing the overall risk profile of the business unit on a consolidated basis and for recommending corrective action if necessary.
ABN Amro	Not mentioned	Not explicitly quantified	Not mentioned
CIBC	Not mentioned	Not explicitly quantified	Not mentioned
Citigroup	Not mentioned	Not explicitly quantified	Not mentioned

Table 17.5 Benchmarking results: reputational risk

Bank	Definition	Economic capital (%)	Monitoring methodology
Commerzbank	Risk of losses, falling revenues, or a reduction in the bank's market value on account of business occurrences, which erode the confidence of the public, rating agencies, investors, or business associates in the bank Reputational risks may result from other types of risk, or may arise alongside them	Not explicitly quantified	Reputational risk may result in particular from wrong handling of other risk categories The basis for avoiding it is therefore sound risk control ... in addition Commerzbank avoids transactions which entail extreme tax, legal, or environmental risk ... Observance of international laws is monitored through compliance ... avoidance of conflicts of interest and insider trading ...
JP Morgan Chase	Attention to reputation has always been a key aspect of the firm's practices, and maintenance of reputation is the responsibility of everyone at the firm	Not explicitly quantified	Code of conduct, training, policies, and oversight functions that approve transactions These oversight functions include a Conflict Office, which examines wholesale transactions with the potential to create conflicts of interest for the firm The firm has an additional structure to address certain transactions with clients, especially complex derivatives and structured finance transactions that have the potential to adversely affect its reputation
ING	Not mentioned	Not explicitly quantified	Not mentioned
Barclays	Not mentioned	Not explicitly quantified	Not mentioned

Continued

Table 17.5 Continued

Bank	Definition	Economic capital (%)	Monitoring methodology
Fortis	Not mentioned	Not explicitly quantified	Not mentioned
RBC Financial Group	Mentioned but not among the "controllable risks"	Not explicitly quantified	Not mentioned
CSFB	Reputation risk is the risk that the group's market or service image may decline	Not explicitly quantified	Not mentioned
ABN Amro	Not mentioned	Not explicitly quantified	Not mentioned
CIBC	Mentioned in the operational risk section	Not explicitly quantified	Enhancing the management of reputation and legal risk continues to be a focus and is overseen by the Financial Transactions Oversight Committee, which was established in 2004
Citigroup	Not mentioned	Not explicitly quantified	Not mentioned

Again, we found very little comment on reputation risk, which was mentioned in only three annual reports. It is not quantified and is managed through qualitative measures such as the setting up of transactional committees that verify that complex transactions do not bear excessive risks (legal, environmental ...). Particular attention is also devoted to the avoidance of conflicts of interests.

Business risk

Business risk is usually defined as the risk of too low a profitability of certain business lines (decrease of margins, higher fixed cost ...). In the CEBS paper (2005) it is called "Earnings risk" (Table 17.6).

We can see from Table 17.6 that business risk is said to be managed in most of the banks in the study. The classical method that is used to quantify capital is to use a volatility model for the P&L to stress costs and revenues and to see if the activity line remains profitable. The most delicate issue is the need to take care about *double counting*: the elements taken into account should not be already integrated in other risk measures (for instance, losses on credits should be removed as they are already integrated in the credit risk). In fact, as it is a risk measured with the P&L, we could consider that it covers all the risks that have not been taken into account by other models, because all those risks should have an impact on the P&L (of course, this supposes that the P&L reflects economic reality, which we concede is quite a hazardous hypothesis). Some banks consider then that business risk covers the strategic risk mentioned by the CEBS paper (2005). The British Bankers Association (BBA) mentioned in one of its comments on the CEBS paper that "strategic and earnings risk can be combined in a business risk definition as both risks relate primarily to earnings risk or risk to net operating profit." We could even consider that reputation risk is also covered if the bank has already experienced events that might have put it under pressure to maintain its reputation.

Liquidity risk

Table 17.7 shows the results of our study.

We can see from Table 17.7 that liquidity risk is generally not translated into economic capital requirements, or is sometimes already integrated into other risk types. The main tools used to manage liquidity are usually liquidity ratios (short-term assets:short-term liabilities, for instance), keeping a large portfolio of liquid assets, and contingency plans to respond to stress scenarios.

Table 17.6 Benchmarking results: business risk

Bank	Definition	Economic capital (%)	Measurement methodology
Commerzbank	Unexpected negative developments in results, which may be due to unforeseeable changes in business volume or the margin situation on accounts of changed overall conditions such as the market environment, customers' behavior, or technological developments	5	Business risk is worked out using an earnings/cost – volatility model based on the historical monthly deviation of the actual from the planned result for the fee income (99.95%, one-year)
JP Morgan Chase	The risk associated with volatility in the firm's earnings (ineffective design of business strategies, volatile economic or financial market activity, changing clients' expectations and demands, restructuring to adjust to the competitive environment) due to factors not captured by other parts of its economic capital framework	5	Capital is allocated based on historical revenue volatility and measures of fixed and variable expenses Earnings volatility arising from other risk factors such as credit, market or operational risk is excluded from the measurement of business risk capital as those factors are captured under their respective risk capital model
ING	Business risk is used to cover unexpected losses that may arise as a result of changes in margins, volumes, and costs Business risk can be seen as a result of management strategy (strategic risk) and internal efficiency (cost-efficiency risk)	12	n.a.
Barclays	Business risk is the risk of an adverse impact resulting from a weak competitive position or from poor choice of strategy, markets, products, activities, or structures Major potential sources of business risk include: revenue volatility due to factors outside our control; inflexible cost structures; uncompetitive products or pricing; and structural inefficiencies	5	n.a.

Fortis	Change in business volumes/changes in margins and costs Changes in the structural and/or competitive environment	Business + operational = 9	n.a.
RBC Financial Group	Risk of loss due to variances in volume, price, and cost caused by competitive forces, regulatory changes, reputational, and strategic risk (primarily uncontrollable risks)	8	A factor determined annually applied against annualized gross revenues to arrive at EC for business risk
CSFB	Business risk is the risk that businesses are not able to cover their ongoing expenses with ongoing income subsequent to a severe crisis, excluding expense and income items already captured by the other risk categories	n.a.	Given the lack of consensus regarding the EC needs to cover business risk ... Group's business risk ERC estimates are designed to measure the potential difference between expenses and revenues in a severe market event, excluding the elements captured by position risk ERC and operational risk ERC, using conservative assumptions regarding the earnings capacity and the ability to reduce the cost base in a crisis situation
ABN Amro	Business risk is the risk that operating profit may decrease because of lower revenues – for example, due to lower margins or market downturns – or an increase in costs, which are not covered by the other risk types	12	Business risk is calculated by estimating the volatility of net revenues while taking account of the bank cost structure
CIBC		Not mentioned	
Citigroup		Not mentioned	

Note: n.a. = Not available.

Table 17.7 Benchmarking results: liquidity risk

Bank	Definition	Economic capital (%)	Monitoring methodology
Commerzbank	<p>Liquidity risk is the risk of the bank not being able to meet its current and future payment commitments, or of not being able to do so on time (solvency or refinancing risk)</p> <p>In addition, the risk that market liquidity (market liquidity risk) will prevent the bank from selling trading positions at short notice or hedging them plays an important role in risk management</p>	Not explicitly quantified	<p>Use of supervisory method that weights liquid assets available within thirty days to cover weighted payment during this period</p> <p>In 2004, this ratio ranged from 1.13 to 1.19</p> <p>This is complemented by an internal approach, the Available Net Liquidity (ANL), that computes legal and economic cash flows, both for balance sheet and off-balance sheet items, including expected customers' behavior</p> <p>The ratio is calculated daily and liquidity limits are set-up</p>
JP Morgan Chase	Liquidity risk arises from the general funding needs of the firm's activities and in the management of its assets and liabilities	Not explicitly quantified	<p>The three primary measures are: the holding company short-term positions (measures the ability of the holding company to repay all obligations with a maturity less than one year in time of stress), cash capital surplus (measures the firm's ability to fund assets on a fully collateralized basis, assuming that access to unsecured funding is lost), and basic surplus (measures the ability to sustain a ninety-day stress event assuming that no new funding can be raised)</p> <p>A stress scenario of a downgrade of one to two notches of the rating is also used</p>
ING	Liquidity risk is the risk that the bank cannot meet its financial liabilities when they come due, at reasonable costs, and in a timely manner	Not explicitly quantified	Strategies used to manage liquidity are: monitoring of day-to-day liquidity needs, maintaining an adequate mix of sources of funding, maintaining a broad

<p>Barclays</p>	<p>Liquidity risk is the risk that the group is unable to meet its payment obligations when they fall due and to replace funds when they are withdrawn</p>	<p>Not explicitly quantified</p>	<p>Monitoring of day-to-day liquidity needs, maintaining a strong presence in global money markets, maintaining a large portfolio of highly marketable assets, maintaining the capability to monitor intra-day liquidity needs</p> <p>Cash flows over the next day, week, and month are projected and submitted to stress scenarios</p>	<p>portfolio of highly marketable securities, having an up-to-date contingency funding plan</p>
<p>Fortis</p>	<p>A project aimed at improving the management of liquidity risk was launched in 2004.</p> <p>The basic principles of the Fortis group-wide liquidity risk have now be defined, and all Fortis companies will further define or adjust their current liquidity policy taking into account these basic principles and their respective needs and regulations</p>	<p>EC for liquidity risk is not calculated separately but is embedded in the other risk types</p>	<p>Liquidity risk is managed dynamically, and exposures are continuously measured, monitored, and mitigated</p> <p>A cash capital model is used to assist in the evaluation of balance sheet liquidity and in the determination of the appropriate term structure of their debt financing</p>	<p></p>
<p>RBC Financial Group</p>	<p>Liquidity risk is the risk that we are unable to generate or obtain sufficient cash or equivalents on a cost effective basis</p>	<p>Not explicitly quantified</p>	<p>Credit Suisse Group manages its funding requirements based on business needs, regulatory requirements, rating agency criteria, tax, capital, liquidity, and other considerations</p> <p>This is mainly managed through diversifications of liabilities and investors' relations, and through the use of contingency plans</p>	<p></p>
<p>CSFB</p>	<p>Liquidity and funding risks are the risk that the group or one of its businesses is unable to fund assets or meet obligations at a reasonable or, in case of extreme market disruptions, at any price</p>	<p></p>	<p></p>	<p></p>

Table 17.7 Continued

Bank	Definition	Economic capital (%)	Monitoring methodology
ABN Amro	Liquidity risk arises in any bank's general funding of its activities For example, a bank may be unable to fund its portfolio of assets at appropriate maturities and rates, or may find itself unable to liquidate a position in a timely manner at a reasonable price	Not explicitly quantified	Liquidity is managed on a daily basis As each national market is unique in terms of scope and depth, competitive environment, products, and customer profiles, the local management is responsible for managing local liquidity
CIBC	Liquidity risk is the risk of having insufficient cash resources to meet current financial obligations without raising funds at unfavorable prices or selling assets on a forced basis	Not mentioned	Limits are established on net cash outflows in both Canadian dollars and foreign currencies, and minimum liquid asset inventories and guidelines are set to ensure adequate diversification of funds Daily monitoring of both actual and anticipated inflows and outflows of funds are generated from both on- and off-balance sheet exposures Liquidity contingency plans exist for responding to stress events A pool of highly liquid assets is maintained
Citigroup	Liquidity risk is the risk that some entity, in some location and in some currency, may be unable to meet a financial commitment to a customer, creditor, or investor when due	Included in market risk	Each principal operating subsidiary must prepare an annual funding liquidity plan Liquidity limits, liquidity ratios, markets triggers, and assumptions for periodic stress test are established and approved

Other risks

We end this review by looking at other types of risk sometimes mentioned in annual reports (Table 17.8).

We can see from Table 17.8 that the risks that can be found most often are insurance risk (for banking groups that also run insurance businesses), legal risk, and capital risk.

In the CEBS paper (2005), capital risk is defined as:

an inadequate composition of own funds for the scale and business of the institution or difficulties for the institution to raise additional capital, especially if this needs to be done quickly or at a time when market conditions are unfavourable.

In banks, the management of capital risk seems to be more focused on maintaining a good balance between having a capital buffer to be able to finance growth opportunities and insuring the rating, and having a capital structure that is not too costly (as debt financing is much cheaper).

What is somewhat surprising is the fixed-assets risk at RBC, as it represents 28 percent of their economic capital consumption. They consider a planned amortization schedule of fixed assets (real estate, computers, activated software development costs ...) as the expected loss, and then compute any potential deviation as the unexpected loss (economic capital). Capital is attributed by looking at share prices of firms that invest heavily in those assets. Goodwill is covered by 100 percent of equity.

In fact, the possible difference (but this is our hypothesis) with other banks that do not explicitly set up economic capital reserves for fixed-asset risk is that banks usually treat this at the level of the available equity, as it is usually considered on a net basis (goodwill and intangibles are deducted), as in the regulatory definition. However, the impact is that the weight of goodwill and intangibles is shared by all businesses in the bank, while they may be linked, for instance, to an acquisition in a particular business line. Then, considering available capital on a gross basis and charging 100 percent of economic capital for goodwill located in specific business lines may be an interesting approach ...

Summary

To summarize, Table 17.9 describes all the risks encountered in annual reports, and states their frequency.

We can see from Table 17.9 that credit risk, market risk, operational risk, interest rate risk, and liquidity risk are mentioned in all the reports. The Basel 2 documentation covers the three first of these and quantification techniques are relatively standard (VAR approaches complemented by other tools such as stress scenarios). Interest rate risk and liquidity risk are also quantified

Table 17.8 Benchmarking results: other risk

Bank	Risk	Definition
Commerzbank	Legal risk	Included in operational risk The legal department has to monitor potential legal risk at an early stage
JP Morgan Chase	Private equity risk	For listed and unlisted equities in the private equity portfolio VAR is considered as not a sufficient risk measurement tool because of the low liquidity of these exposures Additional reviews are undertaken
	Fiduciary risk	Included in reputation risk The bank wants to ensure that businesses providing investment or risk management products or services pay attention to delivering sufficient disclosures, communications, and performances to meet clients' expectations
ING	Insurance risk	Currently not really measured in terms of EC methodologies but covered with a formula that should give a conservative estimate of what it might be
Barclays	Legal risk Capital risk	Risk of legal proceedings against the group Capital risk management aims at maintaining a sufficient capital level to maintain the group rating and to be able to finance its growth
	Regulatory and compliance risk	Arises from the failure or inability to comply with laws, regulations, and codes

Fortis	Insurance risk	Underwriting risk relates to the risk inherent in the insurance activities (variations in mortality for life products, variability of future claims for non-life products)
RBC Financial Group	Insurance risk Fixed-assets risk	Risk inherent in the design and underwriting of insurance policies Risk that the values of those assets (including goodwill and intangibles) will be less than their net book value at a future date (28% of EC)
CSFB	Insurance risk	Risk that products pricing and reserves do not appropriately cover claims' expectations
ABN Amro	n.a.	
CIBC	Legal risk Capital risk	Included in operational risk Management of capital resources (mainly preferred shares and subordinated debts) The goal is to balance the need to be well capitalized with a cost-effective capital structure
Citigroup	Environmental risk n.a.	Integrated in credit risk, with credit policies, guidelines, and environmental risk management standards in place covering lending to SME and corporate

Note: n.a. = Not available.

Table 17.9 Summary of benchmarking study

Risk type	% Mentioned in annual reports	Mentioned in CEBS paper (2005)
Credit risk	100	Yes
Market risk	100	Yes
Interest rate risk	100	Yes
Operational risk	100	Yes
Strategic risk	40	Yes
Reputation risk	50	Yes
Business risk	80	(Called earning risk)
Liquidity risk	100	Yes
Legal risk	30	Included in operational risk
Insurance risk	40	No
Capital risk	20	Yes
Private equity risk, fixed-assets risk, fiduciary risk, environmental risk	10 (once)	No

and managed but techniques are less standard, and the regulators did not consider that they could be translated into a formal capital requirement in the new Accord.

Business risk is mentioned in 80 percent of the reports, and is often presented in the banks' annual reports as one of the categories of the economic capital split.

Other types of risks are mentioned at a maximum 50 percent of the time, and we investigated only the annual reports of the large international banks. This seems to show that there is still work needed in terms of risk definition and classification.

QUANTIFICATION AND AGGREGATION

The list of the various risk types that may be quantified is important. However, as shown above, they do not all translate into formal capital requirements. Some are managed qualitatively.

For those that are subject to quantitative measurement, banks that want to implement an economic capital approach have to determine two key risk dimensions: the *time horizon* and the *confidence interval*.

The time horizon is the period used to compute capital requirements. For instance, will the bank estimate the capital needed to cover the losses of its credit portfolio over the next six months, over the next year, over the next five years ...? There is no single good answer to this question. In fact, we

might consider that it should correspond to the time period necessary for the bank to react, which means to identify that it is living in a stress period and to take corrective action (decreasing risk exposures, increasing capital ...). In practice, most banks work with a time horizon of one year. This is the period used for regulatory capital, and is usually the horizon of the budgets, and it should be enough to respond to crises. However, we may also find arguments in favor of both shorter and longer time spans.

The confidence interval (CI) is the degree of confidence that will be used in all statistical measurements of economic capital: $(1 - \text{this interval})$ will in fact correspond to the probability that the capital will not be sufficient to cover the losses. The classical way to determine the interval is usually first to fix what is the *target rating* of the bank (a strategic issue that should be decided by the board). Then, looking at the historical default rates published by rating agencies, the CI can be inferred. This is illustrated in Table 17.10.

Table 17.10 Determination of the confidence interval

Rating	1 year PD (%)	Confidence interval (%)
AAA	0.01	99.99
AA+	0.02	99.98
AA	0.03	99.97
AA-	0.04	99.96
A+	0.05	99.95
A	0.06	99.94
A-	0.07	99.93
BBB+	0.18	99.82
BBB	0.25	99.75
BBB-	0.65	99.35
BB+	0.90	99.10
BB	1.15	98.85
BB-	2.68	97.32
B+	3.95	96.05
B	9.07	90.93
B-	13.84	86.16
CCC	23.61	76.39

Finally, when the risks have been identified, and quantified at a given time horizon and CI, we have to *aggregate* them. This is probably the most difficult task as there are very few data to calibrate this step.

First, some banks simply add up the various risk measures. That is what is done in Basel 2. Of course, simply adding stand-alone risk measures involves

the hypothesis that all the risks are perfectly correlated (stressed losses on the credit portfolio will occur the same year as stressed operational risk losses ...). This is obviously unrealistic.

Other banks try to integrate some *diversification effects*. To do this, we need to know what the shapes are of the distributions of the various loss functions (credit, market, operational ...). Credit loss distributions are heavily skewed, market risk distributions are more bell-shaped (more close to the normal distribution), and there is little consensus about the shape of the operational loss distribution (it might indeed be specific to each bank). For other risk types, it is even more obscure.

Having agreed on the distribution shape, we need to use historical data to measure the correlation between the distributions and aggregate them using techniques such as *copulas*. Copulas are a hot topic in finance: they basically allow us to link univariate margins to the full multivariate distributions (we then have a function that is the joint distribution of N standard uniform random variables). We shall not go into the details of this rather technical field, but interested readers can easily find documentation on the Internet (see, for instance, the GRO website of Credit Lyonnais that has good papers on the subject www.gro.creditlyonnais.fr). We shall just mention the fact that because of unavailability of the data, the use of copulas for economic capital is a nice tool but one that cannot really be calibrated (as there may be many different copulas that might fit the very scarce data that banks may have).

A simpler technique is the use of *variance-covariance matrixes*. This technique uses a simple formula well known in finance (in portfolio theory or in market risk, for instance):

$$UL_{A+B} = \sqrt{UL_A^2 + UL_B^2 + 2\rho_{AB}UL_AUL_B} \quad (17.1)$$

With this formula, we make the implied hypothesis that the various distributions have the same shape. We know that this is not the case, and the results may well also be an under-estimation or an over-estimation of the reality, but without a lot of data it is often better to do things in a simple way.

But even with this formula, we have to estimate the *correlation level* between the various risk types. There are almost no data to do this, as banks have often not identified their historical losses by risk category. Even in the literature we find very few references. We have to use our brains and a conservative bias.

The correlation between credit risk and market risk may depend on the historical time period we consider. If we compare historical default rates with interest rates for the last twenty years, for instance, we may find a negative correlation: in periods of stress, the central banks decreased interest rates to help the economy while bankruptcies were numerous. If we look

at the 1970s, the huge inflation caused both increasing rates and a lot of bankruptcies; the correlation was then positive.

Operational risk is of a different nature from the other financial risks, and we may suppose a low correlation.

A conservative correlation matrix might then be like that shown in Table 17.11.

Table 17.11 Correlation matrix: ranges

Correl. matrix	Credit risk (%)	Market risk (%)	Operational risk (%)	Business risk (%)
Credit risk	100			
Market risk	50–100	100		
Operational risk	0–50	0–50	100	
Other risks	30–70	30–70	0–50	100

The ranges are important, but is hard to get more precise estimates. For instance, a bank that had 100 EUR of unexpected loss in each risk type (credit, market, operational, and business), and that assumed a 50 percent correlation between credit risk and market risk, and a 40 percent correlation in all other cases would end with a capital requirement of 300 EUR (see the worksheet file “Chapter 17 –1 Risk aggregation.xls”). The diversification benefit is then 25 percent, which is not negligible.

TYPICAL CAPITAL COMPOSITION

If we look at the way banks communicate their economic capital approaches, we find that risks are often grouped in three–five categories. Using the results of our benchmarking study, we can show a typical split of the economic capital allocation between various risk types, using an average (excluding the minimum and maximum observed values) (Figure 17.1).

Figure 17.1 confirms that credit risk is the main concern. Then comes market risk, which usually includes interest rate risk. Note that market risk in the banking book is much higher than market risk in the trading book, which is the scope of the VAR models approved by the regulators. For instance, average VAR for interest rate risk at CIBC in 2004 was 4.4 million CAD for the trading book and 42.4 million CAD for the banking book. At Commerzbank, the economic capital allocated to the market risk for the banking book is 50 percent higher than that for the trading book.

Operational risk and business risk usually range between 5 percent and 15 percent of the global amount. Operational risk has received increased focus thanks to Basel 2, and business risk seems to be a rather generic

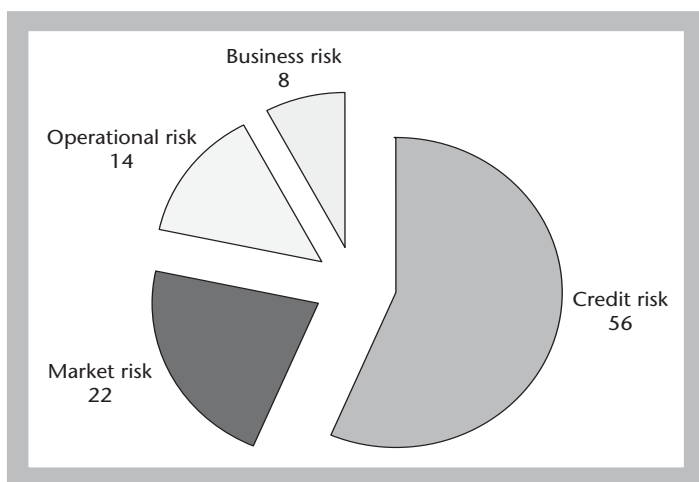


Figure 17.1 A stylized bank economic capital split, percent

category that allows banks to integrate all the rest (as it is often based on a P&L volatility model, it can be assumed to capture the other risks).

CONCLUSIONS

The conclusion is that the old vision of the dual credit–market risk analysis is being eroded. Advanced banks explicitly consider many more risks (we found fifteen types of risk in the annual reports of our ten surveyed banks), even apart from the operational risk introduced by Basel 2. Some types of risks are shared by all (operational risk, business risk ...), others are more specific (environmental risk, private equity risk ...). We have to pay attention to the fact that if a bank does not mention a given risk in its annual report, it does not mean that it is not managed, or even quantified. Banks usually summarize their economic capital allocation in four or five types of risk for communication purposes, but the internal segmentation is more granular.

We can see that there is still a need for some standardization of definitions and measurement approaches for certain risk types, but clearly the industry is moving forward on this issue, as disclosures in annual reports are increasingly detailed.

Aggregation of the various risk types in a single final economic capital figure is one of the more delicate issues, as there are few data on the correlation between the various risk types: even the shape of the distribution is an open question. We have mentioned the copulas that have received increased focus in the industry for such issues, and we have illustrated in our Excel

workbook files the variance–covariance method that still seems to be the standard. Finally, we have illustrated the typical split of economic capital figures, using data from annual reports.

Economic capital approaches will certainly gain increased focus when banks try to meet the pillar 2 requirements. Although it is still a discipline where much has to be done, we have tried to show that we can find some common denominators and common practices between what is being done by the leading financial institutions.

Conclusions

OVERVIEW OF THE BOOK

We have seen that banks are subject to heavy regulation because they play a vital role in modern economies, and that banking failures are not such rare (and are certainly not impossible) events.

After a (limited) overview of banking regulation and bank failures, Part 1 summarized the 1988 current banking regulation (Basel 1). The Market Risk Amendment was briefly discussed after having been introduced in its historical context. The strengths and weaknesses of Basel 1 regulation were then discussed to highlight the need for a revision of the Accord.

In Part 2, we first gave a global overview of the structure of the new Basel 2 Accord. Then we went into greater detail concerning the requirements of the core Basel text and of its update of July 2005. The basic mechanics were explained, and illustrated with examples, and the potential impacts of Basel 2 discussed in light of the QIS 3 results.

Part 3 was dedicated to the operational implementation of Basel 2. After a few words on IT architectures, we discussed in detail the construction of scoring models and illustrated theory with practical examples. The quantification of LGD was also discussed, and the various possible estimation methods presented.

Part 4 was dedicated to an in-depth study of the Basel 2 formula. The rationale behind it was explained; the original model was examined and implemented in a workbook file environment. The possible future of Basel 2 was discussed as being the full recognition of internal models for risk quantification, and credit value at risk models were presented. Finally, global economic capital frameworks were introduced and some of the many remaining challenges examined.

THE FUTURE

Basel 2 is a tremendous improvement on Basel 1. Nearly twenty years after the 1988 regulation, market developments, product innovations, and quantitative research advances on the credit risk side have made the original rules totally out of date.

Basel 2 offers many opportunities, in the sense that the regulatory requirements are much more closely aligned to the economic capital approaches that are becoming one of the key dimensions for performance measurement, resources allocation, and products pricing in many banks. The end of the 1988 rough weighting scheme can only be welcomed by the industry.

But the Basel 2 reform creates many challenges. First, most sophisticated banks consider that it does not go far enough: they will still have to manage two parallel systems – the regulatory one and the internal (economic) one.

Although, for the vast majority of financial institutions, simply complying with Basel 2 will be made only at the price of tremendous effort and investment in upgrading their risk management systems and capabilities, and this should ultimately benefit everybody.

Today, credit risk quantification and measurement tools are well developed and easily accessible. But secondary credit markets are still quite limited in the sense that they are concentrated on some large investment banks acting as market-makers, and liquid risk-transfer tools are limited in terms of the scope of borrowers (usually large corporate names). There is clearly an ongoing requirement in terms of data collection (to calibrate models), standardization of the quantification tools, and education of investors and less advanced financial institutions if we want secondary credit markets to become both more deep and more liquid. Regarding this long-term perspective, the requirements that Basel 2 impose on the whole industry will clearly be a catalyst to reach this goal.

It is clearly stated in the Basel 2 text that this reform has to be seen as only a point on the continuum towards a more advanced recognition of banks' internal models. We have seen that if we look at the key risk parameters to estimate credit risk – PD, LGD, EAD, Maturity and Correlation – banks using the IRBA are already authorized to estimate for themselves all but correlation. There is one obstacle before full internal model recognition (which already exists for market risk and operational risk) can occur. The approval of internal credit VAR models (complemented with stress tests and using a suite of qualitative and quantitative requirements) is the most likely next development (it is a topic already being discussed among regulators in the groups preparing Basel 3).

Over a longer horizon, the same trend should be followed for all kinds of risk. For instance, when we discussed the interest rate risk of the banking book, we mentioned a regulators' paper which clearly stated that no formal capital requirement had been imposed in Basel 2 because of a lack

of consensus on the quantification approach, but that it was their goal to reach a common method.

If one message should be retained from this book, it is that banks that can leverage the investments made for Basel 2 to work on their in-house credit VAR and holistic economic capital models will have an important competitive advantage regarding both markets and regulatory expected developments over the next twenty years.

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Index

- adjusted exposure 54
 - in case of netting 57
- arbitrage (of capital) 33–4
- asset returns 219–20
 - normalized asset returns 220
- back-testing sample 174
- Basel 1 18, 19, 20–1
- Basel 2
 - consultative papers (CP) 39
 - formulas 219–23
 - goals 39–40
 - innovations 47–8
 - IRB 58–63
 - solvency ratios 44
 - standardized approach 50–7
 - time table 47
- Basel 3 211–12
- bilateral netting (in Basel 1) 20–1
- concentration risk (in Basel 2 formula) 235, 237–8
- confidence interval (in Basel 2 formula) 222
- correlation
 - estimation procedure (of asset correlation) 223–8
 - factor in Basel 2 219, 223–30
 - of assets in Basel 2 59–61
 - of default rates 215–17, 224–8
 - of risk types in economic capital models 278–9
- correlation analysis
 - multivariate 177
 - of financial ratios 171–3
- coverage ratios 165–8
- credit crunch 143
- credit risk mitigation
 - in IRBA 62–3
 - in IRBF 62
 - in standardized approach 53
- credit VAR model (MTM) 232
 - loading factor 245
 - multi-factor MTM 245–6
 - one factor – default mode 238–40
 - one factor – MTM 240–3
- crisis
 - Barings 14
 - Black Monday 12
 - Bretton Woods 7–8
 - Continental Illinois 11
 - deregulation 9
 - disintermediation 9
 - great depression 6
 - Herstatt 8
 - Japanese crisis 14–15
 - LTCB 15
 - Mexico 10
 - Norwegian crisis 13
 - paperwork crisis 25
 - Rumasa 10
 - savings and loans 9–10, 12
 - Swedish crisis 13–14
 - Swiss crisis 14
- critics (of Basel 2 formula) 234
- currency mismatch
 - for collateral 57
 - for guarantee 57
- default dataset 147–8
- default mode 231

- default type 148
- Delivery Versus Payment (DVP in Basel 2) 87–8
- derivatives (in Basel 1) 19–20
- distance to default (for portfolio credit risk) 218
 - standardized distance to default 221
- diversification (in Basel 2 formula) 235
- double default 40, 82–5
- double gearing 42

- EAD 63
 - CCF (in standardized approach for measurement of market-driven deals) 80
 - CCF (in Basel 1) 20
 - CCF (in standardized approach) 52
 - Current Exposure Method (CEM) 79
 - Expected Exposure (EE) 76–9
 - Expected Positive Exposure (EPE) 76–9
 - for market-driven deals in Basel 2 76–82
 - Internal Models Method (IMM) 81–2
 - Potential Future Exposure (PFE) 76–9
 - standardized method (for EAD calculation) 79–81
- Easyreg 145, 174
- economic capital 211–12
- economic capital models (and pillar 2) 44, 248
 - aggregation of economic capital 277–9
 - confidence interval for economic capital 277
 - copulas 278
 - diversification 278
 - quantification of economic capital 276–7
 - variance–covariance matrix 278
- expected loss 233–4
- explanatory variables 148
- extreme values 152

- financial ratios 149–50
- fraction issues (for financial ratios) 153

- GAAP (and pillar 3) 96

- haircuts
 - internal 56
 - IRBF 62
 - regulatory 53–5
- holding period (minimum) 55

- ICAAP 90–3
- idiosyncratic risk 220

- IFRS (and pillar 3) 96
- incremental approach (for IT systems) 110–13
- integrated approach (for IT systems) 110–13

- joint default probability (JDP) 227

- Kondratief cycles 143

- leave-one-out process 176
- leverage ratios 163–5
- LGD
 - censoring data 191
 - correlation (with PD) 197
 - discount rate 192–4
 - implied LGD 189
 - market LGD 188–9
 - stressed 198–9
 - workout LGD 189–94
- limit system 237–8
- liquidity ratios 160–2
- logarithmic transformation (for size ratios) 151–2
- logistic regression 120, 128–9, 133–5
 - binary 133–4
 - ordered 125
 - ordinal 134–5

- Madrid compromise 106, 233
- market risk
 - general risk 28
 - Internal Models Approach 29–30
 - specific risk 28
 - standardized approach 28–9
 - VAR models 29–30
- Market Value Accounting (MVA) 96
- maturity adjustment 85, 231–3
- maturity mismatch 57
- Merton model (for portfolio credit risk) 217–19
- migration matrix 240
- missing values 152

- NGR 21

- off-balance (in Basel 1) 19
- one-factor simulation model
- operational risk
 - Advanced Measurement Approach (AMA) 75
 - Basic Indicator Approach (BIA) 73
 - Standardized Approach (SA) 73

- outliers 155
- overrulings (of ratings) 203
- past-due loans (in standardized approach) 52
- PFE 40–1
- point-in-time (rating system) 142–3
- portfolio approach (for credit risk) 214–17
- procyclicality 96, 99
- profitability ratios 155–60
- Public Sector Entity (PSE) 51
- purchased receivables 61
- quantification (of risk parameters) 201–2
- Quantitative Impact study 3 (QIS 3) 101–6
- rating dataset 146–7
- rating systems requirements 115–16
- ratings models construction 171, 174–5
 - backward selection 129
 - best-subset selection 129
 - calibration (of the PD) 129, 178–9
 - constrained expert models 118
 - decision trees 121
 - deterministic method 129
 - distance to default (for default prediction) 120
 - expert rating systems 118, 120–1
 - forward selection 128–9
 - gamblers' ruin 119–20
 - genetic algorithms 122
 - horizon 116
 - induction engine 121
 - likelihood function 134
 - logit model 120
 - Merton model (for default prediction) 120
 - monotonic relationship 128
 - Multivariate Discriminant Analysis (MDA) 119
 - neural networks 121–2
 - over-fitting 126, 131
 - overrides 116
 - probit model 120
 - qualitative assessment 179–81
 - qualitative scorecards 180–1
 - ratio selection (principles for) 130–3
 - ratio transformation 128
 - statistical models 117–18
 - stepwise selection 129
 - survivor bias 125–6, 147
 - univariate analysis 119, 127, 155–71
 - Z-score 119
- ratings models validation 175–7
 - Accuracy Ratio (AR) 140–2
 - confidence interval (for PD estimates) 183
 - correlation 137–9
 - cost function 138–9
 - Cumulative Notch Difference (CND) 139
 - economic performance measures 138
 - goodness-of-fit 137–8
 - graphical approach 139
 - G-test 136
 - hypothesis tests (for PD estimation) 182–7
 - low default portfolios 187
 - R^2 137
 - Receiver Operating Characteristic (ROC) 140–2
 - score test 137
 - Spearman rank correlation 139
 - statistical tests 136
 - type I and type II errors 138
 - Wald-test 137
- regulators
 - FDIC 6
 - FED 6
 - IMF 7
 - Office of the Comptroller of the Currency 6
 - SIPC 25
- regulatory texts
 - 1988 Basel Capital Accord 12–13
 - financial reconstruction law 15
 - Financial Service Act 12, 25
 - Glass–Steagall Act 7, 24
 - home country control 8
 - ILSA 10
 - liberalization of capital flows 12
 - Market Risk Amendment (1996) 27
 - National Banking Act 6
 - Second Banking Directive 13, 25
 - Securities Act 24
 - Securities Exchange Act 24
 - Single European Market 11–12
 - Treaty of Rome 7
 - Uniform Net Capital Rule 25
- risk parameters 58
- risk quantification
 - credit VAR models 249
 - duration 258
 - gap analysis 258
 - simulation approach (for interest rate risk) 258

- risk types
 - basis risk 258
 - business risk 267, 268–9
 - capital risk 273
 - counterparty risk 249
 - country risk 249
 - credit risk 249, 241–53
 - fixed asset risk 273
 - interest rate risk 250, 257–8
 - liquidity risk 267, 270–2
 - market risk 250, 254–6
 - operational risk 259, 260–2
 - optionality risk 257
 - repricing risk 257
 - reputational risk 259, 265–6, 267
 - settlement risk 249
 - strategic risk 259, 263–4
 - yield curve risk 257
- risk weights
 - Basel 1 18
 - Basel 2 – standardized approach 50
- sample selection 154–5
- scaling factor 41, 106
- securitization
 - arbitrage with 34–5
 - early amortization 67
 - eligible liquidity facility 66, 67
 - in Basel 2 63–73
 - investing banks 65
 - liquidity facility 71
 - originating banks 64
 - remote origination 35
 - supervisory formula (SF) 69
 - synthetic 64
 - traditional 64
- selection bias 168
- size variables 168–71
- sovereign (exposure type) 51
- sovereign ceiling effect 154
- specialized lending
 - definition 59
 - risk weights 60
- systematic risk 220
- through-the-cycle (rating system) 142–3
 - Tier 1 17–18
 - Tier 2 17–18
 - Tier 3 27
- too big to fail 16
- trading book 27
- trading book (in Basel 2) 86–7
- unexpected loss 233–4
- variance (of default rates) 217
- Vasicek, O.A. 217